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Taking the Pulse of the Real Economy Using Financial Statement Analysis: Implications for Macro Forecasting and Stock Valuation

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ABSTRACT: In this study, we hypothesize and find that financial statement analysis of firm profitability drivers applied at the aggregate level yields timely insights that are relevant for forecasting real economic activity. We first show that focusing on the 100 largest firms offers a cost-effective way to extract information embedded in accounting profitability data of the entire stock market portfolio. We then show that accounting profitability data aggregated across the 100 largest firms have predictive content for subsequent real Gross Domestic Product (GDP) growth. We also show that stock market returns have predictive content for future real GDP growth, while their predictive power varies with the length of the measurement window with annual stock market returns being the most powerful. Importantly, we find that the predictive content of our indices of aggregate accounting profitability drivers is incremental to that of annual stock market returns. An in-depth investigation of consensus survey forecasts shows that professional macro forecasters revise their expectations of real economic activity in the direction of the predictive content of aggregate accounting profitability drivers and stock market returns. Although macro forecasters are fully attuned to stock market return data, their forecasts of real GDP growth can be improved in a statistically and economically significant way using our indices of aggregate accounting profitability drivers. Our findings suggest that professional macro forecasters and stock market investors do not fully impound the predictive content of aggregate accounting profitability drivers when forecasting real economic activity. In additional analysis, we examine the association between stock market returns and the portion of subsequent real GDP growth that is predictable based on our indices of aggregate accounting profitability drivers but that is not anticipated by stock market investors. We find that this portion is positively related to stock market returns, suggesting that the macro predictive content of aggregate accounting profitability drivers is relevant for stock valuation. Overall, our study brings

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financial statement analysis to the forefront as an incrementally useful tool for gauging the prospects of the real economy that should be of interest to academics and practitioners.

Keywords: *accounting; financial statement analysis; macro forecasting; stock valuation; macroeconomics.*

JEL Classification: *E01; E32; E60; M41.*

Data Availability: *Data are available from public sources indicated in the text.*

I. INTRODUCTION

How will the macroeconomy fare in the future? The answer to this question is the "holy grail" for macroeconomists and a wide range of decision makers. In this study, we investigate the usefulness of financial statement analysis based on accounting profitability data from individual firms for taking the pulse of the U.S. real economy.

Using financial statement analysis to forecast economic activities at the firm level has long been a topic of academic research in accounting (Ou and Penman 1989; Penman 1992; Lev and Thiagarajan 1993; Abarbanell and Bushee 1998; Nissim and Penman 2001; Konchitchki 2011; Patatoukas 2012). A key building block of financial statement analysis conducted at the firm level is DuPont profitability analysis, which decomposes a firm's accounting rate of return on net operating assets (*RNOA*)—the primary measure of a firm's core operating performance—into asset turnover and profit margin. Prior studies provide evidence that changes in *RNOA* and its drivers are useful for forecasting economic activity at the firm level (Fairfield and Yohn 2001; Nissim and Penman 2001; Soliman 2008), yet little is known about the usefulness of financial statement analysis for understanding the prospects of the overall economy. Our study helps fill this gap.

Publicly traded firms in the U.S. are required to report financial statements on a quarterly basis. These quarterly reports provide timely information about each listed firm's underlying economic activities. Because listed firms represent a large part of the U.S. economy, changes in their respective economic activities can be informative about shifts in overall economic activity (Fama 1981). We therefore conjecture that if the financial reporting system captures changes in economic activity at the firm level on a timely basis, then financial statement analysis of firm profitability drivers at the aggregate level can provide timely clues as to the prospects of the U.S. real economy.

To test the above conjecture, we collect income statement and balance sheet data for a sample of publicly traded U.S. firms and construct indices of aggregate changes in profitability and DuPont profitability drivers using value-weighted cross-sectional averages. To mitigate the costs of collecting and aggregating financial statement data imposed on macro forecasters, we restrict our sample to the 100 largest firms. Over our 1981:Q3 to 2011:Q3 sample period, we document that the 100 largest firms represent the vast majority of the stock market in terms of market capitalization. Hence, understanding fluctuations in their performance can offer insights into the performance of the universe of listed U.S. firms. Indeed, we find that aggregate changes in profitability and profitability drivers for the 100 largest firms are almost perfectly correlated with the corresponding changes for *all* listed U.S. firms. Focusing on the 100 largest firms therefore offers a cost-effective way to extract information embedded in the accounting profitability data of the entire stock market portfolio.

Consistent with our conjecture, we find that financial statement analysis of firm profitability drivers at the aggregate level is useful for macro forecasting. We document a significantly positive association between our index of aggregate changes in accounting profitability ($\Delta RNOA$) and subsequent real GDP growth. The DuPont profitability analysis reveals that aggregate changes in asset turnover and profit margins are leading indicators of real economic activity. However, over our sample period, the predictive ability of profit margins swamps that of asset turnover, with the predictive ability of $\Delta RNOA$ driven primarily by aggregate changes in profit margins. After decomposing profit margins into operating margins, given by the ratio of operating income before depreciation to sales, and the ratio of depreciation to sales, a proxy for tangible capital intensity (Lev 1983; Cheng 2005), we find that aggregate changes in both components are significantly positively associated with subsequent real GDP growth. Taken together, aggregate changes in accounting profitability drivers anticipate 26 percent of the time-series variation in subsequent real GDP growth.

To evaluate the incremental usefulness of aggregate accounting profitability drivers for macro forecasting, we focus on the stock market. Consistent with rational expectations asset pricing models (Fama 1981; Fischer and Merton 1984; Barro 1990; Fama 1990), we find that stock market returns contain leading information about overall economic activity. Specifically, stock market returns positively predict subsequent real GDP growth, while their predictive power varies with the length of the measurement window with annual stock market returns being the most powerful. Importantly, we show that the predictive content of aggregate accounting profitability drivers is not subsumed by that of annual stock market returns, suggesting that financial statement analysis of firm profitability drivers at the aggregate level is *incrementally useful* for macro forecasting. Indeed, the use of aggregate accounting profitability data leads to significant improvements in terms of explanatory power with the adjusted R^2 rising from 20 percent when annual stock market returns are included as stand-alone predictors of subsequent real GDP growth, to 36 percent when annual stock market returns are included together with aggregate changes in accounting profitability drivers.

