Financial Analysts' Herding Behavior in a Fluctuating Macro-economy

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ABSTRACT

Financial analysts make forecasts that are either herded or bold. The accuracy of the forecast varies, and could be influenced by economic- and personal matters. The aim of the present study is to analyze herding and relate this behavior to macro-economic factors to add further explanation to existing literature on why analysts herd their earnings forecasts. Firstly, the study shows that analysts increase their herding during unfavorable economic conditions, in terms of GDP growth, due to career concerns. Secondly analysts' forecasts are less accurate during unfavorable economic conditions, in terms of GDP growth, since increased herding leads to decreased accuracy. Thirdly, when the credit risk in the economy increases analysts will rely less on their counterparts and herd less, increasing accuracy. Finally, analysts' behavior and stock returns are related to each other and the study reveals that firms that are followed by, on average, herding forecasters have a significantly higher market return than firms followed by bold forecasters during the forecasting period. In summary, macro-economic factors affect herding behavior.

Key Words: Herding, Analyst behavior, Forecasting, Macro-economy

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Introduction

In the world of finance there are mechanisms that are dependent on expectations, e.g. stock prices that are derived from the company's future earnings expectations (Bernard 1993). Analysts that forecast these earnings therefore play an important role to many actors in the financial market.

Prior studies show that the performance of an analyst's work lay the ground for her future career (Hong, Kubik & Solomon 2000) (Hong, Kubik 2003). Forecast accuracy is one of the most important aspects that analysts need to deliver (Lim 2001) (Hong, Kubik 2003). Whether an analyst's accuracy is seen as good or bad, depends on the accuracy of her counterparts (Mikhail, Walther & Willis 1999). Due to this, many studies investigate the herding behavior among financial analysts. An analyst that is herding revises her forecast towards the forecast consensus of her counterparts. Prior studies find several potential explanations to why analysts herd. Career concern and personal characteristics are major reasons to why analysts herd their forecasts (Hong, Kubik & Solomon 2000) (Clement, Tse 2005). Young inexperienced analysts are found to herd more than their older counterparts, which can be explained by the fact that younger analysts suffer greater risk of termination for being bold (moving the forecast away from the consensus) and inaccurate (Hong, Kubik & Solomon 2000).

Furthermore, information asymmetry is a reason to herd. In this case, analysts herd their forecasts with the belief that other analysts possess more relevant information about the specific firm, and their forecast will be more accurate if they herd towards the other analysts' estimates (Cipriani, Guarino 2014) (Park, Sabourian 2011).

Previous studies also show that herded forecasts are less accurate than bold forecasts, which implies that bold forecasters use more relevant information in their forecasting (Clement, Tse 2005).

This study goes beyond the personal characteristics that explain herding and investigate how macro-economic factors explain the dynamics of herding. In this paper, herding means that a forecasting analyst revises her forecast closer to the consensus, than her previous forecast. All other forecasts are considered to be bold.

Our first research question is how business cycles affect the level of herding among earnings forecasters. Proxies for business cycles in this study are US GDP growth and the Corporate Bond Yield relative to the Yield on a 10-year Treasury Note. We found that herding behavior tended to increase during low GDP growth. A possible explanation could be that since the risk of termination is higher during unfavorable conditions, analysts will herd their forecasts to avoid releasing a relatively inaccurate forecast, and risk negative job separation. Regarding the second macro-economic variable, the credit risk, we found that herding behavior tended to decrease with an increased credit risk. The explanation is related to the information asymmetry aspect of herding, and that the overall trustworthiness among actors in the economy decreases with a higher credit risk. Therefore, analysts will not herd because they do not believe that the forecasts of their counterparts are more accurate.

Our second research question concerns the accuracy of analysts during different forecasting behaviors and economic conditions. First we could confirm prior studies, that accuracy decreases with herding (Clement, Tse 2005). Further, the study concluded that the accuracy of analysts increases during favorable conditions, in terms of GDP growth, which can be explained by our findings related to question one. Since herding decrease with high GDP growth, this implies that the accuracy will increase with GDP growth.

The third research question aims to make a connection between analyst behavior and the stock market return of the firms, for which the analysts are making earnings forecasts. It could be shown that firms that, on average, had herding forecasters, performed better *during* the forecasting period compared to firms with bold forecasters. This can be explained by herded forecasts being more positively biased (Olsen 1996), which is reflected in the stock price (Bernard 1993).

The remainder of the paper is structured as follows: Section I presents the prior literature in the study of herding, Section II gives an overview of the data that is used in the study, Section III describes the research methods, Section IV describes the results, Section V includes Robustness tests, Section VI describes the implications of our results as well as potential future research questions and finally, in Section VII, the conclusions are presented.

I. Prior Literature

Studies of the relation between herding and reputation concerns first appeared in the 1990s (Scharfstein, Stein 1990), (Trueman 1994) and (Zwiebel 1995). Rational analysts aim to make as accurate forecasts as possible, and should as extensively as possible use all information available to increase accuracy, (Lim 2001). Though, for psychological reasons, analysts tend to be reluctant to consider new information and thus not revise their earnings forecast to the extent that the new private information indicate. One of the reasons analysts ignore private information is related to reputation consciousness (Trueman 1994).

Trueman finds that analysts are unwilling to make significant revisions because that would make their prior forecasts appear less reliable (Trueman 1994). New information may also be ignored by analysts beacause it may be unfavorable for the analyzed firms and will thus limit the analysts' future access to firm-specific information (Diether, Malloy & Scherbina 2002).

Herding is also found to be related to career concerns. Hong et al find that career concerns tend to make analysts move their forecasts towards consensus (Hong, Kubik & Solomon 2000). This is especially true for younger analysts, who are more sensitive to career concerns, compared to older and more experienced analysts. The mechanism behind increased herding due to career concerns can be explained by the fact that the potential drawbacks of being bold and inaccurate, exceeds the potential benefits of being bold and successful. These mechanisms are more pronounced for young analysts in terms of career outcome. Hong et al find that favorable job separations are related to accuracy in forecasts, when controlling for accuracy forecast optimism is also an important factor to favorable job separation (Hong, Kubik 2003). Gu et al also shows that accuracy is one of the most important aspects of analysts' forecast performance (Gu, Wu 2003).

Herding behavior is also found to be related to information asymmetry. When analysts do not fully trust their own information, or believe that the counterparts information is more trustworthy, they will herd their forecasts since they believe that it will increase accuracy. This is referred to as informational herding (Park, Sabourian 2011) (Cipriani, Guarino 2014).

Clement et al offer additional explanations for herding behavior, and its opposite boldness, i.e. that boldness is dependent on, and positively correlated with, factors such as analysts' prior forecasting accuracy, analysts' brokerage firm size and analysts' experience (Clement, Tse 2005). They also find that boldness is negatively associated with the number of industries that the analyst follows. Further, they also find that bold forecasts are more accurate than herding forecasts, which Olsen (Olsen 1996) also indicates, and that bold forecast revisions are more accurate than herding forecast revisions. This is due to the fact that analysts disregard private information when herding, which should have lead to more accurate forecasts if taken into account (Clement, Tse 2005). Several authors also describe that herding increases with the level of earnings unpredictability, and that this leads to greater forecasting errors (Olsen 1996) (Huberts, Fuller 1995).

Dreman et al test whether the accuracy of the consensus is dependent on business cycles (Dreman, Berry 1995) and Welch et al look at the relation between buy/hold recommendations and previous firm returns (Welch 2000), but no previous studies look at the relationship between macro-economic factors and herding among earnings analysts.

Therefore, the primary aim of this study is to address this issue by analyzing whether analyst herding is dependent on GDP growth and a market credit risk factor.

