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Is there a consensus trap in earnings forecasts?

An empirical study

Eirik Thune Øritsland

Supervisor: Adjunct Professor Thorsten Hens

Finance

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

This paper revisits Grüner (2009) and seeks to establish whether there is a consensus trap in earnings forecasts. There is a consensus trap if analysts' forecasts are more likely to be wrong when forecasts are homogeneous, than heterogeneous, all else equal. This hypothesis is tested by using a standardized measure of the forecast distribution to explain forecast errors. The empirical research is based upon earnings forecasts recorded on Thomson Reuters I/B/E/S Summary-Level Historical Earnings Estimates Database. Our results rejects that there is a consensus trap in earnings forecasts. The empirical research de facto shows evidence of a significant positive relationship between forecast errors and heterogeneity. Idiosyncratic risk in earnings is then offered as a mechanism explaining the findings, by showing that heterogeneity proxy idiosyncratic risk.

The paper contributes to the literature on forecast dispersion and systematic forecast errors. It also offers an empirical founded mechanism explaining why there should be a positive association between forecast errors and heterogeneity. As this research is based upon summary-level data, we would recommend subsequent researchers to examine detailed data.

Acknowledgements

This thesis is written as a part of my master degree in finance at the Norwegian School of Economics (NHH). Attending a behavioral finance course during my student exchange at Universitá Bocconi laid the pathway for this thesis, but the idea of examining the consensus trap was brought by Adjunct Professor Thorsten Hens to a discussion on behavioral finance topics.

The writing of this thesis has been a challenging and meaningful experience. I hope that my paper will contribute to the literature on systematic errors in forecasts and that it may inspire other researchers to examine this issue further.

There are several people who deserve a special thank you for contributing to the progress. Especially, I wish to thank my supervisor, Adjunct Professor Thorsten Hens, for his thorough feedback and inspiring attitude towards my work. I will also like to thank the University of Zürich, Adjunct Professor Thorsten Hens and his assistant, Elias Bräm, for providing me with data from Thomson Reuters I/B/E/S. Conducting such an extensive research would not have been possible without this dataset.

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1. Introduction

Analyst forecasts have been discredited for decades. Cowles (1993) examines the ability of analysts to foretell elusive fluctuations and finds that the average forecasting agency is no better than performances achievable by pure chance. Ariely, Loewenstein and Prelec (2003) show that valuations are strongly influenced by anchoring, which is the use of irrelevant information as reference to estimate an unknown value. Misperceptions can also emerge from overoptimism. Bordalo, Gennaioli, La Porta and Shleifer (2017) show that analysts, as well as investors who follow them or think like them, extrapolate and make systematic errors of excessive optimism for stocks with rapidly growing earnings, and conversely for stocks with deteriorating earnings (Bordalo et al., 2017). An experiment in Törngren and Montgomery (2004) studies forecasts in two groups – experts and laypeople. The experiment reveals that there is overconfidence in expert judgments, meaning there are discrepancies between the experts' subjective probability estimates and relevant objective probabilities. The experiment also confirms the experts' poor ability to foretell, where only 40% were successful – a performance below what could be expected from chance alone (Törngren and Montgomery, 2004).

Grüner (2009) examines systematic behavioral errors and establish investment strategies exploiting them. More specifically, Grüner (2009) establishes investment strategies exploiting a hypothesis identified as a consensus trap – that homogeneous expert forecasts are more likely to be wrong than heterogeneous expert forecasts. This hypothesis is also examined and supported by Lammer (2012).

A consensus trap is not consistent with economic theory, which would implicate the opposite – that forecast disagreement should be positive associated with forecast errors. Heterogeneous forecasts would suggest that expected earnings are more uncertain and thus that forecast errors should increase, not decrease. The dataset examined in Grüner (2009) is obtained from Handelsblätt – a leading German newspaper. One weakness with the dataset is that it constitutes of only five years. Another weakness is that the dataset from where Grüner (2009) concludes that there is a consensus trap constitute of only 51 forecasts, which also raises questions to the findings. While Lammer (2012) accounts for these weaknesses, there are still weaknesses with the dataset that have not yet been accounted for. Lammer (2012) also studies a dataset from Handelsblätt, but, in addition, datasets from Sentix, the Economic Research Center of ETH Zürich and Yale School of Management are studied. Although Lammer (2012) supports the findings from Grüner (2009), robust findings can only be established in one dataset. In addition, datasets are obtained from surveys where only directions of the forecasts are included, causing unclear measurements. Consequently, a more reliable dataset should be examined.

Similar issues have already been studied in past research. Clement and Tse (2005) find that bold forecasts are better than forecasts that move away from past forecast and toward mean analysts' forecasts.[1] The paper suggests that forecasts that are revised towards the average and away from past forecast do not incorporate private information, but are revised only so that they reduce the deviation from consensus. This can be explained from findings in Hong, Kubik and Solomon (2000) – that less experienced sell-side analysts are easier discharged for bold forecasts. These findings are consistent with the findings in Grüner (2009) and can explain why homogeneous forecasts could have a higher forecast error than heterogeneous forecasts. Another interesting issue can be found in Diether, Malloy and Scherbina (2002) who show that shares with higher dispersion in earnings forecasts produce lower returns, and thus arguing that heterogeneity does not proxy for risk.[2] Johnson (2004) revisits Diether et al. (2002) and concludes that "this finding is important in that it directly links asset returns with a quantitative of an economic primitive – information about fundamentals – but the sign of the relationship is apparently wrong" (Johnson, 2004). The study further assumes that forecast dispersion is driven by information risk about earnings and purposes a theoretical mechanism in which expected equity returns for a levered firm decreases with such idiosyncratic risk (Johnson, 2004).

The purpose of this study, however, is to conduct an extensive empirical research, testing whether the hypothesis that the investment strategy purposed in Grüner (2009) is based upon holds, not the strategy per se.[3] Subsequently, an attempt to explain the conclusive relationship is made. This research methodology is not identical to the research methodology in Grüner

[1] Bold forecasts are forecasts above both the analyst's own past forecast and the consensus forecast, or else below both.

[2] Diether et al. (2002) show that dispersion is significant positive associated with earnings volatility, standard deviation of returns and market beta, but as a consequence of the negative association with cross-sectional returns conclude that heterogeneity does not proxy risk.

[3] This study examines earnings data, while Grüner (2009) examines return data.

(2009), and does not examine whether the investment strategy produces abnormal returns, only the hypothesis that the strategy is based upon.

This study is unique in the sense that it is the first to my knowledge to examine the effect of heterogeneous earnings forecasts on forecast errors using I/B/E/S data. The paper contributes to the existing literature on systematic forecast errors and more detailed research within forecast dispersion.

My first hypothesis (H_1) addresses the effect forecast dispersion has on forecast errors. Based on economic theory, I believe forecast dispersion to be positively associated with forecast errors. My second hypothesis (H_2) examines the association between heterogeneity and idiosyncratic risk, and seeks to establish an empirical explanation to the conclusion from H_1.

The proceeding sections of this thesis are structured as follows: Chapter 2 provides descriptive statistics and a detailed description on how we constructed the dataset. Chapter 3 specifies the methodology we use and the choice of variables. Chapter 4 presents the empirical findings from H_1, and robustness checks, before H_2 is presented and discussed in chapter 5. Finally, chapter 6 concludes this thesis.

2. Data processing and descriptive statistics

2.1 Data processing

Below we describe the measures used in the paper and, in parentheses, provide their mnemonics in the primary datasets.

