The Role of the Length of the Operating Cycle on Analysts' Forecasts Accuracy

Juliana Molina Queiroz
Universidade Federal do Rio de Janeiro
Jose Elias Feres de Almeida
Universidade Federal do Espirito Santo

Abstract

This paper examines the role of the length of the operating cycle on analysts' forecasts. Dechow (1994) shows that firm's performance measured by cash flows and earnings is less useful and reliable when the operating cycle is longer, since predictions can suffer more of timing and matching problems. Accruals are produced as a solution of the timing and matching problems which cause the poor firms performance measures. But, even considering accruals, the measures of firm performance for firms with longer operating cycle are not good, because of the unpredictability that longer operating cycles can generate. To the best of our knowledge it was still an open question how firms operating cycle may affect analysts' forecasts, mainly because they use business fundamentals to predict future cash flows. As a consequence of poor measures, the predictions for firms with longer operating cycle can be worse as the market cannot confirm or make good predictions as the losses are confirmed during a longer period. Our hypothesis is based on the idea that operating cycle plays an important role in explaining the accuracy of the forecasts. Then, our prediction is that the longer the operating cycle, the lower the analysts' forecasts accuracy. By testing regressions with interacted variables, we test the hypothesis by analyzing the U.S. public companies, from 1992 to 2017, available by Compustat, Thomson Reuters, and I/B/E/S. We use three proxy variables for accuracy based on the mean, median, and standard deviation of the consensus of the analysts' forecasts. Our results show that the longer the operating cycle, the lower the analysts' forecasts accuracy.

Keywords: Length of the Operating Cycle, Operating Cycle, Trade Cycle, Analysts' Forecasts, Analysts' Forecasts Accuracy.

1. INTRODUCTION

In this paper, we analyze the role of the length of the operating cycle on analysts' forecasts accuracy. Analysts elaborate their forecasts based on firm's performance. Those measures of performance are grounded on earnings and cash flows information. That information is useful to analyze firm's performance because it can reflect the accounting policies and procedures used to generate financial information. However, firms performance that is measured by cash flows and earnings may be less useful and reliable when the duration of the operating cycle is longer (Dechow, 1994).

According to Dechow (1994), firms with longer operating cycle suffer more from timing and matching problems, whether compared to firms with shorter operating cycles. For example, a firm with 65 days of operating cycle may recognize either receivables or payments during the same year while firms with more than 365 days may recognize these values during the entire duration of the operating cycle. Then, the consequence of the problems of timing and matching is the production of poor measures. As a consequence of poor measures, the predictions for firms with longer operating cycle can be worse as the market cannot confirm or come up good predictions as the losses are confirmed during a longer period.

Accruals are produced as a solution of the timing and matching problems which causes the poor firms performance measures. But, even considering accruals, the measures of firm performance for firms with longer operating cycle are not good, because of the unpredictability that longer operating cycles can generate. Then, analysts provide their forecasts based on information which can suffer more from these problems. If the performance is measured on information that suffers more from timing and matching problems, the results can be worse forecasts accuracy for firms with longer operating cycles. To the best of our knowledge, it was still an open question of how firms operating cycle affects analysts' forecasts accuracy. Our hypothesis is based on the idea that operating cycle plays an important role in explaining the accuracy of the forecasts.

Firms with longer operating cycles suffer more from timing and matching problems (Dechow, 1994). Then, for our hypothesis, we hypothesize that the longer the operating cycle, the lower the analysts' forecasts accuracy (H1). We test our hypothesis by analyzing the U.S. public companies, from 1992 to 2017, available by Compustat, Thomson Reuters, and I/B/E/S. We use three proxy variables for accuracy based on the mean, median, and standard deviation of the consensus of the analysts' forecasts.

We also use two proxy variables for the length of the operating cycle. The first proxy of the operating cycle, we calculate as the traditional operating cycle, and the second one is trade cycle (Dechow, 1994).

First, to answer how the length of the operating cycle affects analysts' forecasts accuracy, we use different models of regressions with proxies for accuracy and operating cycle. We find evidence that shows the longer the operating cycle, the worse the analysts' forecasts accuracy is by testing H1. We believe that analysts make the same mistake forecasting for firms with longer operating cycles, because our results also reveal that analysts are more optimistic for firms with longer operating cycle by overestimating their EPS.

Forecasts are essential as a guide for decision making and also telling about the continuity of the business, the literature has given attention to the studies which have documented some related factors with the analysts' forecasts accuracy such as disclosure practices of the firms (Kross et al., 1990; Lang and Lundholm, 1996), analysts' characteristics (Clement, 1999), analysts career outcomes (Groysberg et al., 2011; Mikhail et al., 1999; Wu and Zang, 2009a), firm life cycle stages (Vorst and Yohn, 2018), analysts' incentives to get access to the management (Francis and Philbrick, 1993), predictability of the firm (Das et al., 1998), management or economic motivations (Kothari et al., 2016; Michaely and Womack, 1999), social and professional network (Westphal and Clement, 2008; Brochet et al., 2013) and existence of compensation incentives (Stickel, 1991).

Following this line of investigation, our research expands prior literature about analysts' forecasts by adding the analysis of operating cycle. We believe that our analysis can be important to understand and overcome the simple analysis of accounting values by adding some advanced analysis of them.

We contribute to the literature examining the extent of how the operating cycle affects forecasts accuracy. While prior research documents that the measurement of firms performance are less reliable for firms with longer operating cycle (Dechow, 1994), there is surprisingly no research examining how operating cycle can affect firms performance forecasts.

Finally, we believe that our results shed some light on how critical the analysis of accounting measures is, such as operating cycle and analyses of cash flows patterns to understand the stage and the situation of the firm. That understanding can be useful to help increase analysts' forecasts accuracy.

From now on, we believe that either analysts and investors can pay attention to the relationship between the length of the operating cycle and the predictions. Also, we believe that for better forecasts, it is necessary to revise the estimates, rethink the forecast of future cash flows, and consider firms life cycle stages that capture the fundamentals of firm's operations that are reflected in cash flows.

The remainder of the paper is organized as follows. In the next section, we discuss the related literature. In the third section, we develop our hypotheses. We describe the method in the fourth section, and in the fifth section, we present our results. Finally, in the last section, we present the conclusions.

2. RELATED LITERATURE

2.1 ANALYSTS' FORECASTS ACCURACY

Two properties of analysts' forecasts have received considerable attention in the literature: (1) forecast accuracy and (2) forecast bias. Accuracy generally refers to the absolute difference between the analysts' predictions and the real earnings. Forecast bias usually refers to the average of. the difference between these values.