Furthermore, previous studies have vaguely analyzed the relationship between market return and herding. Hubert et al find that the return of firms with unpredictable earnings is abnormally negative compared to firms with predictable earnings (Huberts, Fuller 1995). Olsen et al find that firms with unpredictable earnings are followed by herding forecasters, and have significantly negative returns, in the period after the reports are released (Olsen 1996). Diether et al test the relationship between asset pricing, company size and dispersion in analysts' forecasts' by using the methodology of trying to find results of average returns, pioneered by Jegadeesh (Diether, Malloy & Scherbina 2002) (Jegadeesh, Titman 1993).

The second aim of this study is to take this research further by relating herding to stock market return.

II. Sample Selection

The original dataset from I/B/E/S consists of 3 090 080 observations from 6 663 different analysts working for US companies. The time frame of the dataset is from December 2000 until September 2016. The number of firms analyzed is 6 840, and the number of forecasting quarters is 61. The earnings estimates in the sample are estimates of Earnings Before Interest and Tax (EBIT) that analysts have submitted to the I/B/E/S. The study focuses on EBIT because it is a key earnings metric which has an essential impact on firms' stock performance.

To complement the dataset from I/B/E/S, GDP growth was included in the dataset. The US GDP growth is measured quarterly and calculated by the U.S. Bureau of Economic Analysis, on 2009 US dollars (Bureau of Economic Analysis 2017).

Further, as a credit risk metric this study uses Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant

Maturity (Federal Reserve Bank of St. Louis 2017). This credit risk metric is a proxy for the variation in the credit default risk (Hamilton 2007).

For the study of average returns for companies followed by analysts, monthly stock prices were used from the Center for Research in Security Prices (CRSP). This action limited the dataset to 715 951 observations, i.e. companies and periods that existed in both the I/B/E/S and in the CRSP database.

The study focused on data that consisted of observations from the normal fiscal year, i.e. the quarters end in March, June, September and December.

If the original dataset did not contain a sufficient number of observations for a specific company and period, the observations for that specific company and period were excluded. Observations fewer than 10 for a single period and company were excluded. Observations that had fewer than three analysts issuing forecasts for a specific company and period were excluded. Further, the consensus calculation needed to be based on at least three observations.

III. Research Methods

This section begins with a discussion of the concept of herding and why this is interesting to look at in the light of macroeconomic fluctuations.

A stock analyst, in this study, was considered to be herding if her revision of an EBIT forecast was closer, in absolute measures, to the consensus than the pre-revision forecast, for that company and period. Figure 1 illustrates how the variable is defined. All other forecast revisions were considered to be bold.

To study the herding behavior of stock analysts, in the light of macroeconomic fluctuations is in the special interest of two groups; financial analysts themselves and investors.

Financial analysts' compensation depends directly or indirectly on their forecast accuracy (Hong, Kubik 2003). Thus, it is in the analysts' interest to consider all available information when issuing a new forecast or when making a revision to an existing one (Clement, Tse 2005). Information that the analyst needs to consider when making forecasts, could be the relationship between the macro-economy, the probability that other analysts are herding and the accuracy of other analysts.

Investors use forecast information in their decision making, consequently, the information released by analysts and the reliability of this information is therefore of great interest to investors. It has previously been shown that a bold forecast is more accurate than a herded forecast (Clement, Tse 2005), but not how this relationship is affected by the macro-economy.

The first research question studied how macroeconomic factors affect the herding behavior and the probability of herding. We expected the variable $Growth\_GDP_t$ to be negatively associated with the probability to herd, and the herding index, because analysts tend to herd during uncertainty and due to career concerns (Hong, Kubik & Solomon 2000). Further we presumed the credit risk factor (Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury) to be positively associated with the probability to herd and the herding index. The reasoning behind this was that we presumed that the correlation between the GDP growth and the credit risk would be negative, and thus the credit risk would decrease in a favorable economy. In addition to this we analyzed how different characteristics (e.g. Days_Elapsed; days since last issued forecast, $Forecast\_Horizon_{itc}$; Number of days to the release of the interim report, PTD_Dist1_{itc}; Distance between the pre-revision forecast and the pre-revision consensus and $lag\_accuracy_{itc}$; the accuracy in the previous period for the specific analyst and company) affected herding. We expected these characteristics to be associated with the probability to herd and the herding index in the same way as in previous literature (Clement, Tse 2005). Specifically, $Days\_Elapsed_{itc}$ and PTD_Dist1_{itc} were expected to be positively associated with herding, and $Forecast\_Horizon_{itc}$ and $lag\_accuracy_{itc}$ to be negatively associated with herding.

To test these relations, the following regressions were used:

Regression 1:

$$Herd\_dummy_{itc} = \alpha_0 + \alpha_1 Growth\_GDP_t + \alpha_2 Credit\_Risk_t + \alpha_3 Days\_Elapsed_{itc} + \alpha_4 Forecast\_Horizion_{itc} + \alpha_5 PTD\_DIST1_{itc} + \alpha_6\, lag\_accuracy_{itc} + \varepsilon_{itc}$$

Regression 2:

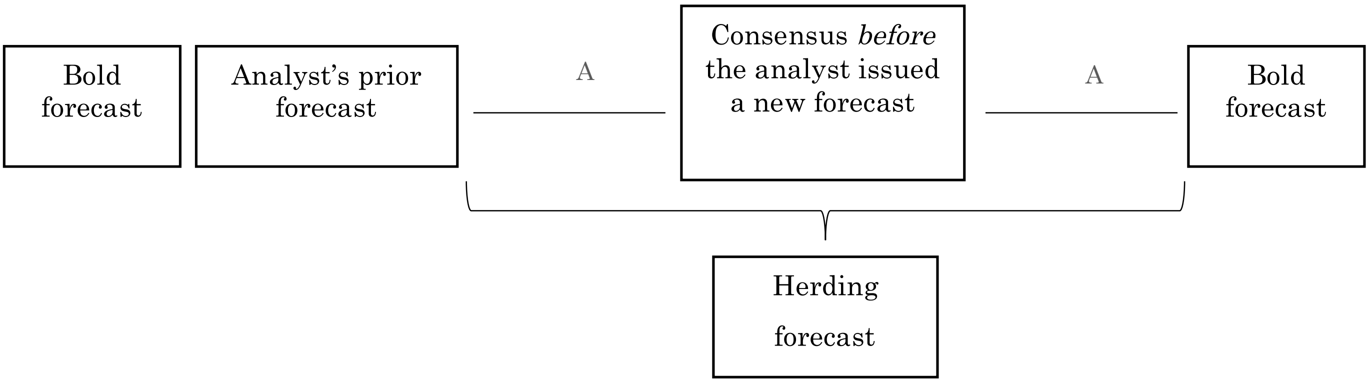
$$\begin{aligned} lHerding\_index_{itc} &= \beta_0 + \beta_1 Growth\_GDP_t + \beta_2 Credit\_Risk_t + \beta_3 Days\_Elapsed_{itc} \\ &+ \beta_4 Forecast\_Horizon_{itc} + \beta_5 PTD\_DIST1_{itc} + \beta_6\, lag\_accuracy_{itc} \\ &+ \varepsilon_{itc} \end{aligned}$$

where:

Herd_dummy$_{itc}$ is equal to 1 if the analyst issues a revision of its own forecast that is closer to the mean (consensus), immediately before the revision, than the pre-revision forecast. In this study, the analyst is considered to issue a bold forecast if a revision of a forecast is further away from the mean (consensus) than the pre-revision forecast, in absolute measures, and in these cases Herd_dummy is equal to zero. The variable definition is illustrated in Figure 1.

