TAKING THE PULSE OF THE REAL ECONOMY

Improving macro forecasts through Alternative Breakdown implementation and reducing aggregation bias

MASTER THESIS

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Abstract

In this research, I show that aggregate information from financial statement analysis helps in predicting real economic development. Further, I show that using the top 100 U.S. public companies, ranked by market capitalisation, represents a convenient method to proxy for the entire portfolio of traded companies. I then show that aggregate accounting information of the same 100 biggest companies has predictive information for next quarter real Gross Domestic Product (GDP) growth, after controlling for the traditional stock market returns, and explains a portion of professional macro forecasters' revisions and errors. Konchitchki and Patatoukas (2014a) provide an intuitive framework for these findings. Yet, I contribute by finding that aggregate accounting drivers from the Alternative Breakdown provide greater predictive power when compared to DuPont and that introducing financial and nonfinancial data split reduces heterogeneity. Another contribution of mine is introducing out-of-sample analysis. Although, I find that current methods used by professional macro forecasters exhibit slightly lower root-mean-square error (RMSE), I only use annual stock market returns and aggregate accounting profitability drivers in my model.

Keywords: financial statement analysis; accounting; stock valuation; macro forecasting; macroeconomics; aggregate accounting profitability drivers.

Contents

List of Abbreviations

Abbreviation	**Meaning**
13D	SEC form for over 5% shares
AB	Alternative Breakdown
ATO	Asset Turnover
BAT	Business Asset Turnover
FSA	Financial Statement Analysis
FYR	Fiscal-Year-End
IV	Independent Variable
OM	Operating Margin
PM	Profit Margin
Rd	Cost of Debt
RMSE	Root-mean-square error
ROBA	Return on Business Assets
ROE	Return on Equity
SE	Standard Error
SIC	Standard Industrial Classification
SME	Small and Medium Enterprises
SPF	Survey of Professional Forecasters
VIF	Variance Inflation Factor

1. Introduction

Understanding the direction of an economy is crucial for both public and private decision makers. From employers who set workers' money compensations and production schedules to macro economists setting federal budgets and forecasting consequent economic growth. Macroeconomics studies the aggregate economic behaviour of a country through examining specific accounts such as inflation, price levels, national income, rate of growth, gross domestic product, and unemployment. The responsible authority in the United States for economy-wide decisions is the Federal Reserve (The Fed). The Fed is accountable for setting monetary policy and keeping the economy either from overheating or triggering growth (Carlin and Soskice, 2015).

In this paper, I further develop the research done by Konchitchki and Patatoukas (2014a) on the link between macroeconomics and financial statement analysis (FSA). The building block of FSA is that companies disclose financial statements in timely fashion, providing accounting information to the general public, thus, reducing noise and information asymmetry among investors. Financial analysis can be conducted by two tools, either ratio analysis or cash flow analysis. In this research, I focus on ratio analysis which examines the relation between different line items in companies' financial statements. Evaluating current and prior performance based on ratios is often used as a foundation to predict consequent performance on firm level (Penman, 1992; Fairfield et al.,1996; Abarbanell and Bushee, 1997, 1998). The building block in analysing firm's performance is its own return on equity (ROE). ROE shows the ability of managers to generate returns on the funds provided by firms' shareholders. An important indication for the company's health is whether return of equity is in excess of its cost of capital (Palepu et al., 2015). DuPont analysis, invented by DuPont Corporation in 1920, breaks down ROE in three separate components: Profitability, Asset Efficiency, and Financial Leverage. Net income divided by sales yields the profit margin of a company, which measures profitability. Revenue divided by assets shows the asset turnover of a company and is known as asset efficiency. And assets divided by equity results in equity multiplier or as previously defined financial leverage (Palepu et al., 2015). Breaking down ROE in these three components provides analysts with additional information which is the main driver of higher or lower return compared to competitors. High profit margins attract new entrants and lead to mean reversion, asset turnover is unique, therefore more sustainable competitive advantage, and financial leverage gains depend on financing policies. Although, the accounting fundamentals established in

Konchitchki and Patatoukas (2014a) stem from the Classic DuPont breakdown, the two researchers ignore the financial leverage component. The focus of their research is on return on net operating assets (RNOA), and its further breakdown to profit margin and asset turnover (Fairfield and Yohn, 2001; Soliman, 2008). Konchitchki and Patatoukas argue that RNOA offers a more attractive measure at firm level since it is composed from unlevered financial statement items. Nevertheless, understanding whether companies earn returns higher than its cost of capital is crucial. Ivanov (2016) shows that the spread component, which is return on assets minus financing cost, is significant[1] and positive predictor for consequent real GDP growth. And the spread component is amplified by the capital structure of the enterprise.

Therefore, my first contribution is utilising the Alternative Breakdown (AB) instead of DuPont (Palepu et al., 2015; Ivanov, 2016). AB provides a more thorough perspective because it encompasses return on business assets (ROBA), spread and financial leverage. ROBA measures the efficiency of the company to generate profits by its investment and operating assets scaled by the business assets. Introducing the spread, presents the economic effect of whether the return is enough to cover the borrowing cost. Companies unable to meet their financial obligations have a deteriorating effect on the return on equity. The financial leverage amplifies the positive or negative result by the corresponding liability and equity allocation. To sum up, there are three essential differences between my paper and Konchitchki and Patatoukas (2014a). First, I use ROBA which measures company's ability to deploy both operating and investment assets, compared to only operating in RNOA. Second, I include spread component, accounting for the incremental usefulness of introducing debt into the capital structure. And third, I control for financial leverage. I conjecture that changes in the Alternative Breakdown ratios have significant relationship with the consequent real GDP growth. Consistent with my conjecture, financial statement analysis performed at aggregate level, provides useful information for consequent economic growth. ΔROBA is a significantly positive independent variable and explains 14.6 percent of the variation in consequent real GDP growth. Decomposing ΔROBA into ΔBAT, ΔOM, and ΔCapInt improves the predictive content to 24.0 percent. Breaking down AB further increases the explanatory power up to 26.7 percent.

Second contribution is introducing data splits by the two sub-hypotheses. The intuitive logic behind this decision stems from sample's heterogeneity which has been pointed as a driver of insignificant results for some variables (Konchitchki and Patatoukas, 2014a; Ivanov, 2016). I

[1] At 95 percent significance level.

motivate my data separation by the following criteria, previous academic motivation, easiness for implementation and whether at least 100 companies remain in each filter. I first test whether domestic companies provide better proxy for corporate profits' component of the GDP. Companies operating in the domestic market must pay 100% of their taxes in the U.S. and multinational companies (MNCs) might not. MNCs use a wide range of techniques to pay the least possible taxes through ambiguous transfer prices, company debt location and tax system loopholes. On the contrary to my prediction, the explanatory power of the domestic companies is significantly lower compared to the overall sample. The change in return on business assets of domestic companies explains 6.7 percent of the consequent real GDP variation compared to the 14.6 percent in all companies. Although, the domestic companies exhibit similar increase in explanatory power as all companes, it peaks at 9.7 percent in Column four. There is one apparent limitation in the way I split the data. I use Compustat Domestic and International tickers, which do not allow to examine the percentage of international activity, thus, companies with little to almost none international activity are also dropped.

Most of the empirical literature developed between 1960s and early 2000s has been suggesting that credit growth to the financial industry is contributing to growth boost. On the contrarily, more recent research suggests that high credit to GDP is dampening the economy growth if it is extended to the financial industry. The main reasons behind that are diminishing returns from an increase of the financial industry. The human intensity of the above-mentioned sector, which draws people from R&D and the high capital to income ratios are leading causes (Bezemer et al., 2016; Cecchetti and Kharroubi 2012). Therefore, I conjecture that separating companies in nonfinancial and financial will have a positive impact on the predictive content. Coinciding with my conjecture, changes in the AB ratios of nonfinancial companies predict variations of consequent real GDP growth with higher precision. All columns exhibit higher predictive content, except the first one. Nonfinancial companies' peak in adjusted R squared is 29.6, compared to 26.7 percent in all companies and 14.7 percent in financial. Furthermore, the independent variables also exhibit higher overall significance level which can be a sign of reduced heterogeneity.

Per Fama (1981; 1990), the stock prices depict the investors' expectations regarding the future economic development and provide information regarding the consequent economic growth or decline. To address the question, I first examine if the stock markets contain any predicting power for subsequent real GDP growth. The 12-month buy-and-hold returns (*ret12*) exhibit the highest goodness of fit. In my third contribution, I investigate if the aggregated accounting profitability drivers can provide additional forecasting power which is not contained in stock prices. The results, which are based on the AB ratios of nonfinancial companies[2], provide incremental explanatory power over consequent real GDP growth, even after controlling for stock market returns. Furthermore, the adjusted R squared increases from 19.3 percent for stock market returns to 34.1 percent when aggregated accounting drivers are included.

The authority setting interest rate policies in the US is the Federal Reserve. The Federal Reserve uses credible forecast information provided by Survey of Professional Forecasters (SPF), executed by the Federal Reserve Bank of Philadelphia. However, I predict that macro forecasters are unaware of the usefulness of accounting information (Konchitchki and Patatoukas, 2014). Coinciding with my conjecture and marking my fourth contribution, the alternative breakdown and stock market returns explain 22.3 percent of macro forecasters' revisions. Moreover, forecasting errors of SPF are also predictable through aggregate changes in business asset turnover and stock market returns. Both independent variables explain 6.0 percent of next quarter prediction error. Expanding on the previous results, I test the impact of aggregate accounting drivers on future stock market returns. The aggregated accounting profitability drivers have no explanatory power for the future stock market returns.

In Konchitchki and Patatoukas (2014a), their model provides significant predictability power of consequent real GDP growth and macro forecasters' errors. Therefore, providing them with a low-cost and efficient model to improve SPF forecasting accuracy. In my fifth contribution, I examine whether the same aggregate accounting profitability drivers can predict the macro forecasters' revisions after the article has been made available. I run auxiliary tests on the different regressions, which are not presented in the paper, but show that the macro accounting literature had impact on forecasters. However, the post publishing period is rather short, only 25 more observations, therefore, I cannot draw definitive conclusions. In my final contribution, I test the predictive ability of the model in an out-of-sample situation. Comparing to the RMSE of the SPF forecasts, my model has larger errors by 0.23 percent, but the results are promising and provide ground for further research.

The remainder of the paper goes as follows. Section 2 presents prior research in the field of financial statement analysis and connects it to economic growth prediction. In Section 3, I motivate my research hypotheses. Section 4 describes my research design. Section 5 contains

[2] I also ran additional analysis to test if all companies do not provide higher predictive content. The Adjusted R-squared of all companies was lower than nonfinancial with 0.53%.

empirical results. Section 6 presents out-of-sample comparison to current macro forecasters' methods. Finally, Section 7 contains concluding remarks, limitations and paths for further research.

2. Literature Review

The modern society metaphor for King Arthur seeking for the holy grail is the public and private sector' eagerness to predict economic development. Macroeconomic volatility is significant not only for the development of the gross domestic product but also important in equity market valuation (Aked, Mozzoleni and Shakernia, 2017). The remainder of this section will lead the reader through the development of financial statement analysis and its link to forecasting macroeconomic growth. By examining the prior literature, I interlink this section to the next, where I develop the hypotheses of this research. First, I explain the origin of financial statement analysis and its predictive power for earnings on firm level. Second, I examine the literature on DuPont analysis and the choice of certain ratios. Third, I show the founding papers on macro accounting published by Konchitchki and Patatoukas, where the authors link financial statement analysis and DuPont profitability ratios to forecasting economic development.

The purpose of financial statement analysis is to improve comparability between companies and reduce informational asymmetry between stakeholders. The works of Beaver (1968), Ball and Brown (1968) set the foundation of accounting researchers analysing the relation between earnings and security returns. There are several different approaches to earnings forecasting. Starting with Kormendi and Lipe (1987) who decompose the earnings into six components and document diminishing relation between transitory[3] components and stock returns. In 1993, Lev and Thiagarajan propose an alternative approach by establishing a set of financial ratios proposed by "experts"[4] and test their correlation with contemporaneous stock returns. In their article *"Fundamental Information Analysis"*, Lev and Thiagarajan identify 12 fundamental signals[5] based on practitioners' toolset when valuing company's future. Inventory, Receivables, Capital Expenditures, Gross Margin, S&A Expenses, Order Backlog, Labour Force and Effective Tax are significant predictors of excess return variance. Furthermore, Lev and Thiagarajan (1993), find that the fundamental signals can also predict the analysts' forecast errors. I establish this article as a relevant founding paper to my research since it provides an academic proof of the relationship of the fundamental signals and consequent returns. Abarbanell and Bushee (1997, 1998) further extend the research done by Lev and Thiagarajan (1993) to prove that fundamental analysis can deliver alpha as the market underuses the

[3] Transitionary items refer to items which are further down the balance sheet (Bagnoli and Watts, 2007).
[4] Which is referred to as guided research, compared to statistical procedure. The difference is that the former uses intuitive motivation whereas the latter might identify hard-to-justify balance sheet items.
[5] All twelve variables can be found in Appendix 3.

available information. Abarbanell and Bushee use the same fundamental signals as defined by Lev and Thiagarajan (1993) and find that analysts misuse fundamental analysis information and their *ex post* forecast errors are predictable. Abarbanell and Bushee (1998) also examine a holdout sample period which leads to the same conclusions as previous tests. Furthermore, they find that sizeable firms are less exposed to trading influence. Thus, contributing to the decision to use the top 100 U.S. companies ranked by market capitalisation. Followed by Fairfield et al. (1996) who apply different income statement items to predict the return on equity (ROE). Their conclusion is that income statement items are less persistent moving down the profit and loss statement.

Moving further, Nissim and Penman (2001) propose a method to equity valuation by using the DuPont analysis and decomposing the company's return into return on operating assets (RNOA). The profit margin of a company is a composition of different factors such as first mover advantages, product differentiation, positioning, branding, and uniqueness. Asset Turnover (ATO), on the other hand, is internal measurement as it represents efficiency of a company and asset usage. The nature of the two components is different as high profit margins draw new competition and profits exhibit mean-reversion. On the other hand, production efficiency is harder to imitate. Per prior research, ATO changes provide significant predictive capabilities for subsequent RNOA and are of more persistent nature (Fairfield and Yohn, 2001). Soliman (2008) tries to establish if the DuPont composition retains its persistency when the Fama-French risk factors and Abarbanell and Bushee fundamental signals are included. The risk factors control whether abnormal returns are subject to an increase in company's exposure. The fundamental signals control whether DuPont analysis provides any incremental predictive power. Since the gross margin (GM) and profit margin (PM) have similar definition, and ATO and CapEx, too. The findings confirm previous research which suggests that level of PM and ATO have insignificant relation with changes in RNOA. On the other hand, changes in ATO explain consequent period's RNOA variation and retain significance even with the inclusion of fundamental signals and risk-factors. Another compelling evidence is that all fundamental factors from Abarbanell and Bushee retain consistency in terms of magnitude, sign, and significance as per prior research (Abarbanell and Bushee, 1998; Lev and Thiagarajan, 1993). Suggesting that both fundamental signals and DuPont analysis provide explanatory information regarding subsequent period changes in RNOA. The two models are not self-excluding and increase the explanatory power when both of them are included. Changes in ATO is also significant in predicting consequent stock return, analysts forecast revisions and errors withal

(Soliman, 2008). A limitation of this study is that the author does not include the fundamental signals to control if those do not already predict these forecast errors. Considering that Lev and Thiagarajan (1997) establish a correlation between fundamental signals and forecast errors of analysts[6]. All in one, the research proves that DuPont analysis is incrementally useful in forecasting consequent profitability. Supplementary to earlier studies, Soliman (2008) examines the behaviour of analysts and stock market investors to understand to what extend they consider PM and ATO when predicting future behaviour of returns. Accordingly, the market recognises RNOA's significance but does not fully apprehend the magnitude. Therefore, forecasters' revisions and errors are predictable by changes in ATO.