Prior literature analyze which factors may influence analysts' predictions, for example, some factors related to the characteristics of the companies under analysis, such as size of the company (Lang and Lundholm, 1996), the number of analysts that follow each com- pany (Clement, 1999), historical variability of earnings (Kross et al., 1990) and available information of the company (Kross et al., 1990; Lang and Lundholm, 1996). In addition, the literature has shown the relation between accuracy and analysts characteristics, such as number of companies analysts follow (Kross et al., 1990), analysts experience (Clement, 1999), existence of compensation incentives (Stickel, 1991; Groysberg et al., 2011), other career results (Mikhail et al., 1999; Wu and Zang, 2009b; Groysberg et al., 2011) and other career factors, such as analysts turnover (Mikhail et al., 1999; Wu and Zang, 2009b).

In addition, researchers have been trying to determine how some factors may bias the forecasts, such as information provided by management or economic motivations (Kothari et al., 2016; Michaely and Womack, 1999), analysts' incentives to get access to the administration

(Francis and Philbrick, 1993), predictability of the firm (Das et al., 1998) and social and professional network (Westphal and Clement, 2008; Brochet et al., 2013).

Some factors can influence and are related to the most accurate prediction forecast. These factors can be related to both the company that generates the forecasts and the company that is analyzed to create the forecasts. There are also factors related to analysts, to the estimates themselves and others. Our research will expand the analysts' forecasts literature by providing pieces of evidence of the relationship between the accuracy of these predictions and the length of the operating cycle, even considering firm life cycle and firm industry life cycle stages.

In our research, we analyze analysts' forecasts accuracy by using three measures: absolute bias, bias, and standard deviation (std). We calculate them as following:

$$\text{Absolute Bias} = |(\text{AF} - \text{Actual})|/\text{Price} * 100$$

$$\text{Bias} = (\text{AF} - \text{Actual})/\text{Price} * 100$$

$$\text{std} = \text{standard deviation}/\text{Price} * 100$$

Where AF is the consensus of EPS (Earnings Per Share) analysts' forecasts. Actual is the real value of EPS, and Price is the beginning-of-period share price. In that way, we calculate absolute bias and bias by comparing the analysts' forecasts consensus and the real value of EPS. All proxies for Analysts Forecasts are scaled by actual Price of the beginning of the period. Also, we multiply for 100 for scaling purposes. Then we analyze the analysts' forecasts percentage rather than fraction.

Following the calculation, the only difference between accuracy and bias is that the accuracy shows the absolute error of the forecast, independent of the signal. On the other hand, the bias shows the difference between the forecast and the actual value. It means that the analyses of the bias permit us to understand if the analysts were optimistic or pessimistic regarding firms EPS. Analysts are considered optimistic when their forecasts are higher than the actual value of EPS and pessimists when the forecasts are lower than the actual EPS. Regarding the last measure, std shows the volatility of the analysts' forecasts across analysts. The more volatility the forecasts are, the lower the accuracy is.

3. HYPOTHESES DEVELOPMENT

We develop one hypothesis to test the relation between the operating cycle and the analysts' forecasts accuracy. In this section, we develop the thinking behind our hypothesis. We discuss the hypothesis in the first subsection, where we relate analysts' forecasts accuracy and the operating cycle.

3.1 ANALYSTS' FORECASTS AND THE OPERATING CYCLE

Investment decisions are based on the future expectation of returns. The valuation theory is well known and straightforward. The value of the investment is compared to the valuation of the net present value of the future cash distributions that they are expected to generate.

However, the theory runs away of reality, particularly regarding predictions, since predictions are necessarily surrounded by uncertainty. Thus, many ways can be useful to mitigate the inaccuracy of these predictions. Commonly, one of the first steps to start making these predictions is understanding the valuation theory and, then, examining the business and financial statements of the companies. Despite being able to gather all this information which can reduce the uncertainty, there will still doubt about the forecasts. That is why the business literature has made an effort to try to figure out the situations in which the estimates would be more accurate.

The analyses of the financial statements play an essential role to mitigate the gap between the theory and the practice. Nevertheless, analyzing financial statements does not necessarily allows the user to forecast earnings; they can reveal a detailed description of the firm's historical business activities. Additionally, information such as earnings reflect almost all the procedures, choices, and accounting polices made during the production of the reports. Wherefore, that is the reason why the most commonly used financial information for forecasts are the values of earnings and cash flows. That information is useful to identify the performance of both the present and the future (forecasts) of the firms. Thus, analysts use those pieces of information as a way to predict possible future gains and, consequentially, the performance of the firm, either earnings or share prices in subsequent periods.

Dechow (1994) identifies the relation between earnings and cash flows with share prices and returns. One of the findings shows that the measure of the firm performance may be less useful and reliable when the duration of the operating cycle is longer, because of the timing and matching problems. The author highlights that accruals can explain these findings. When firms have a longer operating cycle, it gives rise to generate more accruals and then, more problems of matching and timing. On that way, analysts make their forecasts based on the information available to them, which could suffer more of the timing and matching problems because of the longer operating cycles. The result of that process can be less accuracy of the estimations in the cases in which forecasts are made based on the information which suffers more of such problems. Hence, longer operating cycles produce naturally worse measures of firm performance. Considering that analysts' forecasts are based on cash flows and earnings information to measure actual performance and future performance, it is possible that those forecasts are less precise to those firms that have longer operating cycles.

Moreover, using findings of (Dechow, 1994) as a starting point, DeFond and Hung (2001) analyzed whether firms with shorter operating cycles have a higher probability of having analysts making cash flows' forecasts. Hence, the study provides evidence that there is a relation between the propensity of analysts producing estimates of cash flows of firms with shorter operating cycles. Thus, due to the relationship between the demand and offer of cash flows' forecasts, it may be expected that these forecasts are more precise, corroborating the idea developed based on Dechow (1994). Then, H1 is:

H1: The longer the operating cycle, the worse the analysts' forecasts accuracy.

4. RESEARCH DESIGN

In this section, we describe the Research Design regarding the creation of the variables proxy for analysts' forecasts accuracy, operating cycle, firm life cycle stages, and firm-industry life cycle stages. Lastly, we describe the tests we have run, and in the last subsection, we describe our Sample Selection.

4.1 PROXY FOR ANALYSTS' FORECASTS ACCURACY AND OPERATING CYCLE

Our study focuses on the relation between analysts' forecasts and operating cycle, also considering the firm stages life cycle and firm-industry life cycles. Therefore, we create proxy variables for Analysts Forecasts, Operating Cycle, and Control Variables based on previous literature. The organization of the specification of the variables is described in Table 1.

Table 1: Tables of Specification of Variables

Variables	Description - Tables/Panels
AF	Analysts' Forecasts (Table 2/Panel A)
LOC	Length of the Operating Cycle (Table 2/Panel B)
QOC	Operating Cycle Quartiles (Table 2/Panel C)
Controls	Control Variables (Table 3)

First, to test our hypotheses, we use the dependent variable AFjit, which represents the different proxies for the analysts' forecasts. The first two proxies we use to examine analysts' forecasts based on the earnings estimation consensus and the actual earnings, as reported by I/B/E/S, scaled by the beginning of fiscal period price and multiplied by 100. The last proxy is the standard deviation of the forecasts, as reported by I/B/E/S, scaled by the beginning of fiscal period price and multiplied by 100. We analyze the following five values: mean and median of the absolute bias, mean and median of the bias, and the standard deviation of the analysts' forecasts consensus of the Earnings Per Share (EPS) as reported by I/B/E/S. The analysts' forecasts variables are described in Table 2 - Panel A.

