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THE ROLE OF THE RELATIONSHIP BETWEEN THE LENGTH OF THE OPERATING CYCLE AND FIRM AND FIRM-INDUSTRY LIFE CYCLE STAGES ON ANALYSTS? FORECASTS ACCURACY

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Resumo

This paper examines analysts? forecasts research. We summarize the large literature on analysts? forecasts by presenting a bibliometric analysis. We present information related to the number of published papers, number of citations and h-index of journals and authors. It is possible to identify the main journals which have been publishing about analysts? forecasts over the years and the most relevant authors in the field. Additionally, the results show that there is only a modest correlation between number of publications and number of citations. Regarding h-index, the findings confirm that there is a mix of those with more publications and those with more citations.

Palavras-chave: Analysts? Forecasts; Analysts? Forecasts Accuracy; Forecasts? Accuracy; Forecasts Bias; Bibliometric Analysis.

THE ROLE OF THE RELATIONSHIP BETWEEN THE LENGTH OF THE OPERATING CYCLE AND FIRM AND FIRM-INDUSTRY LIFE CYCLE STAGES ON ANALYSTS' FORECASTS ACCURACY

ABSTRACT

This paper examines the role of the length of the operating cycle on analysts' forecasts. We hypothesize that analysts make their predictions based on accounting figures that can face timing and matching problems, then the forecasts' accuracy can reduce. We also expand the literature by examining the influence of the life cycle stages on the relation between analysts' forecasts and the operating cycle. Our prediction is that the forecasts are less accurate for firms with longer operating cycles in the earlier and later life cycle stages. Our results show that the longer the operating cycle, the worse the analysts' forecasts accuracy. In other words, the role of accruals in the long run can bias analysts' predictions since some accruals could not reverse or map cash flows accurately. Moreover, our results show that firms with longer length of operating cycle in introduction and decline life cycle stages are negatively associated with analysts' forecasts accuracy.

Keywords: Analysts' Forecasts; Operating Cycle; Firm Life Cycle; Firm-Industry Life Cycle.

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 performance because it can reflect the accounting policies and procedures used to generate financial information. However, firm 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 make good predictions as the losses are confirmed during a longer period.

Accruals are produced as a solution of the timing and matching problems which cause poor measures of firm performance. But, even after the considering the effect of 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 suffer 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 affect analysts' forecasts accuracy. Our hypotheses are based on the idea that operating cycle plays an important role in explaining the accuracy of the forecasts.

Additionally, we analyze the relation between analysts' forecasts and the operating cycle, considering firm and firm-industry life cycle stages. Dickinson (2011) and Cantrell and Dickinson (2019) provide a proxy for firms life cycle stages based on patterns of cash flows. The authors find out that firms follow a cash flows pattern depending on the stage of their life cycle. Forecasts can be better if analysts consider the analysis of the life cycle stages of the firms. Prior empirical research lacks an analysis of the relationship between life cycle and analysts' forecasts accuracy. The point is that there are some stages of firm's life cycle that are less predictable. For instance, the results of the operations and the measures of firm performance at the beginning of their life are less predictable because the market still doesn't know exactly how the firm operates and their reactions from internal and external changes. On the other hand, for mature firms, the market already knows their operations, including cash flows patterns and their reactions. Thus, we analyze how the length of the operating cycle can affect the accuracy of the forecasts in these more unpredictable stages.

We examine three hypotheses to test how the length of the operating cycle can affect analysts' forecasts accuracy and considering firms and firms industry life cycle stages. Our first hypothesis, $H1$, regards to the relationship between the operating cycle and analysts' forecasts accuracy. $H2$ introduces the concept of firm life cycle stages (introduction, growth, maturity, shake-out, and decline). We analyze how the relation between the length of the operating cycle can be affected by firm's life cycle stages. Finally, our last hypothesis $H3$ introduce the analysis of firm-industry life cycle stages (laggard, diagonal, and leader). We analyze how the relation between the length of the operating cycle can be affected by firm industry life cycle stages.