Expanding previous research and connecting two streams of literature Konchitchki (2013) lays the foundations of the macro accounting. In the paper "Accounting and the Macroeconomy: The Case of Aggregate Price-Level Effects on Individual Stocks" (Konchitchki, 2013) proves that as financial statements are in nominal terms and not inflation adjusted, there are discrepancies in the purchasing power. He provides an example where a company buys land 60 years and 1 year ago for $100 each, adding up to $200 in the financial statement. But under U.S. GAAP only downward revaluation are possible, otherwise the book value is kept at purchase price. Konchitchki (2013) proposes a cost-efficient way by separating accounting information into two components: monetary holdings and nonmonetary holdings. Prior research concludes that on aggregate levels the correlation between inflation and stock returns is negative (Bodie 1976; Fama and Schwert 1977; Fama 1981). During high inflation periods stocks deliver inferior returns and are inadequate hedging technique. Konchitchki (2013) challenges this assumption by developing *ex ante* strategy based on company-by-company foundations. The method yields significant results and provides a stock-hedging strategy against inflation. Additional contribution to the literature is establishing connection between accounting data on company-level to the forecast of macroeconomic performance. Yet, Konchitchki is using a complex algorithm to adjust for inflation effects. Implementing it at aggregate level is difficult which is limitation of my study as the financial statement items are not inflation adjusted[7]. Concluding, this article sets the foundation for their further research by demonstrating a correlation between financial statement data and consequent economic realisations.

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[6] Abarbanell and Bushee's fundamental signals are identical to those established in the preceding research done by Lev and Thiagarajan.

[7] I further discuss the inflation issue in the limitations section.

Konchitchki and Patatoukas (2014b) argue that using aggregated quarterly data of all listed companies is more consistent approach. The aforementioned articles discuss the informational context of accounting data on firm-level, yet, Konchitchki and Patatoukas (2014b) establish a link between financial statement data and gross domestic product growth. Corporate profits are integral part of GDP, under the income approach, and must exhibit correlation with the other components (Fischer and Merton, 1984; BEA, 2004). Public companies are obliged to report their quarterly earnings compared to the current method implemented by BEA, where corporate profits are forecasted based on IRS' tax return extrapolation with a two-year lag. Additionally, financial statement analysis is a significant predictor of consequent company performance, therefore, a good proxy for taxes payable by the company. On the other hand, economists consider accounting as non-sense, and do not apply it to their predictions (Konchitchki and Patatoukas 2014b). This is best represented by a quote from McCloskey (1993, p,111): "We economists spurn accounting - another course I never took. But we end up reinventing it. Maybe we should study the subject a little, or at least make our students learn it. After all, it's what we really, truly know.". And further proven by the lack of references to the topic in the meetings minutes of Federal Open Market Committee. The aggregate accounting earnings prove to be significant and positive over a horizon of up to four quarters. Therefore, it is a clear that aggregate accounting earnings growth have substantial forecasting power regarding the successive GDP growth. Furthermore, the predictive capabilities in one quarter ahead are the strongest, in terms of significance and slope coefficient. Additionally, aggregate accounting earnings growth explains forecasters' errors in up to three quarters in the future. Again, as with the GDP growth, the most significant is predicting one-quarter-ahead. All in one, Konchitchki and Patatoukas (2014b), prove that aggregate accounting earnings growth has predictive power for up to four quarters but is strongest in the consequent. Furthermore, they prove that macro forecasters do not consider accounting earnings as relevant and that forecast errors can be explained by the data available on company-level. These findings provide foundation for the next paper.

Konchitchki and Patatoukas (2014a) hypothesize that financial statement analysis can be utilised to predict future real economic growth. Widely accepted technique is to use return on net operating assets (RNOA) as an indicator of the company performance[8] (Soliman, 2008). Operating income is the difference between sales and cost of goods sold, depreciation expense

[8] The link between previous papers is obvious, by predicting enterprises' earnings they funnel in the taxable income which in turn is a component of GDP (Soliman, 2008; Konchitchki and Patatoukas, 2014b)

selling, general, and administrative expense. Net operating assets is operating assets minus non-operating cash and short-term investments, minus non-interest-bearing liabilities. This type of breakdown presents RNOA as an unlevered estimate of company business performance.

$$RNOA = \frac{Sales}{Net\ Operating\ Assets} \times \frac{Operating\ Income\ After\ Depreciation}{Sales}$$

Equation 1. RNOA decomposition (Konchitchki and Patatoukas, 2014)

The first component is referred as asset turnover (ATO) and provides an overview of company's efficiency to generate sales relative to its assets. The second part know as profit margin (PM) determines how well a firm controls its expenses. Konchitchki and Patatoukas (2014a) fill a much-needed gap in research literature by trying to predict overall economic activity by aggregating firm-level data. I contribute to this research by replacing the DuPont analysis with Alternative Breakdown (AB). Consisting of three essential differences, return on equity, role of leverage within a company, and whether a company earns returns higher than cost of debt. I further discuss the reasons for choosing AB in the next chapter. The results show that aggregate accounting profitability drivers, and especially ΔOM and ΔDEP have significant predictive content for consequent real GDP growth. Konchitchki and Patatoukas (2014a) prove a significant importance of accounting data and underutilisation by macro forecasters, but also investors. Yet, some of the variables expected to be significant in the research are not. With a possible explanation being the heterogeneity of the sample. Thus, I include two different splits in my data, the financial to nonfinancial and domestic to MNCs. In the following sections, I back the choices by previous research conducted on the topics.

3. Hypothesis Development

3.1. The Alternative Breakdown

The Alternative Breakdown (AB) is a similar decomposition as DuPont analysis with one essential difference, it shows broader range of variables in the decomposition of return on equity. AB provides an overview of company's activities both on the business and investment side, therefore, supporting a more thorough examination of firm's performance (Ivanov, 2016; Palepu et al., 2015). In Konchitchki and Patatoukas (2014a), the two researchers only use profitability and asset efficiency perspective of DuPont - return on net operating assets (RNOA). RNOA shows the operating picture of a company, whereas return on business assets (ROBA) also accounts for investment assets. Additionally, the Alternative Breakdown also includes two extra components Spread and Financial Leverage as it can be seen in Equation 2 and also in Appendix 1: Derivations and Ratio list.

$$ROE = Return\ on\ Business\ Assets + (Return\ on\ business\ assets - Interest\ expense\ after\ tax) \times Financial\ Leverage$$

Equation 2. Classic Alternative Breakdown (Palepu, Healy, and Peek, 2015)

When a company finances its activities solely with equity, return on business assets (ROBA), would equal ROE. Return on business assets minus cost of borrowing, referred to as spread, indicates if operating and investment returns are greater than interest cost paid. If a company's business returns are lower than cost of debt, introducing debt to their financial structure destroys value for equity holders. Furthermore, this economic effect is magnified by debt to equity ratio, referred to as financial leverage in the equation. All in one, a clear predictor of future returns is whether companies deliver higher returns than their cost of debt. Otherwise, companies will either become insolvent or need a major financing restructuring which would have negative implications for consequent period's GDP growth. Moreover, ROBA can be decomposed into extended DuPont breakdown utilised by Konchitchki and Patatoukas (2014a). Therefore, providing a clear understanding if the additional variables provide any incremental usefulness for prediction next period GDP growth.

$$ROE = (1 - Tax\ Rate) \times \big((Operating\ Margin\ Before\ Depreciation - Capital\ Intensity) \times Business\ Asset\ Turnover - Rd\big) \times Financial\ Leverage$$

Equation 3. Extended Alternative Breakdown Model (Ivanov, 2016)

Each separate variable from the Alternative Breakdown flows differently into the gross domestic product and its consequent growth patterns. Based on the literature review, I expect significant and positive relationship between changes in financial statement items and consequent company growth. Therefore, the same variables should show persistency and significance in predicting consequent GDP growth (Soliman, 2008; Konchitchki and Patatoukas, 2014a, 2014b). Leading to my first and most prominent conjecture.

H1. Fluctuations in aggregate accounting profitability drivers from the Alternative Breakdown can be utilised to predict consequent real GDP growth.

In the following subsubsections I define each variable used as a component of the Alternative Breakdown and conjecture their impact on consequent real GDP growth predictions. The derivation of the Alternative Breakdown and the corresponding components are available in Appendix 1: Derivations and Ratios.

3.1.1. Business Asset Turnover (BAT)

Business Asset Turnover is the ability of a company to generate revenues in relation to business assets (Fairfield and Yohn, 2001). The ratio is referred as asset utilisation and shows how much sales a company makes per dollar of business asset. A change in ATO is linked to improving or deteriorating productivity and is a sound predictor of future profitability. Efficiency materializes from better utilisation of property, plant, and equipment which is difficult to imitate by existing competitors or new entrants. Therefore, the benefits of these changes are less transitory (Soliman, 2008). Furthermore, Romer (1986) proves that changes in capital returns are more persistent predicter of consequent company performance compared to profit margins due to mean reversion and accounting reasons.

Although, previous theoretical works support the hypothesis of ATO being a better predictor, Konchitchki and Patatoukas (2014a) find that on aggregate level asset turnover does not provide useful information regarding consequent GDP growth. There is a twofold explanation for the results. Firstly, heterogeneity of the sample and different asset usage. And secondly, largest companies in the US economy have high efficiency levels with relatively no to infrequent changes in their asset utilization (Ivanov, 2016). Yet, predicting the impact of business asset turnover is difficult due to the opposite findings of the articles before and after 2014 (Romer, 1986; Fairfield and Yohn, 2001; Konchitchki and Patatoukas, 2014a; Ivanov, 2016).

3.1.2. Capital Intensity

Changes in depreciation are a sound predictor of future economic activity at firm level (Ou and Penman, 1989; Cheng, 2005). In my sample, the top 100 companies are ranked by market capitalisation, but most of them are also leaders based on physical assets, too (Murphy, 2018). Therefore, depreciation expense is substantial, and large changes can be related to replacement or enhancement of existing assets. The purchases represent large investments and can be expected to have positive link to real GDP growth. Company acquisitions of new assets funnel into the income approach twice – firstly, new machines are either more efficient or provide greater capacity and secondly, it is a corporate sale for another company.

On the other hand, real earnings management (REM) cuts in selling, general and administrative expenses and consequent reversals are a significant predictor of lower future performance (Vorst, 2015). If the management manages earnings with an objective to meet earnings benchmarks, issuance of debt or equity, or achieving compensation thresholds, their consequent performance will be damaged. In the light of Vorst (2015), a decrease in new asset investments compared to their competitors can lead to lower future efficiency and profitability. Hence, sacrificing company’s competitive position in the market and potentially leading to bankruptcy. Yet, this effect can be muted on aggregate level and large U.S. companies are thoroughly followed by analysts, leaving less room for earnings manipulation by management. In Konchitchki and Patatoukas (2014a), changes in depreciation exhibits significant and positive relationship. I conjecture that in my findings the results are also significant and with positive sign.

3.1.3. Tax Rate

In the income approach to measure GDP, corporate profits are a main driver. Therefore, using the extended AB in which the effective tax rate is calculated, should yield significant correlation with the consequent GDP growth (Konchitchki and Patatoukas, 2014b). The effective tax rate is a better predictor compared to statutory rates since it incorporates tax reliefs and benefits. Referring to Appendix 3, where all twelve variables from Lev and Thiagarajan (1993) are explained, an increase in effective tax rate provides only transitionary benefits. The impact of increased company net earnings and decreased effective tax rate[9] has a negative effect on corporate profits component of GDP. On the other hand, due to the transitionary nature of these changes, Lev and Thiagarajan (1993) conjecture that a decrease in effective tax rate will have positive effect on GDP growth when a reversal occurs. However, increased effective tax rate will result in more corporate profits which drive GDP growth and increased effective tax rate depresses nominal growth based on Keynesian tax theory (Furceri and Karras, 2011; Ivanov, 2016). Additionally, tax smoothing theory suggests that companies issue debt during recession with repayment schedule in expansion (Barro, 1979). Therefore, I conjecture that the impact of tax rate is ambiguous as an increase in tax rate will mean more income from taxes for the government, but also reduce the willingness of companies to produce.

3.1.4. Financial Leverage

The debt and equity composition of companies has been extensively discussed in theory of Modigliani-Miller (1959). Under certain set of key assumptions[10] the framework hypotheses that firm value is only determined by its earnings power and is not dependent on financing decisions. In the described environment, returns only switch from equity to debt holders and vice versa. I will not examine in-depth the best aggregate capital structure strategy due to sample's heterogeneity which is translated into different per sectors optimal capital structures. For example, utility companies have steady cash-flows allowing them to take on greater debt. Additionally, in the sample there are both financial and nonfinancial firms which highly differ in their capital structure. Loans are liabilities for the latter companies, but assets for the banking industry. Furthermore, under the Basel III regulators have imposed non-risk leverage ratio restrictions which limits the financial exposure (Smith, Grill and Lang, 2017). An undeniable benefit for increasing debt is the tax shield, however, very high leverage ratio can trigger covenants and destabilise the company further resulting in higher financing costs.

On the other hand, Karpavicius (2014) proposes an alternative argumentation suggesting a significant relationship between optimality theory and capital structure. By modifying the sample to account for behavioural biases, namely the short-term outlook of management, also discussed previously under Vorst (2015). Under favourable market conditions high levels of debt can be sustainable, refinancing risk low and threat of triggering covenants insignificant. Nonetheless, financial difficulty can prompt banks to downsize loans based on asymmetric

[9] Without the respective increase in statutory tax rate. Analysts consider such decrease transitionary (Wall Street Journal, 1990).
[10] Such as no taxes, no bankruptcy costs, symmetry of market information, no transaction costs, equal borrowing costs, and no effect of the debt on EBIT of the company

information also damaging healthy companies. From the financial perspective of the sample, in time of crisis, the interbank markets experience considerable pressures and pose a liquidity pressure to serve its existing obligations to companies (Allen and Carletti, 2008).