From the Thomson Reuters I/B/E/S Summary-Level Historical Earnings Estimates Database we obtain mean analysts' forecasts for earnings per share (*meanest*), their standard deviation (*stdev*) and the actual earnings per share (*actual*) for the period January 1980 through January 2018.[4]

The I/B/E/S Summary History File consists of chronological snapshots of consensus level data taken on a monthly basis. The snapshots are as of the Thursday before the third Friday of every month. Summary Statistics contains one record for each forecast period for each Thomson Reuters statistical period. The forecast periods (*forpers*) represent the period end for which the forecasts were made for (in days) while the Thomson Reuters statistical period (*statpers*) is the date when the set of summary statistics was calculated. The forecast periods are thus obtained from the time distance between the I/B/E/S Announcement Dates of actual earnings per share (*anndats_act*) and the Thomson Reuters statistical period (*statpers*).[5]

There are, however, some issues with I/B/E/S Announcement Dates and the Thomson Reuters statistical period. The Thomson Reuters statistical period is the date when the set of summary statistics was entered into the database, not the date when the estimate was released by an analyst. Thus, there might be some unobservable information bias in the summary statistics. Acker and Duck (2009) found that 24% of the I/B/E/S announcement dates between January 1 1999 and December 31 2006 was misreported. Such discrepancies should however not affect the sampling, nor the conclusions of the findings. There are also estimates that are dated after the announcement date, but these observations are excluded from the dataset.

[4] Earnings per share will hereby be referred to as the abbreviation "eps".

[5] e.g. if the forecast is made for actual eps announced 13 January 2008 and calculated 13 October 2007, the forecast period is the number of days between the two dates.

The actual earnings per share are obtained from news services and company filings and adjusted by Thomson Reuters' market specialists to be comparable to the estimates made by analysts. I/B/E/S estimates are adjusted for stock splits in order to produce a smooth time series of earnings per share estimates. This means that earnings per share estimates reported January 1980 are reported with the number of shares in January 2018. Thomson Reuters market specialists also examine incoming data for extraordinary items, accounting changes, anomalies and inconsistencies so that estimates and actuals can be compared. In cases where a guidance follows a different accounting standard than the majority of the estimates, the guidance will be excluded (Thomson Reuters, 2013). There are also some issues with I/B/E/S Estimates that stems from data errors or other transitory factors, such as M&A activity, that are excluded from the dataset.

There must be at least one analyst making forecasts on the company to be included in the I/B/E/S history files. For this research, however, there must be at least two analysts (*numest*) making forecasts on the company to be included, as looking at summary data from only one analyst does not make sense for the purpose of this study.

The company filings are also sorted into industries defined by their Standard Industrial Classification code (*sic*) which is reported below.

Table 2.1: summary data distribution by Standard Industrial Classification code

Industry	Obs	*sic*
Agriculture, forestry and fishing	382	0100-0999
Mining	11,624	1000-1499
Construction	2,745	1500-1799
Manufacturing	103,569	2000-3999
Transportation, communication, electric, gas and sanitary services	28,531	4000-4999
Wholesale trade	4,824	5000-5199
Retail trade	18,194	5200-5999
Finance, insurance and real estate	32,952	6000-6799
Services	26,466	7000-8999
Public administration	975	9100-9729

"Agriculture, forestry, and fishing", "mining" and "construction", are in this study defined as one industry. "Services" and "public administration" are also defined as one industry. This is to avoid issues with small samples. The categorical *sic* variables serves as unit-specific terms that should be controlled for in longitudinal data.[6]

2.2 Descriptive statistics

Below we describe the observations used in the paper.

From the Thomson Reuters I/B/E/S Summary-Level Historical Earnings Estimates Database we obtain summary statistics from U.S. companies for the period January 1980 through January 2018. The summary statistics obtained are described in detail in the section above. Results are also crosschecked with a summary data sample with constituents of the Nikkei 225 Index, Deutscher Aktienindex, OBX Index and S&P UK Index. Table 2.2 reports the descriptive statistics for the U.S. summary data. The U.S. summary data constitute of companies listed on S&P 500.[7]

Table 2.2: descriptive statistics from U.S. summary data

This table shows the descriptive statistics from U.S. summary data. Variables are described under data processing (chapter 2.1) and empirical methodology (chapter 3.1).

Variable	Obs	Mean	St. Dev.	Min	Max
actual	230,262	1.729	2.878	-50.28	135.09
numest	230,262	15.45	8.303	2	56
medest	230,262	1.795	2.607	-38.13	116
meanest	230,262	1.796	2.603	-38.92	111.6
stdev	230,262	0.0966	0.294	0	28.34
dispers	230,262	0.0736	0.134	0	1.308
forerror	230,262	0.187	0.430	0	5.100
statpers	230,262	-	-	1/1/1980	1/1/2018
anndats_act	230,262	-	-	1/20/1980	1/18/2018
forpers	230,262	180.4	104.9	1	365

It is evident, from the table above, that the descriptive statistics for mean analysts' forecasts for earnings per share and median analysts' forecasts for earnings per share are more or less

[6] Standard Industrial Classification codes (*sic*, hereby referred to as sic codes) generates a unit-specific term for the pooled OLS regression model that is explained in chapter 3.1 and 4.2. Each company filings' classification is obtained from Thomson Reuters I/B/E/S Summary-Level Database.

[7] U.S. summary data also include constituents of Dow Jones Industrials and Nasdaq 100 that have not also been a constituent of the S&P 500.

undifferentiated. Thus, empirical evidence should be indifferent between these two measures. This research paper treats only mean analysts' forecast for earnings per share in the empirical study, but all findings are crosschecked with median analysts' forecast for earnings per share.

3. Empirical methodology and hypothesis

3.1 Empirical methodology

When examining the association between heterogeneity and forecast errors, we will in this study use a pooled OLS regression model. The methodology that we will use embeds a numeric measure of analysts' forecast disagreement, and controls for other sources to variation in forecast errors. The forecast error for earnings per share is given by:

$$forerror_{i,t} = \beta_0 + \beta_1 * dispers_{i,t} + \beta_2 * numest_{i,t} + \sum(\delta_3 * D_i^{sic}) + \sum(\delta_4 * D_t^{year}) + u_{i,t},$$

where subscript *i* denotes the company and subscript *t* denotes the statistical period.

The analysts' forecasts for earnings per share are defined as the mean analysts' forecasts for earnings per share, while the analysts' forecast error for earnings per share (*forerror*) is defined as the absolute relative distance between the mean analysts' forecasts and actual earnings per share:

$$forerror_{i,t} = \frac{|meanest_{i,t} - actual_{i,t}|}{|actual_{i,t}|}$$

Measuring relative forecast errors ensures that the effect from where high-earnings-per-share (high-eps) companies might have higher forecast errors are scaled, as it is reasonable to believe that forecast errors increase with the magnitude of earnings per share. Absolute values (modulus) ensure that negative and positive forecast errors are uniformly accounted for. Thus, this model does not distinguish between optimistic and pessimistic forecasts. Forecast errors, by the definition used in this study, can be interpreted as how many times the actual eps the mean analysts' forecasts misses.

The analysts' forecast dispersion for earnings per share (*dispers*) is defined as the cross-sectional standard deviation deflated by absolute actual earnings per share:

$$dispers_{i,t} = \frac{stdev_{i,t}}{|actual_{i,t}|}$$

Increasing disagreement between analysts about earnings forecasts are thus captured by a larger cross-sectional standard deviation. The cross-sectional standard deviation is deflated to adjust for disproportional impacts from where high-eps companies might have higher standard deviations than low-eps companies. Adjusting the cross-sectional standard deviation also give a more consistent relationship with the scaled forecast error. Here the standardization factor is also an absolute value so that negative dispersion is avoided.

Information is accumulated from company reports, and other sources of information, throughout the fiscal year. Companies release reports with information about periodic earnings related to each quarter, which means that forecasts issued before such reports are published are issued with less information available. Forecasts issued after such reports are published do not only incorporate more information from the company, but also have a lower risk for information shocks as the forecast period is shorter, thus leaving less room for information shocks before actual earnings are announced. Consequently, both the magnitude and dispersion of forecast errors are expected to diminish as the announcement date draws closer. The figures below confirm this information bias, which is controlled for by splitting the forecast periods into four lengths constituting of forecasts between 1-90 days, 91-180 days, 181-270 days and 271-365 days.