Growth_GDP$_t$ is the growth in US GDP for the previous quarter. The variable is lagged 3-months, in order for the effect to be mirrored in the analysts behavior. The growth is defined as the change in percent in US GDP from the preceding period, calculated as the quarterly seasonally adjusted annual GDP based on chained 2009 dollars. The percent change is calculated by the Bureau of Economic Analysis from the U.S. Department of Commerce.

Figure 1.
The analyst issues a herding forecast if the revised forecast is closer to the consensus immediately before the revision than the previous forecast. The area of a herding forecast is illustrated below. Note that the distance marked *A* is equal on both sides of the previous consensus.



$Credit\_Risk_{t}$ is a proxy for credit risk, that is Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity, calculated by the U.S. Federal Reserve Bank of St. Louis.

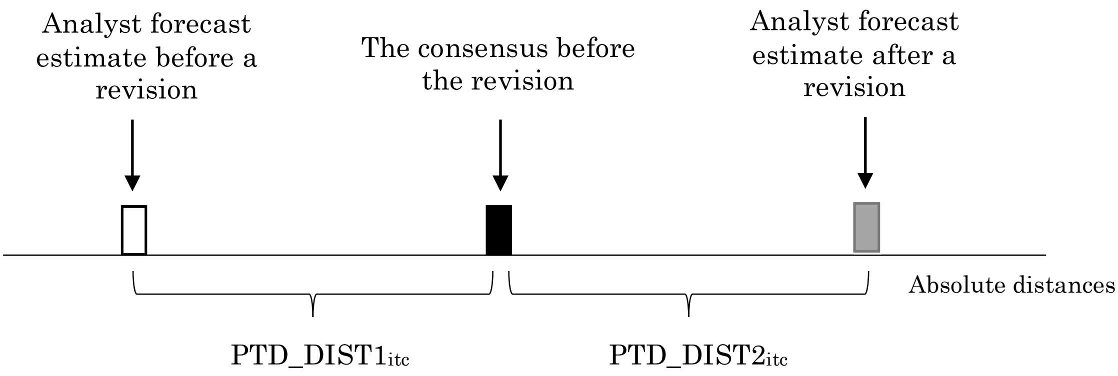
$Days\_Elapsed_{itc}$ measures the number of days that has passed without any analyst following the company issuing or revising a forecast, for the specific company and period.

$Forecast\_Horizon_{itc}$ measures the number of days between the analyst's issue of an estimate to the release date of the interim report, for every company and period.

PTD_DIST1_{itc} (Period to Date Distance 1) is defined as the absolute distance between the consensus *before* a revision and the analyst's forecast estimate *before* a revision, for every issued forecast, forecast period and company. This distance in EBIT forecasts is illustrated by Figure 2.

PTD_DIST2_{itc} (Period to Date Distance 2) is defined as the absolute distance between the consensus *before* a revision and the analyst's forecast estimate *after* a revision, for every issued forecast, forecast period and company. This distance in EBIT forecasts is illustrated by Figure 2.

Figure 2.



$Lag\_Accuracy_{itc}$ is the accuracy in the previous period for every analyst and company. The accuracy is defined as below.

$Accuracy_{itc}$ measures the accuracy for the last forecast issued by an analyst for every period and company, relative to the actual EBIT of the analyzed company. This variable is scaled relative to the other forecasts issued for the specific period and firm. *FPE_DIST_{itc}* is defined below.

$$Accuracy_{itc} = \frac{Max(FPE\_DIST)_{tc} - FPE\_DIST_{itc}}{Max(FPE\_DIST)_{tc} - Min(FPE\_DIST)_{tc}}$$

FPE_DIST_{itc} (Forecast Period End Distance) is the absolute distance between the actual quarterly EBIT for a company and the last EBIT estimate published by every analyst for the specific firm and period.

Additional variables for regression 2:

$Herding\_Index_{itc}$ is an index variable of herding, defined as the absolute distance between the consensus *before* a revision and the analyst's forecast estimate *before* a revision (PTD_DIST1_{itc}) divided by the absolute distance between the consensus before a revision and the analyst's forecast estimate *after* a revision (PTD_DIST2_{itc}). If the analyst's revision is very close to their previous consensus the variable PTD_DIST2_{itc} will be very low and the quotient will consequently be very high. To solve this problem, the variable $lHerding\_index_{itc}$ was introduced.

$$Herding\_Index_{itc} = \frac{PTD\_DIST1_{itc}}{PTD\_DIST2_{itc}}$$

lHerding_index$_{itc}$ is the natural logarithm of the Herding_Index$_{itc}$ variable. The variable Herding_Index increases in an exponential fashion as the PTD_DIST2$_{itc}$ decreases, to be able to study the variable in a more constructive way the natural logarithm was used.

Like Clement et al the characteristic variables have been converted in a fashion that scale the observations between 0 and 1[1] (Clement, Tse 2005). The scaling is relative to the other observations for the same forecast period (t) and company (c). This was done to increase the comparability between the variables and the characteristics that they represent.

$$Scaled\ Characteristic_{\ itc} = \frac{\text{Characteristic}_{\ itc} - Min(\text{Characteristic})_{tc}}{Max(\text{Characteristic})_{tc} - Min(\text{Characteristic})_{tc}}$$ [2]

The macro factors were scaled in relation to the total sample. This is due to the variation of the macro factors in a single forecast period are very small or non-existent.

All variables are calculated for every interim period, company and analyst. This means that all characteristics variables have a unique value, but the macro factors and stock returns have the same value for every interim period.

The second research question concerned the association between the accuracy of analyst's forecasts and the macro factors, controlling for other previously shown determinants of accuracy. We expected accuracy to be negatively associated with herding (lHerding_Index$_{itc}$), because we

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[1] Except lHerding_Index, because this variable is scaled with the natural logarithm.

[2] Accuracy and lag_accuracy are scaled as described in their definition above.

presumed herding forecasters to disregard private information and thus be less accurate, consistent with previous literature (Clement, Tse 2005). Due to this, the GDP growth was expected to be positively associated with accuracy, since accuracy decreases with herding. The credit risk metric ($Credit\_Risk_t$) was expected to have a negative association with accuracy, because an increase in credit risk would imply worse economic conditions and thus lead to herding behavior. Other variables that were included in the regression were the distance between the analyst's previous forecast and the consensus immediately before the release of the new forecast (PTD_DIST1_{itc}) and accuracy in the previous period (lag $accuracy_{itc}$). The rationale behind PTD_DIST1_{itc} is that a large distance from the consensus will increase the likelihood of herding and thus be less accurate. If an analyst is skilled and issues a relatively accurate forecast, we expected the next issued forecast by the same analyst, for the same company, to be accurate as well.

The following regression was used, the variables have the same definition as in the first research question:

Regression 3:

$$Accuracy_{itc} = \gamma_0 + \gamma_1 Growth\_GDP_t + \gamma_2 Credit\_Risk_t + \gamma_3 lHerding\_Index_{itc} + \gamma_4 PTD\_DIST1_{itc} + \gamma_5 lag\_accuracy_{itc} + \varepsilon_{itc}$$

The third research question investigated the relationship between herding and the market return for the companies' during the forecast period, in different states of the macro economy (in terms of GDP Growth). This research question was included for further exploration of the importance for investors to include the relation of herding and macro factors in their investment decisions. The structure of this test was to compare the average returns for three terciles of the Herding Index at the same time as comparing the return for three terciles of the GDP growth. The sample was divided in terciles of GDP growth to control for the relation between GDP growth and market return. Both the Herding Index and GPD growth were defined as in the first research question. The stocks in each portfolio were equally weighted. The difference in average return was calculated and statistically tested if different from zero.