An in-depth investigation of consensus forecasts from the Survey of Professional Forecasters (SPF)—the longest and most highly regarded quarterly survey of macro forecasts in the U.S.—reveals that macro forecasters revise their expectations of real economic activity in the direction of the predictive content of aggregate accounting profitability drivers and stock market returns. However, macro forecasters are not fully attuned to aggregate accounting profitability drivers and thus their real GDP growth forecast errors are predictable based on lagged accounting profitability data. Indeed, we find that macro forecasters' projections of real GDP growth can be improved in a statistically and economically significant way using our indices of aggregate accounting profitability drivers. In contrast, real GDP growth forecast errors are not predictable based on lagged stock market returns, suggesting that macro forecasters fully impound the predictive content of stock market returns for the prospects of the real economy. Our evidence is consistent with the fact that stock market return data are known to have predictive ability for the real economy (Fama 1981) and are readily available to macro forecasters, while aggregate accounting profitability data are not.

Given our evidence that stock market returns do not subsume the macro predictive content of aggregate accounting profitability drivers, it follows that investors' projections of real economic activity embedded in stock market prices can also be improved based on aggregate accounting profitability data. In additional analysis, we examine the association between stock market returns and the portion of real GDP growth that is predictable based on our indices of aggregate accounting profitability drivers but that is not anticipated by stock market investors. We find that this portion is positively related to stock market returns, suggesting that the predictive content of aggregate accounting profitability drivers for real economic activity is relevant for stock valuation.

Our study brings financial statement analysis of firm profitability drivers to the forefront as an incrementally useful tool for macro forecasting. Our evidence shows that aggregate accounting profitability drivers embed timely information about the prospects of the U.S. real economy. Accordingly, our study can lead to improvements in macro forecasting using accounting profitability data from individual firms. Importantly, from a practical implementation standpoint, our evidence on the informativeness of the 100 largest firms offers academics and practitioners a cost-effective way to extract information embedded in accounting profitability data of the entire stock market portfolio. Although our study focuses on the U.S., the analysis can be extended to the international context.

We contribute to several streams of literature. First, our findings complement the evidence in Konchitchki and Patatoukas (2013) that aggregate accounting earnings growth is a leading indicator of the nominal economy. Our study extends the evidence in Konchitchki and Patatoukas (2013) along many dimensions by combining income statement and balance sheet data in a cost-effective way and by investigating the relevance of financial statement analysis of firm profitability drivers for forecasting real GDP growth and stock valuation. Second, we contribute to macroeconomics research by identifying an incrementally significant link between aggregate accounting profitability drivers and subsequent real GDP growth. We further contribute to the macro forecasting literature by showing that professional macro forecasters can improve real GDP growth projections by incorporating accounting profitability data from large publicly traded firms in a cost-effective way. Finally, we contribute to capital markets research in accounting and finance by providing evidence that the predictive content of aggregate accounting profitability drivers for real GDP growth is relevant for stock valuation.

Viewed as a whole, our findings have implications for a wide range of decision makers who are interested in macro forecasting. In line with recent calls to make accounting research more useful (Moehrle et al. 2009; Merchant 2012), we believe that our study has the potential to make a contribution to the advancement of macro forecasting practice. Our findings should also be of interest to accounting standard-setters. We identify an important group of users of accounting information, namely, those parties interested in gauging macroeconomic activity, including professional macro forecasters and macroeconomists staffing the Federal Reserve and the White House. This group is often overlooked by the Financial Accounting Standards Board as users of accounting information.

Section II next provides background and motivates our research questions. Section III describes our research design. Section IV examines the *usefulness* of financial statement analysis and stock market returns for macro forecasting. Section V investigates the *use* of financial statement analysis and stock market returns by macro forecasters. Section VI concludes.

II. BACKGROUND AND RESEARCH QUESTIONS

A long line of accounting research investigates the usefulness of financial statement analysis for forecasting future changes in firm fundamentals (Ou and Penman 1989; Penman 1992; Lev and Thiagarajan 1993; Abarbanell and Bushee 1998; Nissim and Penman 2001; Konchitchki 2011; Patatoukas 2012). Researchers typically use the ratio of operating income after depreciation to net operating assets, referred to as the return on net operating assets (*RNOA*), as a comprehensive measure of overall firm performance. Operating income is defined as sales minus cost of goods sold, selling, general, and administrative expense, and depreciation expense. Net operating assets are defined as operating assets, which are total assets minus cash and short-term investments, minus operating liabilities, which are total liabilities minus long- and short-term debt. Both operating income and net operating assets abstract away from the effects of financial leverage, so *RNOA* provides an unlevered measure of firm operating performance.

The return on net operating assets can be decomposed into two profitability drivers as follows:

$$RNOA = \frac{Sales}{Net\ Operating\ Assets} \times \frac{Operating\ Income\ After\ Depreciation}{Sales}. \qquad (1)$$

The first driver, the ratio of sales to net operating assets, captures asset turnover (*ATO*). Asset turnover measures a firm's ability to generate revenues from its assets. The second driver, the ratio of operating income after depreciation to sales, captures profit margin (*PM*). Profit margin measures a firm's ability to control the costs incurred to generate revenues and to charge premium prices. This decomposition of *RNOA* is commonly referred to as DuPont profitability analysis.

Textbooks such as Penman (2001) advocate the use of DuPont profitability analysis as a building block of financial statement analysis. Also academic research provides empirical evidence that changes in *RNOA* and its drivers are useful for forecasting firm fundamentals (Fairfield and Yohn 2001; Nissim and Penman 2001; Soliman 2008). Yet despite the prominence of financial statement analysis of firm profitability for forecasting economic activity at the firm level, there is a dearth of evidence on its usefulness for forecasting *overall* economic activity.