Figure 3.11: analysts' forecast dispersion over forecast periods

The figure shows the relationship between forecast dispersion and how many days before the announcement date the forecasts was calculated (forecast period). Each observation represents summary-level data from company *i* at statistical period *t*.

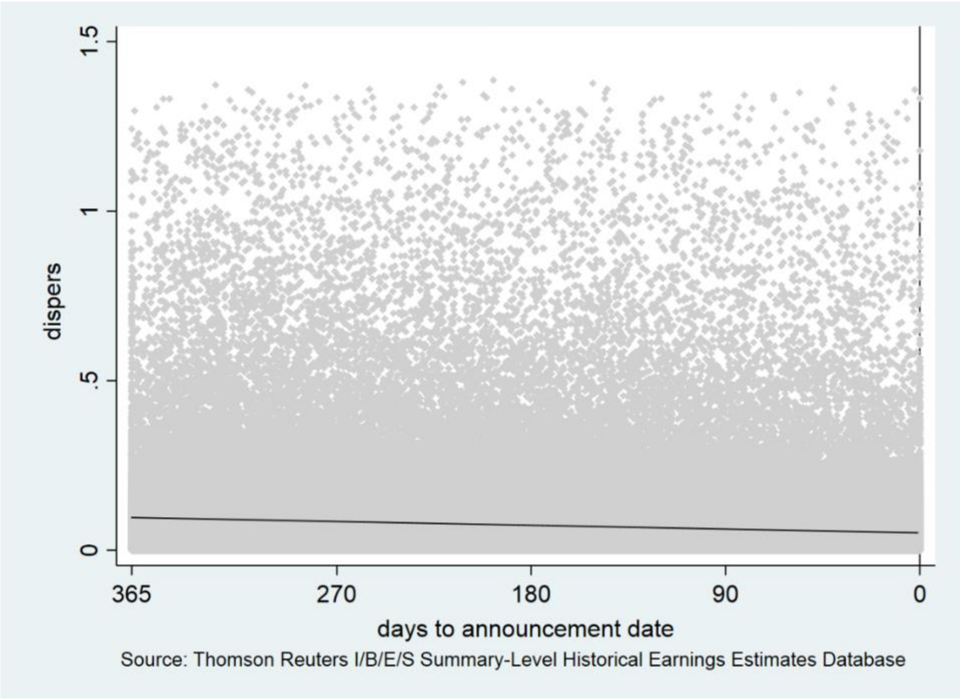
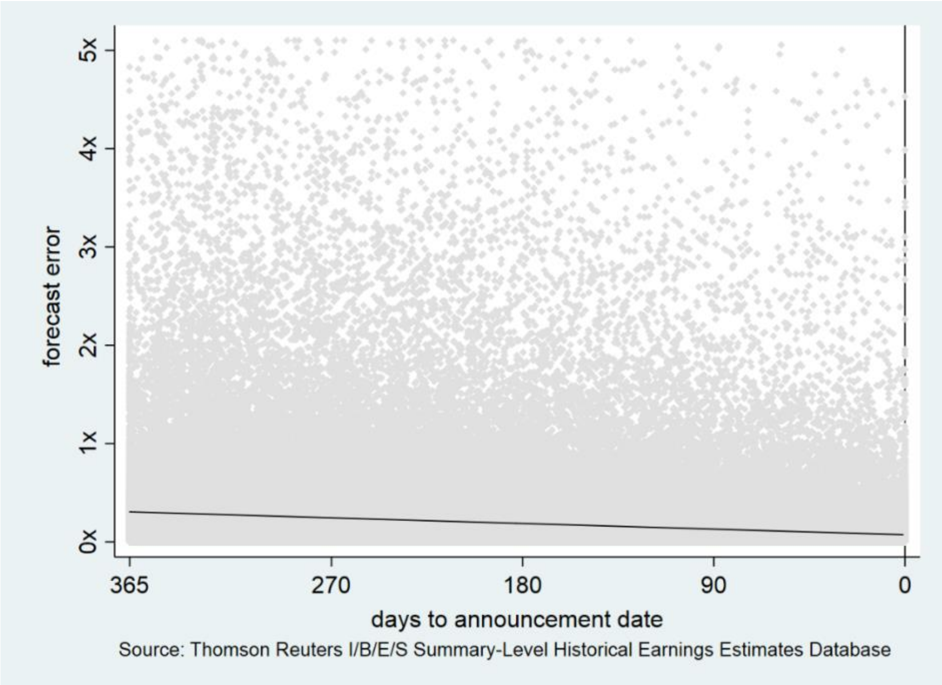


Figure 3.12: analysts' forecast error over forecast periods

The figure shows the relationship between forecast errors and how many days before the announcement date the forecasts was calculated. The y-axis reports how many times the actual eps the consensus estimate misses. Each observation represents summary-level data from company *i* at statistical period *t*.



To avoid issues with omitted variable bias, we have to control for other sources to changes in the analysts' forecast errors by including control variables.

Research from Alford and Berger (1999) conclude that the number of analysts making forecasts on a company (*numest* in our model) can explain the analysts' forecast errors, and argue that more analysts making forecasts on a company leads to more scrutiny and information. Thus, the number of individual forecasts that the summary-level data is comprised of, is controlled for in our model. The number of analysts making forecasts on a company can also proxy the omitted variable for market capitalization. Large cap companies have a larger number of analysts following their company.[8] Larger companies have relatively less optimistic bias, and start-ups are more prone to losses than mature companies because of the nature of their operations (Brown, 1997).

Espahbodi, H., Espahbodi, P., and Espahbodi, R. (2015) show that forecast errors and analysts' forecast dispersion have shifted over time between 1993 and 2013. The figures below show

[8] "cap" is an abbreviation that refers to the market capitalization.

the development in forecast errors and analysts' forecast dispersion between January 1980 and January 2018.