Second, we estimate an independent variable of OCit, which represents the different proxies for the operating cycle. The proxies we use to examine operating cycles are based on prior literature Dechow (1994). The first proxy is the traditional measure of the operating cycle, which we calculate by the summation of the inventory days outstanding (inventory period) and the accounts receivable days outstanding (accounts receivable period). The second proxy for the operating cycle is trade cycle, which is calculated by the summation of the traditional operating cycle and the accounts receivable days outstanding (accounts receivable period). Besides that, we analyze the natural logarithm of the proxy variables for Operating Cycle and trade cycle. The operating cycle variables are described in Table 2 - Panel B.

Third, we divide the firms in groups according to quartiles of operating cycle and trade cycle. Thus, we investigate two groups were based on OCit. The first group we analyze is the group composed of the firms in the first quartile (firms with shorter operating cycles – Low OCit). The second group is composed of firms in the third quartile (firms with longer operating cycles – Up OCit). We use the dummy variable Low OCit to represent the firms with shorter operating cycles, and the dummy variable Up OCit to represent the firms with longer operating cycles. The variable Low OCit receives the value 1 when the firm is in the first quartile, which means it has shorter operating cycles, and 0 otherwise. On the other hand, the variable Up OCit receives the value 1 when the firm is in the third quartile, which means it has longer operating cycles and 0 otherwise. We apply the same procedure for trade cycle, the second proxy variable of operating cycles. Thus, we use the variable QOCjit which represents Low OCit, Up OCit, Low TCit and Up TCit. The variables for quartiles of the proxies of the operating cycle are described in Table 2 - Panel C.

Table 2: Specification of Variables of Interest

Variables	**Description**
Panel A: Specification of the Analysts' Forecast Variables.	
AF	Proxy for analysts' forecasts accuracy. It can be abs mean, abs med, af mean, af med and std.
abs mean	Absolute difference between the mean of the analysts' forecasts consensus and the actual earnings, multiplied by -100, scaled by beginning-of-the-period price [I/B/E/S].
abs med	Absolute difference between the median of the analysts' forecasts consensus and the actual earnings, multiplied by -100, scaled by beginning-of-the-period price [I/B/E/S].
af mean	Difference between the mean of the analysts' forecasts consensus and the actual earnings, multiplied by -100, scaled by beginning-of-the- period price [I/B/E/S].
af med	Difference between the median of the analysts' forecasts consensus and the actual earnings, multiplied by -100, scaled by beginning-of- the-period price [I/B/E/S].
std	Standard deviation of the analysts' forecasts [I/B/E/S].
Panel B: Specification of the Length of the Operating Cycle Proxy Variables.	
LOC	Proxy for Length of the Operating cycle. It can be OC, TC, LnOC or LnTC.
OC	Operating Cycle = Inventory Period (IP) + Accounts Receivable Pe- riod (ARP) [Compustat].
TC	Trade Cycle = Inventory Period (IP) + Accounts Receivable Period (ARP) - Payable Deffered Period (PDP) [Compustat].
IP	Average Inventory * 365 / Cost of Good Sold [Compustat].
ARP	Average Accounts Receivables * 365 / Sales
PDP	Average Accounts Receivables * 365 / Purchases [Compustat].
LnOC	Natural Logarithm of Operating Cycle.
LnTC	Natural Logarithm of Trade Cycle.
Panel C: Specification of Operating Cycle Proxy Variables.	
QOC	Dummy for Quartile, wich can be Q1OC, Q3OC, Q1TC or Q3TC.
Low OC	Dummy for Lower Quartile, wich 1 is for firm-year observations with shorter operating cycles and 0 for firms with longer operating cycles.
Up OC	Dummy for Upper Quartile, wich 1 is for firm-year observations with longer operating cycles and 0 for firms with shorter operating cycles.
Low TC	Dummy for Lower Quartile, wich 1 is for firm-year observations with shorter operating cycles and 0 for firms with longer trade cycles.
Up TC	Dummy for Upper Quartile, wich 1 is for firm-year observations with longer operating cycles and 0 for firms with shorter trade cycles.

We use control variables accordingly to the previous literature. We analyze control variables for basic firms characteristics such as Size, Debt, ROA, MTB, Loss and Sector (Lang and Lundholm, 1996; Yang, 2012), number of analysts that follow each company (Clement, 1999; Yang, 2012), Industry Concentration (Verrecchia, 1983) and Institution Ownership (Baginski et al., 2019), CEO Tenure (Feng et al., 2009), Litigation Risk and Acquisition (Yang, 2012). In addition to the control variables, we include year variables in the models to control macro effects from the market. Table 4 describes the control variables.

Table 3: Specification of Control Variables

Variables	Description
Size	Market-value of the previous year [Compustat].
Debt	Total debt over total assets [Compustat].
ROA	Net Income / Average Total Assets [Compustat].
MTB	Market value / Equity value [Compustat].
Loss	Dummy variable where it is equal to 1 if the firm reported loss in the fiscal year forecasted and 0 otherwise [Compustat].
ANAfollow	Number of analysts following the firm-year observation [Compustat].
IndConcent	Product market competition proxied by HHI [Compustat].
InstOwn	Percent of shares held by institutions, measured as the average institutional ownership during the year in which the management forecast was released [Thompson Reuters].
CEOTenure	In years, how long the CEO has held his/her current title, measured in the year in which the management forecast was released [Execucomp].
LitRisk	Indicator variable equal to 1 if firm is in one of the following high-litigation risk industries: biotech (2833-2836), computers (3570-3577/7370-7374) , electronics (3670-3674) , retailing (5200-5961), R&D (8731-8734) service and suffers a 20% or greater decrease in earnings; zero otherwise.
Acquisition	Indicator variable equal to one if the firm had a merger or acquisition during the forecast period [Compustat].

The first model is:

$$AF_{jit} = \beta_0 + \beta_1 \text{LOCjit} + \beta_n Control_{jit} + \beta_n Year_{jit} + \beta_n Sector_{jit} + \varepsilon$$

where AF is a variable for analysts' forecasts proxies (abs mean, abs med, AF mean and AF med), OC is the variable for operating cycle proxies (OC, LnOC, TC and LnTC), Control, Year and Sector are the control variables.

The second model is:

$$AF_{jit} = \beta_0 + \beta_1 \text{QOCjit} + \beta_n Control_{jit} + \beta_n Year_{jit} + \beta_n Sector_{jit} + \varepsilon$$

where AF is a variable for analysts' forecasts proxies (abs mean, abs med, AF mean and AF med), QOC is the proxy variable for Lower and Upper quartile of operating cycle proxies (Low OC, Up OC, Low TC and Up TC) and, finally, Control, Year, and Sector are the control variables.