Furthermore, the equity holders, as residual claimants, can be viewed to hold a long call with strike price of the liabilities value. Therefore, they only make money if the assets are worth more than the debt.

[Insert Figure 2 here]

Viewing the company from this perspective, we can use Black-Scholes option pricing model to determine the call value. Establishing that debt holders have a fixed pay-out and the excess is claimed by equity holder brings conflicting interests. Considering two alternative projects, equal investment value, yet Project A is riskier than Project B. The latter project has larger variance, higher payoff in the up state *(favourable)* and lower payoff in the down state *(bankruptcy)*. Therefore, shareholders' decision favours the riskier project since in down state the company is bankrupt, and their payoff is zero but have a higher upside (Amaro de Matos, 2008).

Moreover, shareholders have voting majority and can exert power over the direction of a company, thus, shareholder activism becomes a threat for the optimal capital structure. Furthermore, Klein and Zur (2011) find evidence that shareholder activism reduces bond holders' wealth. Hedge fund activism results in excess return of -3.9 percent in the day before and after the 13D filing, and -4.5 percent in the following year subsequent of the filling date. Targeted companies decrease their cash at hand, double common shareholder dividends and increase debt-to-asset ratio. Thus, companies face prospective interest and principal payments with depleted cash accounts, resulting in credit risk increase. Hence, leading to substantial amount of companies being downgraded after the initial 13D filing. These finding are not contradictory to earlier positive abnormal returns attributed to shareholder, but rather to wealth expropriation from debt to equity holders (Klein and Zur, 2011).

All in one, increased debt can be beneficial for a company in terms of tax benefits, but this can also be caused by shareholder activism raising company's volatility and overall risk. Therefore, the relationship between GDP growth and companies' leverage is ambiguous at aggregate level. Not in terms of the weight attributable to changes in debt level, but the causality of this variation is unknown.

3.1.5. Cost of Debt

A conventional method to estimate the cost of debt is through defaultable bond pricing. Investors in corporate bonds suffer an extra risk of the company going bankrupt, thus, demand a higher return. Figure 3 represents a usual connotation of such formula, where YTM_C and YTM_G are yield to maturity of a corporate bond and government bond with identical maturity, and G_{SPREAD} is an additional yield investor requires for the extra risk. Although, there are more sophisticated methodologies[11], this model provides the basic option pricing foundation (Pereira, 2018).

$$YTM_c = YTM_G + G_{SPREAD}$$

Equation 4. G-Spread (Pereira, 2018)

YTM_G is a proxy for the risk-free rate set by the Central Bank and is an essential tool of monetary policy kit to regulate inflation levels. Under the three-equation model of macroeconomic policy, proposed by Carlin and Soskice (2015), an increase in policy rate is to tackle inflationary shocks. Therefore, an increase in risk-free is related to a decrease in consequent period economic output and results in lower GDP growth. On the other hand, if the change in cost of debt is only due to increased risk of a company[12], I expect the effect on real GDP growth to be insignificant. On an occasion that the change is on aggregate level, decreased cost of debt can be perceived as lower risk economic risk. To understand better if cost of debt fluctuations are due to the policy rate or mark-up, the analysis must evaluate the companies on firm-level. Yet, the purpose of this study is to use aggregate changes.

All in one, the cost of debt fluctuations provide ambiguous relationship to the consequent real GDP growth as they can be of double nature. Increasing the risk-free rate is a tool used by the Central Banks, to contract the economy. On the other hand, aggregate risk premium increase can also have a negative impact on the economy because investors predict greater risk for which they must be compensated.

3.2. Domestic Sales

The published research by Konchitchki and Patatoukas (2014a, 2014b), provides findings that aggregate accounting earnings variation is a significant predictor about the future GDP. As

[11] For example, interest swap rate interpolation, option adjusted spread and risk-neutral pricing model
[12] I assume the risk-free remains unchanged and the change is only in the mark-up

previously discussed in *Section 2 Literature Review,* accounting earnings are better predictor for current taxable income than the annual tabulations of IRS.

A critique to the income approach is provided by Viet (2009) in her book for the United Nations Statistics Division. The argumentation behind is that operating surplus can be calculated only for an enterprise and not for its belonging establishments. An example would make it clearer: we have a corporation with three locations, two of which are subsidiaries which produce and sell items and the last one is the headquarter. The operating surplus derivation can be done only on aggregate level and not separately per location. Thus, the consolidated corporate profit cannot be separated for multinational corporations (MNCs) which operate in multiple countries.

In this line of thinking Grubert (2012) provides information that from 1996 to 2004, the unrepatriated foreign income[13] rose from 17.4 percent to 31.4 percent. Furthermore, investments abroad also rose significantly. Redirecting money outside U.S. through tax differentials by which companies shift income to lower tax places through manipulating the transfer price, company debt location, and other loopholes in the tax systems.

Including home sales of the company, which is an indicator in Bloomberg Professional, will be a good predictor of consequent GDP growth. The main reason is that aggregate accounting is used as a proxy for corporate profits in U.S., but international activities are going to be taxed abroad and only the subsidiaries' dividends are taxed under American laws (Grubert, 2012). However, including the Bloomberg Professional indicator provides information for only 10 years behind and proved hard to use on aggregate level. Therefore, I use the Compustat Domestic and International variables to determine the nature of their operation.

H1a. Changes in aggregate accounting profitability drivers of the Domestic Companies provide larger predictive content over consequent real GDP growth in comparison to the whole sample.

3.3. Financial and Non-Financial Breakdown

Most of the empirical literature developed between 1960s and early 2000s suggests that credit growth to the financial industry is contributing to positive economic activity. Rajan & Zingales (1998) provide empirical evidence that industries dependent on external funding exhibit higher growth rates in more financially developed countries. Since financial development decreases

[13] The definition used of foreign income in the paper is subsidiaries' before foreign tax income of U.S. parent corporations. Where domestic income equals U.S. taxable income minus dividends from subsidiaries.

cost of raising funds, reduces asymmetrical information and moral hazards (Greenwood & Jovanovic, 1990).

On the contrarily, more recent research suggests that high credit to GDP is dampening the economic growth if it is extended to the financial industry. The main reasons behind that are the financial industry exhibits diminishing returns and its high human intensity which draws people from R&D positions, potentially impeding the growth of science breakthroughs (Bezemer et al., 2016; Cecchetti & Kharroubi 2012).

Thus, the USA, with its well-developed financial industry and high credit to GDP ratio, will exhibit relatively no correlation to consequent GDP growth.

Furthermore, Konchitchki and Patatoukas (2014a) suggest that their research can be improved by separating the data and further segmenting the sample. I assume that the biggest difference would come from financial and non-financial companies due to their difference in accounting of assets and liabilities (Pariente, 2018). In banks, earning assets represent loans extended to companies, whereas this is liabilities for a non-financial company (Pariente, 2018)

H1b. Changes in the aggregated accounting profitability drivers of the Nonfinancial Companies provide larger predictive content over consequent real GDP growth compared to financial companies and overall sample

3.4. The Stock Market Variable

In the context of rational expectations, we would suppose that stock market investors have anticipated future economic activity, and this is represented in stock prices. Per Fama (1981; 1990), stock prices depict investors' expectations regarding future economic development and provide information regarding the consequent economic growth or decline. Rational investors are comparable to macro forecasters as they use their knowledge to predict future economic activity (Konchitchki & Patatoukas, 2014a).

Previous empirical research identifies S&P 500 as a suitable proxy for the U.S. market due to its easiness to obtain and interpretation (Konchitchki & Patatoukas, 2014a). Furthermore, S&P 500 is also used as a benchmark to active investing funds, but also replicated by passive investment funds. Therefore, changes in the index have significant effects on the economy since it is comprised of the top 500 public companies in the U.S.

H2. Aggregated accounting profitability drivers are beneficial in macro forecasting and are not subsumed by stock market returns

To address the question, I first examine if stock markets contain any predicting power for subsequent real GDP growth. Afterwards, I investigate if aggregate accounting profitability drivers can provide additional forecasting power which is not contained in stock prices.

3.5. History of Macro-Forecasting

The Federal Reserve administers the interest rate policies in the US. In targeting equilibrium output the Federal Reserve gathers its information from the Survey of Professional Forecasters (SPF) which is executed by the Federal Reserve Bank of Philadelphia. As the oldest and most reputable source of quarterly macro forecasts, SPF has a network of financial professionals, academia, government, labour unions and trade associations who provide quarterly predictions. Given that reputation is an important factor for those individuals and institution, they have an intrinsic incentive to provide accurate forecasts. The survey focuses on 27 different variables, weighting on mainly CPI inflation, GDP growth, and yields on long-term T-bonds. Therefore, macro forecasters should consider all available information to them at the time of their predictions. I test whether the AB ratios on aggregate level predict the macro forecasters' revisions from q-1 to q. Consequently, I test if their forecast errors are predictable by the same aggregate accounting information.

Provided that aggregate accounting profitability drivers are not subsumed by stock investors, Konchitchki and Patatoukas (2014a) conjecture that macro forecasters are also unaware of the informative power of DuPont analysis. As in "Accounting earnings and gross domestic product", the two researchers use SPF consensus forecasts as a proxy for the assumptions made by the U.S. Federal Budget (Konchitchki and Patatoukas, 2014a, 2014b). Since Federal Reserve's Board of Governors utilises the SPF forecasts in the preparation of the "Greenbook" prior to the Federal Open Market Committee, Sims (2002) discovers that Greenbook predictions are identical to the SPF panellists as both groups' reputation and jobs are at stake.

Broadening previous results that DuPont ratios on firm-level predict analysts' forecast errors and on aggregate level DuPont explains variation in macro forecast errors (Soliman, 2008; Konchitchki and Patatoukas, 2014a). I predict that macro forecasters do not fully utilise the information in the financial statements of companies, in particular the AB ratios. Since, economists consider accounting as irrelevant to their work and lacks any useful information for their forecasts.

H3. Whether the macro forecasters (SPF) embed aggregate accounting profitability drivers from the alternative breakdown when forming their revisions of real GDP growth

H4. Whether SPF forecast errors are predictable by aggregate accounting profitability drivers from the alternative breakdown and stock market returns

3.6. Stock Valuation

Previous research provides evidence for the significant importance of the macroeconomic fluctuations in stock valuation. An important relation was established among stock pricing and its corresponding firm fundamentals with the inclusion of inflation and real GDP variables. Whether macro variables are included, fundamental factors results were insignificant (Lev & Thiagarajan, 1993). As discussed in the financial literature, the firm-level delay in accounting data assimilation provides the investors with an opportunity to earn abnormal returns (Abarbanell & Bushee, 1998; Soliman, 2008). If the model developed using accounting drivers can predict future real GDP growth and improve macro forecasters' accuracy, I expect that stock market prices are not immediately affected but with a lag[14].

H5. How do accounting profitability drivers affect the stock valuations based on the real GDP information provided?

[14] I structured my report in a way that cornerstone articles are examined in detail in section 2. Allowing me to briefly summarize the paragraph leading to the research questions. The main reason behind that is readers with satisfactory knowledge on the topic can benefit from easier composition and time-saving.

4. Methodology

4.1. Sample

I retrieve quarterly income statement and balance sheet data from Compustat Quarterly Preliminary History Dataset. The focus is only on companies which fiscal quarter ends align with calendar quarter ends - March, June, September, and December. I calculate quarterly ratios changes of profitability which are composed by ROBA[15], Financial Leverage, and Cost of Debt. To tackle any data seasonality, I multiply all income statement variables by four. Consequently, I use year-over-year changes when compiling quarterly profitability ratios[16]. Furthermore, I eliminate companies which lack information for ratio calculation. To mitigate for the outlier's effects, I exclude the top and bottom one percent of each profitability driver. Companies with negative Cost of Debt are also excluded from the sample[17].

I retrieve SPF data from the Federal Reserve Bank of Philadelphia[18] with a date span of 1981Q3 to 2018Q1, with only one missing data for the period of 1995Q4. The missing data point happened as a result of a governmental shutdown because of budgetary reform conflict. There are two reasons for the beginning point of my sample period to be 1981Q3. Firstly, Compustat data is limited beforehand. And secondly, SPF's reports have been delivered in a consistent manner only after 1981Q3. I source the data on GDP preliminary growth from National Income and Product Accounts (NIPA) which is governed by the Bureau of Economic Analysis (BEA). I collect GDP growth forecast data of the mean[19] SPF consensus for consecutive quarter q+1 denoted $E_q[g_{q+1}]$. I use S&P 500 as a proxy for stock market portfolio and measure this by the equites market return of a buy-and-hold portfolio with holding period of 3, 6, 12, and 24 months.

Once, I have all the necessary data, I calculate each ratio for companies which have FYR as calendar quarters using Excel. In Stata, I filter the data to top 100 enterprises by market capitalisation, aggregate the ratios quarterly, and compute the changes from the same quarter, but the previous year. Second, I test if segregating the data to companies operating solely in the home market (U.S.) and multinational companies provide different predictive power. I filter by

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[15] As previously discussed in Section 2.4. ROBA differentiates slightly from RNOA presented in the Konchitchki and Patatoukas (2014a).
[16] Konchitchki and Patatoukas (2014a, 2014b) use this method, moreover, Fairfield (2001) proves its effectiveness to tackle biasness by annualizing data.
[17] This is not a representation of survivorship bias, but rather safeguarding my data from outliers. It seems unreasonable to assume that a company would receive money for taking a loan.
[18] The Federal Reserve Bank of Philadelphia started facilitating the Survey of Professional Forecasters since 1990.
[19] I obtain the mean consensus forecast of the SPF analysts compared to the individual predictions which are statistically proven to be inferior to the average (Zarnowitz & Braun, 1993; Graham, 1996; Croushore, 2011)

Compustat domestic and international indicators. The filtering of the data is easily done by introducing an if test or simple dummy variable. Consequently, I implement an identical process as with the data for all companies. Third, previous research suggests that financial sector expansion has diminishing contributions to economic growth. Thus, I conjecture that, a well-developed financial sector as in U.S., will explain smaller variation of consequent GDP and nonfinancial enterprises' predictive content will raise since heterogeneity will be reduced. I use the SIC codes and separate the dataset in financial industry 6000-6799 and the rest which I refer to as nonfinancial industries. The rest of remaining procedures are duplicated as per Hypothesis 1. Fourth, if the initial hypothesis is proven, next step will be to include stock market return in macro forecasting models. This would determine if the information provided in AB ratios is not already included in stock market return. Konchitchki and Patatoukas (2014a), find that the greatest predicting power for consequent quarter is provided by the returns in previous 12 months[20]. Therefore, it suggests that investors' forecasts of economic development is strongest at one year horizon. Hypothesis 2 examines the relationship between the 12 months buy-and-hold returns and test whether the aggregate ratios provide additional information. Expanding on the previous regressions, it would be useful to test whether forecast errors of SPF forecasters can be predicted by stock market returns and aggregate profitability drivers. Predicting that macro forecasters do not utilise accounting data due to being "too coarse" will be proven if any β is significant. The concluding test examines whether the stock participants utilise the accounting information in their prediction of the future stock market returns. The final model conjectures whether the future S&P returns can be predicted by the fitted value of real GDP growth ($\hat{g}$) based on the AB ratios, yet not already subsumed by the returns from the previous year (*ret12*). I use only the significant independent variables from Table 6 which are ΔBAT, ΔOM, ΔCapInt, and ΔSPREAD, to predict $\hat{g}$. I follow by estimating residuals and regressing them on future returns.