Figure 3.13: forecast errors between January 1980 and January 2018

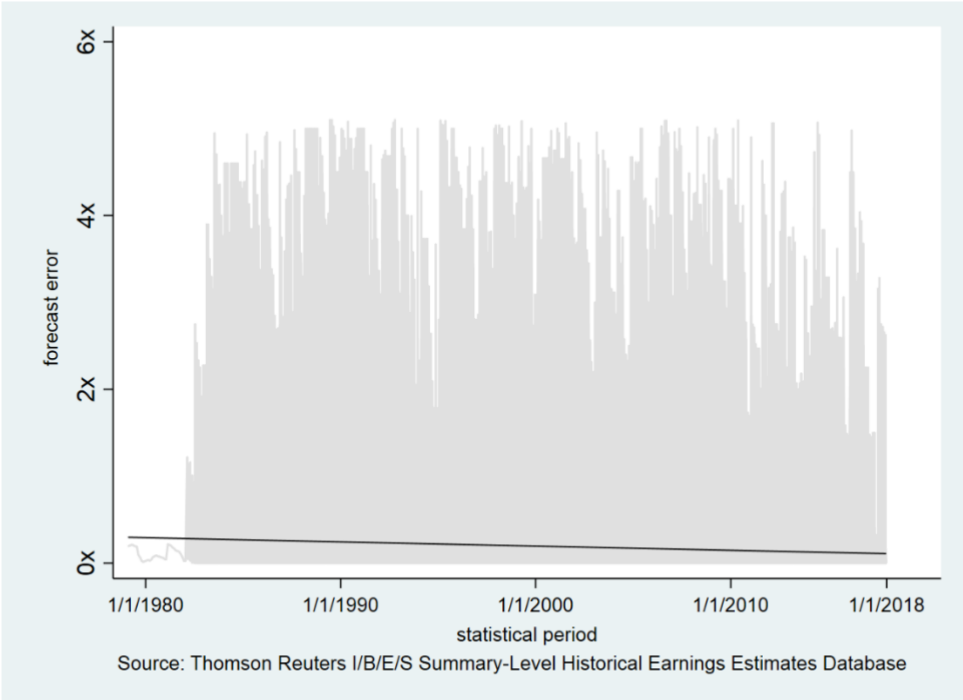
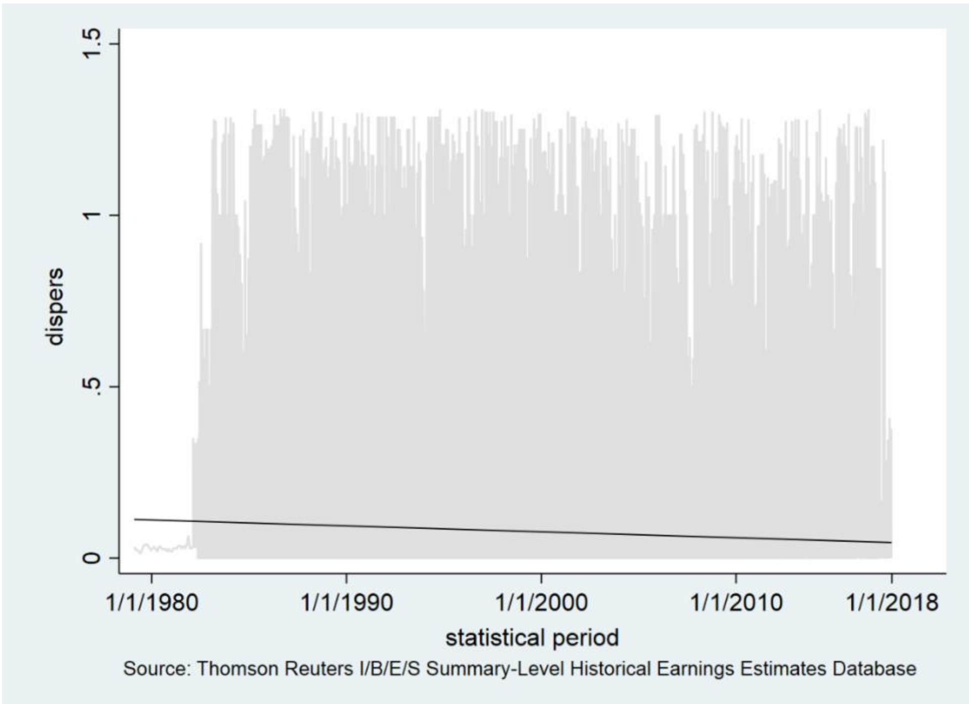


Figure 3.14: forecast dispersions between January 1980 and January 2018



The figures show significant shifts in forecast errors and analysts' forecast dispersion between January 1980 and January 2018. Ignoring this can lead to a spurious regression. Including a time trend variable in the regression model eliminates this problem. In this empirical study, shifts over time in forecast errors and analysts' forecast dispersion are controlled for with time-dummies taking the value 1 for observations within the subscripted period, 0 otherwise. Insignificant time-dummies are used as reference.

Deviations between forecasts and actuals that can be explained by the companies' operations are controlled for with categorical variables constructed by ranges of sic codes, which are defined in detail in the section above. In the regression output hereinafter, companies with sic codes between 0100 and 1799 are treated as a reference group.

There are also some additional variables that ideally should have been controlled for in the above regression model.

One variable that could have influence on forecast errors, but that has not been controlled for in this regression model, is the aggregate experience that each analyst obtain. Hong et al. (2000) document that less experienced sell-side analysts issue forecasts that are close to the mean analysts' forecasts. The paper argue that less experienced sell-side analysts are easier discharged for bold forecasts and thus issue forecasts near the mean analysts' forecasts. Combining these findings with the findings in Clement and Tse (2005) – that bold forecasts are better than forecasts that move away from past forecast and toward mean analysts' forecasts – we can conclude that more experienced sell-side analysts issue forecasts that are better. Consequently, the aggregate experience of the analysts following the company should ideally have been controlled for in this model.

Another important aspect of the recommendation environment is conflicts of interest within investment banks and with their clients. Corporate finance divisions complete transactions while equity research departments issue presumably unbiased information to their clients. One source of conflict lies in the compensation structure for equity research departments. Often, a significant share of compensations in equity research departments is determined by their contribution to the corporate finance division (Michaely and Womack, 2005). Thus, equity research departments have incentives to issue biased recommendations. Controlling for conflicts of interest is however difficult, as we in this study examine summary-level data and not detailed data about each individual forecast.

3.2 Hypothesis (H_1)

The objective of this paper is to test whether there is a consensus trap in earnings forecasts. There is a consensus trap when homogeneous forecasts have higher forecast errors than heterogeneous forecasts. Thus, the resulting hypothesis is that there is a significant negative relationship between forecast errors and their heterogeneity. Conversely, the resulting null hypothesis is that there is a significant positive, or not significant, association between forecast errors and their heterogeneity.

The forecast dispersion measures the heterogeneity, where an increased forecast dispersion can be interpreted as an increased disagreement between the analysts. Thus, if the evidence supports our alternative hypothesis – that there is a consensus trap in earnings forecasts – the slope coefficient explaining the association between forecast dispersion and forecast errors needs to be significant negative. Otherwise, if the slope coefficient explaining the association between forecast dispersion and forecast errors is positive, or not significantly different from zero, we cannot reject the null hypothesis that there is not a consensus trap in earnings forecasts.

4. Empirical evidence and robustness

4.1 Empirical evidence

This section presents the empirical evidence from the U.S. summary dataset using a pooled OLS regression. Rationales for using pooled OLS on panel data are discussed under robustness.

Table 4.1: regression results for forecast errors (pooled OLS estimation)

This table reports the regression coefficients from a regression of the forecast error on the forecast dispersion (*dispers*), controlling for operations (*sic*), number of analysts following the company (*numest*) and different time periods (*statpers*). Estimates from control variables are omitted from the regression table. The regression is performed on forecast periods (*forpers*) between 1-90, 91-180, 181-270 and 271-365 days.

Variable	*1<forpers<90*	*91<forpers<180*	*181<forpers<270*	*271<forpers<365*
dispers	1.270***	1.645***	1.974***	2.069***
	(0.0323)	(0.0332)	(0.0342)	(0.0344)
Constant	0.0415***	0.0222***	0.0305***	0.0584***
	(0.00652)	(0.00762)	(0.00920)	(0.0109)
Observations	57,751	57,222	56,572	58,717
R-squared	0.284	0.327	0.345	0.330

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The empirical evidence is remarkably supportive – there is not a consensus trap in earnings forecasts. From the pooled OLS estimation above, we cannot reject the null hypothesis that there is a significant positive, or not significant, relationship between forecast errors and their heterogeneity. A consensus trap in earnings forecasts would show that there is a negative relationship between the forecast errors and their heterogeneity, while the pooled OLS estimation shows the opposite – that the relationship between heterogeneity and forecast errors are positive significant for all forecast periods. The regression output show that an increased forecast dispersion can be associated with an increased forecast error, or conversely, that decreasing forecast dispersion leads to decreasing forecast errors. All the reported slope coefficients for forecast dispersion are significant on a 99% significance level.

We also observe that, for shorter forecast periods, the slope coefficients for analysts' forecast dispersion diminish. This can be explained by the public signals that the sell-side analysts absorb from company reports, and other sources of information, throughout the fiscal year. The company reports give directions to the sell-side analysts and, consequently, the forecasts are revised towards the direction the company is giving. Thus, forecasts with shorter forecast periods should have lower forecast errors and forecast dispersions, as shown in chapter 3, and consequently the slope coefficient explaining their association should decrease with forecast periods.