Publicly traded firms in the U.S. are required to report financial statements on a quarterly basis. These reports provide timely forward-looking information about each listed firm's underlying economic activities. Because listed firms represent a large part of the U.S. economy, changes in their respective economic activities can be informative about shifts in overall economic activity (Fama 1981). Accordingly, we conjecture that if the financial reporting system captures changes in economic activity at the firm level on a timely basis, then financial statement analysis of firm profitability drivers applied at the aggregate level can offer a window to timely macroeconomic clues.

Based on the above discussion, our first research question is whether aggregate changes in profitability and profitability drivers are useful for forecasting growth in overall economic activity. We use real GDP growth as our measure of economic growth. Real GDP, featured in the National Income and Product Accounts (NIPA) prepared by the Bureau of Economic Analysis (BEA), measures the inflation-adjusted value added at each stage of the production process of goods and services produced in the U.S. economy (BEA 2007). Although recent research focuses on the link between accounting data and nominal economic activity (Basu, Markov, and Shivakumar 2010; Cready and Gurun 2010; Shivakumar 2010; Konchitchki 2011; Kothari, Shivakumar, and Urcan 2013; Konchitchki and Patatoukas 2013; Patatoukas 2013), we focus on real GDP growth because we want to abstract from the link between accounting data and inflation.

We focus on the usefulness for macro forecasting of aggregate changes in *RNOA* and its drivers rather than their levels because our objective is to forecast growth in economic activity rather than the level of economic activity. Compared to other accounting rates of return, such as return on equity or return on assets, *RNOA* offers a more appealing means for gauging economic activity at the aggregate level. This is because *RNOA* is based on unlevered financial statements and offers a measure of economic activity at the enterprise level that lies at the center of value creation for equity and debt capital providers, paralleling GDP as a measure of value added at the aggregate level.

In the vein of rational expectations asset pricing models, one could envisage stock market investors as a group of macro forecasters (Fama 1981; Fischer and Merton 1984; Barro 1990; Fama 1990). Given that stock market prices are related to investors' expectations of future overall economic activity, our second research question is whether aggregate accounting profitability drivers are *incrementally useful* for macro forecasting. To directly address this research question, we begin by testing whether stock market returns measured over different windows anticipate future real GDP growth. We then investigate whether aggregate accounting profitability drivers embed forward-looking information for real GDP growth that is not subsumed by stock market returns.

Our next set of research questions examines whether professional macro forecasters use forward-looking information embedded in aggregate accounting profitability drivers and stock market returns when forecasting real economic activity. We obtain consensus forecasts of real GDP growth from the SPF—the oldest and most highly regarded quarterly survey of macro forecasts in the U.S.[1] The SPF forecasts are produced by a broad-based group of professionals affiliated with financial institutions, including Bank of America Merrill Lynch, Barclays Capital, Credit Suisse, Deutsche Bank, Goldman Sachs, JPMorgan Chase, Moody's, and Wells Fargo, as well as nonfinancial institutions, including academic institutions, the government, trade associations, and labor unions. The SPF panelists have incentives to provide accurate forecasts because their reputation with the Federal Reserve is at stake and they report to the survey the same forecasts that they sell to market participants (Baghestani and Kianian 1993).[2]

The SPF consensus forecasts are used as benchmarks for the assumptions underlying the U.S. Federal Budget. The SPF forecasts are also central for monetary policy because they are used by the research staff of the Board of Governors of the Federal Reserve when preparing the "Greenbook" before each meeting of the Federal Open Market Committee. To gain more insights into whether the SPF panelists are sufficiently incentivized, we compare GDP growth projections from the SPF with those from the Greenbooks. The Federal Reserve Board of Governors is incentivized to produce accurate projections of the U.S. economy because its Greenbook projections are used, for example, when formulating monetary policy. Unfortunately, the Greenbook projections become available to the public only after a five-year embargo. Because of the five-year embargo macro forecasters cannot use these projections in real time and so they are not within the feasible information set of the SPF panelists. Consistent with Sims (2002), we find that the Greenbook projections are indistinguishably different from the SPF consensus forecasts, which indicates that the incentives of the SPF panelists are aligned with the incentives of those with the strongest incentives to produce accurate forecasts.

Our first objective is to test whether professional macro forecasters respond to any incremental predictive content embedded in aggregate accounting profitability drivers. Toward this end, we examine the association of revisions in SPF consensus forecasts of future real GDP growth with aggregate accounting profitability drivers and stock market returns. Our second related objective is to test whether professional macro forecasters fully impound leading information embedded in aggregate accounting profitability drivers and stock market returns when forecasting real GDP

[1] The SPF began in 1968 and was originally conducted by the National Bureau of Economic Research (NBER) and the American Statistical Association (ASA). The Federal Reserve Bank of Philadelphia took responsibility of the SPF in 1990. We note that the Livingston Survey, started in 1946 by the late financial columnist Joseph Livingston, is the oldest semi-annual survey of macro forecasts in the U.S. The Federal Reserve Bank of Philadelphia also took over responsibility of the Livingston Survey in 1990. There are two limitations to the Livingston Survey. First, it provides only six-month forecasts twice a year and thus is not as timely as the quarterly SPF. Second, it is characterized by inconsistencies and *ad hoc* adjustments prior to 1990 (see Livingston Survey Documentation available on the website of the Federal Reserve Bank of Philadelphia, available at: http://www.phil.frb.org/research-and-data/real-time-center/livingston-survey). Another survey of professional forecasters is the Blue Chip Survey. Unlike the SPF and the Livingston Survey, the Blue Chip Survey is not publicly available; it is available for purchase from Aspen Publishers.