4.2. Timing of the experiment

The main reason to align fiscal and calendar quarters is to match the timing of SPF. The Federal Reserve Bank of Philadelphia sends the questionnaires to macro forecasters within one month after each quarter ends. Therefore, companies without financial statement data available by the end of first month (t) after fiscal quarter (q) are excluded from the sample. Using this method

[20] I also test if this is the case in my dataset by regressing consequent real GDP growth by 3, 6, 12, and 24 month returns. As per Konchitchki and Patatoukas (2014a), I find that the 12 month return has the highest predictive ability.

assures that all information is available to macro forecasters *ex-ante*. To align the financial information, I use conditional formatting provided by Compustat and fix the Fiscal-Year-End (FYR) to 3, 6, 9, and 12. Figure 4 illustrates the process and research design timeline, providing an example for 2011 (Konchitchki & Patatoukas, 2014a). SPF sends the questionnaires by the end of July 2011, thus financial statements information released by that time is readily available for their analysis. Analysts must deliver their prediction by the middle of next month. In Figure 4 macro forecasters receive prediction questionnaires by the end of July 2011 and return them by middle of August 2011.

[Insert Figure 4 here]

4.3. Descriptive statistics

Figure 5 shows the top 100 U.S. firms, ranked by market capitalisation, as a fraction from the total market with aligning fiscal and calendar quarters. During the sample period, I find that my sample accounts for 79% on average of the population. However, in recent years we can see that line hoovers closer to 70% rather than 80%. Benjamin Graham, the father of value investing, provides a good explanation for this phenomenon. In the rise of a bull market, investors focus their money in fewer, bigger companies. But if the upward trend persists, smaller and mid-size companies exhibit interesting returns, too. Luring investors to spread their funds among more companies. Evidence points to a conclusion that positive returns in the SMEs are mainly driven by speculation. This explanation fits in the current state of the economy, where stocks exhibit all time high, therefore high market capitalisation is not clustered to few large companies (Graham, 2003).

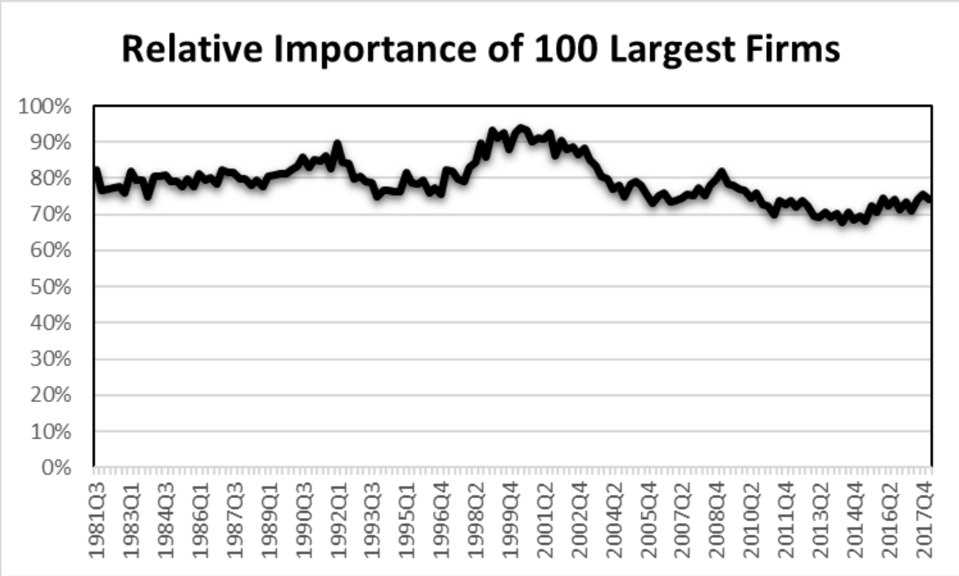

Figure 5. Relative Importance of 100 Largest Firms by Market Capitalisation

Next, I present the descriptive statistics in Table 1 and the pairwise correlations in Table 2. The first noticeable divergence in the descriptive statistics of Konchitchki and Patatoukas (2014a) and mine are between values of assets turnover and return on assets. This can be explained as Konchitchki and Patatoukas (2014a) calculate those ratios based on the net operating assets where I use business assets which include also investment assets. Thus, the denominator of ROBA ratio is expected to be larger. Profit and Operating margins are very close to the original paper, but as expected 43 basis and 160 basis points higher, respectively. This can be explained as in the calculation of those ratios I include the investment profits as well. The cost of debt is between 54 and 250 basis points which can be attributable to the size of the companies, but also the monetary policies. The mean effective tax rate of the sample is 32 percent which is very close to the statutory tax rate[21].

[21] Although the statutory tax rate was changed to 21 percent in the end of 2017 by the Tax Cuts and Jobs Act (TCJA), the effect can be observed only in 2018Q1 which is not enough to drive the mean downwards (Congress, 2017).

TABLE 1

Descriptive Statistics

Variable	Mean	Std.Dev.	Min	Max
BAT	0.34	0.051	0.218	0.456
SPREAD	0.023	0.008	0.005	0.038
FinLev	0.91	0.215	0.493	1.453
PM	0.174	0.029	0.115	0.227
OM	0.249	0.03	0.173	0.303
CapInt	0.075	0.009	0.049	0.104
ROBA	0.035	0.005	0.022	0.049
Rd	0.012	0.004	0.005	0.025
T	0.32	0.054	0.143	0.44
BAT	-0.007	0.03	-0.104	0.083
SPREAD	0	0.005	-0.023	0.022
ΔFinLev	0.013	0.15	-0.464	0.393
ΔPM	0.002	0.016	-0.055	0.058
ΔOM	0.003	0.015	-0.043	0.045
ΔCapInt	0.001	0.008	-0.025	0.021
ΔRd	0	0.002	-0.005	0.007
ΔROBA	0	0.005	-0.024	0.022
ΔT	-0.006	0.034	-0.095	0.093
g_{q+1}	0.024	0.023	-0.061	0.087

Table 1 reports descriptive statistics for the quarterly time-series of the following aggregate ratios: BAT, SPREAD, FinLev, OM, PM, CapInt, Rd, T, and ROBA. Aggregate year-over-year changes are represented by Δ symbol. The sample period is from 1981Q3 to 2018Q1.

*All numbers are presented in decimals

Although Ivanov (2016) ranks companies based on their assets, the mean, min, and max values of the variables are very close to each other. Understandably, the biggest companies in terms of assets and market capitalisation are not identical, but similar (Murphy, 2018). This serves as a good check due to the similarity of the ratio definition.

Second, pairwise correlations are presented in Table 2. The table already hints which variables will have a predictive power over consequent GDP growth. Yet, I test their combined significance in the following section. The correlation matrix also brings the multicollinearity problem as cost of debt is correlated to the financial leverage and tax rates. Therefore, in the following regressions I compute multicollinearity diagnostics, yielding very low Variance Inflation Factor (VIF) in all test regressions and proving no multicollinearity signals. I also check whether the results are different when excluding the cost of debt, financial leverage, and tax rates, the results yielded negligible differences in the overall predictive content and independent variable wise. As expected, some of the other variables exhibit correlation since they represent parts of the decomposed ratios. The changes in BAT, SPREAD, PM, OM, ROBA, and T, as shown in the last line of Table 2, show correlation at the 5 percent significance level.

TABLE 2

Pairwise correlations All Companies

	1	2	3	4	5	6	7	8	9	10
1 ΔBAT	1									
p-value										
2 ΔSPREAD	0.479*	1								
p-value	*< 0.001*									
3 ΔFinLev	-0.311*	-0.168*	1							
p-value	*< 0.001*	*0.042*								
4 ΔPM	-0.027	0.610*	-0.049	1						
p-value	*0.744*	*< 0.001*	*0.553*							
5 ΔOM	-0.269*	0.405*	0.021	0.864*	1					
p-value	*0.001*	*< 0.001*	*0.796*	*< 0.001*						
6 ΔCapInt	-0.435*	-0.466*	0.136	-0.401*	0.116	1				
p-value	*< 0.001*	*< 0.001*	*0.1*	*< 0.001*	*0.163*					
7 ΔROBA	0.504*	0.956*	-0.262*	0.570*	0.367*	-0.458*	1			
p-value	*< 0.001*	*< 0.001*	*0.001*	*< 0.001*	*< 0.001*	*< 0.001*				
8 ΔT	0.303*	0.308*	0.026	0.234*	0.173*	-0.147	0.193*	1		
p-value	*< 0.001*	*< 0.001*	*0.757*	*0.004*	*0.037*	*0.076*	*0.019*			
9 ΔRd	0.077	-0.16	-0.314*	-0.138	-0.132	0.033	0.138	-0.389*	1	
p-value	*0.352*	*0.053*	*0*	*0.095*	*0.111*	*0.693*	*0.095*	*0*		
10 g_{q+1}	0.260*	0.426*	-0.109	0.319*	0.327*	-0.034	0.390*	0.301*	-0.127	1
p-value	*0.001*	*< 0.001*	*0.189*	*< 0.001*	*< 0.001*	*0.68*	*< 0.001*	*< 0.001*	*0.126*	

Table 2 reports Pearson correlation and two-sided p-values in italics. The sample period is from 1981Q3 to 2018Q1.

* shows significance at the .05 level

4.4. Additional tests

I briefly go through few of the additional tests I ran to confirm that the correlation between variables in the descriptive statistics is not affecting the following regressions. I estimate the regressions in *Section 5: Results* using ordinary least squares regressions, I further perform standard errors Newey and West (1987) test with lag length of 4. I find no autocorrelation beyond four quarters behind. Assuring that the standard errors (SEs) are robust is important, otherwise, it can lead to incorrect rejection or acceptance of null hypothesis, Type I error. All regressions have robust SEs and exhibit no systematic pattern in residuals[22].

[22] I also double check the results through using *vce (robust)* function in Stata.

Moving our attention to the multicollinearity threat. Having a high correlation between independent variables can lead to large standard errors, which in turn will damage the representativeness of the current sample. Since some of the variables are defined as composite measures, they can be representative of perfect multicollinearity (Allen, 1997). Therefore, I exclude the ΔROBA after the first column and ΔRd which proves to be insignificant in the first regression, as those two variables are used to construct ΔSPREAD. Although perfect multicollinearity presents a threat, the solution is rather simple by excluding the composite measure or the constructing variables (Allen, 1997). I also test for extreme multicollinearity, to determine if the independent variables are exhibiting any signs. Allen (1997) suggests that multicollinearity can also be detected by examining the magnitude of the coefficients and standard deviations of the regressors. However, the VIF test suggests that there is no multicollinearity between the variables[23]. As Ivanov (2016) argues in his research, the insignificant relationship between the variables can be due to the heterogeneity of the sample, company specifics also affect the capital structure, and prior research focuses on long-term effects compared to my short-term horizon.

[23] I have run the VIF test as an auxiliary test after every regression.

5. Results and Discussion

In this section, I provide the statistical results followed by an interpretation of the numbers. Each subsection will introduce the regression model utilised to substantiate the underlying results.

5.1. Alternative Breakdown profitability ratios and its predictive content

Elaborating on previous research conducted in the area of macro accounting, the following models use a sample of the top 100 public companies in the U.S. economy ranked by their market capitalisation (Konchitchki and Patatoukas, 2014a, 2014b; Ivanov, 2016). The $\Delta AlternativeProfitabilityRatios_q^k$ and their specification are available in Appendix 1.

$$g_{q+1} = \alpha + \sum_k \beta_k \times \Delta AlternativeProfitabilityRatios_q^k + \varepsilon_{q+1}$$

I test the joint predictive power of all variables by breaking down ΔROE in ΔROBA, ΔSPREAD, ΔFinancial Leverage and their building components. Table 3 presents the predictive power of aggregate profitability drives from AB on next period's real GDP growth. Correspondingly to Konchitchki and Patatoukas (2014a) and Ivanov (2016) changes of variables are on small scales and I illustrate their effects through standard deviations. Table 3 has five different columns each representing a separate regression with different variables. The adjusted R squared shows goodness of fit of models and if including extra variables improves the predictive power. The first column shows the results of Return on Business Assets (ΔROBA) as the sole independent variable. ΔROBA shows significance at the 1 percent level and one standard deviation change resembles real GDP growth expansion in the next quarter by 0.83 percent. The next column breaks down ΔROBA into Business Asset Turnover (ΔBAT), Operating Margin (ΔOM), and Capital Intensity (ΔCapInt) which improves adjusted R squared from 14.6 percent to 24.0 percent. Although, the second column has better explanatory power for real GDP growth, only ΔBAT and ΔOM are significant at 99 percent interval. One standard deviation increase in ΔBAT and ΔOM is associated with 1.60 percent and 2.02 percent subsequent real GDP growth, respectively. Column three includes two additional variables changes in spread (ΔSPREAD) and in cost of debt (ΔRd). Although ΔSPREAD is only significant at 10 percent level, by including the two new variables ΔCapInt becomes significant at confidence level of 95 percent, too. One standard deviation in ΔSPREAD is associated with 0.47 percent subsequent real GDP growth. And one standard deviation change in ΔCapInt is associated with 0.40 percent consequent real GDP growth. I computed multicollinearity diagnostics in Stata which yields Variance Inflation Factor (VIF) of 1.85 which rejects the issue of multicollinearity.