To assure that the findings are not only applicable to constituents of the S&P500, we also estimate the pooled OLS regression model on constituents of the Nikkei 225 Index, Deutscher Aktienindex, OBX Index and S&P UK Index.[9] The results confirm the findings above – that a higher forecast dispersion can be associated with a higher forecast error. Here the slope coefficients for forecast dispersion also diminish as forecast periods decrease.

By examining each consecutive year separately, we can also examine whether the association between heterogeneity and forecast errors changes in certain periods. Generating an interaction variable between the statistical period and forecast dispersion allows us to estimate the association between heterogeneity and forecast errors in each year included in the dataset. The interaction variables are consistent over different time-periods and we can thus exclude that the relationship between the two variables changes in certain periods. Although there was a negative association between forecast errors and forecast dispersions in 1980 for forecast periods between 271 and 365 days, this slope coefficient should be interpreted with caution, as the subsample constitutes of only three observations.[10]

As a result of the absolute forecast error, constant terms are positive in all cases. The constant represents an average forecast error from where there are no disagreement and no analysts following the company. Thus, the constant terms does not provide a meaningful interpretation in this case and as a consequence it is also ignored in this chapter.

[9] Estimates from constituents of the Nikkei 225 Index, Deutscher Aktienindex, OBX Index and S&P UK Index can be found in Appendix 2.

[10] See Appendix 3 for estimates from interaction variable between forecast dispersion (*dispers*) and the statistical period (*statpers*).

4.2 Robustness

This section discusses the robustness of the results presented in the pooled OLS regression above. The section includes a discussion about the inference of the slope coefficient before testing the robustness of the pooled OLS regression model.

Reported slope coefficients are unaffected by heteroscedasticity, but statistical inferences are invalid. Thus, all reported standard errors are robust to heteroscedasticity, as reported in the tables. Only if the estimator is unbiased can we justify a causal interpretation of the estimated coefficient. We have an endogeneity problem if there is a correlation between one or more explanatory variables and the error term. The omitted variable for idiosyncratic risk is potentially correlated with forecast dispersion. The positive association we have found between forecast errors and dispersion indicate that dispersion and idiosyncratic risk might be correlated. It is reasonable to believe that a higher idiosyncratic risk is associated with increased disagreement, as a consequence of higher uncertainty related to earnings forecasts.[11] The potential correlation is violating the zero conditional mean and thus slope coefficients might be biased. In this section, we test whether endogeneity is a problem with a Durbin-Wu-Hausman Endogeneity test (augmented regression test). The augmented regression test concludes that the potential correlation between idiosyncratic risk and analysts' forecast dispersion is unproblematic in the pooled OLS estimation.[12]

The endogeneity tests examine potential correlations with the explanatory variables and the idiosyncratic error term, which is the error term that is both time- and unit-varying. When we deal with longitudinal data, correlation between one of the explanatory variables and the error term might also occur as a consequence of unobserved unit-specific terms in the error term (a_i):

$$u_{i,t} = a_i + v_{i,t}$$

The unit-specific error terms do not vary over time, only between different units. In our case, there might be systematic differences in forecast errors between companies (e.g., some

[11] This is examined in chapter 5.

[12] See Appendix 1 for Durbin-Wu-Hausman Endogeneity test results.

companies disclose more information). Although we use control variables in the pooled OLS regression model, there is still a potential correlation with an unobservable unit-specific term that is violating the zero conditional mean, and thus slope coefficients might be biased and inconsistent in the pooled OLS estimation. Consequently, we need to get rid of the unit-specific term, or at least remove it from the error term.

One of the main advantages of panel data is to allow for correlation between a unit-specific term and explanatory variables by removing the unit-specific term. The within group estimator is a fixed-effect estimator that removes the unit-specific term from the error term by demeaning. Thus, a within group transformation will give an unbiased estimator. Random-effect estimates, however, give us a chance to estimate the effect of non-time varying explanatory variables and still take account of unobserved individual specific effects and it does not consume parameters as the fixed-effects estimators do. Consequently, the random-effect estimator is more efficient than the within group estimator. Thus, if possible, we would like to use random-effect estimators instead of fixed-effects estimators. While the within group estimator allows for correlation between the explanatory variables and the individual specific effect, the random-effect model cannot be used if there is correlation between one of the explanatory variables and the unobserved individual specific effect. The decision has to be based on a Hausman test where random-effects can be used if the difference between the slope coefficient for random-effects and fixed-effects is insignificant.

The Hausman test concludes that the difference between the slope coefficients are systematic and thus that there might be a correlation between one of the explanatory variables and the individual specific effect. Consequently, the fixed-effects estimates are preferred. The fixed-effect estimator that we present is a within group estimator. The within group estimator allows for correlation between the individual-specific effect and explanatory variables by removing the individual-specific effect. Thus, within group estimates are only using the variation within each group, which in this case is each company (*cusip*).

Table 4.2: regression results for forecast errors (fixed-effects estimation)

This table reports the regression coefficients from a fixed-effect regression of the forecast error on the forecast dispersion (*dispers*), controlling for the number of analysts following the company (*numest*) and a time-dummy (*year*). Estimates from the control variables are omitted from the regression table. This regression is a modified version of the pooled OLS. The within group transformation removes individual-specific effects to allow for correlation between the explanatory variables and the unobserved individual-specific effect, and consequently the individual-specific dummies that was controlled for in the pooled OLS regression are not included in this model.

Variable	*1<forpers<90*	*91<forpers<180*	*181<forpers<270*	*271<forpers<365*
dispers	1.208***	1.573***	1.891***	1.947***
	(0.0565)	(0.0572)	(0.0636)	(0.0689)
Constant	0.0793***	0.0902***	0.106***	0.137***
	(0.00664)	(0.00884)	(0.0111)	(0.0136)
Observations	57,751	57,222	56,572	58,717
R-squared	0.228	0.258	0.268	0.242
Number of *cusip*	1,322	1,304	1,298	1,280

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As evident in table 4.2, the fixed-effects regression results tell the same story as the pooled OLS estimation in table 4.1. From the within group estimators above, we still cannot reject the null hypothesis that there is a significant positive, or not significant, relationship between forecast errors and their heterogeneity. The slope coefficients that are explaining the association between forecast dispersion and forecast error are all still significantly positive at a 99% significance level, and the deviations from the pooled OLS estimates are rather small, although the fixed-effect estimators are slightly lower, which indicate that the pooled OLS estimators might be slightly upward-biased. This does, however, not affect the conclusion – that there is not a consensus trap in earnings forecasts. Thus, we can conclude that the findings in table 4.1 are robust, and that there are no correlations between any explanatory variables and unobservable individual-specific error terms that are causing problems with the conclusion from the pooled OLS estimation.

5. Mechanisms

The purpose of this section is to present explanations and mechanisms for the empirical findings in the section above. The first section seeks to establish a mechanism with an empirical study, while the subsequent section offers theoretical mechanisms that cannot be tested with the dataset obtained in this research.

5.1 Heterogenity proxy idiosyncratic risk (H_2)

One logic mechanism that supports the empirical findings above is that heterogeneous forecasts implicate that the idiosyncratic risk is high. Risk is uncertainty, and when the earnings are highly uncertain, the forecasts should be more heterogeneous and thus errors increase. It is also reasonable to believe that when the consensus estimates are weak and uncertainty is high, sell-side analysts are less accountable for errors and, as a consequence, more encouraged to deviate from a weak consensus. Thus, such incentive bias might strengthen the effect that risk has on heterogeneity. Forecasts for eps are, however, in this study defined as an average of all forecasts, which is used to calculate the forecast error. Thus, when heterogeneity increases, there is no reason that the average of all individual forecasts should change if individual forecast errors increase uniformly in both directions. This question will be examined after establishing whether or not heterogeneity proxy for idiosyncratic risk.