[2] The SPF consensus forecasts of subsequent GDP growth are known to outperform benchmark projections obtained from a naïve random walk and from more sophisticated time-series models (Zarnowitz and Braun 1993; Fildes and Stekler 2002; Stark 2010; Wieland and Wolters 2011). Despite the superior accuracy of the SPF consensus forecasts relative to time-series benchmarks, however, there is evidence that SPF forecasters have made errors when the U.S. economy was subject to perturbations. Specifically, macro forecasters have over-predicted GDP growth in slowdowns and recessions, and under-predicted growth in recoveries and booms (Zarnowitz and Braun 1993; Schuh 2001; Fildes and Stekler 2002; Stock and Watson 2003). In untabulated analysis, using the business-cycle classification dates from the NBER we find that real GDP growth forecast errors tend to be negative during recessions and positive during expansions, suggesting that macro forecasters tend to be negatively surprised during recessions and positively surprised during expansions. One could argue, however, that macro forecasting is more difficult during periods characterized by a high degree of economic turbulence (McNees 1992; Croushore 2002; Krane 2003). A point of general agreement is that, given the importance and widespread use of GDP growth projections, the rewards from even a slight improvement in forecast accuracy are clearly large.

growth. To do so, we search for predictability in real GDP growth forecast errors based on aggregate accounting profitability drivers and stock market returns.

In the absence of evidence that financial statement analysis applied at the aggregate level is useful for forecasting real economic activity, professional macro forecasters may simply be unaware of potential "net" benefits from collecting and aggregating income statement and balance sheet data. To the extent that macro forecasters do not fully incorporate relevant accounting profitability data in their projections, real GDP growth forecast errors could be predictable based on lagged accounting information. In contrast, we have reasons to believe that macro forecasters are attuned to the idea that stock market returns are useful for macro forecasting. This is because stock market return data are known to have predictive ability for real economic activity (Fama 1981) and are readily available to macro forecasters.

Overall, our study is positioned to provide new evidence on both the *usefulness* and the *use* of financial statement analysis and stock market returns for forecasting real economic activity. We do so by addressing the following research questions: (1) Do aggregate accounting profitability drivers include forward-looking information about real GDP growth? (2) Is there macro predictive content in aggregate accounting profitability drivers incremental to that in stock market returns? (3) Are macro forecasters' revisions in expectations related to aggregate accounting profitability drivers and stock market returns? (4) Do macro forecasters fully impound any macro predictive content in aggregate accounting profitability drivers and stock market returns when forecasting real GDP growth? (5) What are the implications for stock valuation of any macro predictive content of aggregate accounting profitability drivers? Answers to these questions should be of interest to academics and practitioners.

III. RESEARCH DESIGN

We collect a sample of U.S.-listed firms with income statement and balance sheet data on the Compustat quarterly file. To align fiscal quarters with calendar quarters, we use firms with calendar fiscal quarter-end dates of March, June, September, and December. For each firm-quarter, we measure profitability (*RNOA*) and the DuPont profitability drivers, asset turnover (*ATO*), and profit margin (*PM*). Profit margin, the ratio of operating income after depreciation to sales, can be further decomposed into the ratio of operating income before depreciation to sales, or operating margin (*OM*), and the ratio of depreciation to sales (*DEP*), a proxy for tangible capital intensity (Lev 1983; Cheng 2005). To obtain annualized profitability ratios, we multiply all income statement variables by 4. To seasonally adjust accounting data, we use year-over-year changes in quarterly profitability ratios, indicated by Δ. To mitigate the influence of outliers, we exclude observations falling in the top or bottom 1 percent of each quarterly cross section of the levels or changes in *RNOA* and its drivers.

Our research design is geared towards the timing of the SPF. As Figure 1, Panel A illustrates, the survey questionnaires are sent to the SPF panelists by the end of the first month after the quarter ends. Accordingly, we restrict our sample to firms with accounting data available by the end of the first month, month t, after quarter q ends. Figure 1, Panel B illustrates the timing for the 2011 third-quarter SPF, which is the most recent survey in our sample. The questionnaires were sent to macro forecasters by the end of July 2011, so the accounting data released by that time were within the feasible information set of the SPF panelists. We note that the SPF panelists are required to submit the survey questionnaires by the middle of the second month after the end of each quarter, which would be the middle of August for the third-quarter SPF. Effectively, our research design allows macro forecasters time to collect and aggregate income statement and balance sheet data.

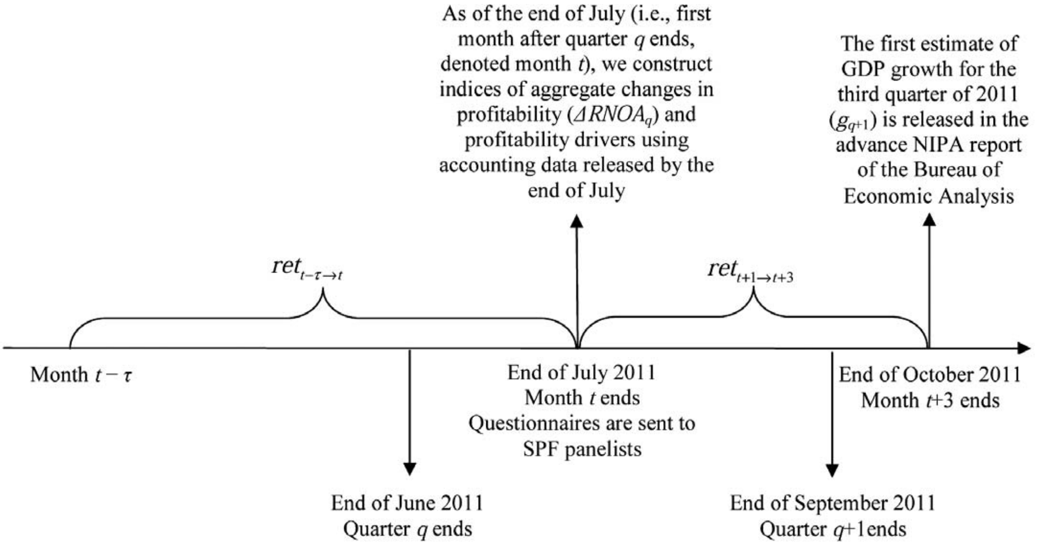
We acknowledge that collecting and aggregating data from corporate financial reports imposes non-trivial acquisition and processing costs on macro forecasters. To mitigate such costs, we further