The stock return was the return over the company's interim period, specifically the three month return for the company's stock. The variable was defined as follows:

Return 3 months is the stock return for a company during an interim period. The stock prices are imported from the Center for Research in Security Prices.

$$Return\ 3\ month = \frac{Stock\ price\ end\ of\ interim\ period}{Stock\ price\ begining\ of\ interim\ period} - 1$$

It was expected that the relation between herding and stock return would be positive because it has been found that a herding forecast is more positively biased than a bold forecast (Olsen 1996). This would lead the stock price to increase *during* the interim period.

IV. Results

1. *Descriptive Statistics*

Table 1 reports the descriptive statistics of the characteristics, macro variables and stock market returns used. Panel A reports the mean, max, min, standard deviation and percentiles for the unscaled variables. For example, the maximum GDP growth during our time window were 6,9 % and the minimum was – 8,2 %. The maximum spread between the Corporate Bond Yield and 10-year Treasury Note were 6,16 and the minimum were 1,48.

Panel B reports the mean, max, min, standard deviation and percentiles of the characteristics that we have scaled between 0 and 1. For example, we can now see that Growth_GDP$_t$ takes on the minimum value 0 and the maximum value 1. As mentioned above, the characteristics are scaled as: $Scaled\ Characteristic_{itc} = \frac{\text{Characteristic}_{itc} - Min(\text{Characteristic})_{tc}}{Max(\text{Characteristic})_{tc} - Min(\text{Characteristic})_{tc}}$.

Panel C reports the comparison of the mean of the characteristics, macro variables and stock market returns between herding and bold forecasts. Consistent with prior studies (Clement, Tse 2005), is that bold forecasts are significantly more accurate than herding forecasts. Bold forecasts have significantly more accurate *previous* forecasts, which implies that bold forecasters tend to stay bold, and thus stay more accurate than herding forecasters.

Bold forecasters tend to be significantly closer to the consensus before they make a revision (PTD_DIST1$_{itc}$) than herding forecasters are, which is in line with (Clement, Tse 2005). The analysts' last forecast (FPE_DIST$_{itc}$) are significantly closer to the actual EBIT than herding forecasters, which is in line with accuracy.

Table 1.

Descriptive Statistics, Unscaled

Table 1, report the descriptive statistics. The variables are: *PTD DIST1$_{itc}$*, which is defined as the absolute distance between the consensus before the revision and the analyst's forecast estimate *before* a revision; *PTD_DIST2$_{itc}$* is defined as the absolute distance between the consensus *before* a revision and the analyst's forecast estimate *after* a revision; *Days_Elapsed$_{itc}$*, measures the number of days that has gone by without any new issued forecast or revised forecast by any other analyst following the firm; *Forecast_Horizon$_{itc}$* measures the number of days between an analyst's issue of an estimate to the release date of the interim report; *FPE_DIST$_{itc}$* is the absolute distance between the actual quarterly earnings and the last estimate published by an analyst for that firm and period; *Accuracy* is the accuracy of an analyst's last estimate during the period; *Lag_accuracy$_{itc}$* is defined as the analyst's accuracy in the previous period; *Growth GDP$_t$* is the quarterly US GDP growth; *Credit Risk$_t$* is the Corporate Bond Yield relative to the 10-year Treasury Note; *Return 3 month$_{tc}$* is the average three month return of a firm during an interim period; *Herding_Index$_{itc}$*, describes herding in relative numbers and is defined as $\frac{PTD\_DIST1}{PTD\_DIST2}$; *lHerding_Index$_{itc}$* is the natural logarithm of the Herding_Index$_{itc}$ variable.

Panel A shows the distribution over the unscaled variables in number of observations, mean, min, max, standard deviation and percentiles.

Panel B shows the distribution over the scaled characteristics between 1 and 0, the characteristics are scaled as:

$$Scaled\ Characteristic_{itc} = \frac{\text{Characteristic}_{itc} - Min(\text{Characteristic})_{tc}}{Max(\text{Characteristic})_{tc} - Min(\text{Characteristic})_{tc}}.$$

Panel C reports a comparison of the mean of the characteristics, macro factors and stock market return between bold and herding forecasts as well as the total mean of the characteristics.

Panel D reports the correlation between the characteristics.

Table 1

Panel A: Unscaled Descriptive Statistics

	count	mean	p25	p50	p75	min	max	sd
PTD_Dist1: Previous forecast distance to previous consensus distance	111 300	55,55	2,30	8,18	29,71	0,00	29980,38	253,54
PTD_Dist2: New forecast distance to previous consensus distance	111 300	67,76	2,95	10,25	36,65	0,00	12362,16	280,55
Days Elapsed: Days since last forecast	111 300	9,50	0,00	1,00	8,00	0,00	247,00	19,43
Forecast Horizon: Number of days to interim report	111 300	104,19	44,00	95,00	104,00	2,00	785,00	96,94
Forecast Period End: Distance to actual company result	111 300	60,46	2,95	9,06	30,60	0,00	16148,20	317,47
Logarithm of Herding Index	111 300	-0,23	-0,73	-0,13	0,26	-11,16	13,58	1,24
Growth GDP	111 300	2,03	0,80	2,00	3,10	-8,20	6,90	1,84
Credit Risk: Corporate Bond Yield to 10-Year Treasury	111 300	2,73	2,42	2,68	2,91	1,48	6,16	0,47
Return in 3 months	111 300	0,02	-0,09	0,01	0,11	-0,03	14,27	0,31

Table 1
Panel B: Scaled Characteristics

	count	mean	p25	p50	p75	min	max	sd
Accuracy	111 300	0,67	0,48	0,75	0,90	0,00	1,00	0,27
Lag accuracy: Accuracy in previous period	111 300	0,64	0,44	0,73	0,90	0,00	1,00	0,30
Growth GDP	111 300	0,68	0,60	0,68	0,75	0,00	1,00	0,12
Credit Risk: Corporate Bond Yield to 10-Year Treasury	111 300	0,27	0,20	0,26	0,31	0,00	1,00	0,10
Days Elapsed: Days since last forecast	111 300	0,11	0,00	0,01	0,10	0,00	1,00	0,21
Forecast Horizon: Number of days to interim report	111 300	0,12	0,02	0,10	0,14	0,00	1,00	0,15
PTD_Dist1: Previous forecast distance to previous consensus distance	111 300	0,13	0,03	0,08	0,17	0,00	1,00	0,16

Table 1

Panel C **Comparison Between Bold and Herding Forecasts**

	Bold Forecasts	Herding Forecasts	Total Forecasts	Difference	t-Statistic for Difference
PTD Dist1	47,00	197,32	123,98	-150,32[a]	-180,0
PTD Dist2	76,09	50,11	62,79	25,98[a]	53,5
FPE Dist	53,96	55,95	54,93	-2,02[b]	-2,0
Days Elapsed	13,22	13,69	13,46	-0,47[a]	-14,0
Forecast Horizon	241,19	261,85	251,77	-20,67[a]	-88,5
Growth GDP	2,02	2,04	2,03	-0,03[a]	-9,8
Credit Risk	2,78	2,77	2,77	0,01[a]	7,4
Accuracy	0,64	0,61	0,63	0,03[a]	25,2
lag accuracy	0,63	0,54	0,59	0,09[a]	79,3
Herding Index	0,55	4550,35	2330,40	-4549,79[b]	-2,1
lHerding Index	-0,87	1,35	0,26	-2,22[a]	-1300,0
Return 3 month	0,82%	2,66%	1,55%	-1,84%[a]	-10,1