Firms with longer operating cycles suffer more from timing and matching problems (Dechow, 1994). Then, for our first hypothesis, we hypothesize that the longer the operating cycle, the lower the analysts' forecasts accuracy ($H1$). We hypothesize that this effect increases for firms in more unpredictable stages of the life cycle. Thus, for our hypothesis two, we expect to find worse accuracy for firms in these stages ($H2$). Lastly, laggard and leaders (firm-industry life cycle stages) have unpredictable profits from different strategies (Cantrell and Dickinson, 2019). So, for our last hypothesis, we argue that the longer the operating cycle for these firm-industry life cycle stages, the worse the analysts' forecasts accuracy ($H3$).

We test our hypotheses 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). We use dummy variables to distinguish firms between firm life cycle stages (introduction, growth, maturity, shake-out, and decline) as Dickinson (2011). Finally, we use dummy variables for firm-industry life cycle stages (laggard, diagonal, and leader) (Cantrell and Dickinson, 2019). 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 $H1$. Based on the results, 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. Second, our results also show the relation between analysts' forecasts accuracy and the length of the operating cycle by firm life cycle stages. Following Dickinson we use proxies for firm life cycle to test $H2$. The results show that the length of the operating cycle can affect the accuracy of the forecasts for firms in more unpredictable stages of their "life" (introduction, growth, shake-out, and decline). Additionally, the results show that for firms in these stages, the longer the operating cycle, the higher the volatility of the forecasts. Finally, using the same proxies of Cantrell and Dickinson (2019), we do not find evidence that the length of the operating cycle does not interfere on the forecast's accuracy for leader and laggard firms. Interacted variables of firm-industry life cycle stages with proxies for operating cycle do not disclose significant explanation for higher bias by testing $H3$.

Our research expands prior literature about analysts' forecasts by adding the analysis of operating cycle, as well as the joint effect of the length of the operating cycle and life cycle. We believe 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. We also contribute to the firm and firm-industry life cycle literature. Prior research discusses how firms can be unpredictable depending on their stage of life, but there isn't research trying to identify how forecasts are less accurate for firms in these stages. By adding the analyses of the operating cycle, we show how the length of the operating cycle can play an important role to explain the accuracy of the 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 considering how that relation may be affected by firms and firm industry life cycles stages. 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 operations that are reflected in cash flows.

2. HYPOTHESES DEVELOPMENT

2.1 Analysts' Forecasts and 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 the 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.

Prior literature analyze which factors may influence analysts' forecasts accuracy, 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 company (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, 2009; Groysberg et al., 2011) and other career factors, such as analysts turnover (Mikhail et al., 1999; Wu and Zang, 2009). In addition, researchers try to determine how some factors may bias the forecasts, such as information provided by management or economic motivations (Mikhail et al., 1999; 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; Clement et al., 2007; Brochet et al., 2013).

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 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 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) analyze 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 is expected that these forecasts are more precise, corroborating the idea developed based on Dechow (1994). Then, our H1 is:

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

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. According to the previous 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 allow 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.

2.2 Analysts' Forecasts, Operating Cycle, and Firm Life Cycle Stages

Forecasts are not used only for "buy or sell recommendations" but also for other situations, such as adopting a type of strategic activities as investments or leveraging. Certain kinds of strategies can be perceived by analyzing the cash flows of the companies. Dickinson (2011) has developed a proxy of firm life cycle stages based on the pattern of the cash flows. For instance, firms at the beginning of their lives are considered in the introduction stage because their cash flows show high debt (borrowings from banks for example) to begin the business, a large amount of investment and knowledge lack about the returns of the company. On the other hand, mature firms have cash flows that show less investment and more operating earnings.

Dickinson (2011) indicates that the life of a company is influenced by internal (such as strategy choices and financial resources) and external (such as macroeconomic factors) factors. Based on that idea, the author develops a life cycle proxy using cash flow patterns. It means that the proxy can capture the stage in which the firm is in its life by analyzing the signal of the cash flows. Thus, the proxy seeks to identify different behavior of the companies depending on the life cycle stages. That can be explained since the firm life cycle stage reflects the evolution of the companies, such as the internal and external changes. Thus, firm life cycle stages serve as an explanatory factor for firm behaviors, such as a firm business management and strategy. (Habib and Hasan, 2015). The proxy defines life cycle stages depending on the cash flow values. It can be a robust tool that has applications for forecasting analysis, evaluations, and as a control variable. Following the proxies of Dickinson (2011) for firm life cycle, Vorst and Yohn (2018) shows that the analysis of the firm life-cycle stage has a substantial impact on the forecasting models. They show the study of life cycle stages in forecasting can predict more accurate values of growth and profitability of the companies in detriment to Economy-wide and Industry-specific models. Following Dickinson (2011) and Vorst and Yohn (2018), the life cycle stage of the firm is defined according to figure 1.