FIGURE 1
Timeline of Research Design

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

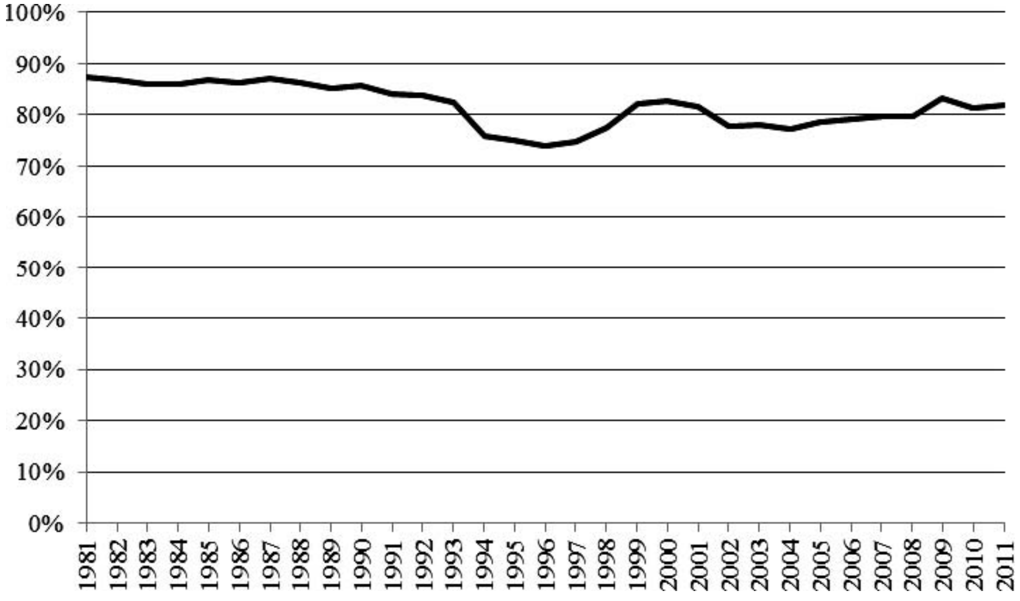
Panel B: Example for 2011 Third-Quarter SPF



Panel A summarizes the timing of the SPF. The questionnaires are sent to the SPF panelists by the end of the first month, month t, after quarter q ends. The accounting data released by the end of month t as well as stock market returns realized by the end of month t are within the feasible information set of SPF panelists when forming their expectations.

Panel B illustrates the timeline of our research design. Panel B also illustrates the measurement of buy-and-hold stock market returns (*ret*) over the $\tau = 3$, 6, 12, and 24 months leading to the end of month t as well as over the 3 months after the end of month t.

FIGURE 2
Relative Importance of 100 Largest Firms



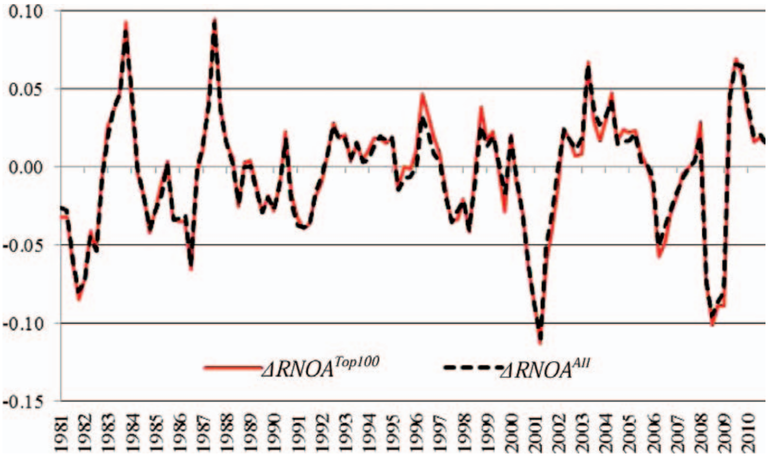
This figure presents the time-series of the sum of the market capitalization of the 100 largest firms as a percentage of the sum of the market capitalization of all firms with accounting data released by the end of the first month, month t, after quarter q ends. The sample period is from 1981:Q3 to 2011:Q3.

restrict our sample to the 100 largest firms in terms of market capitalization measured at the beginning of each quarter. Figure 2 reports the time-series of the total market capitalization of the 100 largest firms as a fraction of the total market capitalization of all firms with available accounting data within one month after the quarter ends. Over our sample period, the 100 largest firms account for 82 percent of the total market capitalization of all firms, and thus understanding fluctuations in their performance could offer considerable insights into the performance of *all* publicly traded firms. Indeed, Figure 3 shows that profitability changes for the 100 largest firms move in lockstep with profitability changes for all firms: the correlation between the two series is 0.99, a finding that also holds for profitability drivers. Clearly, the evidence in Figures 2 and 3 suggests that focusing on the 100 largest firms offers a cost-effective way to extract information embedded in accounting profitability data of the entire stock market portfolio.

Our final sample includes 12,000 firm-quarter observations, representing the 100 largest firms per quarter with accounting data released within one month after the quarter ends, over 120 quarters from 1981:Q3 to 2011:Q3. The composition of the 100 largest firms can change from one quarter to another depending on data availability and changes in the cross-sectional distribution of market capitalization. The sample period begins in 1981:Q3 because from that point onward the SPF's schedule has been consistent over time.[3] The sample period ends in 2011:Q3 because this is the last quarter for which we can obtain data necessary for our analyses. We construct aggregate indices of

[3] Our inferences are similar when we repeat our analysis for the post-1990 period after the Federal Reserve Bank of Philadelphia took responsibility of the SPF from the NBER/ASA.