The idiosyncratic risk parameter is not controlled for in the above regression, but analysts' forecast dispersion may proxy idiosyncratic risk. This hypothesis can be tested. The forecast dispersion can be derived by:

$$dispers_{i,t} = \beta_0 + \beta_1 * idiosync_{i,t} + u_{i,t},$$

where subscript i denotes the company and subscript t denotes the announcement date of actual earnings per share.[13] This simple regression model includes only the idiosyncratic risk

[13] The number of observations is hereby reduced to include only one observation of each company per annum, so that idiosyncratic risk can be derived, as the dataset include only one actual eps per annum.

parameter, hereinafter defined as the cross-sectional actual earnings per share volatility.[14] Cross-sectional actual earnings per share volatility is measured by their standard deviations:

$$idiosync_{i,t} = \sqrt{\frac{\sum(actual_{i,t} - \overline{actual_i})^2}{N}}$$

Thus, if the evidence supports the alternative hypothesis, that analysts' forecast dispersion proxy idiosyncratic risk, then the slope coefficient for idiosyncratic risk needs to be significant positive.

Table 5.11: regression results for forecast dispersion on cross-sectional standard deviation of earnings per share

This table reports the regression coefficients from a regression of the forecast dispersion on the cross-sectional standard deviation of earnings per share (*idiosync*). The regression is performed on forecast periods (*forpers*) between 1-90, 91-180, 181-270 and 271-365 days.

Variable	*1<forpers<90*	*91<forpers<180*	*181<forpers<270*	*271<forpers<365*
idiosync	0.0130***	0.0129***	0.00727***	0.0123***
	(0.00242)	(0.00238)	(0.00194)	(0.00186)
Constant	0.0524***	0.0601***	0.0734***	0.0797***
	(0.00353)	(0.00347)	(0.00323)	(0.00316)
Observations	5,311	4,942	4,864	4,928
R-squared	0.010	0.010	0.003	0.009

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The empirical evidence is remarkably supportive, and we can reject the null-hypothesis that analysts' forecast dispersion does not proxy idiosyncratic risk. The findings show that a higher cross-sectional standard deviation in eps can be associated with a higher analysts' forecast dispersion. All the reported slope coefficients for forecast dispersion are significant on a 99% significance level. R-squared, which tells us how much of the variation in forecast dispersion that can be explained by the cross sectional standard deviation in eps, is however highest between 91 and 180 days, with only 1%.

[14] Earnings per share volatility might also pick up risk that is not idiosyncratic.

An ex-ante risk measure is more dynamic than the ex-post risk measure above, which is static.[15] Thus, we should check the robustness of the findings in table 5.11 using an ex-ante risk measure. By replacing the ex-post risk measure with the change in the last period's eps, we can derive the forecast dispersion using a similar method to the one above:

$$dispers_{i,t} = \beta_0 + \beta_1 * \Delta eps_{i,t-1} + u_{i,t},$$

where subscript *i* denotes the company and subscript *t* denotes the announcement date of actual earnings per share. Delta-eps is defined as the lagged relative change in absolute earnings per share from announcement date *t-2* to announcement date *t-1*:

$$\Delta eps_{i,t-1} = \frac{|actual_{i,t-1} - actual_{i,t-2}|}{|actual_{i,t-2}|}$$

The resulting null hypothesis is similar to the one above – that heterogeneity does not proxy idiosyncratic risk. Thus, if the evidence supports the alternative hypothesis, then the slope coefficient explaining the relationship between delta-eps and forecast dispersion needs to be significant positive.

Table 5.12: regression results for forecast dispersion on lagged delta eps

This table reports the regression coefficients from a regression of the forecast dispersion on the lagged relative change in absolute earnings per share (Δeps_{t-1}). The regression is performed on forecast periods (*forpers*) between 1-90, 91-180, 181-270 and 271-365 days.

Variable	*1<forpers<90*	*91<forpers<180*	*181<forpers<270*	*271<forpers<365*
Δeps_{t-1}	0.00191**	0.0151***	0.00490***	0.00594**
	(0.000826)	(0.00300)	(0.00140)	(0.00259)
Constant	0.0694***	0.0642***	0.0744***	0.0886***
	(0.00254)	(0.00241)	(0.00205)	(0.00267)
Observations	4,379	4,392	4,309	4,475
R-squared	0.003	0.027	0.007	0.011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[15] An ex-ante risk measure is hereby defined as a backward-looking risk measure calculated from past actual earnings, while an ex-post risk measure is defined as a risk measure that considers the whole time-series, both forward-looking and backward-looking.

As evident in the table above, we can reject the null hypothesis that heterogeneity does not proxy idiosyncratic risk. The regression table tells us that a higher change in lagged eps gives rise to a higher forecast dispersion, which is consistent with an ex-post risk measure (table 5.11). The effect that both risk measures have on heterogeneity is, however, weak. This is evident from the slope coefficients in front of the risk measures, which are no more than 0.0151. Also in the ex-ante risk model, the R-squared is low, with no more than 2.7% explaining the variation in dispersion.

Now that we have established that heterogeneity proxy for idiosyncratic risk, we need to examine the association between idiosyncratic risk and forecast errors. Although we have established a clear link between heterogeneity and idiosyncratic risk, we cannot yet conclude that idiosyncratic risk should give increased forecast errors. Why should forecast errors increase when forecast errors are calculated from an average of all forecasts that are issued? If all individual forecasts increase in both directions, the average would still be unaffected. Thus, this mechanism explaining the findings in chapter 5 is only valid if idiosyncratic risk causes the individual forecasts to increase more in one direction. One explanation to such asymmetric behavior could be momentum. From chapter 1 we know that analysts extrapolate and make systematic errors of excessive optimism for stocks with rapidly growing earnings, and conversely for stocks with deteriorating earnings (Bordalo et al., 2017). These findings tell us that the direction of forecast errors might be influenced by the direction that the eps is growing. If this effect increase with idiosyncratic risk, it can help us understand why forecast errors also increase with idiosyncratic risk. We should therefore examine the relationship between the direction of the forecast errors and the direction that the eps is growing.

Examining the direction of the forecast errors requires a redefinition of the measurement used in chapter 4. By removing the modulus (absolute values) from the numerator, but still keeping the modulus in the denominator, the forecast errors will be able to distinguish between optimistic and pessimistic forecast:

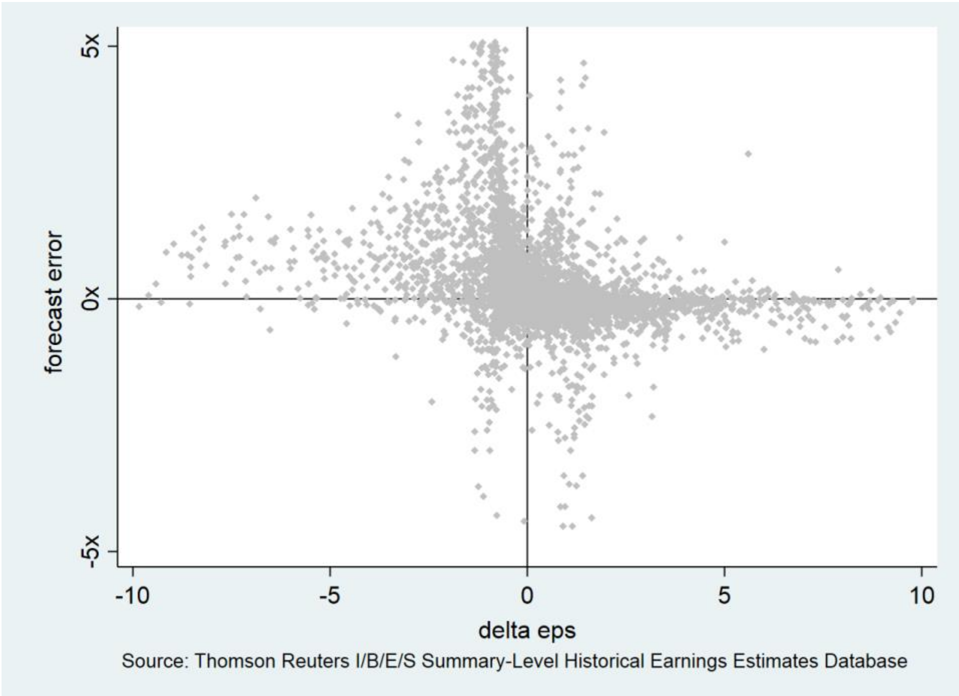
$$forerror_{i,t} = \frac{meanest_{i,t} - actual_{i,t}}{|actual_{i,t}|},$$

where a positive forecast error represents an optimistic forecast and a negative forecast error represents a pessimistic forecast. We then define this period's change in eps, where we distinguish between negative and positive changes, not just the absolute change as the measurement that is used in table 5.12:

$\Delta eps_{i,t} = \frac{actual_{i,t} - actual_{i,t-1}}{|actual_{i,t-1}|}$,

where a positive delta-eps represents a positive change in eps and vice versa. Now we can plot these two measurements to examine whether there is abundance of optimistic or pessimistic forecasts, and how this relates to the change in actual earnings per share.