Figure 1: Firm Life Cycle Stages

	Firm Life Cycle Stages							
	Introduction	Growth	Maturity	Shakeout			Decline	
Cash Flow Type	1	2	3	4	5	6	7	8
Operating Activities	-	+	+	-	+	+	-	-
Investing Activities	-	-	-	-	+	+	+	+
Financing Actitivities	+	+	-	-	+	-	+	-

Anyway, the bottom line here is that, over long periods, the business of the firms become well known (i.e., many years), such as cash flows of operating and investing activities. Therefore, for mature firms, the business is well known by the market. The market has a better understanding of the companies and how they deal with the economic changes, including the cash flows. In that sense, the length of the operating cycle should not interfere in the accuracy of the forecasts' analysts. On the other hand, for firms in the earlier stages of their "life", firms in the stages of introduction or growth, the length of the operating cycle should interfere in the accuracy of the analysts' forecasts, since the business is still being unveiled. The same unpredictable forecasts can be made for firms in the later two stages of firm life cycle (shake-out and decline) because although the firm's operation can be well known, the business is unstable so that the cash flows can change more. That instability was documented in Dickinson (2011), and that is why there are three ways to analyze cash flows, and the firm still is considered in the stage of shake-out. The same happens with firms in decline stage, where there are two ways for that stage. Following that idea, for firms in the later two stages, longer operating cycles can increase the forecasts bias. Thus, our H2 is:

H2: The longer the operating cycle in firms in the earlier (introduction and growth) and later (shake-out and decline) life cycle stages, the worse the analysts' forecasts accuracy.

2.3 Analysts' Forecasts, Operating Cycle, and Life Cycle Stages

Cantrell and Dickinson (2019) develop another approach of the idea on firm life cycle stages. The authors divide firms between three groups: laggards, diagonals, and leaders regarding the industry life cycle stage. In short, the authors developed a proxy for firm- industry life cycle stages by analyzing the cash flows of the firms and the industry.

Cantrell and Dickinson (2019) analyze the stages of the industry. Besides considering characteristics of the company to examine the firm life cycle stage, they also consider characteristics of the industry. According to the authors, the results indicate that there is a lack in the literature because there is not a generalized proxy to capture leadership behavior versus followers. They present a proxy to distinguish between leadership and laggard behavior and for those firms which accompany the growth of the industry, called by the authors as "diagonals". In that sense, they also indicate that there are limitations in the research results that consider firm life cycle stages without analyzing industry life cycle stages. Following Cantrell and Dickinson (2019), the firm-industry life cycle stages are defined according to figure 2.

Figure 2: Firm Industry Life Cycle Stages

	Firm Life Cycle Stage				
Industry Life Cycle Stage	Introduction	Growth	Maturity	Shakeout	Decline
Introduction	Diagonal	Leader	Leader	Leader	Leader
Growth	Laggard	Diagonal	Leader	Leader	Leader
Maturity	Laggard	Laggard	Diagonal	Leader	Leader
Shakeout	Laggard	Laggard	Laggard	Diagonal	Leader
Decline	Laggard	Laggard	Laggard	Laggard	Diagonal

For the calculation of the firm-industry life cycle stage, the authors aggregate industry cash flows and use the aggregated cash flow pattern to capture the life cycle of the entire industry. It means that they sum all the values of each type of cash flow of the firms in each industry sector. Then, they compare the firm life cycle with the industry life cycle to settle the firm-industry life cycle stage.

According to Cantrell and Dickinson (2019) leader firms are pioneering in the industry and are exploring the market to find out how to do the business for themselves, and, consequently, for the industry. For instance, those firms can do some hard work, as finding and breaking possible barriers or developing the best way to operate. As leader firms are pioneers, the business is still being unveiled, including how the industry is affected by economic factors. In that way, for firms with a longer operating cycle, the bias of the forecasts is increased, because besides having longer operating cycles, the business and the industry are not known yet.