FIGURE 3
Aggregate Changes in Accounting Profitability



This figure presents the time-series of aggregate changes in the rate of return on net operating assets. We construct the aggregate time-series using value-weighted cross-sectional averages based on two samples: (1) the sample of 100 largest firms (in terms of lagged market capitalization) with accounting data released by the end of the first month, month t, after quarter q ends ($\Delta RNOA^{Top100}$, denoted for brevity as $\Delta RNOA$ throughout the rest of the manuscript); and (2) the sample of all firms with accounting data released by the end of the first month, month t, after quarter q ends ($\Delta RNOA^{All}$). The sample period is from 1981:Q3 to 2011:Q3.

levels and changes in *RNOA* and its drivers based on value-weighted cross-sectional averages and use market capitalization measured at the beginning of each quarter to weight observations.[4]

To evaluate the incremental usefulness of our indices of accounting profitability drivers for macro forecasting, we measure buy-and-hold stock market returns ($ret_{t-\tau\rightarrow t}$) over the $\tau = 3$, 6, 12, and 24 months leading to the end of the first month, month t, after quarter q ends. We proxy for the stock market portfolio using two well-accepted indices, namely, the CRSP value-weighted index including distributions, and the S&P 500 index.

We obtain data on subsequent real GDP growth, denoted g_{q+1}, from the BEA's first, also known as the advance, NIPA report published by the end of the first month after the quarter ends.[5] The advance GDP growth data are available from the Real-Time Data Set for Macroeconomists of the Federal Reserve Bank of Philadelphia. Figure 1, Panel B, illustrates that the advance realization of GDP growth for the third quarter of 2011 was released by the end of October 2011. The advance realization of GDP growth is unavailable for the third quarter of 1995 from the Real-Time Data Set

[4] Our inferences are not sensitive to whether we construct the aggregate indices using value- or equal-weighted averages. As an additional sensitivity test, we construct the aggregate series of accounting profitability ratios by dividing the cross-sectional sum of each ratio's numerator by the cross-sectional sum of the ratio's denominator. Consistent with Kothari, Lewellen, and Warner (2006), we observe that the value-weighted series are highly correlated with the series constructed based on cross-sectional sums. Our inferences are unchanged using aggregate series based on cross-sectional sums.

[5] We focus on the advance realization of GDP growth because NIPA revisions tend to be small and most of the information about the state of the economy is known over the period leading to the BEA's advance NIPA report (Fixler and Grimm 2005; Lahiri and Wang 2006; Landefeld, Seskin, and Fraumeni 2008). The advance and final realizations of GDP growth have a correlation coefficient of 0.96 and our inferences are not sensitive to this choice.

for Macroeconomists due to a government shutdown, so our sample includes 120 quarters from 1981:Q3 to 2011:Q3. As explained in Section II, we focus our efforts on forecasting real GDP growth because we want to abstract from the link between accounting data and inflation.

We obtain the mean SPF consensus forecast of quarter q+1 real GDP growth, denoted $E_q[g_{q+1}]$, from the Federal Reserve Bank of Philadelphia. We focus on the quarter q+1 forecasts because professional macro forecasters focus on the one-quarter-ahead forecast horizon (Stark 2010). We focus on the SPF consensus forecasts and not on individual forecasters' projections because none of the individual forecasters is better than the average (Zarnowitz and Braun 1993; Graham 1996; Croushore 2011). We note that the distribution of individual quarterly GDP growth forecasts is fairly symmetric, so our results are insensitive as to whether we use mean or median SPF consensus forecasts. Over our sample period there are, on average, 35 individual forecasters or forecasting groups per survey, for a total of 4,224 responses.

IV. THE INCREMENTAL USEFULNESS OF FINANCIAL STATEMENT ANALYSIS FOR FORECASTING REAL ECONOMIC ACTIVITY

Descriptive Statistics

Table 1, Panel A provides descriptive statistics for aggregate accounting profitability ratios. All accounting variables are measured at the end of the first month, month t, after quarter q ends. At the aggregate level, accounting profitability (*RNOA*) has fluctuated between 15.8 percent and 39.5 percent, with a mean of 27.2 percent and a standard deviation of 4.5 percent. Aggregate changes in accounting profitability ($\Delta RNOA$) exhibit substantial time-series variation, with a mean of −0.4 percent and a standard deviation of 3.9 percent. Aggregate changes in *RNOA* are decomposed into changes in asset turnover (ΔATO) and profit margin (ΔPM). The descriptive statistics show that the variability of $\Delta RNOA$ is driven by time-series variation in aggregate changes in both drivers. Untabulated statistics indicate that aggregate changes in *RNOA* and its drivers are mostly autocorrelated at one lag. Based on the BEA's advance NIPA reports, the annualized growth rate in the real U.S. economy has fluctuated between −6.1 percent and 8.7 percent, with a mean of 2.5 percent and a standard deviation of 2.4 percent.

Table 1, Panel B reports pairwise correlations between aggregate changes in the profitability ratios and subsequent real GDP growth. The correlation matrix provides preliminary evidence that aggregate changes in *RNOA* and its drivers contain leading information about real economic activity. Indeed, the correlation between aggregate changes in *RNOA* and subsequent real GDP growth is 0.30. Across accounting profitability drivers, the strongest univariate correlation is 0.48 between aggregate changes in operating margins (ΔOM) and subsequent real GDP growth.