a,b Statistically significant at the one and five percent levels

Table 1
Panel D: Correlation Matrix

	PTD_Dist1: Previous Forecast Distance to Previous Consensus Distance	Days Elapsed: Days Since Last Forecast	Forecast Horizon: Number of days to interim report	Accuracy	Lag accuracy: Accuracy in previous period	Growth GDP	Credit Risk: Corporate Bond Yield to 10-Year Treasury	Herd dummy	Herding Index	Logarithm of Herding Index	Return in 3 months
PTD_Dist1: Previous Forecast Distance to Previous Consensus Distance	1,00000										
Days Elapsed: Days Since Last Forecast	0,04900***	1,00000									
Forecast Horizon: Number of days to interim report	-0,04965***	-0,03060***	1,00000								
Accuracy	-0,01695***	-0,04157***	-0,14879***	1,00000							
Lag accuracy: Accuracy in previous period	-0,04397***	-0,06108***	-0,06484***	0,28743***	1,00000						
Growth GDP	-0,00844**	-0,01317***	0,03138***	0,00627*	0,01763***	1,00000					
Credit Risk: Corporate Bond Yield to 10-Year Treasury	0,04452***	0,02498***	-0,01897***	-0,00043	-0,01902***	-0,37697***	1,00000				
Herd dummy	0,16045***	0,01602***	0,01595***	-0,03117***	-0,03584***	-0,00573	-0,01702***	1,00000			
Herding Index	-0,00021	0,01223***	0,00403	-0,00641*	0,00033	0,00322	-0,00061	0,00546	1,00000		
Logarithm of Herding Index	0,23289***	0,02131***	0,00388	-0,01972***	-0,02317***	-0,00216	-0,00586	0,64813***	0,04099***	1,00000	
Return in 3 months	-0,00915**	0,00820**	0,01212***	-0,00620*	-0,00660*	-0,03449***	-0,01734***	0,03021***	-0,00012	0,02229***	1,00000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Regarding firms stock return, Panel C reports that the firms with bold forecasters tend to have a significantly lower 3-month return, than those with herding forecasters.

Panel D reports a correlation matrix table that displays the correlation among all the characteristics. The table shows that there is a significantly positive correlation between herding and the 3-month stock return, and that there is a significantly negative correlation between herding and accuracy. It also reports a significantly positive correlation between accuracy and GDP growth, which supports that forecasters tend to herd more in a bad economic environment (measured by GDP growth). Furthermore, the correlation between GDP growth and the credit risk is significantly negative, in line with our hypothesis.

2. *The association between macro factors and analyst herding behavior*

Table 2 and Table 3 show the results when estimating the two models that explain herding with macro factors and analyst characteristics.

Table 2 displays the robust logit regression on $Herd\_dummy_{itc}$ as the dependent variable. Included in the regression are the two variables that proxies for the macro fluctuations, $Growth\_GDP_{t}$ and $Credit\_risk_{t}$, and the characteristics; $Days\_Elapsed_{itc}$, $Forecast\_Horizon_{itc}$, PTD_DIST1_{itc} and the $lag\_accuracy_{itc}$. The regression shows a negative association between GDP growth and the probability of herding, at the 1 percent level of significance. The credit risk measure, $Credit\_Risk_{t}$, has a significantly negative association with herding, at the 1 percent level of significance, given a fixed GDP growth, in contrast to the hypothesis.

Further, the results are consistent with previous research (Clement, Tse 2005), that herding tends to increase with the number of days between the forecast and the interim date, and decrease with previous accuracy. What is not consistent with Clement et al, is that the forecast horizon is positively associated with the probability of herding, which Clement et al find to be positively correlated with *boldness*. The probability of herding increases with the number of days to the interim date. This may be explained by forecasting being more difficult with a long horizon, and under uncertainty analysts tend to herd. Clement et al explain the association as analysts are less likely to herd since the consensus contains relatively few estimates.

The regression was calculated with 248 598 observations and all variables are significant on a 1 % level.

Table 2

Six variable logit regression on the Probability of Herding in a quarter

This table reports an estimate of the six-factor model, $Herd\_dummy_{itc} = \alpha_0 + \alpha_1 Growth\_GDP_{it} + \alpha_2 Credit\_Risk_{it} + \alpha_3 Days\_Elapsed_{itc} + \alpha_4 Forecast\_Horizion_{itc} + \alpha_5 PTD\_DIST1_{itc} + \alpha_6\ lag\_accuracy_{itc} + \varepsilon_{itc}$, for the probability of herding. The variables are: $Growth\_GDP_t$; the growth in US GDP in percent over the previous quarter. $Credit\ risk_t$; the Corporate Bond Yield relative to the 10-year Treasury Note. $Days\_Elapsed_{itc}$; the days to the last previously issued or revised forecast. $Forecast\_Horizon_{itc}$; the days to the release of the interim report. PTD_Dist1_{itc}; the absolute distance between the consensus *before* a forecasters revision and the analysts estimate *before* the revision. $Lag\_accuracy_{itc}$; the forecast accuracy of an analyst, for the specific firm, in the previous period.
n = 248 598.

	Regression 1. Logit Probability of Herding
VARIABLES	Herd dummy
Growth GDP	-0.17728*** (3.7968e-02)
Credit Risk: Corporate Bond Yield to 10-Year Treasury	-0.39832*** (4.4129e-02)
Days Elapsed: Days Since Last Forecast	0.06988*** (1.9432e-02)
Forecast Horizon: Number of days to interim report	0.18535*** (2.6903e-02)
PTD_Dist1: Previous Forecast Distance to Previous Consensus Distance	2.06146*** (2.8269e-02)
Lag accuracy: Accuracy in previous period	-0.14215*** (1.3601e-02)
Constant	-0.39348*** (3.3479e-02)
Observations	248,598

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

Table 3

Six variable regression on the natural logarithm of Herding index

The table reports the estimates of Regression 2, $lHerding\_index_{itc} = \beta_0 + \beta_1 Growth\_GDP_t + \beta_2 Credit\_Risk_t + \beta_3 Days\_Elapsed_{itc} + \beta_4 Forecast\_Horizon_{itc} + \beta_5 PTD\_DIST1_{itc} + \beta_6\, lag\_accuracy_{itc} + \varepsilon_{itc}$. The variables are: *Growth_GDP*$_t$; the growth in US GDP in percent over the previous quarter. *Credit risk*$_t$; the Corporate Bond Yield relative to the 10-year Treasury Note. *Days_Elapsed*$_{itc}$; the days to the last previously reported forecast. *Forecast_Horizon*$_{itc}$; the days to the release of the interim report. *PTD_Dist1*$_{itc}$; the absolute distance between the consensus *before* a forecasters revision and the analysts estimate *before* the revision. *Lag_accuracy*$_{itc}$; the forecast accuracy of an analyst, for the specific firm, in the previous period.
n = 248 598.

	Regression 2. Herding Index and exploratory variables
VARIABLES	Logarithm of Herding Index
Growth GDP	-0.05056**
	(2.2416e-02)
Credit Risk: Corporate Bond Yield to 10-Year Treasury	-0.16343***
	(2.5849e-02)
Days Elapsed: Days Since Last Forecast	0.05275***
	(1.1451e-02)
Forecast Horizon: Number of days to interim report	0.05658***
	(1.6380e-02)
PTD_Dist1: Previous Forecast Distance to Previous Consensus Distance	1.82388***
	(1.1432e-02)
Lag accuracy: Accuracy in previous period	-0.02942***
	(7.9357e-03)
Constant	-0.38364***
	(1.9968e-02)
Observations	248,598
R-squared	0.055

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

Table 3 reports the results of Regression 2 which explain herding with the same independent variables and characteristics as Regression 1. Though, instead of using the dependent variable $Herd\_dummy_{itc}$, the natural logarithm of the herding index, $lHerding\_Index_{itc}$, was used. This regression provides the same results as shown in Table 2 and further supports the results that herding behavior among analysts tends to decrease in a favorable economy, defined with GDP growth. The regression is based on 248 598 observations. For all variables the null hypotheses, that the coefficient is equal to zero, can be rejected at the 1 percent level.