On the other hand, laggard firms can surf on the wave of the leaders, and it means that the industry is already well known, so the market already should make estimates upon a stable base. But actually, Cantrell and Dickinson (2019) findings show that laggard firms increase future profit margins through product differentiation. Also, they found that for laggard firms, returns are explained by expenditures in advertising and marketing. In that way, contrary to expectations, laggard firms have returns based on both product differentiation and marketing. The profits from these types of strategies are unpredictable. New products or returns because of expenditure in marketing can be a fresh start for some firms, and it can change the results of their business. Therefore, the forecasts for leaders and laggard firms can be more unpredictable, showing less accuracy. Then, our H3 hypothesis is:

H3: The longer the operating cycle of laggard and leader firms, the worse the analysts' forecasts accuracy.

3. RESEARCH DESIGN

3.1 Proxy for Analysts' Forecasts Accuracy, Operating Cycle, Firm Life Cycle Stages, and Firm-Industry Life Cycle Stages

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, Firm Life Cycle Stage, Firm-Industry Life Cycle Stages, and Control Variables based on previous literature. First, to test our hypotheses, we use the dependent variable AF_{jit} which represents the different proxies for the analysts' forecasts. The first two proxies we use to examine analysts' forecasts are 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 1 - Panel A. Second, we estimate an independent variable of OC_{it}, 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 1 - Panel B. Third, we divide the firms in groups according to quartiles of operating cycle and trade cycle, but the results do not show statistical significance of the variables of interest.

Table 1: 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.

We also analyze the relation between analysts' forecasts and the operating cycle by firm life cycle and firm-industry life cycle stages. Therefore, we test multivariate regressions with interactions of the operating cycles variables and life cycle stages variables. We use the variables of the life cycle stages based on Dickinson (2011) and Cantrell and Dickinson (2019), and they are described in table 2 - Panel A and B.

Table 2: Specification of Variables of Interest

Variables	Description
Panel A: Specification of the Firms Life Cycle Stages Variables.	
Intro	Dummy for Introduction stage measured as in Dickinson (2017), where 1 is for firm-year observations in the introduction stage and 0 otherwise.
Growth	Dummy for Growth stage measured as in Dickinson (2017), where 1 is for firm-year observations in the introduction stage and 0 otherwise.

Mature	Dummy for Mature stage measured as in Dickinson (2017), where 1 is for firm-year observations in the introduction stage and 0 otherwise.
Shakeout	Dummy for Shakeout stage measured as in Dickinson (2017), where 1 is for firm-year observations in the introduction stage and 0 otherwise.
Decline	Dummy for Decline stage measured as in Dickinson (2017), where 1 is for firm-year observations in the introduction stage and 0 otherwise.
Panel B: Specification of the Firm-Industry Life Cycle Stages Variables.	
Leaders	Dummy for leaders, where 1 is for firm-year observations that are in a more advanced life cycle than their industry (above and to the right of the diagonal).
Diagonal	Dummy for diagonals, where 1 is for firm-year observations in which firm life cycle and industry life cycle are equivalent (on the diagonal).
Laggard	Dummy for laggards, where 1 if for firm-year observations that are in a less advanced life cycle than their industry (below and to the left of the diagonal).

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., 2018), 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 3 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].

3.2 Empirical Models

To provide empirical evidence of the relationship between shorter operating cycle and accuracy of the analysts' forecasts, we test multivariate regressions using dummy variables which segregate firms in groups with longer/shorter operating cycles. Specifically, to test our $H1$, we estimate the model as follow. The first model is: AF_{jit} = β_0 + β_1LOCjit + $\beta_n Control_{jit}$+ $\beta_n Year_{jit}$ + $\beta_n Sector_{jit}$ + ε, 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.

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). The second model is: AF_{jit} = β_0 + β_1LOCjit + β_2LOCjit

* β_1FLCjit + $\beta_n Control_{jit}$+ $\beta_n Year_{jit}$ + $\beta_n Sector_{jit}$ + ε, where AF is a variable for analysts' forecasts proxies (abs_mean, abs_med, AF_mean and AF_med), LOC is the variable for operating cycle proxies (OC, LnOC, TC and LnTC), FLC is the variable for Firm Life Cycle proxies (Intro. - introduction, Gro - growth, Mat - mature, Shout - shake-out, and Dec - decline) and, finally, Control, Year and Sector are the control variables.