Predictive Content of Aggregate Changes in Accounting Profitability Drivers

Is financial statement analysis of firm profitability drivers applied at the aggregate level useful for macro forecasting? We address this question by estimating time-series regressions of subsequent real GDP growth on aggregate changes in *RNOA* and the DuPont drivers, as follows:

$$g_{q+1} = \alpha + \sum_{\kappa} \beta_{\kappa} \times \Delta \mathit{Profitability\ Ratio}_q^{\kappa} + \varepsilon_{q+1}. \tag{2}$$

Throughout the study, we estimate our regression models using ordinary least squares regressions, and we base our statistical inferences on Newey and West (1987) standard errors and two-sided p-values. For the Newey and West (1987) standard errors, the lag length is based on the number of statistically significant residual autocorrelations. Across all our models, the autocorrelations of the estimated regression residuals are not significant beyond lag 4, so we set

TABLE 1

Descriptive Statistics

Panel A: Empirical Distributions

	Mean	Std. Dev.	Min.	Q1	Median	Q3	Max.
$RNOA_q$	0.272	0.045	0.158	0.247	0.271	0.302	0.395
ATO_q	1.817	0.279	1.322	1.640	1.791	1.952	2.625
PM_q	0.170	0.046	0.079	0.132	0.177	0.210	0.245
OM_q	0.233	0.048	0.138	0.198	0.244	0.274	0.323
DEP_q	0.063	0.007	0.047	0.059	0.062	0.066	0.090
$\Delta RNOA_q$	−0.004	0.039	−0.113	−0.030	0.000	0.019	0.095
ΔATO_q	−0.046	0.144	−0.482	−0.111	−0.020	0.051	0.248
ΔPM_q	0.002	0.016	−0.039	−0.008	0.001	0.011	0.055
ΔOM_q	0.003	0.013	−0.026	−0.005	0.000	0.010	0.050
ΔDEP_q	0.001	0.006	−0.015	−0.003	0.000	0.004	0.023
g_{q+1}	0.025	0.024	−0.061	0.014	0.025	0.039	0.087

Panel B: Pairwise Correlations

	$\Delta RNOA_q$	ΔATO_q	ΔPM_q	ΔOM_q	ΔDEP_q	g_{q+1}
$\Delta RNOA_q$	1.00	0.89	0.82	0.70	−0.68	0.30
		< 0.001	*< 0.001*	*< 0.001*	*< 0.001*	*< 0.001*
ΔATO_q		1.00	0.64	0.49	−0.67	0.18
			< 0.001	*< 0.001*	*< 0.001*	*0.05*
ΔPM_q			1.00	0.94	−0.65	0.37
				< 0.001	*< 0.001*	*< 0.001*
ΔOM_q				1.00	−0.36	0.48
					< 0.001	*< 0.001*
ΔDEP_q					1.00	0.03
						0.73
g_{q+1}						1.00

Panel A reports descriptive statistics for the quarterly time-series of the following aggregate profitability ratios: the rate of return on net operating assets (*RNOA*) measured as the ratio of annualized operating income after depreciation to average net operating assets; asset turnover (*ATO*) measured as the ratio of annualized sales to average net operating assets; profit margin (*PM*) measured as the ratio of operating income after depreciation to sales; operating margin (*OM*) measured as the ratio of operating income before depreciation to sales; and the depreciation-to-sales ratio (*DEP*). Operating income before depreciation is measured as sales minus cost of goods sold minus selling, general, and administrative expenses. Net operating assets are measured as operating assets (i.e., total assets less cash and short-term investments) minus operating liabilities (i.e., total liabilities less long-term debt less short-term debt). Aggregate year-over-year changes in profitability and profitability drivers are indicated with Δ. We construct the aggregate time-series using value-weighted cross-sectional averages based on the 100 largest U.S. listed firms in terms of lagged market capitalization with accounting data released by the end of the first month, month t, after quarter q ends. g_{q+1} is the annualized real GDP growth obtained from the BEA advance NIPA reports. Panel B reports Pearson correlations and two-sided p-values (in italic). The sample period includes 120 quarters from 1981:Q3 to 2011:Q3.

the lag length equal to 4. None of our inferences are sensitive as to whether we use ordinary least squares standard errors, White (1980) standard errors, or Newey and West (1987) standard errors with lag length varying from one to four quarters.

Table 2 reports the results. In line with the pairwise correlations, column 1 of Table 2 documents that Δ*RNOA* is a significant leading indicator of real GDP growth. The estimated

TABLE 2

Predictive Content of Aggregate Changes in Accounting Profitability Drivers for Subsequent Real GDP Growth

	Dependent Variable = g_{q+1}				
	1	**2**	**3**	**4**	**5**
Intercept	0.026	0.027	0.024	0.023	0.023
t-statistic	9.11	8.30	8.47	7.34	8.21
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
$\Delta RNOA_q$	0.19				
t-statistic	2.69				
p-value	0.01				
ΔATO_q		0.03		−0.02	0.02
t-statistic		1.94		−0.81	1.39
p-value		0.05		0.42	0.17
ΔPM_q			0.55	0.64	
t-statistic			2.84	2.54	
p-value			0.01	0.01	
ΔOM_q					0.95
t-statistic					3.74
p-value					< 0.001
ΔDEP_q					1.26
t-statistic					3.34
p-value					< 0.001
Adjusted R^2	8%	2%	13%	13%	26%

This table reports results from time-series regressions of subsequent real GDP growth (g_{q+1}) on our quarterly indices of aggregate changes in profitability and profitability drivers. We obtain data on subsequent annualized real GDP growth from the BEA's quarterly advance NIPA reports. We measure quarterly changes in profitability as the year-over-year changes in the rate of return on net operating assets ($\Delta RNOA$). We decompose $\Delta RNOA$ into changes in profit margin (ΔPM) and changes in asset turnover (ΔATO). Changes in profit margin are decomposed into changes in operating margin (ΔOM) and changes in the depreciation-to-sales ratio (ΔDEP). We construct the aggregate time-series using value-weighted cross-sectional averages based on the 100 largest U.S. listed firms in terms of lagged market capitalization with accounting data released by the end of the first month, month *t*, after quarter *q* ends. The sample period includes 120 quarters from 1981:Q3 to 2011:Q3.

coefficient on $\Delta RNOA$ is significantly positive at the 1 percent level with a t-statistic of 2.69. The magnitude of the estimated coefficient implies that a one-standard-deviation increase in $\Delta RNOA$ is associated with a 0.74 percentage point increase in subsequent real GDP growth. Aggregate changes in accounting profitability explain 8 percent of the time-series variation in subsequent real GDP growth.[6]