3. *The association between Accuracy, herding, macro factors and characteristics*

Table 4 shows the estimates of Regression model 3 that explains the accuracy of forecasts with herding, macro factors and characteristics.

The association between forecasting accuracy and herding was significantly negative, which was consistent with our previous reports and with Clement et al (Clement, Tse 2005). Note that the distance between the analysts' pre-revision forecast and the pre-revision consensus is not significant (PTD_DIST1_{itc}) in the regression model. The association between $lag\_accuracy_{itc}$ and accuracy is significantly positive, which means that analysts that have been accurate in previous periods will continue to release accurate forecasts. We also find that GDP growth is positively associated with accuracy, which means that the accuracy is greater when the economic macro conditions, in terms of GDP growth, are more favorable. This is consistent with our prior reports that imply that herding and favorable market conditions are negatively associated. In contrast to earlier beliefs, the $Credit\_Risk_t$ is also significantly positively associated with accuracy.

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Table 4.

The table reports the estimate of the five variable regression, $Accuracy_{itc} = \gamma_0 + \gamma_1 Growth\_GDP_t + \gamma_2 Credit\_Risk_t + \gamma_3 lHerding\_Index_{itc} + \gamma_4 PTD\_DIST1_{itc} + \gamma_5 lag\_accuracy_{itc} + \varepsilon_{itc}$, for the accuracy with explanatory variables. The independent variables are: *Growth_GDP*$_t$; the growth in US GDP in percent over the previous quarter. *Credit risk*$_t$; the Corporate Bond Yield relative to the 10-year Treasury Note. *lHerding_Index*$_{itc}$; the natural logarithm of the herding index, defined as $\ln\left(\frac{PTD\_DIST1}{PTD\_DIST2}\right)$. *PTD_Dist1*$_{itc}$; the absolute distance between the consensus *before* an analysts' revision and the estimate *before* the revision. *Lag_accuracy*$_{itc}$; the accuracy for the specific company and analyst in the previous period.
n = 248 598.

VARIABLES	Regression 3. Accuracy and exploratory variables Accuracy
Growth GDP	0.01749*** (4.8792e-03)
Credit Risk: Corporate Bond Yield to 10-Year Treasury	0.05277*** (5.7789e-03)
Logarithm of Herding Index	-0.00338*** (4.3217e-04)
PTD_Dist1: Previous Forecast Distance to Previous Consensus Distance	0.00317 (3.6123e-03)
Lag accuracy: Accuracy in previous period	0.23009*** (1.8371e-03)
Constant	0.49465*** (4.3010e-03)
Observations	248,598
R-squared	0.067

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

4. *The relation between stock market returns, herding and GDP growth*

This section explores the difference in market return of the companies that are followed by, on average, herding analysts compared to firms that are followed by, on average, bold analysts. Table 5, reports the analysis of the relationship between analyst herding and market returns, in different economic conditions based on GDP growth. It displays a 3x3 matrix, with three different GDP growth terciles and three different herding terciles. The table reports the average return of the companies that lie within each of these subsamples based on GDP growth and herding among analysts.

In each of the three terciles based on GDP, the 3-month return for the firms increases with the level of herding. The stock market return is significantly higher in the 3rd herding tercile compared to the 1st herding tercile, in all three GDP terciles. For the total sample, the difference in the 3-month return is significantly higher for companies that are followed by, on average, herding analysts.

Table 5.

Table 5 presents the average 3-month stock return when the sample is grouped into terciles, based on the 3 month GDP growth and on herding. The table shows that the market return is higher for the tercile that includes the most herding analyst, than for the tercile with the least herding analysts. The difference is significant for all GDP terciles.

Table 5	**Mean 3-month Returns**			
	3 Terciles of Growth GDP			
	Low		High	
3 Terciles of Herding Index	**T1**	**T2**	**T3**	**Total**
Low **T1**	-0,1%	0,0%	1,5%	0,4%
T2	1,1%	1,4%	3,0%	1,8%
High **T3**	2,6%	3,4%	3,5%	3,1%
Delta T1-T3	-2,7%b	-3,5%a	-2,0%b	-2,8%a
z-Stat	-2,4	-3,5	-2,4	-5,0

a,b Statistically significant at the one and five percent levels

V. Robustness Checks

To ensure that the results are reliable and that they do not consist of statistical bogus, a series of robustness test have been conducted.

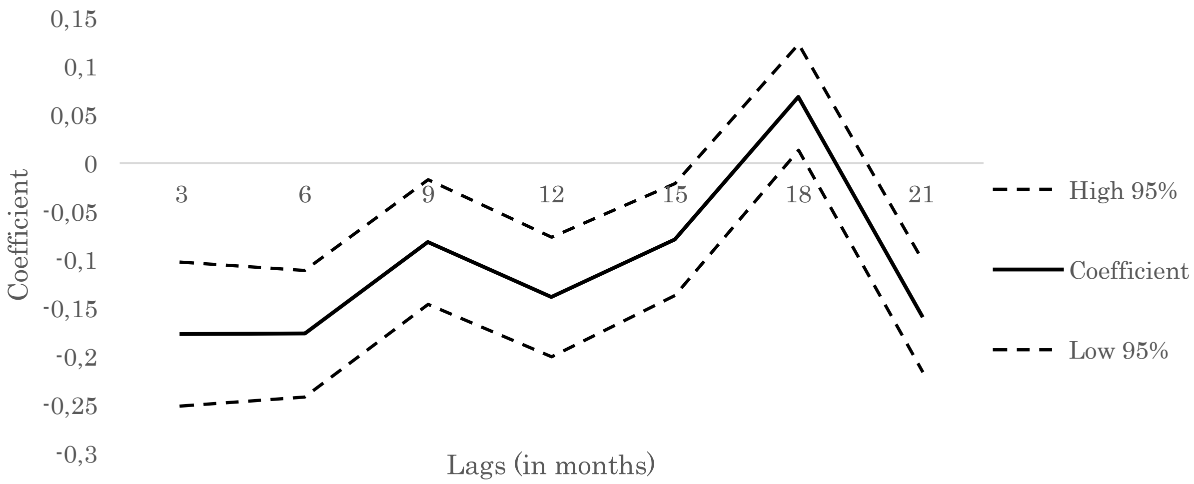

Figure 3. Robustness check: Lags in the Growth_GDP$_t$ variable in Regression 1. The regression is re-run with the variable Growth_GDP$_t$ lagged. The broken lines indicate the 95 percent confidence level and the black line the coefficient for Growth_GDP$_t$ in Regression 1.

1. *Introducing lags to Growth GDP*

One of the main explanatory variables in the study is the Growth_GDP$_t$. To test the reliability of this variable, lags are introduced and the coefficient of Growth GDP in Regression 1 is recalculated.[3] The rationale behind this is that the actors in the economy are not immediately affected by the GDP growth. The original regression is made with one lag (three months), but if there are cases where the GDP growth is not widely known within three months it is interesting to look at the coefficient with multiple lags. Figure 3 shows that as the lag gets longer the coefficient for Growth_GDP$_t$ in

[3] Regression 1: $Herd\_dummy_{itc} = \alpha_0 + \alpha_1 Growth\_GDP_t + \alpha_2 Credit\_Risk_t + \alpha_3 Days\_Elapsed_{itc} + \alpha_4 Forecast\_Horizion_{itc} + \alpha_5 PTD\_DIST1_{itc} + \alpha_6\ lag\_accuracy_{itc} + \varepsilon_{itc}$

Regression 1 increases, but the coefficient is significantly negative up to six lags (18 months).