The third model is:

$$AF_{jit} = \beta_0 + \beta_1 \text{LowOCjit} + \beta_1 \text{UpOCjit} + \beta_n Control_{jit} + \beta_n Year_{jit} + \beta_n Sector_{jit} + \varepsilon$$

where AF is a variable for analysts' forecasts proxies (abs mean, abs med, AF mean and AF med), Low OC is the proxy variable for Lower quartile of operating cycle proxies (Low OC and

Low TC), Up OC is the proxy variable for Upper quartile of operating cycle proxies (Up OC and Up TC) and, finally, Control, Year and Sector are the control variables. Regarding H2 in which we test the relation between analysts' forecasts accuracy (AF) and the operating cycle (OC) by Firm Life Cycle Stages, we create interacted variables between the variables proxy of operating cycle, operating cycle (OC) and trade cycle (TC) with Stages of Firm Life Cycle (FLC). Specifically, to test H2, we estimate the model as follows adding OC and FLC in same regression (forth model).

4.4 SAMPLE SELECTION

The sample is composed of all US non-financial companies listed on the NASDAQ, from 1992 to 2017, available simultaneously by Compustat, Thomson Reuters and I/B/E/S. The choice of the sample period is due to the higher number of analysts providing forecasts, and as reported in Panel A of Table 4, our sample begins with 15058 observations. Thus, we drop observations with negative equity (277), sales less than U$1 (19) and with the price close less than U$5 (403). Finally, we drop firms in the Finance industry (3,673). Lastly, our final sample is composed of 10,686 observations. However, the number of observations in each test may vary according to the availability of the variables information.

As shown in table 4 - Panel B, almost a half of our sample is composed by manufacturing firms (5,175), but the sample also has considerable observations from Transportation and Public Utilities (1,714), Mining (717) and Retail Trade (504). Then, with fewer observations there are the Wholesale Trade (341) and Construction (215). The remaining industry, Agriculture, has less than 5% of the sample. Table 5 - Panel C displays our sample in a group of years. It shows that the data is scarce in the first group of years (between 1992 and 2000), containing about 20% of the sample. On the other hand, the last group that aggregates the most recent information with fewer years has more than 40% of the sample.

Table 4: Data Sample

Panel A: Data selection	
Number of observations in the initial data	15058
Less:	
Negative equity	-277
Sales less than 1	-19
Price close less than U$5	-403
Financial industry	-3673
Total Final Data	**10686**
Panel B: Industry Composition	
Two Digit SIC Industry Sector	
Agriculture, Forestry, & Fishing (1-9)	21
Mining (10-14)	717
Construction (15-17)	215
Manufacturing (10-39)	5175
Transportation & Public Utilities (40-49)	1714
Wholesale Trade (50-51)	341
Retail Trade (52-59)	504

Other	1999
Total	**10686**
Panel C: Observations by year	
1992-2000	2089
2001-2010	3974
2011-2017	4623
Total	**10686**

5. RESULTS

The descriptive statistics of the variables of interest and controls are in Table 5.

Table 5: Descriptive Statistics

Variable	Observations	Mean	Median	St.Dev.	Low. Quartile	Up. Quartile
abs mean	8,707	1.042	0.276	2.211	0.066	0.934
abs med	8,707	1.036	0.277	2.195	0.066	0.934
af mean	8,707	0.3	0.006	2.026	-0.183	0.414
af med	8,707	0.296	0.006	2.021	-0.182	0.403
std	8,525	0.327	0.123	0.588	0.04	0.335
OC	8,506	118.824	101.015	79.221	66.186	150.869
LnOC	8,506	4.556	4.615	0.71	4.192	5.016
TC	8,486	68.661	58.795	82.52	25.754	102.754
LnTC	7,530	4.062	4.211	1.012	3.602	4.704
Size	7,615	7.786	7.606	1.472	6.691	8.698
Debt	10,654	0.234	0.235	0.173	0.081	0.356
ROA	10,675	0.048	0.049	0.08	0.021	0.085
MTB	9,291	3.82	2.467	4.68	1.626	4.013
Loss	10,686	0.145	0	0.352	0	0
ANAfollow	10,686	11.113	9	7.86	5	16
IndConc	10,686	-0.236	-0.172	0.2	-0.295	-0.099
InstOwn	10,686	0.757	0.792	0.205	0.636	0.907
Tenure	10,686	1.411	1.386	0.842	0.693	2.079
Lit Risk	10,686	0.399	0	0.49	0	1
Aquis	10,686	0.535	1	0.499	0	1

Where abs mean is the mean of absolute bias of analysts' forecasts consensus, abs med is the med of absolute bias of analysts' forecasts consensus, af mean is the mean of bias of analysts' forecasts consensus, af med is the med of bias of analysts' forecasts consensus, std is the standard deviation of analysts' forecasts consensus, OC is operating cycle, a proxy variable for operating cycle, LnOC is natural logarithm of OC, TC is trade cycle, a proxy variable for operating cycle, LnTC is natural logarithm of TC, Size is the the market-value of the previous year, Debt is the ratio between total debt and total assets, ROA is the ratio between net income and total assets, MTB is the ratio between market value and equity value, Loss is dummy for reported loss, ANAfollow is the number of analysts following the firm-year observation, IndConcent is a proxy for market competition, InstOwn is the percent of shares held by institutions, CEOTenure is the time in years the CEO has held his/her current title, LitRisk in a indicator variable for high-litigation risk industry, Aquisition in an indicator variable for aquisition during the forecast period.

As shown in table 5, the descriptive statistics are consistent with previous literature. Proxy variables for analysts' forecasts accuracy are similar to Hughes and Ricks (1987), Kimbrough (2005) and Baginski (2018), respecting the proportions showing similar median, lower and upper quartiles for absolute bias. Baginski (2018) shows 0.21, 0.07 and 0.6, respectively for these values of absolute bias. The proxy variables for operating cycle and trade cycle show similar means to Dechow (1994) in which OC has about 120 days and TC about 70 days.

We do not report Spearman (Pearson) correlations because of space issues.

Table 6 shows that the relations between analysts' forecasts and the operating cycle variables. It shows a positive correlation between abs mean and abs med with OC, showing the first footprints of the negative relationship between analysts' forecasts accuracy and the length of the operating cycles. All correlations are significant at the 1 percent level. We omit the rest of the correlations because of space issues.