TABLE 3

Alternative Breakdown profitability ratios and its predictive content for real GDP growth

	Dependent Variable = gq+1				
	1	2	3	4	5
Intercept	0.024***	0.024***	0.024***	0.024***	0.024***
t-statistic	14.191	14.544	14.241	14.336	14.293
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
ΔBAT*q*		0.313***	0.237***	0.194**	0.188**
t-statistic		5.1	3.157	2.442	2.295
p-value		< 0.001	0.002	0.016	0.023
ΔOM*q*		0.672***	0.463***	0.412***	0.407**
t-statistic		5.856	3.04	2.651	2.607
p-value		< 0.001	0.003	0.009	0.01
ΔCapInt*q*		0.293	0.504**	0.509**	0.510**
t-statistic		1.322	2.094	2.127	2.124
p-value		0.188	0.038	0.035	0.035
ΔSPREAD*q*			0.937*	0.979*	0.974*
t-statistic			1.875	1.965	1.948
p-value			0.063	0.051	0.053
ΔRd*q*			-1.222	-0.477	-0.611
t-statistic			-1.164	-0.414	-0.507
p-value			0.247	0.679	0.613
ΔROBA*q*	1.659***				
t-statistic	5.076				
p-value	< 0.001				
ΔT*q*				0.087	0.087
t-statistic				1.524	1.527
p-value				0.13	0.129
ΔFinLevq					-0.005
t-statistic					-0.392
p-value					0.695
Adjusted R-squared	0.146	0.240	0.260	0.267	0.262

Table 3 reports results from panel regression of subsequent real GDP growth (gq+1) from my aggregate accounting indices. The sample period is from 1981Q3 to 2018Q1. All statistical inferences are based on Newey and West (1987) standard errors and two-sided p-values in this and the following tables

*** p<0.01, ** p<0.05, * p<0.1

Moving to Column four, I include the changes in effective tax rate (ΔT) which is insignificant. The only observable difference from column three is that ΔBAT drop from 99 percent to 95 percent level significance. One standard deviation change in ΔBAT results in 0.99 percent increase in real GDP growth next quarter. In the final column, I include financial leverage (ΔFinLev) as a regressor. The significance of ΔBAT and ΔOM decrease to 95 percent level and goodness of fit of the overall model decreases from 26.7 to 26.2 percent. One standard deviation change in each variable - ΔBAT, ΔOM, ΔCapInt, and ΔSPREAD is associated with 0.56, 0.61, 0.41, and 0.49 percent change in the consequent real GDP growth, respectively.

This method reduces the trivial cost of computing ratios on all public companies. Coherent with recent research, accounting data on aggregate level provides insights regarding consequent real GDP growth (Konchitchki and Patatoukas, 2014a). Yet, the significance of changes in the operating margin and capital intensity to g_{q+1} links further back to research conducted on firm level (Ou and Penman 1989; Abarbanell and Bushee 1998). The aggregate changes in Alternative Breakdown ratios contribute to the explanation of over a quarter of future real GDP growth. Although companies within my sample and prior research should be identical[24] up to 2011Q3, I will withhold comparing[25] the papers as my sample includes more observations and consequently, I use only nonfinancial companies. Furthermore, the variables in the papers vary in their definition, thus black and white comparison is not possible. For example, in ROBA I include investing profits in the numerator and investment assets in denominator. Therefore, construction is different from the one in RNOA and it is beyond the scope of this paper to determine whether the greater predictive content of ROBA over RNOA is due to the chosen sample or variable construction[26]. ΔROBA explain 14.6 percent of the variation and one-standard deviation is associated with 0.83 percent change in consequent real GDP growth compared to ΔRNOA – 8 percent adjusted R squared and 0.74 percentage increase in economic activity. I do a robustness test by excluding the observations after 2011Q3 and the adjusted R squared of ROBA is 13.6 percent compared to 8 percent in the Konchitchki and Patatoukas (2014a). Furthermore, Ivanov (2016) finds similar results in his paper, ΔROBA has adjusted R squared of 14 percent. However, including additional variables, besides DuPont analysis, proves to have mixed results in increasing the predictive information. Besides, ΔBAT, ΔOM, and ΔCapInt, which construction is comparable to the DuPont variables, only ΔSPREAD is significant in Table 3, column five. Once, I split the data to nonfinancial companies only, the

[24] I contacted Dr. Konchitchki and Dr. Patatoukas to ask additional information on their process of company alignment. My method of using conditional formatting from Compustat is correct, yet they did not disclose how they did it exactly.
[25] I define comparing as saying which paper is better, my work should develop prior research and contribute to the macro accounting stem of literature.
[26] Although the companies should be identical up to 2011Q3, without knowing how they filtered their sample, I cannot claim that.

significant variables do not change, but the overall predictive content raises from 26.2-26.7 to 29.6 percent. This can be granted to sample heterogeneity, especially, between financial and nonfinancial companies. An example can be capital intensity, which I define as depreciation to sales, and can be a foreign concept for a bank.

5.2. Sample Split: Domestic Perspective

To test whether aggregate accounting profitability drivers of domestic companies have a higher predictive content on economic growth, I use Compustat domestic and international indicators. The methodology is identical as with all companies with one crucial difference, I restrict the sample to solely domestic companies. Since I proxy corporate profits through aggregate changes in the ratios, I expect the adjusted R of the domestic subsample to be larger. There is a limitation with this method as companies with 90 percent domestic and 10 percent international activity are excluded as well. I tried an alternative method by getting percentage of domestic and international sales from Bloomberg Professional, however, they have a limited historical data and do not cover the whole time period in this study. Finally, I test whether the predictive power of domestic companies is greater compared to the overall sample.

$$g_{q+1} = \alpha + \sum_{k} \beta_k \times \Delta DomesticAlternativeProfitabilityRatios_q^k + \varepsilon_{q+1}$$

We turn our attention to Table 4 now, where we can see if the conjecture is correct. In column one, ΔROBA are significant at 99 percent level and have adjusted R squared of 6.7 percent. One standard deviation increase in ΔROBA explains 0.61 percent growth in consequent quarter real GDP growth. I follow the same methodology as in Hypothesis 1 by further decomposing the Alternative Breakdown. In the next four columns only ΔOM is significant throughout each column and ΔBAT is significant only in column two. Including more variables decreases the significance level of ΔOM from 99 to 90 percent. Column five includes all variables which explain only 9.1 percent of consequent real GDP growth. One standard deviation in ΔOM is associated with 0.46 percent next quarter real GDP growth. Furthermore, to determine if the domestic companies contribute greater than all companies, I use goodness of fit. Ergo, I reject the null hypothesis that domestic companies have larger predictive power over consequent real GDP growth. The adjusted R squared are significantly lower, with the highest sitting at 9.7 percent for domestic companies and 26.7 for all companies.

TABLE 4
Alternative Breakdown profitability ratios of domestic companies and its predictive content for real GDP growth

	Dependent Variable = gq+1				
	1	2	3	4	5
Intercept	0.024***	0.025***	0.024***	0.025***	0.025***
t-statistic	13.548	13.517	13.219	13.12	13.072
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
ΔBAT*q*		0.207**	0.160	0.150	0.153
t-statistic		2.257	1.65	1.548	1.564
p-value		0.026	0.101	0.124	0.12
ΔOM*q*		0.244***	0.170**	0.157*	0.158*
t-statistic		3.835	2.114	1.956	1.955
p-value		< 0.001	0.036	0.052	0.053
ΔCapInt*q*		0.200	0.260	0.223	0.232
t-statistic		0.996	1.253	1.068	1.1
p-value		0.321	0.212	0.287	0.273
ΔSPREAD*q*			0.653	0.645	0.664
t-statistic			1.644	1.628	1.654
p-value			0.102	0.106	0.1
ΔRd*q*			0.060	1.508	1.600
t-statistic			0.036	0.782	0.818
p-value			0.971	0.436	0.415
ΔROBA*q*	1.040***				
t-statistic	3.387				
p-value	0.001				
ΔT*q*				0.075	0.074
t-statistic				1.422	1.394
p-value				0.157	0.166
ΔFinLevq					0.005
t-statistic					0.333
p-value					0.74
Adjusted R-squared	0.067	0.086	0.090	0.097	0.091

Table 4 reports results from panel regression of subsequent real GDP growth (gq+1) from my domestic aggregate accounting indices. The sample period is from 1981Q3 to 2018Q1

*** p<0.01, ** p<0.05, * p<0.1

5.3. Sample Split: Financial and Nonfinancial Perspective

The next sub hypothesis I pose is whether the nonfinancial sector contributes to GDP growth predictability proportionally to the financial industry and all companies or even more.

$$g_{q+1} = \alpha + \sum_{k} \beta_k \times \Delta FinancialAlternativeProfitabilityRatios_q^k + \varepsilon_{q+1}$$

$$g_{q+1} = \alpha + \sum_{k} \beta_k \times \Delta NonFinancialAlternativeProfitabilityRatios_q^k + \varepsilon_{q+1}$$

Preceding academic research concludes that after certain threshold the financial industry exhibits diminishing returns related to the economic prosperity of developed countries. To test this hypothesis, I use Standard Industrial Classification codes and filter the data to only financial companies and nonfinancial. Afterwards I run identical regressions to establish which group provides better predictive content. For the financial data I run two samples one from 1981Q3 to 2018Q1 and from 1986Q4 to 2018Q1. The reason behind is that until 1986Q4, the financial companies with available information are scarce and do not meet the condition of at least 100 companies. Turning our attention to Figure 7, we can see that after 1986Q4, the number of enterprises is consistently close to or 100.

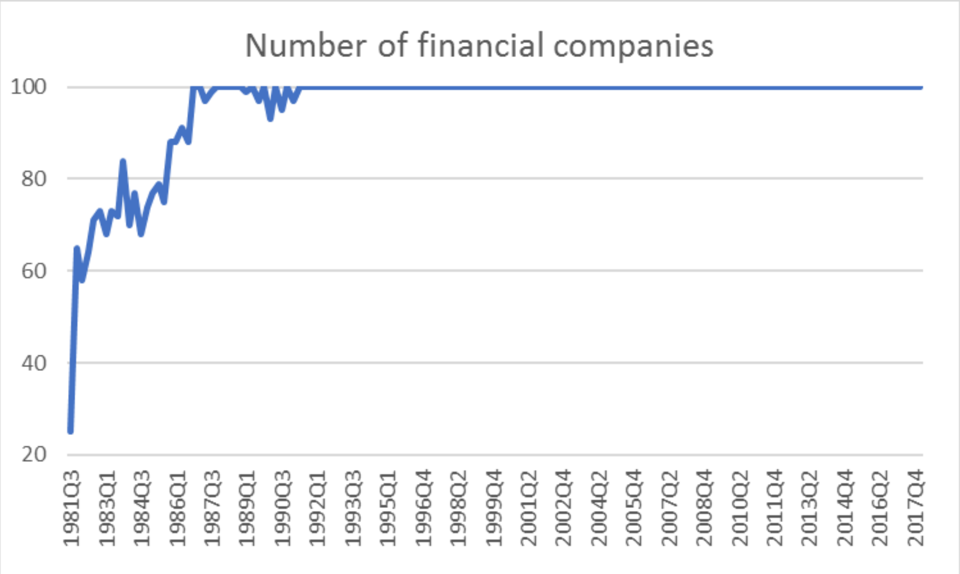

Figure 7. Number of financial companies in the sample

Table 5 shows the results for the financial sector, once the data set satisfies the condition[27] of at least 100 companies and Table 6 presents the predictive content of nonfinancial companies. In Table 5, column one, ΔROBA is insignificant and in column two only ΔOM is significant at the highest significance level, where one standard deviation is associated with 0.50 percent consequent real GDP growth. In columns three, four, and five the ΔOM's significance is

[27] Including information before 1986Q4 decreases the significance of Rd to 95 percent level and lowers the adjusted R squared to 6.6 percent. With brevity concerns in mind, I do not include the results.

swamped by introducing new variables which all are insignificant except ΔRd. In column five one standard deviation in ΔRd is associated with -0.49 percent consequent real GDP growth.

TABLE 5
Alternative Breakdown profitability ratios of the financial industries and their predictive content for real GDP growth

	Dependent Variable = g_{q+1}				
	1	2	3	4	5
Intercept	0.024***	0.024***	0.023***	0.024***	0.024***
t-statistic	14.149	14.034	14.378	14.434	14.195
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
ΔBAT*q*		-0.026	-0.025	-0.033	-0.031
t-statistic		-0.749	-0.712	-0.91	-0.709
p-value		0.444	0.478	0.363	0.479
ΔOM*q*		0.094***	0.046	0.040	0.038
t-statistic		2.878	1.195	1.021	0.901
p-value		0.005	0.226	0.302	0.362
ΔCapInt*q*		0.100	0.234	0.236	0.232
t-statistic		0.435	1.045	1.056	1.024
p-value		0.654	0.294	0.289	0.304
ΔSPREAD*q*			0.189	0.289	0.298
t-statistic			0.585	0.865	0.857
p-value			0.571	0.393	0.397
ΔRd*q*			-1.678***	-1.429**	-1.426**
t-statistic			-2.845	-2.273	-2.254
p-value			0.004	0.023	0.024
ΔROBA*q*	0.434				
t-statistic	1.562				
p-value	0.135				
ΔT*q*				0.024	0.024
t-statistic				1.129	1.123
p-value				0.257	0.26
ΔFinLevq					0.000
t-statistic					0.099
p-value					0.92
Adjusted R-squared	0.012	0.056	0.145	0.147	0.140

Table 5, reports results from panel regression of subsequent real GDP growth (gq+1) from financial aggregate accounting indices. The sample period is from 1986Q4 to 2018Q1

*** p<0.01, ** p<0.05, * p<0.1

Table 6 shows the results of the nonfinancial industry which exhibits very similar patterns as the overall sample in Table 3. In column one, ΔROBA is significant at 99 percent level and one standard deviation change equates 0.86 percent real GDP growth. In column two, one difference from Table 3 is that ΔCapInt is also significant. The ΔBAT, ΔOM, and ΔCapInt are associated with 1.02, 0.99, and 0.41 percent growth in real GDP, respectively. In the remaining three columns, as in Table 3, same variables remain significant ΔBAT, ΔOM, ΔCapInt, and ΔSPREAD. With only one distinction, ΔBAT, ΔOM, ΔCapInt are significant at the highest level, and ΔSPREAD at 95 percent confidence level. One standard deviation change in each one of the variables as listed above is associated with 0.65, 0.62, 0.61, and 0.75 subsequent real GDP growth.

TABLE 6

Alternative Breakdown profitability ratios of the nonfinancial industries and their predictive content for real GDP growth

	Dependent Variable = g_{q+1}				
	1	2	3	4	5
Intercept	0.024***	0.024***	0.024***	0.024***	0.024***
t-statistic	14.147	14.872	14.547	14.72	14.716
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
ΔBAT*q*		0.331***	0.278***	0.226***	0.210***
t-statistic		5.411	3.949	2.958	2.684
p-value		< 0.001	< 0.001	0.004	0.008
ΔOM*q*		0.668***	0.505***	0.445***	0.419***
t-statistic		6.145	3.581	3.076	2.843
p-value		< 0.001	< 0.001	0.003	0.005
ΔCapInt*q*		0.506**	0.670***	0.716***	0.750***
t-statistic		2.216	2.774	2.963	3.069
p-value		0.028	0.006	0.004	0.003
ΔSPREAD*q*			0.782*	0.909**	0.922**
t-statistic			1.726	1.988	2.016
p-value			0.087	0.049	0.046
ΔRd*q*			-1.101	-0.197	-0.557
t-statistic			-1.109	-0.174	-0.467
p-value			0.269	0.862	0.641
ΔROBA*q*	1.535***				
t-statistic	4.934				
p-value	< 0.001				
ΔT*q*				0.087	0.088
t-statistic				1.635	1.651
p-value				0.104	0.101
ΔFinLevq					-0.012
t-statistic					-0.959
p-value					0.339
Adjusted R-squared	0.139	0.275	0.287	0.296	0.296

Table 6 reports results from panel regression of subsequent real GDP growth (gq+1) from nonfinancial aggregate accounting indices. The sample period is from 1981Q3 to 2018Q1

*** p<0.01, ** p<0.05, * p<0.1

Furthermore, I use goodness of fit as a criterion to establish which set of companies is superior at providing information for consequent GDP growth. As a conclusion, the nonfinancial companies have greater predictive content, suggesting that separating the sample in financial and nonfinancial companies is beneficial. In each of the different set of variables the nonfinancial industry has larger adjusted R squared compared to the financial. Furthermore, the results in Table 6 are superior compared to Table 3, based on the adjusted R squared. Ergo, I utilise the nonfinancial subsample for further regressions[28].