To test $H3$ in which we examine the relation between analysts' forecasts accuracy (AF) and the length of the operating cycle (LOC) by Firm-Industry Life Cycle Stages, we create interacted variables between the length of operating cycle variables (LOC) with Stages of Firm-Industry Life Cycle ($FILC$). Specifically, to test $H3$, we estimate the model as follows adding OC and $FILC$ in same regression (fifth model). The third model is: AF_{jit} = β_0 + β_1LOCjit + β_2LOCjit * β_1FILCjit + $\beta_n Control_{jit}$+ $\beta_n Year_{jit}$ + $\beta_n Sector_{jit}$ + ε, where AF represents analysts' forecasts proxies (abs_mean, abs_med, AF_mean and AF_med), OC represents operating cycle proxies (OC, LnOC, TC and LnTC), FILC represents Firm-Industry Life Cycle proxies (Laggard, Diagonal, and Leader) and, finally, Control, Year and Sector are the control variables.

3.3 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 fore- casts, and as reported in Panel A of Table 5, 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 variable information.

Table 5: 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**

As shown in table 5 - 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.

4. RESULTS

The descriptive statistics of the variables of interest and controls are in Table 6.

Table 6: 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 6, 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 et al. (2018), respecting the proportions showing similar median, lower and upper quartiles for absolute bias. Baginski et al. (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 present Spearman (Pearson) correlations at the bottom (top) of table 7.

Table 7: 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 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 do not present the rest of the correlations for brevity (paper's limit size). Table 8 shows the number of firms at each stage relative to the industry stage.

Table 8: Firm-Industry Life Cycle Stages

		Firms Life Cycle Stage				
		Introduction	Growth	Mature	Shake-out	Decline
Industry Life Cycle Stage	Introduction	79	9	17	5	6
	Growth	122	2032	996	118	34
	Mature	154	1592	1536	476	79
	Shake-out	11	44	102	227	12
	Decline	2	1	4	4	24

As shown in table 8, firms are concentrated in the same stage of the industry or in stages near the industry stage. The few firms are in stages at the opposite end of the industry. We omit the descriptive statistics for each quartile of the OC and TC by Lower and Upper quartile of OC and TC for brevity (paper's limit size). But the results show that the 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.

We omit the descriptive statistics for each firm-life cycle stage for brevity (paper's limit size). The results show that the absolute bias and bias are higher for firms in introduction and decline stages, followed by the values for firms in growth and shake-out stages. The smaller amount of absolute bias and bias are for firms in a mature stage. These results are expected since firms in the edges of their life cycle are more unpredictable, and firms in a mature stage are more stable, thus less unpredictable. Regarding the operating cycle, the descriptive statistics show that for firms in introduction and decline stage have longer operating cycles as well as when analyzed trade cycle. Shake-out firms show shorter operating cycle than introduction and decline, but longer than mature and growth stages. Also, mature and growth firms have about the same length of the operating cycle.

We omit the descriptive statistics for each firm-industry life cycle stage for brevity. The results show that the absolute bias and bias are higher for laggard and leader firms. The smaller value of absolute bias and bias are for firms in diagonal. Regarding standard deviation, laggard firms show more volatility between analysts, while diagonal firms have approximate forecasts. These results are expected since laggard and leader firms are less predictable. Regarding the operating cycle, the descriptive statistics show that laggard and leader firms have longer operating cycles than firms in the diagonal. When analyzing trade cycle, laggard and diagonal firms seem to have more or less the same length while leaders shoot a little ahead. Shake-out firms show shorter operating cycle than introduction and decline, but longer than mature and grow. Mature and growth have about the same length of the operating cycle. Table 9 shows the tests for our *H*1 hypothesis regarding abs_mean.