Table 6: Correlation between Variables of Interest

	abs mean	abs med	af mean	af med	std	OC	TC
abs mean	1	**0.99*** **	**0.17*** **	**0.18*** **	**0.74*** **	**0.06*** **	**0.11*** **
abs med	**0.99*** **	1	**0.17*** **	**0.17*** **	**0.73*** **	**0.06*** **	**0.11*** **
af mean	**0.44*** **	**0.43*** **	1	**0.99*** **	**0.13*** **	**0.06*** **	**0.05*** **
af med	**0.44*** **	**0.44*** **	**0.99*** **	1	**0.13*** **	**0.06*** **	**0.05*** **
std	**0.67*** **	**0.67*** **	**0.28*** **	**0.28*** **	1	**0.04*** **	**0.07*** **
OC	**0.06*** **	**0.06*** **	**0.06*** **	**0.06*** **	**0.04*** **	1	**0.82*** **
TC	**0.08*** **	**0.08*** **	**0.05*** **	**0.06*** **	**0.05*** **	**0.78*** **	1

Where abs mean is the mean of absolute bias of analysts' forecasts consensus, abs med is the med of absolute bias of analysts' forecasts consensus, af mean is the mean of bias of analysts' forecasts consensus, af med is the med of bias of analysts' forecasts consensus, std is the standard deviation of analysts' forecasts consensus, OC is operating cycle, a proxy variable for operating cycle, TC is trade cycle, a proxy variable for operating cycle. Significance levels: ***p<.01, **p<.05, *p<.10.

Table 7 shows the descriptive statistics for each quartile of the operating cycle and trade cycle.

Table 7: Descriptive Statistics by Operating Cycle and Trade Cycle quartiles

	Lower Quartile - OC			Upper Quartile - OC		
Variables	Observations	Mean	Stand.Dev.	Observations	Mean	Stand.Dev.
abs mean	2127	0.862	1.954	2126	1.159	2.224585
abs med	2127	0.854	1.939	2126	1.152	2.205853
af mean	2127	0.193	1.789	2126	0.47	2.160205
af med	2127	0.189	1.779	2126	0.465	2.155664
std	2081	0.303	0.569	2086	0.339	0.5641343
	Lower Quartile - TC			Upper Quartile - TC		
Variables	Observations	Mean	Stand.Dev.	Observations	Mean	Stand.Dev.
abs mean	2122	0.87	1.959	2121	1.314	2.472
abs med	2122	0.864	1.95	2121	1.306	2.453
af mean	2122	0.218	1.768	2121	0.533	2.351
af med	2122	0.212	1.762	2121	0.519	2.338
std	2089	0.322	0.586	2074	0.382	0.64

Where abs mean is the mean of absolute bias of analysts' forecasts consensus, abs med is the med of absolute bias of analysts' forecasts consensus, af mean is the mean of bias of analysts' forecasts consensus, af med is the med of bias of analysts' forecasts consensus, std is the standard deviation of analysts' forecasts consensus.

As shown in table 7, absolute bias, bias, and standard deviation values are higher for firms with longer operating cycle and trade cycle when compared to those firms with shorter OC. These preliminary results show that forecasts are less accurate for firms with longer operating cycle. Also, analysts seem to be more optimistic for these firms and, finally, higher standard deviation values show that the volatility of the forecast is higher for these firms.

Table 8 shows the tests for our H1 hypothesis regarding abs mean.

Table 8: Tests for H1 – abs_mean

Variables	(1) abs_mean	(2) abs_mean	(3) abs_mean	(4) abs_mean
OC	**0.00164***** **(2.862)**			
LnOC		**0.167**** **(2.365)**		
TC			**0.00151*** **(1.825)**	
LnTC				**0.135***** **(3.157)**
Constant	**2.656***** **(3.936)**	**2.095***** **(6.338)**	**2.785***** **(4.94)**	**2.714***** (6.233)
Observations	7,418	7,418	7,398	6,582
R-squared	0.147	0.146	0.146	0.16
Adj. R-squared	0.142	0.141	0.142	0.155
F-stats	8.57	8.386	8.539	8.051
p-value	0.000	0.000	0.000	0.000

Where abs mean is the mean of absolute bias of analysts' forecasts consensus, OC is operating cycle, a proxy variable for operating cycle, LnOC is natural logarithm of OC, TC is trade cycle, a proxy variable for operating cycle, LnTC is natural logarithm of TC; We do not show the results for control variables because of space issues (Size is the the market-value of the previous year, Debt is the ratio between total debt and total assets, ROA is the ratio between net income and total assets, MTB is the ratio between market value and equity value, Loss is a dummy for reported loss, ANAfollow is the number of analysts following the firm-year observation, IndConcent is a proxy for market competition, InstOwn is the percent of shares held by institutions, CEOTenure is the time in years the CEO has held his/her current title, LitRisk in a indicator variable for high-litigation risk industry, Aquisition in an indicator variable for aquisition during the forecast period). Significance levels: ***p<.01, **p<.05, *p<.10.

Table 8 shows that there is a positive relation between abs mean and the proxies of operating cycle (OC, LnOc, TC, and LnTC). Specifically, it indicates that there is a positive and statistically significant relationship between absolute error and the length of the operating cycle for all four of our proxies for operating cycle. For example, the coefficient on the OC variable is 0.00164 with a t-statistic of 2.862. This relationship also seems economically significant. To illustrate, using the above coefficient of 0.00164 and the standard deviation of OC of 79 days (see table 6) indicates an implied effect on the dependent variable of 0.13, which corresponds to about 15% of the interquartile range of the dependent variable. The interquartile range is better measure of the typical change in the dependent variable because abs_mean is highly right-skewed.

Thus, the results confirm our H1 that is, the longer the operating cycle, the worse the analysts' forecasts accuracy. Also, the results show that all the models (models 2,3,4 and 5) with the proxy variables for LOC are more powerful (higher adjusted R-squared) when compared to the model without the variables of interest (model 1). The results for abs med are in Appendix A and it shows the same positive relationship between abs med and the proxies of operating cycle (OC, LnOc, TC, and LnTC). We also test the relation between the abs mean and the proxies of operating cycle quartiles in the same and separated regressions and the results are in Appendix B and C and show that there is a positive relationship between absolute bias and the length of operating cycle for the proxies Up TC and Up LnTC, that is the longer the operating cycle, the higher bias.

Table 9 shows the tests for our H1 hypothesis regarding af_mean.