Table 7
Adjusted R squared comparison between all companies, financial, and nonfinancial

	1	2	3	4	5
All companies	0.146	0.240	0.260	0.267	0.262
Nonfinancial companies	0.139	0.275	0.287	0.296	0.296
Financial Companies	0.012	0.056	0.145	0.147	0.140

Adjusted R squared of the nonfinancial model explains 29.6 percent[29] of the subsequent real GDP growth. I discuss the separate superiority of the nonfinancial companies in the variable analysis. Thus, moving forward, all regression results are based on aggregate accounting changes from the nonfinancial industry.

5.4. Variables Analysis

I further discuss each one of the independent variables from the first model *(all companies)* in a separate section and include a section for the results from Hypothesis 1a and 1b. I include domestic companies' explanation in only ΔBAT and ΔOM, because these are the only significant variables in regression 2. I also include nonfinancial sections in the significant variables only. Since, the other variables do not exhibit any differences between samples.

5.4.1. Business Asset Turnover

Business Asset Turnover (ΔBAT) refers to the relation between company's sales and its business assets or as defined in literature asset utilisation. Coinciding with my conjecture the ΔBAT is significant in Table 3 within all columns. Since it is harder to replicate the efficiency of a company, academic research proves that it is less transitory (Fairfield and Yohn, 2001; Soliman, 2008). I contribute to this line of research by providing information on the aggregate significance of ΔBAT to consequent real GDP growth. Compared to both Konchitchki and Patatoukas (2014a) and Ivanov (2016), where they find ATO/BAT insignificant.

Moreover, I find significant results in using aggregate ratios of all companies and only nonfinancial, leading to the conclusion that the heterogeneity of the sample is not a determinant. However, if seen from a different perspective maybe in Konchitchki and Patatoukas (2014a) heterogeneity and the definition of Asset Turnover can be one of the issues. As they take both

[28] I also examine the parsimoniousness of the model by using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), using only the significant variables yields the lowest AIC and BIC scores.
[29] Compared to 26.7 percent in Table 3, column four

financial and nonfinancial companies but define ATO as sales to average net operating assets, which excludes investment assets. Therefore, it does not consider that some sectors have most of their assets under investments and put upward pressure on the ratio. With regards to Ivanov (2016), it can be assumed that since he ranks the companies based on business assets, they already operate at very high efficiency. Thus, changes within those companies occur infrequently and puts downward pressure on BAT due to the very large denominator.

Domestic Companies

In Table 4, column two ΔBAT is significant at the 95 percent level, but when the other variables are introduced in the following columns it becomes insignificant. Yet, the predictive content of the whole model is low, and this should also be considered.

Nonfinancial Companies

In the nonfinancial sample, the ΔBAT show even greater significance when compared to Table 3. Along all columns they are at the highest significance level and are not affected by the introduction of extra independent variables. The results suggest that excluding financial companies from the sample increases the predictive content of ΔBAT. One standard deviation increase in business asset turnover in all companies is associated with 0.56 percent consequent real GDP growth and one standard deviation increase in business asset turnover of nonfinancial companies is associated with 0.65 percent consequent real GDP growth.

5.4.2. Operating Margin

Changes in Operating Margin (ΔOM), yield significant results in every one of the four columns they are included in Table 3, leading to the conclusion that they are an important factor in predicting the consequent economic activity. Furthermore, building up on prior research ΔOM prove significant at predicting firm level profitability (Abarbanell and Bushee, 1998; Soliman, 2008). But also, at the aggregate level as proven by Konchitchki and Patatoukas (2014a). Although, the significance of ΔOM decreases from 99 to 95 percent level when all variables are included this is not the case when financial companies are excluded. Since the companies in the sample can be referred as the most powerful, ΔOM do not experience the transitory effects mentioned in the literature review or the microenvironmental forces (Fairfield and Yohn, 2001; Soliman, 2008). Since they represent market leaders with high market recognition, they impose reputational barriers of entry for competition to enter and reduce the impact on their profitability.

Domestic Companies

In terms of domestic companies ΔOM exhibits similar traits as ΔBAT. In column two is significant at the highest level but consequently by the introduction of new independent variables it drops to 10 percent level only.

Nonfinancial Companies

The changes in the operating margins as with changes in business assets turnover are significant along all columns with the highest level of significance. Again, excluding financial companies, results in improved impact of the IV. One standard deviation change in all companies' ΔOM is associated with 0.61 percent change in consequent real GDP growth and 0.62 percent in the nonfinancial companies.

5.4.3. Capital Intensity

Coinciding with my conjecture Capital Intensity (ΔCapInt), or as prior research refers to it as Depreciation-to-Sales ratio, is significant predictor of consequent economic activity. An interesting factor is that ΔCapInt becomes significant from column two to three after including additional variables. Therefore, I pose the question of multicollinearity by conducting the variance inflation factor test. The results are considerably below the rule of thumb of 10 (UCLA, 2018). A second explanation is that even truly orthogonal independent variables can exhibit identical behaviour. For example, when regressing Y against X_1, it yields an insignificant result, but when including X_2 in the regression both independent variables become significant (Allen, 1997). Yet, this is not the case as in a separate analysis, I run the same regression as in column three, but exclude ΔRd entirely. Both variables are again significant. Furthermore, when either ΔSPREAD or ΔCapInt is dropped, the other variable becomes insignificant. As mentioned, this is not due to multicollinearity, but rather due to the construction of the variables and detected during the descriptive statistics analysis. Moreover, when we move our attention to Table 6, we can see that ΔCapInt is significant along all columns, hinting for the heterogeneity of the sample[30].

Moving to the implications of these results, my findings are in line with prior research which proves that changes in capital intensity are a significant predictor of consequent firm level activity (Ou and Penman, 1989; Cheng, 2005). Thus, based on the transitive property and the previous research, if the capital intensity can predict firm level dynamics, which in turn can be

[30] I further test the predictive content of the overall model by excluding ΔSPREAD and ΔRd altogether. The model remains significant and the drop in adjusted R squared is negligible.

aggregated and proxy for corporate profit, then ΔCapInt at aggregate level should predict consequent real GDP growth.

Nonfinancial Companies

Although in Konchitchki and Patatoukas (2014a), the aggregate changes in capital intensity are muted when including additional variables, I do not find such evidence. Furthermore, looking at nonfinancial companies only, the significance increases to the highest level. Therefore, an explanation for the insignificance can be the heterogeneity of their sample. One standard deviation increase in capital intensity in all companies is associated with 0.41 percent consequent real GDP growth and one standard deviation increase in capital intensity of nonfinancial companies is associated with 0.61 percent consequent real GDP growth Additionally, I pose the potential threat of real earnings management (REM), which can lead to ambiguous relationship between the ΔCapInt and consequent real GDP growth. I do not find such relationship, yet I do not include industry controls which can be examined as a further research topic.

5.4.4. SPREAD

The spread component provides an understanding if company's returns are above their cost of servicing the debt. Therefore, providing important information whether the company is creating or destroying value. I discussed in the previous section that the correlation between ΔCapInt and ΔSPREAD is significant and they exhibit significance only when included together. I detect no multicollinearity between the two variables. Furthermore, ΔSPREAD is only significant at the 10 percent level, though it helps to improve the explanatory power of the overall model. My results align with Ivanov (2016) who also finds that ΔSPREAD are not significant at the highest level.

Nonfinancial Companies

The ΔSPREAD component increases in significance from 90 to 95 percent in Table 6, Panel B compared to a constant 90 significance in Table 3. Another reason to believe that the aggregate Alternative Breakdown ratios from the nonfinancial companies provide superior model than all companies. By tackling the distinctive difference between financial and nonfinancial industries, but also proving hypothesis 1b that the finance sector growth after certain threshold does not help economic growth. One standard deviation increase in spread in all companies is associated with 0.49 consequent real GDP growth and one standard deviation change in spread in nonfinancial companies is associated with 0.75 percent consequent real GDP growth.

5.4.5. Cost of Debt

Cost of Debt (ΔRd) is insignificant across all column, suggesting that the link between what companies pay to service their loans is not related to consequent real GDP growth. Although, there can be two-fold explanation of the insignificance. To proxy for cost of debt I use the interest item in Compustat which provides an overall expense both for short and long-term interest-bearing liabilities. Therefore, not only we have a great heterogeneity among the sample in terms of companies, but also insufficient information regarding maturity and expense by smoothing the expense to the total. Referring to *Section 3.1.5. Cost of Debt*, I differentiate between the impact of increase on a company level and an increase of the risk-free rate. Given, the information available, such separation is not feasible, thus, the insignificance of the ΔRd does align with the underlying theory (Carlin and Soskice, 2015; Pereira, 2018). This is observable in Table 5, the cost of debt variable is highly significant and negative. Financial industry borrows money at interbank rate or federal funds rate which are closely related to the risk-free rate. Therefore, interpreting the results from Table 5, an increase in cost of debt of the financial industry is closely associated with negative real GDP growth in the consequent period. Which funnels in the monetary policy theory, increasing risk-free rate is a tool used by the Central Banks to contract the economy (Carlin and Soskice, 2015).

5.4.6. Tax rate

Tax rate (ΔT), as cost of debt, is insignificant in all columns included in Table 3. The results do not align entirely with my prediction that ΔT have impact on the consequent real GDP growth. Lev and Thiagarajan (1993) and Abarbanell and Bushee (1998) argue that decreased effective tax rate will have a negative impact on consequent real GDP growth. Yet, the tax rate has a twofold implication for the economy. Although increasing the tax rate will result in more money collected from taxes, it will also supress nominal growth as pointed out in Keynesian tax theory (Furceri and Karras, 2011). Furthermore, the Laffer curve provides a useful tool to visualise the impact of increasing taxes on collected revenue. The relationship between increasing tax rates and collection is nonlinear. In Figure 8 we can see that the Laffer curve has positive skewness and a revenue maximising point after which increasing the taxes only deteriorates economic growth.

5.4.7. Financial Leverage

Financial Leverage (ΔFinLev) changes are insignificant predictor of consequent real GDP growth. A clear explanation for the poor outcome is the heterogeneity of the sample where different sector require specific capital structure. These results pose the question whether separating the companies according to the sector they operate and aggregating them industry wise would be beneficial. However, such breakdown might lead to extra costs associated with compiling the data. Prior research proves that there is significant relationship between optimality theory and capital structure. Furthermore, seeing the company through the lenses of a shareholder holding a long call, can result in short-term outlook which involves raising the risk (Vorst, 2015). The added risk increases the volatility which results in a higher option value. On the other hand, increased debt can be beneficial for reasons such as tax shields. Therefore, I pose the question for further research to distinguish whether the increase in leverage is due to shareholder activism or optimal capital structure (Klen and Zur, 2011).

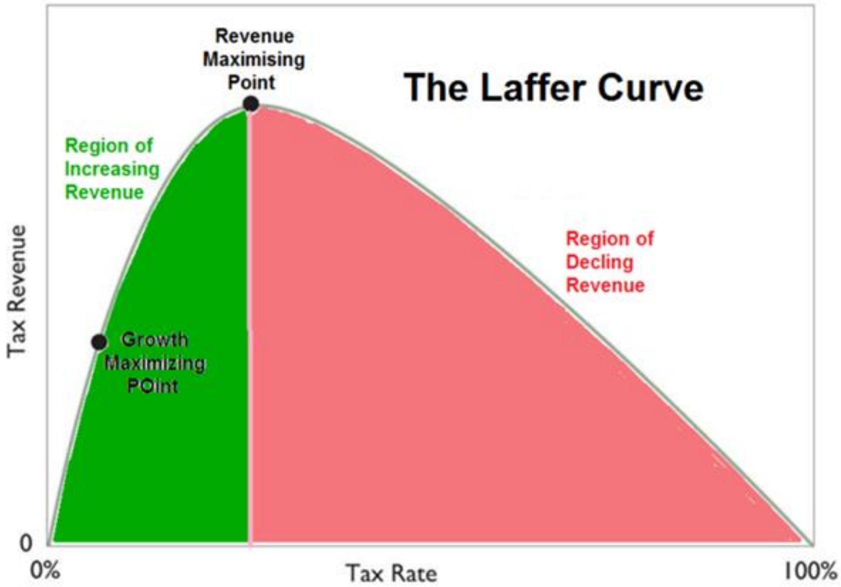

Figure 8. The Laffer Curve (Kimbarow, 2018)

5.5. The incremental usefulness of AB over stock returns

The succeeding hypothesis is whether the Alternative Breakdown ratios are beneficial to predicting subsequent real GDP growth after controlling for stock market returns. Stock prices provide an explanation of investors' prediction for subsequent economic developments (Fama, 1981; 1990). I align the returns with available information to macro forecasters when they make their predictions. Contingent upon the stock market returns being a significant predictor, I examine if aggregate accounting drivers provide any incremental information.

$$g_{q+1} = \alpha + \rho \times ret_{t-\tau \to t} + \varepsilon_{q+1}$$

Table 8 presents the results of different time horizons of buy-and-hold returns of S&P 500. Coherent with asset pricing models under rational expectations, using 3, 6, 12, and 24 yield significant information regarding q+1 economic growth. The predicting content of the return initially raises with the increase of length but culminates when I extend it to 12-month and declines afterwards. Table 6 shows that 12-month buy-and-hold returns (*ret12*) explain 19.3 percent of the q+1 variation in the time-series. Therefore, based on goodness of fit, I choose 12-month trailing returns to include in the following regressions.

Logically, the next step is to examine whether the predictive content of AB ratios is not subsumed by information already provided by stock market returns.

$$g_{q+1} = \alpha + \beta_1 \times \Delta BAT_q + \beta_2 \times \Delta OM_q + \beta_3 \times \Delta CapInt_q + \beta_4 \times \Delta SPREAD_q + \beta_5 \times ret_{t-12\to t} + \varepsilon_{q+1}$$

Referring to Table 8, where I use all significant variables from Table 6 and *ret12*. All regressors are significant, except ΔSPREAD, which indicates that financial statement analysis on aggregate company level is relevant at predicting next quarter real GDP growth. One standard deviation in ΔBAT and ΔOM are each associated with 0.64 percent real GDP growth expansion. Meanwhile one standard deviation in ΔCapInt is related to 0.40 percent consequent real GDP growth.