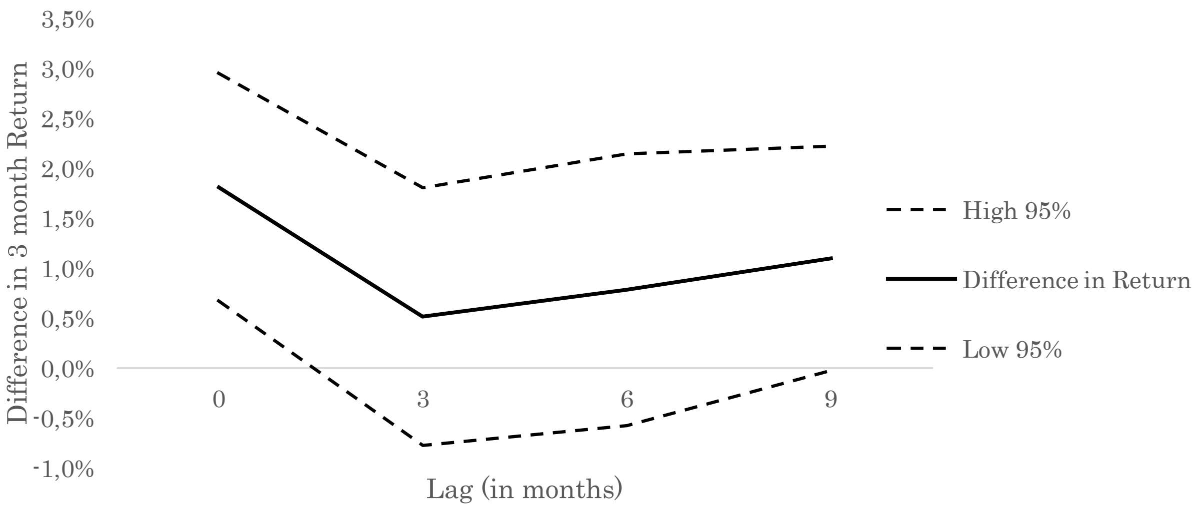

Figure 4. Robustness check: The effect on the difference in return, between bold and herding forecasts, by lags in average herding. The figure shows the difference in return between firms that have on average herded or bold forecasts. The black solid line indicates the difference in the three-month return with respect to the lags, and the broken lines indicate the 95 % confidence interval.

2. *Difference in three-month Return for Herded and Bold Forecasts*

Figure 4 shows the difference in return for firms that have, on average, herded or, on average, bold forecasts issued for their EBIT. Note that there is only a significant difference in three-month return when firms are sorted on the current level of herding. When lags are introduced the difference in return diminishes. This is intuitive because the analysts issue their forecast to, in the best way, reflect the specific (current) periods earnings, not for future periods earnings in a general way.

3. *Presence of heteroscedasticity*

Through White's tests it is concluded that the regressions are subject to heteroscedasticity. Appendix Figure 1 and 2 show how the residuals in Regression 2 and 3 are related to the fitted values in the models. To counteract this flaw all the used regression models are estimated with robust standard errors. Important to note is that the coefficients are not affected by the heteroscedasticity and that the standard errors for the regression models are affected in a very limited way when estimating the regressions with and without corrections for heteroscedasticity.

4. *Multicollinearity*

In the regression models, the coefficient of the Credit_Risk variable takes the opposite sign than hypothesized in part III: Research Method. This raises the concern for multicollinearity between the explanatory variables, especially between the Credit_Risk variable and Growth_GDP. However, Appendix Figure 3, tabulates the Variance Inflation Factors for Regression models 2 and 3. It can be concluded that no severe problem of multicollinearity exists.

VI. Implications & further research

In this section the economic interpretation of the findings is explored, in conjunction with the practical implications that the findings lead to. Finally, some potential future research questions are proposed.

The first research question shows that financial analysts increase their level of herding when economic conditions are unfavorable, in terms of GDP growth. After a period with high GDP growth, and thus good economic conditions, analysts tend to decrease the level of herding. According to Hong et al, analysts who are insecure tend to herd their forecasts (Hong, Kubik & Solomon 2000). After a period of economic slowdown, companies evaluate their employees more thoroughly. During unfavorable economic conditions, the risk of termination increases which will in turn increase the career concerns among analysts. Herding increases with career concerns, and this imply that herding will increase with lower GDP growth, and thus with an unfavorable economic environment.

Regarding the second macro-economic variable, credit risk, the hypothesis was that it would be a good proxy for the overall economy. Though, the regression analysis in this study reveals that this is not the case. The credit risk is significantly negatively associated with herding, which implies that herding decreases when the credit risk increases. These results do not fit within the career concerns argument, since it is very unlikely that the career concerns among analysts would decrease when the credit risk increases. Therefore, the possible explanation to this association follows from the information asymmetry argument, informational herding.

The credit risk is a measure of how much a lender in the economy must receive to be willing to lend out money, to be compensated for the risk of the borrower defaulting. In other terms, it is a measure of how much the lender trusts her counterparts. Thus, when the credit risk increases, the trust level in the economy decreases, i.e. the lender must receive more to compensate for the uncertainty regarding her counterparts' trustworthiness.

The dynamics of herding that are derived from asymmetric information, are built on the assumption that an analyst believes that her forecast is less accurate than the estimates of her counterparts, i.e. that other analysts possess more relevant information than she does. Therefore, when the overall trustworthiness in the economy decreases, this is mirrored among analysts and they do not trust the forecasts of their counterparts.

In conclusion, an increase in the credit risk, ceteris paribus, will decrease the herding among analysts. Note, that the correlation between GDP growth and the credit risk is negative, though their impact on herding is very different, where one factor captures the effect of career concerns, and the other variable captures the effect of information asymmetry. Prior studies also find that "analyst following" increases with market liquidity, thus decreases with market illiquidity, which is related to the credit risk (Roulstone 2003).

The second research question, extends the studies of Clement et al, that bold analysts are significantly more accurate than herding analysts (Clement, Tse 2005). Firstly, we confirmed their findings. Secondly, by adding macro-economic factors, we found that accuracy is positively related to GDP growth. This can be explained with our previous findings taken together with prior literature. During poor economic conditions, i.e. when

GDP growth is low, analysts tend to herd their forecasts more than during good economic conditions, due to career concerns. This illustrates the agency problem between employer and the analysts. The analysts issue forecasts that they believe are more beneficial to themselves, when they perceive the risk of termination to be relatively high, i.e. during periods of low GDP growth, they issue herding forecasts because the consequence of inaccuracy by deviation from the herd is higher. In conflict with such behavior, the employer wants her analysts to, in every state of the economy, issue as accurate forecasts as possible.

The explanation of the positive relationship between GDP growth and accuracy can be derived from analysts' behavior. In times with good economic conditions, analysts will be bolder, because of less personal career concerns, and therefore produce more accurate forecasts. Further, we find that accuracy increases with the credit risk, which can be explained by an increase in credit risk decreasing the level of herding, as explained above.

To summarize, the explanation for the positive relationship between GDP growth, accuracy and credit risk, accuracy are that in times with high GDP growth, analysts will be bolder and thus release more accurate forecasts. However, it is also true that in times with increased credit risk, ceteris paribus, analysts will be bolder and thus release more accurate forecasts.