Figure 5.1: "losses loom more than gains"



From the figure above, we register that losses loom more than gains, which is one of the three pillars of prospect theory. In this case, forecast errors are increasing more when the change in eps was negative in the last period, than if the change was positive, which implicates that negative earnings surprises create more confusion than positive earnings surprises.

We also observe that substantial forecast errors are more optimistic than pessimistic. This is especially evident from the upward skewness towards optimistic forecasts where delta-eps is negative. It also confirms the hypothesis that individual forecasts increase more in one direction, in this case upwards, and can therefore explain why the average of all individual forecasts should increase with heterogeneity. When the change in actual eps was positive, it is, however, not clear whether or not there are more optimistic than pessimistic forecasts – rather the opposite. Nevertheless, the figure above shows clear signs of discrepancies that might explain why average forecast errors increase with idiosyncratic risk.

That the forecast errors should increase with delta eps is, however, not clear from the figure above. The figure suggests a non-linear association where a higher delta eps eventually causes forecast errors to decrease. We should therefore also test whether this is the case in the association between heterogeneity and delta eps.

Table 5.13: regression results for forecast dispersion on delta eps (non-linear model)

This table reports the regression coefficients from a regression of the analysts' forecast dispersion on the relative change in absolute earnings per share (Δeps_t) and the change in absolute earnings per share squared (Δeps_t^2). The regression is performed on forecast periods (*forpers*) between 1-90, 91-180, 181-270 and 271-365 days.

Variable	*1<forpers<90*	*91<forpers<180*	*181<forpers<270*	*271<forpers<365*
Δeps_t	0.0217***	0.00688***	0.0186***	0.0191***
	(0.00299)	(0.00232)	(0.00234)	(0.00246)
Δeps_t^2	-0.000338***	-3.04e-05**	-0.000251***	-0.000198***
	(6.88e-05)	(1.27e-05)	(4.41e-05)	(2.80e-05)
Constant	0.0567***	0.0702***	0.0728***	0.0810***
	(0.00221)	(0.00237)	(0.00213)	(0.00226)
Observations	4,876	4,605	4,565	4,842
R-squared	0.027	0.010	0.025	0.027

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As figure 5.1 suggested, there is a non-linear relationship between forecast dispersion and delta-eps, where there is a positive but decreasing relationship. The turning point for forecast periods between 1-90 days is approximately 32, meaning that delta-eps has a negative effect on forecast dispersion, in our model, when absolute eps changed with 32x last period's eps. Such high changes are not materialized in our dataset and we can thus conclude that delta-eps has a positive-decreasing effect on forecast dispersion, but never negative. By comparing the R-squared with the ones from table 5.12, we can also conclude that this model better explains the variation in forecast dispersion.

5.2 Theoretical mechanisms

In addition to idiosyncratic risk, there are also other theoretical mechanisms for the findings above that can explain there should not be a consensus trap in earnings forecasts, but that cannot be proven using the data obtained in this study.

One mechanism that could explain the findings is shared error created by published research. Published research may replace many independent forecasts. Thus, forecast errors can be derived from errors in published research and how credible the research is. It is reasonable to believe that the more credible research stems from experienced analysts. Given that the experienced analysts' target eps is closer to actual eps than the less experienced analysts, the empirical findings can be explained by less experienced analysts that revise their targets after the experienced analysts have published their research. The revisions can be explained by the findings in Hong et al. (2000) – that less experienced sell-side analysts are easier discharged for bold forecasts and therefore issue forecasts close to the mean analysts' forecasts.

Another mechanism that could explain the findings is that dispersion proxy disclosure. Goss and Waegelein (1993) examine the association between executive compensation and analysts' forecast dispersion in an agency setting. This study shows that higher managerial shares leads to less dispersed forecasts and argues that higher managerial shares leads to less manipulation, and thus more homogeneous forecasts. Consequently, a mechanism that can explain the results in this study is that dispersion proxy how much information that is disclosed. When more information is disclosed, it is reasonable to believe that forecasts will be more homogenous, but also that forecast errors will decrease. More information available when calculating earnings forecasts makes the task easier and targets will reflect more information. This mechanism is also related to the idiosyncratic risk in the sense that more information might reduce the idiosyncratic risk.

The theoretical mechanisms proposed above are, however, only hypotheses and should be considered as ideas for further examination.

6. Concluding remarks

This study revisits Grüner (2009) and seeks to establish whether there is a consensus trap in earnings forecasts. To summarize, the paper's stance is that an increasing analysts' forecast disagreement can be associated with an increasing forecast error, and that the analysts' forecast disagreement is likely to be a manifestation of idiosyncratic risk related to the unobservability of the underlying value.

The objective of this thesis has been to establish whether there is a consensus trap in earnings forecasts. There is a consensus trap if analysts' forecasts are more likely to be wrong when forecasts are homogeneous, than heterogeneous, all else equal. The paper finds a robust positive association between forecast errors and analysts' forecast dispersion, rejecting the hypothesis that there is a consensus trap in earnings forecasts. More specifically, estimates from both a pooled OLS and a within group transformation show that forecast errors are positively associated with heterogeneity, after controlling for different time-periods, forecast periods and additional variables affecting the forecast errors. The regression results are calculated from summary statistics with constituents of the S&P 500 from January 1980 to January 2018, but crosschecked with constituents of the Nikkei 225 Index, Deutscher Aktienindex, OBX Index and S&P UK Index. Although we find a consensus trap in earnings forecasts between 271 and 365 days in 1980, this result contains only three observations, which compared to the total constituents of 230,262 are too small, and not representing a random sample of size.

The paper further examines whether the positive association between forecast errors and forecast dispersion can be explained by the risk within each company. Here we conclude that heterogeneity proxies for risk. More specifically, we find a positive significant association between heterogeneity and both an ex-post and ex-ante risk measure that account for volatility in earnings per share. As an explanation to why idiosyncratic risk should cause increased forecast errors, we argue that individual forecasts errors do not increase uniformly upwards and downwards as heterogeneity increases, thus affecting the average forecast, by showing that forecast errors are skewed.

In the end, some theoretical mechanisms to why we should not observe a consensus trap are also offered. These hypotheses are, however, not empirically tested in this thesis and should be considered as ideas for further examination of the findings.

7. References

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Appendices

Appendix 1: Durbin-Wu-Hausman Endogeneity test (augmented regression test) on forecast dispersion. This table reports the regression coefficients from a regression of the analysts' forecast dispersion on the predicted residuals (*v1_hat*, *v2_hat*, *v3_hat*, *v4_hat*) from the regression in table 3. The regression is performed on forecast periods (*forpers*) between 1-90, 91-180, 181-270 and 271-365 days and controls for different time-periods. Estimates from the control variables are omitted from the regression table.