TABLE 8

Stock Market Returns as real GDP predictor and the incremental usefulness of the Alternative Breakdown

	Dependent Variable = gq+1				
	1	2	3	4	5
Intercept	0.022***	0.020***	0.018***	0.019***	0.021***
t-statistic	11.72	10.77	9.31	8.02	10.924
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
ret3	0.089***				
t-statistic	3.57				
p-value	< 0.001				
ret6		0.087***			
t-statistic		5.26			
p-value		< 0.001			
ret12			0.063***		0.037***
t-statistic			5.97		3.565
p-value			< 0.001		< 0.001
ret24				0.027***	
t-statistic				3.66	
p-value				< 0.001	
ΔBAT*q*					0.206***
t-statistic					2.963
p-value					0.004
ΔOM*q*					0.428***
t-statistic					3.123
p-value					0.002
ΔCapInt*q*					0.483**
t-statistic					2.038
p-value					0.043
ΔSPREAD*q*					0.634
t-statistic					1.448
p-value					0.15
Adj. R-squared	0.070	0.154	0.193	0.080	0.341

Table 6 reports results from panel regression of subsequent real GDP growth (gq+1) from aggregate accounting indices incremental to stock market returns. The sample period is from 1981Q3 to 2018Q1

*** p<0.01, ** p<0.05, * p<0.1

The addition of aggregate accounting profitability drivers clearly improves the predictive content compared to solely using market returns. AB ratios increase the adjusted R squared from 19.3 percent to 34.1 percent when both *ret12* and changes in AB ratios are included. Only ΔSPREAD loses its significance, compared to Table 6, which is understandable. First, the significance was not at the highest level. And second, analysts cover thoroughly if a company is creating value and thus, subsumed by the *ret12*. The results are in line with previous research and represent more than a third of the variations in consequent real GDP growth (Konchitchki and Patatoukas, 2014a; Ivanov, 2016)

5.6. The predictability of macro forecasters' revisions

In the previous regressions, I establish a relationship between consequent economic growth, stock market returns and aggregate profitability ratios. The next step, inevitably, is to examine whether the revisions of the macro forecasters are in direction of AB changes and market returns. I drop ΔSPREAD since it becomes insignificant when ret12 is included

$$E_q[g_{q+1}] - E_{q-1}[g_{q+1}]$$
$$= \alpha + \beta_1 \times \Delta BAT_q + \beta_2 \times \Delta OM_q + \beta_3 \times \Delta CapInt_q + \beta_4 \times ret_{t-12 \to t} + \varepsilon_{q+1}$$

Although, Table 9 yields significant results for ΔBAT, ΔOM, and *ret12*, ΔCapInt loses significance. Compared to previous regressions ΔBAT is significant only at the lowest level, while ΔOM is significant at the 95 percent confidence level. Stock market returns shows significance at the 1 percent level.

TABLE 9
Aggregate accounting profitability drivers and macro forecasters' revisions of real GDP growth
Dependent Variable = Eq[gq+1]-Eq-1[gq+1]

	1
Intercept	-0.322***
t-statistic	-4.748
p-value	< 0.001
ΔBAT*q*	4.158*
t-statistic	1.858
p-value	0.065
ΔOM*q*	9.270**
t-statistic	2.37
p-value	0.019
ΔCapInt*q*	6.042
t-statistic	0.758
p-value	0.450
ret12	1.723***
t-statistic	4.588
p-value	< 0.001
Adjusted R-squar	0.223

Table 9 reports results from panel regression of quarter q-1 to quarter q revision of the mean consensus forecast of quarter q+1 real GDP growth. The sample period is from 1981Q3 to 2018Q1

*** p<0.01, ** p<0.05, * p<0.1

In line with previous research done on this topic, my findings provide additional proof that returns, and AB ratios explain consequent revisions (Konchitchki and Patatoukas, 2014a; Ivanov, 2016). Changes in aggregate alternative breakdown ratios and 12-month buy and hold returns explain 22.3 percent of the variation in the revisions of macro forecasters from q-1 to q. Which compared to Konchitchki and Patatoukas (2014a) and Ivanov (2016) lies in the middle. Interestingly, when I conduct a robustness check whether the macro forecasters started taking into consideration the research published by Konchitchki and Patatoukas (2014a), the prove is significant. I split the data in two - up to 2011Q3 and after. The adjusted R squared of the sample up to 2011Q3 becomes even larger – 24.0 percent. And after 2011Q3 all variables and the model are insignificant at predicting the macro forecasters' revisions. Although those results should be taken with a pinch of salt since there are only 25 observations after 2011Q3.

5.7. The predictability of macro forecasters' errors

One step further is to understand if macro forecasters fully impound the power of stock market returns and aggregate level financial statement analysis.

$$g_{q+1} - E_{q-1}[g_{q+1}] = \alpha + \beta_1 \times \Delta BAT_q + \beta_2 \times \Delta OM_q + \beta_3 \times ret_{t-12\rightarrow t} + \varepsilon_{q+1}$$

Directing our attention to Table 10, I test whether the macro forecaster errors are predictable through stock market returns and Alternative Breakdown ratios. I find that stock market returns on its own are not a significant predictor of forecast errors and have an adjusted R squared of 0.4 percent. In column two, ΔOM is insignificant predictor, but ΔBAT is significant at 95 percent confidence level, and the two independent variables explain 3.5 percent of the variations in forecast errors. Furthermore, removing ΔOM, increases the explanatory power of ΔBAT to 4.0 percent at the highest significance. I run additional tests, by including only one variable at a time, only ΔCapInt is significant at 5 percent level. When I regress ΔCapInt and ΔBAT together, their combined predictive power is again lower compared to only ΔBAT as regressor. Last, but not least combining ΔBAT and *ret12* results in significance for both independent variables and adjusted R squared of 6.0 percent.

TABLE 10

Aggregate accounting profitability drivers and stock market returns predictive content over the SPF forecast errors

	Dependent Variable = gq+1-Eq-1[gq+1]			
	1	2	3	4
Intercept	-0.113	-0.093	-0.083	-0.285
t-statistic	-0.646	-0.611	-0.55	-1.587
p-value	0.519	0.542	0.583	0.115
ΔBAT*q*		-12.223**	-12.663***	-15.091***
t-statistic		-2.506	-2.646	-3.09
p-value		0.013	0.009	0.002
ΔOM*q*		5.062		
t-statistic		0.5		
p-value		0.617		
ret12	1.200			1.916**
t-statistic	1.273			2.028
p-value	0.205			0.044
Adjusted R-squared	0.004	0.035	0.040	0.060

Table 10 reports results from panel regression of subsequent Real GDP growth forecast errors and the relation to aggregate changes in profitability drivers. The sample period is from 1981Q3 to 2018Q1

*** p<0.01, ** p<0.05, * p<0.1

The significance of both ΔBAT and stock market returns suggests that macro forecasters are not attuned to the predictive content of those variables.

Both Konchitchki and Patatoukas (2014a) and Ivanov (2016) find that stock market return variables remains highly insignificant. Yet, they also find that only ΔOM are significant compared to my study where ΔBAT have the explanatory power. This can be due to the heterogeneity of the sample of Konchitchki and Patatoukas (2014a) or the asset intensive sample plus heterogeneity in Ivanov (2016). Yet, it is interesting to point out that business asset intensity is proven by prior research to be a better predictor than operating margin. First, because asset utilisation can be retained for longer time and is less influenced by direct competition, especially in the case of the most influential 100 companies (Soliman, 2008, Nissim and Penman, 2001). Second, operating margins and other income statement items have less impact on the firm level performance due to the flexibility of executive managers and high margins usually attract more competition consequently leading to lower profits (Fairfield and Yohn, 2001). Finally, Soliman (2008) proves that asset turnover is a significant predictor of stock market returns, analysts forecast revisions and errors, coinciding with the findings of this research.

5.8. The predictability of stock market returns

The final model conjectures whether the future S&P returns can be predicted by the fitted value of real GDP growth ($\hat{g}$). To do so, I must conduct a two-stage process which sets the foundation for the regression. First, I obtain the fitted values ($\hat{g}$) of consequent real GDP growth (g_{q+1}) based on the significant independent variables (ΔBAT, ΔOM, ΔCapInt, and ΔSPREAD) from Table 6. Second, I regress the $\hat{g}$ on the 12 month buy-and-hold return leading to period *t*. Afterwards, I take the residuals (g_{q+1}^{resid}), since it represents the portion of real GDP growth which is incremental on top of *ret12*.

$$\hat{g} = \alpha + \beta \times ret_{t-12 \to t} + \varepsilon_{q+1}$$

Ultimately, I regress the return realised from end of month *t* to *t+3* by the residuals from the previous regression. Since *t+3* coincides with BEA's first release, it provides us with a timely measurement to whether stock market investors consider the implications of aggregate accounting information.

$$ret_{t+1 \to t+3} = \alpha + \beta \times g_{q+1}^{resid} + \varepsilon_{t+1 \to t+3}$$

Table 11 presents the insignificance of the incremental usefulness of the fitted real GDP growth. The adjusted R squared of the regression is 0, leading to the conclusion that real GDP growth predicted by the AB variables, and not already included in the S&P 500 past annual return does not provide any predictive content for consequent stock market returns.

TABLE 11
Stock Market Returns association to Anticipated Real GDP growth
Dependent Variable = $ret_{t+1 \to t+3}$

	1
Intercept	0.023
t-statistic	3.97
p-value	<0.001
g_{q+1}^{resid}	0.469
t-statistic	0.92
p-value	0.362
Adjusted R-squared	0.00

*** p<0.01, ** p<0.05, * p<0.1

The interpretation of the results is rather straightforward, as investors usually consider changes in ratios of the companies and are familiar with fundamental analysis, those ratios do not exhibit relationship to consequent returns. Yet, in Konchitchki and Patatoukas (2014a), they find significant relationship between their DuPont decomposition and the next three-month stock market return. The two researchers remain agnostic about the explanation of their results. Furthermore, stock markets are adaptive and if a strategy delivers alpha on constant basis, making it public would lead to more people using it and leading to future insignificant results (Graham, 2003).

Lettau and Ludvigson (2005) shed light on the relationship between discount rates and expected growth rates. I also run a robustness check to test whether this change is due to the additional observations I include, but the results remain insignificant. The different ratio formulation can be a reason for the contrast in findings between this research and Konchitchki and Patatoukas (2014a). Further proof to this claim can be the insignificant results of consequent return predicted by AB in Ivanov (2016).

6. Out-of-sample performance

Although the previous regressions provide information that aggregate accounting drivers are useful in predicting consequent real GDP growth, they do not provide information how the model performs out-of-sample. Therefore, this chapter examines how well the Alternative Breakdown ratios are at forecasting next quarter economic growth.

The process I utilise is dictated by macroeconomic literature. I split the sample in two, where two thirds or 96 observations (24 years) serve as a rolling window and one third or 51 observations are predicted out-of-sample. The rolling regression proceeds as following, quarter 1 to 96 predict quarter 97, quarter 2 to 97 predict 98 and so on, with a fixed number of 96 consecutive data points in each sample. Once, I have all the forecasts from my model, I calculate the errors by comparing to the realisations of the Bureau of Economic Analysis which are observable in the National Income and Product Accounts. Consequently, I measure forecast accuracy using the root-mean-square error (RMSE) formula in Equation 5 (Stark, 2010). The article is relevant since it examines RMSE of SPF forecasts and the author is Assistant Director and Research Officer at Federal Reserve Bank of Philadelphia. Additionally, this specific article serves as a foundation in the methodology in Konchitchki and Patatoukas (2014a).

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{\varepsilon}_{t+\tau\,|\,t})^2}$$

Equation 5. Root-mean-square error formula (Stark, 2010)

Moving to the results, real GDP growth estimates (ŷ) from the out-of-sample rolling regression of aggregated accounting drivers has correlation of 62.7 percent to the real GDP realisations. Calculating the root-mean-square error of ŷ yields a result of 1.63 percent, which without another model the compare is meaningless. Therefore, I use Table 1 from "Realistic Evaluation of Real-Time Forecasts in the Survey of Professional Forecasters" and compare to the first realisations of NIPA and the SPF forecast for current quarter ($\tau = 0$) (Stark, 2010). The Root-Mean-Square Error statistics of SPF for real GDP growth is 1.40 percent. Leading to the conclusion that using only the aggregate accounting changes in profitability drivers and the 12-month stock returns does not outperform the predictions of the professionals. I also run a supplemental test using the same time period as in the paper, from 1985Q1 to 2007Q4 with a fixed rolling window of 60 observations which yields even higher RSME of 1.90 percent.

However, the results are close and exhibit RMSE with a difference of 0.23 to 0.5 percent. It is important to mention that I do not use any other variables used by the macro forecasters. And

TABLE 12
Aggregate Accounting Drivers Root-Mean-Square Error Statistics for real GDP growth

	Mean
RMSE	0.0163

* Results are in decimals

using only aggregate changes in profitability drivers and stock market return represents a close model to the one utilised by Survey of Professional Forecasters. Furthermore, my model has lowest RMSE among all the other models used as comparison in Stark (2010).

An interesting topic for future research is to examine if including aggregate accounting profitability drivers next to current set of variables[31] used by Survey of Professional Forecasters will reduce RMSE.

[31] Current set of variables of the Survey of Professional Forecasters is Natural Rate of Unemployment, Nonfarm Payroll Employment, Long-Term CPI Inflation, Short-Term CPI and PCE Inflation, Core CPI and Core PCE Probabilities, Unemployment and Real GDP Probabilities, Baa Interest Rate, Annual Horizons for Unemployment and Real GDP, Annual Horizons for Interest Rates.

7. Conclusion, Limitations and Future Research

This paper builds upon a new hybrid of two very influential streams of literature – accounting and macroeconomics. The macro accounting research term was first coined by Konchitchki and Patatoukas (2014a). Giving the foundation to better understanding the economic development through easily accessible accounting information of public companies. Furthermore, it offers a time-efficient method by only requiring data from the top 100 enterprises by market capitalisation in the given country.

The sample consists of accounting information from the top 100 public U.S. companies which fiscal quarters align with the calendar quarters. Previous academic research proves that aggregate levels of the accounting drivers do not contribute to the predictive content, but only changes do. Therefore, I calculate the Alternative Breakdown ratios and aggregate them per calendar quarter, then difference them on year over year basis to avoid seasonality.