Table 9: Results for H1 - first model (af_mean)

Variables	(1) af_mean	(2) af_mean	(3) af_mean	(4) af_mean
OC	**0.00138***** **(3.376)**			
LnOC		**0.124***** **(3.068)**		
TC			**0.00121***** **(2.850)**	
LnTC				**0.0799***** **(3.103)**
Constant	0.241 (0.762)	-0.167 (-0.473)	0.341 (1.086)	0.255 (0.665)
Observations	7,418	7,418	7,398	6,582
R-squared	0.147	0.146	0.146	0.16
Adj. R-squared	0.142	0.141	0.142	0.155
F-stats	8.57	8.386	8.539	8.051
p-value	0.000	0.000	0.000	0.000

Where af_mean is the mean of the bias of the analysts' forecasts consensus, OC is operating cycle, a proxy variable for operating cycle, LnOC is natural logarithm of OC, TC is trade cycle, a proxy variable for operating cycle, LnTC is natural logarithm of TC; We do not show the results for control variables because of space issues (Size is the the market-value of the previous year, Debt is the ratio between total debt and total assets, ROA is the ratio between net income and total assets, MTB is the ratio between market value and equity value, Loss is a dummy for reported loss, ANAfollow is the number of analysts following the firm-year observation, IndConcent is a proxy for market competition, InstOwn is the percent of shares held by institutions, CEOTenure is the time in years the CEO has held his/her current title, LitRisk in a indicator variable for high-litigation risk industry, Aquisition in an indicator variable for aquisition during the forecast period). Significance levels: ***p<.01, **p<.05, *p<.10.

The results in table 9 show that there is a positive relation between af mean and the proxies of operating cycle (OC, LnOc, TC, and LnTC). Specifically, it indicates that there is a positive and statistically significant relationship between absolute error and the length of the operating cycle for all four of our proxies for operating cycle. For example, the coefficient of OC variable is 0.00138 with a t-statistic of 3.376. This relationship also seems economically significant. To illustrate, using the above coefficient of 0.00138 and the standard deviation of OC of 79 days (see table 6) indicates an implied effect on the dependent variable of 0.11, which corresponds to about 18% of the interquartile range of the dependent variable. The interquartile range is a better measure of the typical change in the dependent variable because af_mean is highly right-skewed.

Thus, the results confirm our H1 that is, the longer the operating cycle, the worse the analysts' forecasts accuracy. Also, the results show that all the models (models 2,3,4 and 5) with the proxy variables for LOC are more powerful (higher adjusted R-squared) when compared to the model without the variables of interest (model 1). The results for af med are in Appendix D and it shows the same positive relationship between af med and the proxies of operating cycle (OC, LnOc, TC, and LnTC). We also test the relation between the af mean and the proxies of operating cycle quartiles in the same and separated regressions and the results are in Appendix E and F and show that there is a positive relationship between absolute bias and the length of operating cycle for the proxies Up TC and Up LnTC, that is the longer the operating cycle, the higher bias.

Table 10 shows the tests for our H1 regarding standard deviation.

Table 10: Results for H1 - first model (std)

	(1)	(2)	(3)	(4)
Variables	std	std	std	std
OC	**0.000349***			
	(1.850)			
LnOC		0.0216		
		(0.881)		
TC			0.000233	
			(1.036)	
LnTC				0.0231
				(1.582)
Constant	**1.076*****	**1.013*****	**1.106*****	**1.012*****
	(8.278)	**(5.949)**	**(8.526)**	**(6.251)**
Observations	7,263	7,263	7,243	6,433
R-squared	0.163	0.161	0.162	0.166
Adj.R-square	0.158	0.157	0.157	0.161
F-stat	9.049	8.967	8.974	8.044
p-value	0.000	0.000	0.000	0.000

Where af mean is the mean of the bias of the analysts' forecasts consensus, OC is operating cycle, a proxy variable for operating cycle, LnOC is natural logarithm of OC, TC is trade cycle, a proxy variable for operating cycle, LnTC is natural logarithm of TC; We do not show the results for control variables because of space issues (Size is the the market-value of the previous year, Debt is the ratio between total debt and total assets, ROA is the ratio between net income and total assets, MTB is the ratio between market value and equity value, Loss is a dummy for reported loss, ANAfollow is the number of analysts following the firm-year observation, IndConcent is a proxy for market competition, InstOwn is the percent of shares held by institutions, CEOTenure is the time in years the CEO has held his/her current title, LitRisk in an indicator variable for high-litigation risk industry, Aquisition in an indicator variable for aquisition during the forecast period). Significance levels: ***p<.01, **p<.05, *p<.10.

The results in table 10 show that there is a positive relation between std and the main proxy of operating cycle (OC). Specifically, it indicates that there is a positive and statistically significant relationship between absolute error and the length of the operating cycle for all four of our proxies for operating cycle. For example, the coefficient of OC variable is 0.000349 with a t-statistic of 1.850. This relationship also seems economically significant. To illustrate, using the above coefficient of 0.000349 and the standard deviation of OC of 79 days (see table 6) indicates an implied effect on the dependent variable of 0.028, which corresponds to about 10% of the interquartile range of the dependent variable3. The interquartile range is a better measure of the typical change in the dependent variable because std is highly right-skewed. We also test std and OC dummies of quartiles in the same and separated regressions, but the results do not show that there is a positive relationship between them (std and Up LOC and Low LOC).

Thus, the results confirm our H1 that is, the longer the operating cycle, the worse the analysts' forecasts accuracy. Also, the results show that all the models (models 2,3,4 and 5) with the proxy variables for LOC are more powerful (higher adjusted R-squared) when compared to the model without the variables of interest (model 1). Our results show the importance of analyzing the length of the operating cycle regarding analysts' forecasts.

7. CONCLUSIONS

In this study, we analyze the relationship between analysts' forecasts accuracy and the length of the operating cycle. Investment decisions are based on the future expectation of returns. The valuation theory is well known and straightforward. The value of the investment is compared to the valuation of the net present value of the future cash distributions that they are expected to generate. However, the theory runs away of reality, particularly regarding predictions, since predictions are necessarily surrounded by uncertainty. Many ways can be useful to mitigate the inaccuracy of these predictions. Commonly, one of the first steps to start making these predictions is understanding the valuation theory and, then, examining the business and financial statements of the companies. Despite being able to gather all this information which can reduce the uncertainty, there will still doubt about the forecasts. That is why the business literature has made an effort to try to figure out the situations in which the estimates would be more accurate.

The analyses of the financial statements play an essential role to mitigate the gap between the theory and the practice. Nevertheless, analyzing financial statements does not necessarily allows the user to forecast earnings; they can reveal a detailed description of the firm's historical business activities. Based on historical information, we analyze the consensus of the analysts' forecasts reported by I/B/E/S. We calculate three metrics for analysts' forecasts based on the values of the mean, median and standard deviation of the consensus. Thus, we use five variables: absolute bias (mean and median), bias (mean and median), and standard deviation (mean and median). Then, we use proxy variables for operating cycle as measured by Dechow (1994) .

Our hypothesis is based on the idea that operating cycle plays an important role in explaining the accuracy of the forecasts for firms with longer operating cycle. Thus, by testing H1 for abs mean, we find evidence that the longer the operating cycle, the higher the absolute bias of the consensus of the forecasts. Based on the idea that analysts make the same mistake forecasting for firms with longer operating cycles, we test H1 for af_mean and we find that the analysts are optimistic for firms with longer operating cycle by overestimating their EPS.