Variable	*1<forpers<90*	*91<forpers<180*	*181<forpers<270*	*271<forpers<365*
v1_hat	7.90e-11			
	(0.00197)			
v2_hat		-9.68e-11		
		(0.00171)		
v3_hat			1.21e-10	
			(0.00150)	
v4_hat				-0
				(0.00135)
Constant	0.146***	0.178***	0.198***	0.223***
	(0.00224)	(0.00249)	(0.00266)	(0.00283)
Observations	57,751	57,222	56,572	58,717
R-squared	0.043	0.046	0.047	0.052

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 2: regression results from summary data with constituents of the Nikkei 225 Index, Deutscher Aktienindex, OBX Index and S&P UK Index. This table reports the regression coefficients from a regression of the forecast error on forecast dispersion (*dispers*), controlling for company's operations (*sic*), number of analysts making forecasts on the company (*numest*) and a time-dummy (*year*). Estimates from the control variables are omitted from the regression table. The regression is performed on four forecast periods (*forpers*) defined as subsamples of the period end for which the forecasts were made for.

Variable	*1<forpers<90*	*91<forpers<180*	*181<forpers<270*	*271<forpers<365*
dispers	1.292***	1.750***	2.210***	2.192***
	(0.0380)	(0.0475)	(0.0567)	(0.0525)
Constant	-0.00341	-0.0281	-0.0561***	-0.0701***
	(0.0327)	(0.0261)	(0.0205)	(0.0213)
Observations	23,926	23,422	22,941	23,597
R-squared	0.316	0.345	0.385	0.378

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 3: regression results from U.S. summary data. This table reports the regression coefficients from a regression of the forecast error on the interaction between forecast dispersion and statistical period (D^{year}**dispers*), controlling for company's operations (*sic*), number of analysts making forecasts on the company (*numest*). Estimates from the control variables are omitted from the regression table. The regression is performed on four forecast periods (*forpers*). There is only one case where there is a negative association between forecast error and dispersion (marked with red).

Variable	1<*forpers*<90	91<*forpers*<180	181<*forpers*<270	271<*forpers*<365
D^{1979}**dispers*	0.165	0.992**	6.449***	5.060***
	(0.123)	(0.435)	(1.500)	(0.603)
D^{1980}**dispers*	1.908***	1.994***	0.867***	-1.696***
	(0.109)	(0.172)	(0.247)	(0.259)
D^{1981}**dispers*	0.870***	2.996***	3.490***	4.585***
	(0.0852)	(0.308)	(0.172)	(0.198)
D^{1982}**dispers*	0.615***	0.998***	1.947***	2.628***
	(0.108)	(0.239)	(0.301)	(0.235)
D^{1983}**dispers*	0.994***	1.666***	1.854***	1.342***
	(0.129)	(0.183)	(0.216)	(0.168)
D^{1984}**dispers*	1.354***	1.846***	1.799***	2.277***
	(0.126)	(0.217)	(0.167)	(0.217)
D^{1985}**dispers*	1.601***	1.714***	2.165***	2.738***
	(0.154)	(0.146)	(0.146)	(0.168)
D^{1986}**dispers*	1.201***	1.231***	1.818***	2.401***
	(0.133)	(0.101)	(0.115)	(0.157)
D^{1987}**dispers*	1.313***	1.424***	1.789***	2.083***
	(0.146)	(0.107)	(0.143)	(0.172)
D^{1988}**dispers*	1.810***	1.921***	2.252***	2.461***
	(0.168)	(0.231)	(0.233)	(0.212)
D^{1989}**dispers*	1.519***	2.261***	2.836***	2.292***
	(0.155)	(0.203)	(0.218)	(0.199)
D^{1990}**dispers*	1.462***	1.925***	2.307***	2.496***
	(0.177)	(0.157)	(0.165)	(0.166)
D^{1991}**dispers*	1.284***	1.801***	2.260***	2.446***
	(0.142)	(0.138)	(0.106)	(0.127)
D^{1992}**dispers*	1.211***	1.712***	2.052***	2.141***
	(0.138)	(0.182)	(0.149)	(0.138)
D^{1993}**dispers*	1.163***	1.434***	1.723***	1.988***
	(0.150)	(0.114)	(0.162)	(0.130)
D^{1994}**dispers*	1.228***	1.152***	1.389***	1.466***
	(0.139)	(0.0771)	(0.102)	(0.124)
D^{1995}**dispers*	1.308***	1.683***	2.087***	2.161***
	(0.210)	(0.177)	(0.193)	(0.213)
D^{1996}**dispers*	1.226***	1.314***	1.793***	2.136***
	(0.210)	(0.140)	(0.139)	(0.163)
D^{1997}**dispers*	0.911***	1.449***	1.790***	2.132***
	(0.0989)	(0.135)	(0.171)	(0.163)
D^{1998}**dispers*	1.236***	1.660***	1.863***	1.946***
	(0.154)	(0.141)	(0.143)	(0.148)
D^{1999}**dispers*	0.987***	1.338***	1.943***	1.880***
	(0.119)	(0.135)	(0.158)	(0.161)
D^{2000}**dispers*	1.582***	2.392***	2.276***	2.486***
	(0.206)	(0.222)	(0.165)	(0.181)
D^{2001}**dispers*	1.403***	2.250***	2.767***	2.959***
	(0.185)	(0.174)	(0.184)	(0.193)
D^{2002}**dispers*	1.016***	1.518***	1.949***	1.889***
	(0.114)	(0.110)	(0.133)	(0.124)
D^{2003}**dispers*	0.905***	1.621***	2.094***	1.838***
	(0.116)	(0.127)	(0.144)	(0.134)
D^{2004}**dispers*	1.121***	1.641***	1.971***	2.026***
	(0.132)	(0.0948)	(0.177)	(0.139)

D^{2005}*dispers	1.346***	1.602***	2.169***	2.264***
	(0.216)	(0.168)	(0.167)	(0.223)
D^{2006}*dispers	0.915***	1.938***	1.792***	1.921***
	(0.146)	(0.239)	(0.213)	(0.193)
D^{2007}*dispers	1.811***	2.419***	2.600***	2.287***
	(0.291)	(0.207)	(0.244)	(0.205)
D^{2008}*dispers	1.371***	2.800***	2.771***	3.280***
	(0.119)	(0.241)	(0.249)	(0.236)
D^{2009}*dispers	1.220***	1.608***	1.759***	1.731***
	(0.156)	(0.130)	(0.129)	(0.112)
D^{2010}*dispers	0.960***	1.417***	1.889***	1.835***
	(0.157)	(0.176)	(0.170)	(0.149)
D^{2011}*dispers	1.084***	1.624***	1.592***	1.774***
	(0.118)	(0.194)	(0.153)	(0.132)
D^{2012}*dispers	1.123***	1.423***	1.571***	2.048***
	(0.160)	(0.136)	(0.125)	(0.130)
D^{2013}*dispers	1.689***	1.386***	1.376***	1.638***
	(0.217)	(0.0922)	(0.110)	(0.128)
D^{2014}*dispers	1.589***	1.456***	1.915***	1.961***
	(0.188)	(0.203)	(0.201)	(0.164)
D^{2015}*dispers	1.267***	1.305***	1.448***	1.182***
	(0.179)	(0.115)	(0.120)	(0.0919)
D^{2016}*dispers	1.173***	1.400***	1.548***	1.625***
	(0.116)	(0.131)	(0.113)	(0.144)
D^{2017}*dispers	1.294***	2.270***	1.204***	0.526**
	(0.210)	(0.404)	(0.254)	(0.217)
Constant	0.0417***	0.0218***	0.0315***	0.0568***
	(0.00604)	(0.00711)	(0.00890)	(0.0105)
Observations	57,751	57,222	56,572	58,717
R-squared	0.292	0.342	0.357	0.344

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1