In the first regression, the results suggest that aggregate changes of the financial statement information serve as a significant predictor of the consequent real GDP growth. In particular ΔBAT is an important influencer of economic growth next quarter due to its competitive sustainability. Asset utilisation is specific to each company and achieved through implementation of unique procedures hard to imitate by competition. Another significant predictor of consequent real GDP growth is ΔOM. Even though, Operating Margin is assumed to have transitory effects in previous literature, I do not find this evidence in the results. Large companies presumably have first-mover advantages and brand recognition which pose a barrier of entry for competition. Capital Intensity also yields significant results as an independent regressor of the consequent real GPP growth. Increasing the capital intensity this period suggests increased capacity of the companies, anticipating for higher demand and output next period, resulting in consequent economic growth. However, the significance is swamped by heterogeneity in the sample, since we can observe in Table 6, ΔCapInt are significant at the highest possible level. Next, the ability of companies to create value for their shareholders is an important indicator. A company can be profitable and have positive returns, yet if it returns are lower compared to cost of debt, a company is destroying value for its shareholders. Therefore, the higher the ΔSPREAD is, the higher is consequent real GDP growth. On the other hand, cost of debt is insignificant and does not contribute to the predictive content for q+1 economic growth. Yet, among the financial industry subsample the cost of debt is significant and negative. Financial companies borrow at a risk-free rate and thus, an increase in cost of debt is connected to the Central Bank controlling the economic output. Tax rate is insignificant along all different set of independent variables, too. Since ΔT can impact the economy in two conflicting[32] ways, the overall impact of the regressor is insignificant. The last regressor is Financial Leverage, which is also insignificant. By virtue of the sample, it is heterogenous, but also when excluding the financial companies, it still comprises of multiple industries. Some of them with stable income without much fluctuations, predisposing them to take on larger amounts of debt and some not. Therefore, the aggregate ΔFinLev cannot distinguish between the optimal capital structure or option price increase.

Subsequently, I test whether the aggregate accounting drivers have the same predictive content when included next to the stock market returns. I proxy for stock market returns by the S&P 500 index where 12 months buy-and-hold returns has the highest predictive content and explains 19.3 percent of the real GDP variation. Furthermore, including the aggregate AB ratios provide incremental usefulness to market returns as it improves the adjusted R squared from 19.3 to 34.1 percent. Establishing that the aggregate financial statement analysis and stock market returns have predicting content over the consequent real GDP growth, the next step is to check whether macro forecasters already make use of those factors. Table 9 shows that 22.3 percent of the revisions of SPF predictions can be explained by business asset turnover, operating margin and 12-month return. On the other hand, when predicting forecast errors, only ΔBAT is significant at the highest level and *ret12* at 95 percent confidence level. Moving to the final hypothesis, future stock market returns cannot be predicted by the aggregate profitability drivers.

Lastly, I test the soundness of the overall sample by conducting out-of-sample rolling regression and comparing it to the RSME of the Survey of Professional Forecasters. My model yields a root-mean-square error of 1.63, which is higher compared to the 1.40 percent of SPF. However, I leave for further research to examine whether including the aggregate accounting profitability drivers will decrease the RMSE of SPF forecasts.

Understanding the limitations of this study can influence the interpretation of the results and thus is important. Moreover, it will also provide gaps which can be filled with further research as the topic of macro accounting is rather new.

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[32] Higher taxes will increase the corporate profit element of the GDP calculation, but after certain threshold will also reduce the willingness of companies to produce.

The first and inevitable limitation of the methodology is the alignment of the fiscal and calendar quarters. I filter out approximately 40 percent of the companies by restricting the sample to have their statements reported at fiscal-year-end 3, 6, 9 and 12. Thus, a large portion of the companies is omitted, some of which unavoidably important. Additionally, companies with no available information for the construction of ratios are also excluded by the conditioning I pose in Compustat. Some of the tabs in Compustat are also limited in terms of information which does not allow me to account separately between financial and operating profits in ROBA, source of debt, and investment assets.

To test Hypothesis 1a, I separate the companies based on the Compustat Domestic and International indicator. A limitation of this process is that companies can have a small percentage of their activities abroad, but I exclude them from the sample. I tried filtering the data by including an indicator from Bloomberg Professional, matching the stickers of the top 100 companies and extracting the data from the terminals. But they do not provide data for the whole period and is limited to 10 years back. Therefore, this can be a topic for further research. In Hypothesis 1b, I also filter the sample to financial and nonfinancial companies. I implement this through the SIC codes where financial industries include all companies in Finance, Insurance and Real Estate.

Furthermore, there is observable difference when I split the data in financial and nonfinancial industries. The significance of the independent variables is positively affected and the overall goodness of fit of the model. Therefore, a meaningful clustering of certain industries can positively impact the predictive content of the model. This, I leave for consequent research to consider.

Finally, I examine the out-of-sample predictive power of the aggregate AB ratios through a rolling window and compare it to the RMSE of SPF. The conclusion is that my model has higher errors by 0.23 to 0.50 percent but leaves a space for further research. Since I do not include variables already used by the macro forecasters, it would be interesting to see the impact of AB drivers included to accounts such as inflation, price levels, national income, rate of growth, gross domestic product, and unemployment.

8. References

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Appendix

Appendix 1: Derivations and Ratios

$$ROE = \frac{Net\ Income}{Equity} = \frac{NOPAT + NIPAT - Interest\ Expense\ After\ Tax}{Equity}$$

$$= \frac{NOPAT + NIPAT}{Business\ Assets} \times \frac{Business\ Assets}{Equity}$$

$$- \frac{Interest\ Expense\ After\ Tax}{Debt} \times \frac{Debt}{Equity}$$

$$= ROBA\ \times \frac{Equity + Debt}{Equity} - Cost\ of\ Debt\ (Rd)\ \times Financial\ Leverage =$$

$$= ROBA + ROBA\ \times Financial\ Leverage - Rd \times Financial\ Leverage$$

$$= ROBA + (ROBA - Rd) \times Financial\ Leverage$$

$$= ROBA + Spread \times Financial\ Leverage$$

Net Operating Profit after Taxes *(NOPAT)* =

$Net\ Proft - NIPAT + Net\ interest\ expense\ after\ tax$

Net Investment Profit after Tax *(NIPAT)* = $(Investment\ income + Interest\ Income) \times (1 - Tax\ rate)$

Interest Expense After Tax = $Interest\ expense\ \times (1 - Tax\ rate)$

Business Assets (Capital) = $Operating + Investment\ assets$

Debt =

$Total\ interest\ bearing\ NC\ liabilities + Current\ debt\ and\ current\ portion\ of\ NC\ debt$

Cost of Debt (Rd) = $\frac{Interest\ expense\ after\ tax}{Debt}$

Financial Leverage = $\frac{Debt}{Equity}$

Appendix 2: Figures

$$leverage = \lambda = \frac{assets}{equity} = \frac{F_0}{e} = \frac{1}{risk - return\ to\ investment\ bank}$$

Figure 1. Leverage of Investment Bank (Carlin and Soskice, 2015)

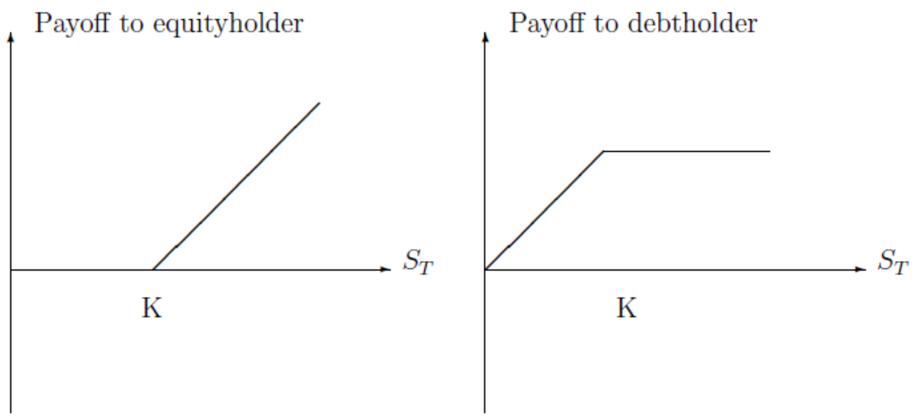

Figure 2. Payoff to equity and debt holders (Amatos, 2008)

Panel A: The Timing of the SPF

Name of SPF	Date Questionnaires Sent to SPF Panelists	Submission Deadline for SPF Questionnaires
First Quarter	End of January	Middle of February
Second Quarter	End of April	Middle of May
Third Quarter	End of July	Middle of August
Fourth Quarter	End of October	Middle of November

Panel B: Example for 2011 Third-Quarter SPF

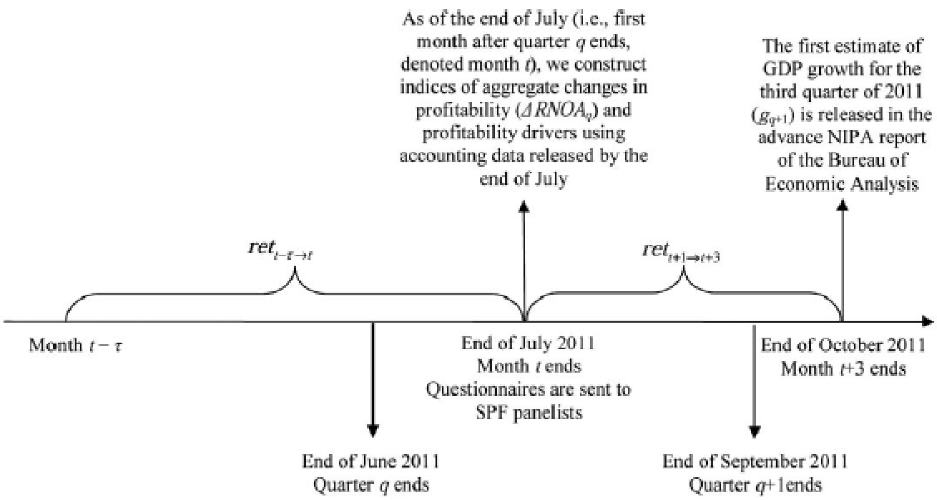

Figure 4. Research Timeline (Konchitchki and Patatoukas, 2014a)

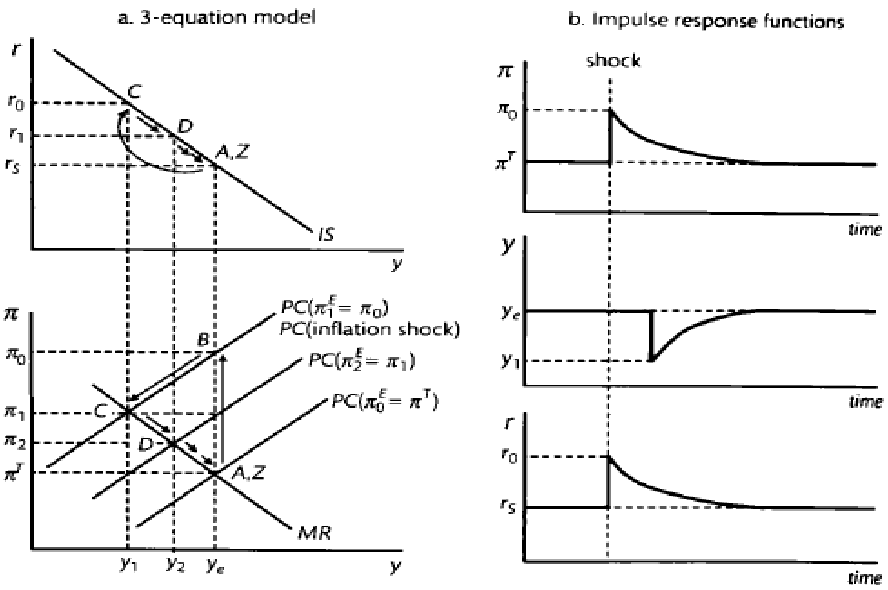

Figure 6. Inflation shock and monetary

Appendix 3: The twelve variables of Lev and Thiagarajan (1993)

The first variable is change in *inventories* compared to change in sales. Whenever the inventory increases disproportionately to the sales, it signals trouble and lower future earnings as inventory becomes obsolete and write-offs occur. Additionally, current inventory buildup helps generate higher current sales as it decreases the overhead cost per unit but affects negatively the future earnings[33].

The second variable is change in *accounts receivable* (AR) to change in sales. Asymmetric increase in accounts receivable to sales increase conveys an identical signal as in inventories. The argumentation behind that is companies expand their receivables to keep existing or attract new customers when sales are decreasing. However, this credit extension can affect consequent period's earnings by increased need for external financing and in receivables' provisions.

The third and fourth variables are changes in *capital expenditures* (CapEx) *and R&D* compared to the change of industry's capital expenditure and R&D. Analysts perceive a decrease in CapEx or R&D compared to the industry as a short-term managerial objectiveness which will increase current earnings at the expense of future. (Maybe include the article of Vorst on reversal prediction here)

The fifth variable is the difference between changes in *gross margin* and sales. Graham et al. (1962, p.244) and Hawkins (1986) prove that disproportionate decrease affects negatively the predictions of analysts. In addition to the fact that gross margin is less transitionary indicator, it provides information to company's efficiency and competitive position[34] (Kormendi and Lipe, 1987; Fairfield et al. 1996).

The sixth variable is *selling and administrative* (S&A) expenses. Most of S&A costs are fixed and an increase larger than in sales is perceived negatively.

The seventh variable is *provision for doubtful receivables*. Companies changing provisions disproportionately to the accounts receivables are assumed to suffer of decreased future earnings. McNichols and Wilson (1988) and O'Glove (1987, p.83) base this on the discretionary nature of the provisions and an increase would either mean inappropriate calculation of the risk (adverse selection) or increased volatility in the market (crisis).

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[33] Smaller batches will be produced, thus, higher overhead cost per unit, consequently lower earnings.

[34] Gross Margin provides an overview of the fixed and variable expenses. These costs are mainly affected by company's microenvironment; thus, those factors are expected to persist in the long-term performance of the given firm.

The eighth variable is *effective tax rate*. Changes in the effective tax rate and not in statutory tax are assumed to be transitory. Therefore, they present a negative signal regarding the earnings persistence in the next periods.

The ninth variable is change in *order backlog* to change in sales. Analysts frequently identify the future level of operations with the unearned service revenues, especially in the heavy-duty industry and technology sector. A sudden decrease in backlog orders can also represent "earnings management" by accounting for undelivered services in the current period.

The tenth variable is *labor force* as denominator and sales as numerator. It provides another perspective of the efficiency of the company through a sales output per employee. Furthermore, analysts relate current employee dismissals with higher costs such as severance expenses increase, therefore, future earnings are expected to be larger.

The eleventh variable is *LIFO earnings.* The LIFO method is perceived as closer proxy of the prospective replacement cost (Hawkins, 1986, p. 208). Therefore, Lev and Thiagarajan perceive companies using the LIFO method as a positive signal to their future earnings. This variable is a dummy represented by 0 for LIFO and 1 for FIFO.

The twelfth variable is *audit qualification.* Negative audit recommendations are bad sign for investors.