Our findings support our hypothesis. Therefore, the length of the firms operating cycle plays an important role in explaining the analysts' forecasts accuracy, including both, the absolute bias, the bias and the standard deviation of the consensus of the analysts' forecast as reported by I/B/E/S. We believe that our findings shed some light on the idea of how the length of the operating cycle may affect analysts' forecasts accuracy. Therefore, either analysts or investors should pay attention on that relationship. Finally, we suggest for future research the analysis of the relation between the length of the operating cycle and analysts' forecasts accuracy taking into account how different stages of life cycle can influence analysts' forecasts accuracy.

REFERENCES

Baginski, S. P., Campbell, J. L., Moon, J., and Warren, J. (2019). Towards a riskneutral disclosure policy: The role of compensation in management forecast quality. Georgia Tech Scheller College of Business Research Paper, (18-47).

Brochet, F., Miller, G. S., and Srinivasan, S. (2013). Do analysts follow managers who switch companies? an analysis of relationships in the capital markets. The Accounting Review, 89(2).

Clement, M. B. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? Journal of Accounting and Economics, 27(3):285–303.

Das, S., Levine, C. B., and Sivaramakrishnan, K. (1998). Earnings predictability and bias in analysts' earnings forecasts. Accounting Review, pages 277–294.

Dechow, P. M. (1994). Accounting earnings and cash flows as measures of firm performance. Journal of Accounting and Economics, 18(1):3–42.

DeFond, M. L. and Hung, M. (2001). An empirical analysis of analysts' cash flow forecasts. Journal of Accounting and Economics.

Feng, M., Li, C., and McVay, S. (2009). Internal control and management guidance. Journal of Accounting and Economics, 48(2):190–209.

Francis, J. and Philbrick, D. (1993). Analysts' decisions as products of a multi-task environment. Journal of Accounting Research, 31(2):216–230.

Groysberg, B., Healy, P. M., and Maber, D. A. (2011). What drives sell-side analyst compensation at high-status investment banks? Journal of Accounting Research, 49(4):969–1000.

Kothari, S., So, E., and Verdi, R. (2016). Analysts' forecasts and asset pricing: A survey. Annual Review of Financial Economics, 8(1):197–219.

Kross, W., Ro, B., and Schroeder, D. (1990). Earnings expectations: The analysts' information advantage. The Accounting Review, 65(2):461–476.

Lang, M. H. and Lundholm, R. J. (1996). Corporate disclosure policy and analyst behavior. The Accounting Review, 71(4):467–492.

Michaely, R. and Womack, K. L. (1999). Conflict of interest and the credibility of underwriter analyst recommendations. The Review of Financial Studies, 12(4):653–686.

Mikhail, M. B., Walther, B. R., and Willis, R. H. (1999). Does forecast accuracy matter to security analysts? The Accounting Review, 74(2):185–200.

Stickel, S. E. (1991). Common stock returns surrounding earnings forecast revisions: More puzzling evidence. The Accounting Review, 66(2):402–416.

Verrecchia, R. E. (1983). Discretionary disclosure. Journal of Accounting and Economics, 5:179–194.

Vorst, P. and Yohn, T. L. (2018). Life cycle models and forecasting growth and profitability. The Accounting Review, 93(6):357–381.

Westphal, J. D. and Clement, M. B. (2008). Sociopolitical dynamics in relations between top managers and security analysts: Favor rendering, reciprocity, and analyst stock recommendations. The Academy of Management Journal, 51(5):873–897.

Wu, J. S. and Zang, A. Y. (2009a). What determine financial analysts' career outcomes during mergers? Journal of Accounting and Economics, 47(1):59 – 86. Accounting Research on Issues of Contemporary Interest.

Wu, J. S. and Zang, A. Y. (2009b). What determine financial analysts' career outcomes during mergers? Journal of Accounting and Economics, 47(1):59–86.

Yang, H. I. (2012). Capital market consequences of managers' voluntary disclosure styles. Journal of Accounting and Economics, 53(1):167–184.

Appendix A. Results for H1: first model (abs_med)

Variables	(1) abs_med	(2) abs_med	(3) abs_med	(4) abs_med
OC	**0.00165*** (2.929)**			
LnOC		**0.168** (2.400)**		
TC			**0.00152* (1.880)**	
LnTC				**0.133***

				(3.118)
Constant	**2.625*** **	**2.060*** **	**2.754*** **	**2.678*** **
	(6.207)	**(6.036)**	**(3.885)**	**(6.317)**
Observations	7418	7418	7398	6582
R-squared	0.147	0.147	0.147	0.161
Adj. R-squared	0.143	0.142	0.142	0.156
F-stats	8.589	8.416	8.56	8.057
p-value	0.000	0.000	0.000	0.000

Where abs_med is the median of the absolute bias of the analysts' forecasts consensus, OC is operating cycle, a proxy variable for operating cycle, LnOC is natural logarithm of OC, TC is trade cycle, a proxy variable for operating cycle, LnTC is natural logarithm of TC; We omit the results for control variables because of space issues (Size, Debt, ROA, MTB, Loss, ANAfollow, IndConcent, InstOwn, CEOTenure, CEO, LitRisk and Aquisition); Significance levels: ***p<.01, **p<.05, *p<.10.

Appendix B. Results for H1: second model (abs_mean)

Variables	(1) abs mean	(2) abs mean	(3) abs mean	(4) abs mean	(5) abs mean	(6) abs mean	(7) abs mean	(8) abs mean
Low OC	-0.15							
	(-1.053)							
Up OC		0.086						
		(0.733)						
Low LnOC			-0.15					
			(-1.053)					
Up LnOC				0.0856				
				(0.733)				
Low TC					-0.108			
					(-0.671)			
Up TC						**0.2*** **		
						(2.039)		
Low LnTC							-0.134	
							(-1.368)	
Up LnTC								**0.19***
								(1.956)
Constant	**2*** **	**2*** **	**2*** **	**3*** **	**3*** **	**3*** **	**3*** **	**3*** **
	-6.38	-6.31	-6.39	-6.31	-6.34	-6.16	-6.54	-6.10
Observations	7418	7418	7418	7418	7398	7398	6582	6582
R-squared	0.144	0.144	0.144	0.144	0.144	0.145	0.157	0.158
Adj.R-sq.	0.139	0.139	0.139	0.139	0.139	0.14	0.152	0.153
F-stat	8.194	8.489	8.194	8.489	8.247	8.522	7.77	8.099
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Where abs mean is the mean of absolute bias of analysts' forecasts consensus, OC is operating cycle, a proxy variable for operating cycle, LnOC is natural logarithm of OC, TC is trade cycle, a proxy variable for operating cycle, LnTC is natural logarithm of TC; We omit the results for control variables because of space issues (Size, Debt, ROA, MTB, Loss, ANAfollow, IndConcent, InstOwn, CEOTenure, CEO, LitRisk and Aquisition); Significance levels: ***p<.01, **p<.05, *p<.10.