Table 9: Results for H1: First model

Variables	(1) abs_mean	(2) abs_mean	(3) abs_mean	(4) abs_mean
LOC	**0.00164*** **	**0.167** **	**0.00151***	**0.135*** **
	(2.862)	**(2.365)**	**(1.825)**	**(3.157)**
Constant	**2.656*** **	**2.095*** **	**2.785*** **	**2.714*** **
	(3.936)	**(6.338)**	**(4.94)**	(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 (1) LOC = OC is operating cycle, a proxy variable for operating cycle; (2) LOC = LnOC is natural logarithm of OC; (3) LOC = TC is trade cycle, a proxy variable for operating cycle; (4) = LnTC is natural logarithm of TC; abs mean is the mean of absolute bias of analysts' forecasts consensus,; We omit the results for control variables for brevity (paper's limit size) (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.

Table 9 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 a better measure of the typical change in the dependent variable because abs_mean is highly right-skewed. Thus, the results confirm our *H*1 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).

We omit the results for abs_med for brevity (paper's limit size), but 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 abs_mean and the proxies of operating cycle quartiles in the same and separated regressions. Also, these results are omitted for brevity (paper's limit size). These results show that there is a positive relationship between absolute bias and the length of operating cycle for the proxies of upper trade cycle, that is the longer the operating cycle, the higher bias. Table 10 shows the results for our *H*2 regarding abs_mean, af_mean and std and firm life cycle stages. 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.

Table 10: Results for *H*2: Second model

Variables	(1) abs_mean	(2) af_mean	(3) std
OC	0.000939	**0.00181*** **	0.000163
	(1.493)	**(4.287)**	(0.91)
intro	0.14	-0.236	**0.197***

	(0.412)	(-0.596)	**(1.77)**
gro	0.038	-0.0186	0.00435
	(0.359)	(0.359)	(0.359)
shout	4.99e-05	4.99e-05	4.99e-05
	(0.660)	(0.660)	(0.660)
decl	1.119	0.647	0.34
	(1.502)	(0.918)	(1.593)
OC*intro	**0.00281***	0.00145	-0.0000357
	(1.942)	(0.655)	(-0.0801)
OC*gro	0.00045	-0.000887	0.000204
	(0.643)	(-1.467)	(0.953)
OC*shout	**0.00204****	-0.00102	**0.000619****
	(2.279)	(-1.487)	**(2.284)**
OC*decl	-0.00123	**-0.00481***	-0.0003
	(-0.438)	**(-1.776)**	(-0.325)
Constant	**2.599*****	0.364	**1.047*****
	(5.227)	(1.049)	**(7.157)**
Control variables	Yes	Yes	Yes
Observations	7418	7418	7263
R-squared	0.151	0.159	0.169
Adj. R-squared	0.146	0.153	0.163
F-stat	8.869	7.785	8.28
p-value	0.000	0.000	0.000

Where abs_mean is the mean of absolute bias of analysts' forecasts consensus, af_mean is the mean of bias of analysts' fore- casts consensus, std is the standard deviation of analysts' forecasts consensus, OC is operating cycle, a proxy variable for operating cycle, intro, gro, mat, shout, decl are dummy variables for firms in introduction, growth, mature, shake-out and decline firm life cycle stages, We omit the results for control variables for brevity (paper's limit size) (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.

In table 10 we examine the relation between the absolute bias and the operating cycle by life cycle stages. We add interactions between the operating cycle and the dummy variables of firm life cycle stage. According to the results, there is a positive relationship between the length of the operating cycle and absolute bias for firms in introduction and shake-out. Specifically, it indicates that there is a positive and statistically significant relationship between absolute error and the length of the operating cycle for firms in the introduction and shake-out stages. For example, the coefficient of OC*intro variable is 0.00281 with a t-statistic of 1.942 and the coefficient of OC*shout variable is 0.00204 with a t-statistic of 2.279. Regarding the results of bias, the variable of OC*shout shows a significant and negative coefficient of -0.00481 with a t-statistics of -1.776. The negative coefficient indicates that, for firms in the decline stage, the longer the operating cycle, the higher the negative bias. Finally, the results for standard deviation show a positive and significant relationship between std and OC*shout with a coefficient of 0.000619 and t-statistics of 2.284. That result shows that for firms in the shake-out stage, the analysts' forecasts tend to vary more in firms with longer operating cycles. Thus, the results confirm our *H*2, the longer the operating cycle in firms in the earlier (introduction) and later (shake-out) life cycle stages, the worse the analysts' forecasts accuracy. Since life cycle stages are measured by the cash flow patterns, we grouped all stages versus mature firms to strengthen the results. Table 11 shows the results for *H*2, non-mature firms versus mature firms (intercept) regarding absolute bias, bias and standard deviation.