The third research question established that during the quarterly forecasting periods, the market returns of the followed firms were related to analyst behavior. Independent of business cycles, a firm that was followed by, on average, herding forecasters had, on average, significantly higher return, during the forecasting period, than a firm that was followed by bold forecasters. According to Olsen, herded forecasts suffer greater positive biases. During a forecasting period with herding forecasts, the analysts with estimates above the consensus are less likely to revise their estimate, due to optimism, which will make the consensus become more positively biased (Olsen 1996). Further, Hong et al find that optimism is one of the most important aspects that is related to favorable job separation (Hong, Kubik

2003). Thus, it is reasonable to assume that a herding analyst releases optimistic forecasts, which is in line with other studies (Huberts, Fuller 1995). The above explains why the return of the firms that are followed by on average herding forecasters is on average higher *during* the forecasting period, since the stock price will be positively affected by the positive bias in the forecasts (Bernard 1993).

Other studies that have looked at the return related to analyst herding behavior, have looked at the time period *after* the interim report has been released and have found a significantly negative relation between herding and return. This is not in contrast with this study's findings since the increase in the stock price *during* the forecasting period should result in a drop in the stock price when the actual earnings are published and the biases are revealed.

The practical implications from these research questions follow from combining the findings. Firstly, the research questions aim to further explain when financial analysts are herding. This is a primary interest because bold forecasts are significantly more accurate than herded forecasts. Further, an investor wants to know during what periods analysts are bold and thus when they can trust their forecasts and act on that information. This is also why the results regarding stock return are interesting. Herding implies an increased return during the forecasting period, though a negative return when the actual earnings are released (Olsen 1996).

In this paper, we have further explained herding among financial analysts, though there are still many unsolved questions that can increase the understanding of analysts' herding behavior.

There is a lot of literature regarding career concerns, though informational herding is a topic for future research in order to add further understanding to the area.

We have also studied the relationship between herding and stock market returns. One interesting question that remains unexplored is if the relationship between herding and future return can be used to construct a portfolio with abnormal returns.

VII. Conclusion

The overall conclusion of this study is that analysts' herding behavior differs over business cycles. Financial analysts tend to herd their forecasts during unfavorable economic conditions, in terms of GDP growth, and be bold during favorable conditions. This is explained by career concerns and is related to agency problems. During bad economic conditions, the risk of termination is greater, which increases career concerns, and thus the herding among analysts. Further, we find that analyst accuracy is positively associated with GDP growth. Therefore, during good times, analysts herd less and thus release more accurate forecasts.

Secondly, the study shows that there is a positive association between herding and credit risk, i.e. as the credit risk in the economy increases, analysts will rely less on their counterparts and herd less, leading to increased accuracy.

Finally, we show a relationship between herding behavior and stock return. Firms followed by, on average, herding analysts tend to have a higher return than those with bold forecasts, *during* the forecasting period. The possible explanation is that herded estimates are more positively biased, which will be reflected in the price and thus lead to a higher return during the forecasting period.

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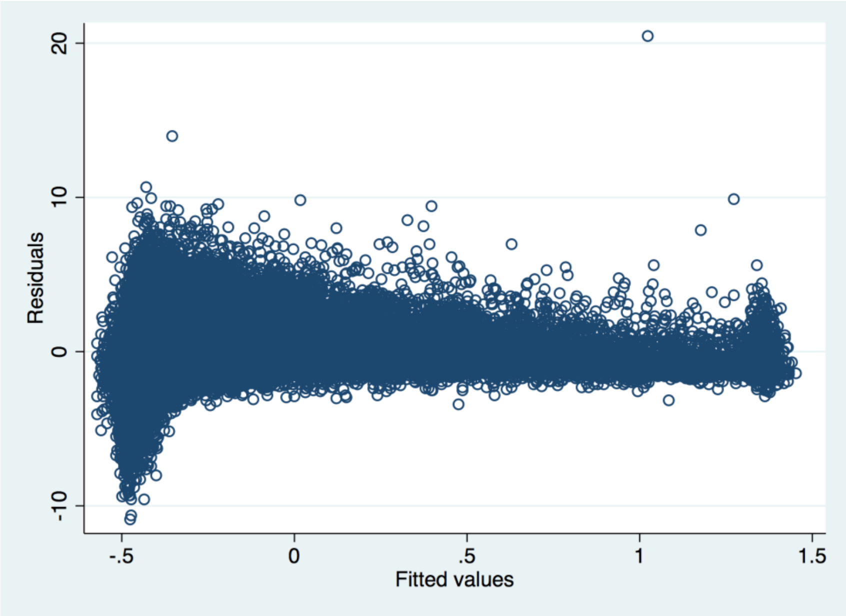
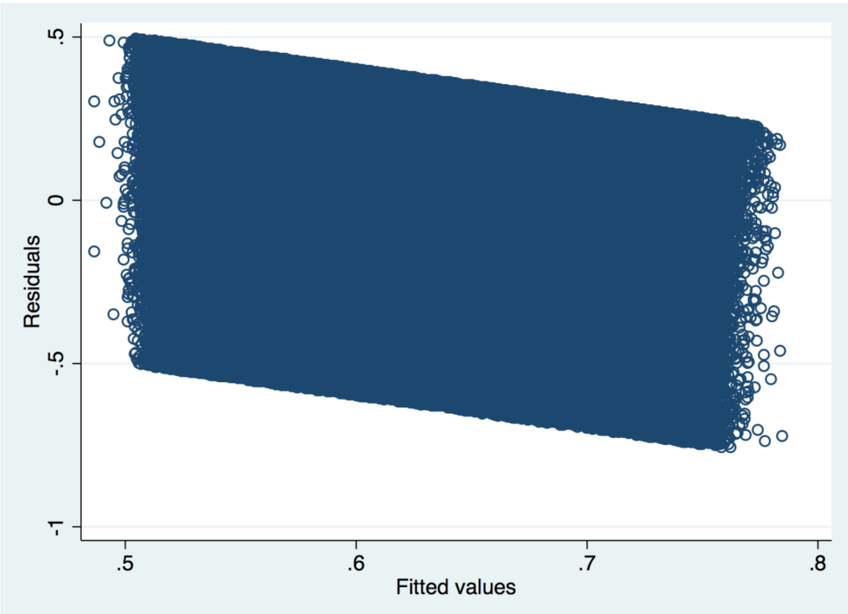
VIII. Appendix



Appendix Figure 1. Robustness check: The error term plotted against the fitted values of Regression 2. The variance of the error terms in Regression 2 appears not to be constant, thus heteroscedasticity exists.



Appendix Figure 2. Robustness check: The error term plotted against the fitted values of Regression 3. The variance of the error terms in Regression 3 appears not to be constant, thus heteroscedasticity exists.

Appendix Figure 3. Robustness check: Test for multicollinearity. The table below shows the Variance Inflation Factors for Regression 2 and 3. Regression 2; $lHerding\_index_{itc} = \beta_0 + \beta_1 Growth\_GDP_{it} + \beta_2 Credit\_Risk_{it} + \beta_3 Days\_Elapsed_{itc} + \beta_4 Forecast\_Horizon_{itc} + \beta_5 PTD\_DIST1_{itc} + \beta_6\ lag\_accuracy_{itc} + \varepsilon_{itc}$. Regression 3; $Accuracy_{itc} = \gamma_0 + \gamma_1 Growth\_GDP_{tc} + \gamma_2 Credit\_Risk_{it} + \gamma_3 lHerding\_Index_{itc} + \gamma_4 PTD\_DIST1_{itc} + \gamma_5 lag\_accuracy_{itc} + \varepsilon_{itc}$. No Variance inflation factor is alarmingly high.

Appendix Figure 3		**Regression 2**	**Regression 3**
Variable	**VIF**		
Credit Risk		1,10	1,10
Growth GDP		1,10	1,10
lag accuracy		1,01	1,00
PTD Dist1		1,01	1,06
Forcast Horizon		1,01	
Days Elapsed		1,01	
lHerding Index			1,06
Mean VIF		**1,04**	**1,06**