Appendix C. Results for H1 by LOC quartiles: Third model (abs_mean and abs_med)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)

Variables	abs mean	abs med	abs mean	abs med	abs mean	abs med	abs mean	abs med
Low OC	-0.132	-0.138						
	(-0.87)	(-0.9)						
Up OC	0.0409	0.04						
	-0.314	-0.31						
Low LnOC			-0.132	-0.138				
			(-0.8)	(-0.9)				
Up LnOC			0.0409	0.04				
			-0.314	-0.31				
Low TC					-0.051	-0.054		
					(-0.3)	(-0.3)		
Up TC					**0.2****	**0.2****		
					-2.01	**-2.02**		
Low LnTC							-0.085	-0.086
							(-0.8)	(-0.8)
Up LnTC							**0.17***	**0.17***
							-1.67	**-1.66**
Constant	**2*****	**2*****	**2*****	**2*****	**2*****	**2*****	**3*****	**3*****
	-6.433	**-6.44**	**-6.43**	**-6.44**	**-6.1**	**-6.1**	**-6.24**	**-6.19**
Observations	7418	7418	7418	7418	7398	7398	6582	6582
R-squared	0.144	0.145	0.144	0.145	0.145	0.145	0.158	0.159
Adj.R-sq.	0.139	0.14	0.139	0.14	0.14	0.141	0.153	0.154
F-stat	8.206	8.224	8.206	8.224	8.397	8.402	7.907	7.92
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Where abs mean is the mean of absolute bias of analysts' forecasts consensus, abs_med is the median of the absolute bias of the analysts' forecasts consensus, OC is operating cycle, a proxy variable for operating cycle, LnOC is natural logarithm of OC, TC is trade cycle, a proxy variable for operating cycle, LnTC is natural logarithm of TC; Low is dummy variable for first quartile and Up is the dummy variable for third quartile; We omit the results for control variables because of space issues (Size, Debt, ROA, MTB, Loss, ANAfollow, IndConcent, InstOwn, CEOTenure, CEO, LitRisk and Aquisition); Significance levels: ***p<.01, **p<.05, *p<.10.

Appendix D. Results for H1: first model (af_med)

Variables	(1) af_med	(2) af_med	(3) af_med	(4) af_med
OC	**0.00136*****			
	(3.396)			
LnOC		**0.124*****		
		(3.105)		
TC			**0.00121*****	
			(2.888)	
LnTC				**0.0801*****
				(3.153)
Constant	0.257	-0.151	0.356	0.278
	(0.800)	(-0.425)	(1.115)	(0.717)
Observations	7418	7418	7398	6582
R-squared	0.157	0.156	0.156	0.169

Adj. R-sq.	0.152	0.151	0.152	0.164
F-stats	9.1	9.051	9.039	8.757
p-value	0.000	0.000	0.000	0.000

Where af med is the med of bias of analysts' forecasts consensus, std is the standard deviation of analysts' forecasts consensus, OC is operating cycle, a proxy variable for operating cycle, LnOC is natural logarithm of OC, TC is trade cycle, a proxy variable for operating cycle, LnTC is natural logarithm of TC; We omit the results for control variables because of space issues (Size, Debt, ROA, MTB, Loss, ANAfollow, IndConcent, InstOwn, CEOTenure, CEO, LitRisk and Aquisition); Significance levels: ***p<.01, **p<.05, *p<.10.

Appendix E. Results for H1 by LOC quartiles: Second model (af_mean)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	af mean	af mean	af mean	af mean	af mean	af mean	af mean	af mean
Low OC	-0.0466 (-0.71)							
Up OC		**0.217***** **(3.430)**						
Low LnOC			-0.0466 (-0.71)					
Up LnOC				**0.217***** **(3.43)**				
Low TC					-0.0789 (-1.05)			
Up TC						**0.263***** **(3.76)**		
Low LnTC							**-0.12**** **(-2.198)**	
Up LnTC								**0.260***** **(3.454)**
Constant	0.361 (1.13)	0.298 (0.943)	0.361 (1.13)	0.298 (0.943)	0.384 (1.186)	0.261 (0.82)	0.595 (1.6)	0.453 (1.193)
Observations	7418	7418	7418	7418	7398	7398	6582	6582
R-squared	0.154	0.156	0.154	0.156	0.154	0.157	0.168	0.17
Adj.R-sq.	0.149	0.151	0.149	0.151	0.149	0.152	0.163	0.165
F-stat	9.25	9.306	9.25	9.306	9.128	9.426	8.729	9.08
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Where af mean is the mean of bias of analysts' forecasts consensus, af med is the med of bias of analysts' forecasts consensus, std is the standard deviation of analysts' forecasts consensus, OC is operating cycle, a proxy variable for operating cycle, LnOC is natural logarithm of OC, TC is trade cycle, a proxy variable for operating cycle, LnTC is natural logarithm of TC; We omit the results for control variables because of space issues (Size, Debt, ROA, MTB, Loss, ANAfollow, IndConcent, InstOwn, CEOTenure, CEO, LitRisk and Aquisition); Significance levels: ***p<.01, **p<.05, *p<.10.

Appendix F. Results for H1 by LOC quartiles: Third model (af_mean and af_med)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	af mean	af med	af mean	af med	af mean	af med	af mean	af med
Low OC	0.028 (0.413)	0.0261 (0.39)						

Up OC	**0.226*****	**0.224*****						
	(3.461)	**(3.443)**						
Low LnOC			0.028	0.0261				
			(0.413)	(0.39)				
Up LnOC			**0.226*****	**0.224*****				
			(3.461)	**(3.443)**				
Low TC					-0.00008	-0.0097		
					(-0.0011)	(-0.126)		
Up TC					**0.263*****	**0.242*****		
					(3.616)	**(3.606)**		
Low LnTC							-0.0455	-0.0559
							(-0.773)	(-0.962)
Up LnTC							**0.247*****	**0.225*****
							(3.075)	**(0.225)**
Constant	0.28	0.297	0.28	0.297	0.261	0.287	0.476	0.513
	(0.862)	(0.898)	(0.862)	(0.898)	(0.787)	(0.857)	(1.238)	(1.32)
Observations	7,418	7,418	7,418	7,418	7,398	7,398	6,582	6,582
R-squared	0.156	0.156	0.156	0.156	0.157	0.157	0.17	0.17
Adj.R-sq.	0.151	0.151	0.151	0.151	0.152	0.152	0.165	0.165
F-stat	9.335	9.247	9.335	9.247	9.292	9.144	8.877	8.836
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Where af mean is the mean of bias of analysts' forecasts consensus, af med is the med of bias of analysts' forecasts consensus, std is the standard deviation of analysts' forecasts consensus, OC is operating cycle, a proxy variable for operating cycle; We omit the results for control variables because of space issues (Size, Debt, ROA, MTB, Loss, ANAfollow, IndConcent, InstOwn, CEOTenure, CEO, LitRisk and Aquisition); Significance levels: ***p<.01, **p<.05, *p<.10.