Table 11: Results for H3: Second model

	(1)	(2)	(3)
Variables	abs_mean	af_mean	std
OC	**0.00113***	**0.00178*****	0.000169
	(1.899)	**(4.202)**	(0.996)
nonmat	0.0845	-0.0422	0.0149
	(0.714)	(-0.476)	(0.412)
OC*nonmat	0.000823	-0.000667	0.000303
	(1.139)	(-0.986)	(1.235)
Constant	**2.534*****	0.315	**1.045*****
	(5.36)	(0.942)	**(7.66)**
Control variables	Yes	Yes	Yes
Observations	7418	7418	7263
R-squared	0.149	0.157	0.165
Adj. R-squared	0.144	0.153	0.16
F-stat	8.277	8.786	8.698
p-value	0.000	0.000	0.000

Where abs_mean is the mean of absolute bias of analysts' forecasts consensus, af_mean is the mean 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, nonmat is a dummy variable for firms in the nonmat stages (introduction, growth, shakeout or de- cline), We omit the results for control variables for brevity (paper's limit size) (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.

According to the results in table 16, there is a positive relationship between the length of the operating cycle and the proxies of analysts' forecasts, absolute bias (OC = 0.00113, t-statistic = 1.899) and bias (OC = 0.00178, t-statistic = 4.202), but there is no difference for firms in non-mature stages. Specifically, it indicates that there is not a statistically significant relationship between the proxies of analysts' forecasts and the length of the operating cycle for firms in the group formed by introduction, growth, shakeout and de- cline stages. Thus, we consider our results of table 15 to confirm our *H*2, the longer the operating cycle in firms in the earlier and later life cycle stages, the worse the analysts' forecasts accuracy. Our results show that there is more information when separating firms considering life cycle stages, than grouping them, because we find evidences for introduction and shakeout shown in table 10. In the other hand, table 11 does not show any statistically significance when we group the stages. So, it is relevant to reinforce the importance of analyzing life cycles separately.

We omit the results for *H*3, where we test the relation between absolute bias, bias and standard deviation and the operating cycle by firm-industry life cycle stages, because they do not show any significance of the interacted variables coefficients. These results may show that there is no difference between the relationship of the length of the operating cycle and the proxies of analysts' forecasts accuracy for leader and laggard firms and firms in the diagonal stage. Thus, the results do not confirm our *H*3, the longer the operating cycle of laggard and leader firms, the worse the analysts' forecasts accuracy. Since firm-industry life cycle stages are measured by the cash flow patterns, we grouped leaders and laggard firms versus diagonal firms to strengthen the results. But, again, the results do not show any statistical significance of the variables of interest. Them, there is not a relationship between the length of the operating cycle and the proxy variables for analysts' forecasts. Then, our results do not confirm *H*3 hypothesis, the longer the operating cycle of laggard and leader firms, the worse the analysts' forecasts accuracy.

To conclude, our results show the importance of analyzing the length of the operating cycle regarding analysts' forecasts. Additionally, the length of the operating cycle has a different relationship with the proxies of analysts' forecasts accuracy depending on firm's life cycle stages. Then, it is also relevant to analyze both, the length of the operating cycle and firm life cycle stages with regards to analysts' forecast accuracy. On the other hand, we do not find any statistically significant difference between firm-industry life cycle stages.

4.1 RESULTS FOR ADDITIONAL ANALYSES

We do not report the tables for the additional analyses for brevity, but they are available upon request. The additional results for our *H*2 regarding abs_mean, where we test the relation between the absolute bias and operating cycle by firm life cycle stages. We add interactions between the operating cycle and the dummy variables of firm life cycle stages. According to the results, there is a positive relationship between the length of the operating cycle and absolute bias for firms in introduction and shake-out. Specifically, it indicates that there is a positive and statistically significant relationship between absolute error and the length of the operating cycle for firms in the introduction and shake-out stages. For example, the coefficient of OC*FLC variable is 0.00240 with a t-statistic of 1.677. Thus, the results confirm our *H*2 hypothesis, the longer the operating cycle in firms in the introduction and shake-out life cycle stages, the worse the analysts' forecasts accuracy. The results for growth and shake-out are not as expected according to our second hypothesis. It is possible that these results can be explained by the idea that introduction and shake-out are the more unpredictable stages as during the introduction the market do not know the firms and during the shake-out stage the results of the firms are also more unpredictable (it can be perceived by the number of different possibilities of cash flows combinations that classify a firm in that stage - three possibilities against two in decline and one in the other stages according to Dickinson (2011). We also test the model with the dummy variables for firm life cycle stages and it shows the same results (significance and signal). The additional results for our *H*2 regarding abs_mean, where we test the relation between the absolute bias and operating cycle by firm life cycle stages. We add interactions between the operating cycle and the dummy variables for mature and non-mature stages. According to the results, there is a positive relationship between the length of the operating cycle and absolute bias for firms in non-mature stages (introduction, growth, shakeout and decline). Specifically, it indicates that there is a positive and statistically significant relationship between absolute error and the length of the operating cycle for firms in the introduction and shake-out stages. For example, the coefficient of OC*nonmat variable is 0.00129 with a t-statistic of 3.166. Thus, the results confirm our *H*2 hypothesis, the longer the operating cycle in firms in non-mature stages, the worse the analysts' forecasts accuracy. We also test the model with the dummy variables for firm life cycle stages and it shows the same results (significance and signal).

The additional results for *H*3 regarding abs_mean, when we test the relation between the absolute bias and operating cycle by firm industry life cycle stages. We add interactions between the operating cycle and the dummy variables of firm industry life cycle stages and non-diagonal stages. According to the results, the interactions do not show any significant results, then our additional analyses also do not confirm *H*3, the longer the operating cycle in leader and laggard firms, the worse the analysts' forecasts. However, the Length of the Operating Cycle remains consistently as a factor that decreases analysts' forecasts accuracy. For example, in the first model, OC shows a coefficient of 0.00204 and t-stat of 3.255.

5. CONCLUSIONS

In this study, we examine the relationship between analysts' forecasts accuracy and the length of the operating cycle. By analyzing 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) and for firm/firm-industry life cycle stages as measured by Dickinson (2011) and Cantrell and Dickinson (2019).

Our hypotheses are based on the theoretical argument that operating cycle plays an important role in explaining the accuracy of the forecasts for firms with longer operating cycle because of the increasing risk of matching and timing problems. Thus, by testing *H*1 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 *H*1 for af_mean and we find that the analysts are optimistic for firms with longer operating cycle by overestimating their EPS.

Also, we analyze the relationship between analysts' forecasts accuracy and the length of the operating cycle across different stages of firm life cycle and *H*2 was confirmed. We find that for firms in more unpredictable stages (introduction, growth, shake-out, and decline), the analysts' forecasts are less accurate (higher bias) for firms with longer operating cycles. It is explained by the idea that over the years, the firms' operations become well known, then, the length of the operating cycle does not interfere in the forecasts. On the other hand, for firms in more advanced stages as the ones in shake-out or decline, the length of the operating cycle also interfere in the forecasts because even though the market knows the business, firms in these stages are more unpredictable (Dickinson, 2011). Also, our findings provide evidence regarding the standard deviation. For firms in the earlier and later stages which have longer operating cycles, the standard deviation of the forecasts is higher. The explanation for these findings can be that the uncertainty increases for firms with longer operating cycle, especially for those in the less predictable stages.

Finally, we do not confirm our last hypothesis, *H*3 regarding firm-industry life cycle stage. For leaders and laggard firms, the longer the length of operating cycles, the higher the absolute bias and the standard deviation. Two different reasons may explain these results. For leader firms that are considered pioneers in their industry, the business and the industry are still unveiled. On the other hand, for laggard firms, the reason is that these firms have unpredictable results based on products differentiation and expenditures in marketing and advertisement. Our findings support our first and second hypotheses.

In sum, our findings show that 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 and how analysts and investors should pay attention on these potential problems with matching and timing. Furthermore, they should take into account how different stages of life cycle can influence analysts' forecasts accuracy.

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