Decomposing $\Delta RNOA$ provides incremental information for forecasting real economic activity. Columns 2 and 3 of Table 2 document that, when considered separately, aggregate changes in asset turnover (ΔATO) and profit margins (ΔPM) are significant predictors of one-quarter-ahead real GDP growth. However, the predictive ability of ΔPM swamps that of ΔATO. Indeed, column 4 documents that when ΔPM and ΔATO are included together as predictors in Equation (2), the

[6] In additional analysis, we do not find evidence of differential predictive ability of positive and negative aggregate changes in accounting profitability.

estimated coefficient on ΔATO is no longer significant, while that on ΔPM remains significantly positive.[7] Looking across columns 1 through 4, it is clear that the predictive power of aggregate accounting profitability drivers for subsequent real GDP growth is primarily driven by ΔPM. On a stand-alone basis, aggregate changes in profit margins explain 13 percent of the time-series variation in subsequent real GDP growth.

As noted in Section III, changes in profit margins are traced to changes in operating margins (ΔOM) and changes in the depreciation-to-sales ratio (ΔDEP). Column 5 of Table 2 shows that the estimated coefficients on ΔOM and ΔDEP are significantly positive at the 1 percent level with t-statistics of 3.74 and 3.34, respectively.[8] The magnitudes of the estimated coefficients imply that a one-standard-deviation increase in ΔOM is associated with a 1.24 percentage point increase in subsequent real GDP growth, while a one-standard-deviation increase in ΔDEP is associated with a 0.76 percentage point increase in subsequent real GDP growth. Overall, aggregate changes in accounting profitability drivers explain 26 percent of the time-series variation in one-quarter-ahead real GDP growth.[9]

The significantly positive association between ΔOM and subsequent GDP growth is consistent with prior evidence on the predictive content of margins for subsequent economic activity at the firm level (Ou and Penman 1989; Abarbanell and Bushee 1998; Kothari 2001). The significantly positive association between ΔDEP and subsequent GDP growth is consistent with Cheng's (2005) finding that the depreciation-to-sales ratio positively predicts economic activity at the firm level. This finding is also consistent with evidence in Ou and Penman (1989) and Barth, Cram, and Nelson (2001) that depreciation deflated by various proxies for scale positively predicts economic activity at the firm level.[10]

To summarize, consistent with our conjecture, we find that financial statement analysis of firm profitability drivers applied at the aggregate level yields timely insights about future real economic activity. At the minimum, our findings establish that aggregate changes in accounting profitability and its drivers are correlated with leading information about the prospects of the U.S. real economy.

Predictive Content of Stock Market Returns

Rational expectations asset pricing models suggest that stock market prices are related to investors' expectations about future economic activity (Fama 1981; Fischer and Merton 1984; Barro 1990; Fama 1990). To examine the predictive power of the stock market for real economic activity, we estimate time-series regressions of quarter $q+1$ real GDP growth on buy-and-hold stock market returns, $ret_{t-\tau\rightarrow t}$, measured over the $\tau = 3$, 6, 12, and 24 months leading to the end of the first

[7] In additional analysis, we do not find evidence that the interaction of ΔATO with ΔPM has predictive content for subsequent GDP growth.

[8] Comparing the multivariate regression results (Table 2) with the pairwise correlations (Table 1, Panel B) reveals that the predictive power of ΔDEP for subsequent GDP growth is muted when correlated changes in the other accounting profitability drivers are omitted.

[9] In additional analysis, we examine the predictive content of the components of aggregate changes in asset turnover, including property, plant, and equipment turnover, inventory turnover, and receivables turnover. We do not find evidence that asset turnover components have incremental predictive content for subsequent real GDP growth. When we decompose aggregate changes in operating margins, we also do not find evidence of incremental predictive content for operating margin components, including changes in sales-deflated ratios of cost of goods sold, selling, general, and administrative expenses, as well as research and development expenses.

[10] The predictive ability of ΔDEP for subsequent real GDP growth is not driven by the deflator of the depreciation-to-sales ratio. First, we find similar results when we include aggregate sales growth as an additional regressor in the right-hand side of Equation (2). Second, we find similar results using different deflators, including current and lagged amounts of book value of total assets, book value of equity, market value of equity, and sales. Also, we note that the estimated persistence of DEP is 0.63, which is significantly different from 1 using two-tailed F-tests.

month, month t, after quarter q ends:

$$g_{q+1} = \alpha + \beta_{\tau} \times ret_{t-\tau\rightarrow t} + \varepsilon_{q+1}. \tag{3}$$

The return measurement window is aligned with the timing of the SPF, thus ensuring that the different measures of stock market returns that we employ are available to macro forecasters. Figure 1, Panel B illustrates the measurement of $ret_{t-\tau\rightarrow t}$. Table 3, Panels A and B present results based on Equation (3) using the CRSP index and the S&P 500 index, respectively.

Consistent with rational expectations asset pricing models, we find that stock market returns contain significant leading information about real economic activity. Table 3 shows that stock market returns positively predict quarter q+1 real GDP growth, with their predictive power varying with the length of the measurement window. The predictive power of stock market returns initially rises as we stretch the measurement window over the 12 months preceding month t, but it then declines beyond one year. The evidence shows that the 12-month stock market return is the most powerful for macro forecasting, explaining 20 percent of the time-series variation in quarter q+1 real GDP growth. This inference holds for both the CRSP index and the S&P 500 index.

Our findings establish that stock market investors anticipate a significant fraction of the variation in real economic activity one year in advance. Given the significant predictive power of stock market returns, the next question becomes whether aggregate accounting profitability drivers are *incrementally useful* for macro forecasting.

Incremental Predictive Content of Aggregate Changes in Accounting Profitability Drivers

From a practical implementation standpoint, the predictive content of aggregate accounting profitability drivers is relevant for macro forecasting only to the extent that it is incremental to the predictive content of stock market returns. This is because collecting and aggregating income statement and balance sheet data entail non-trivial costs, while stock market return data are readily available to macro forecasters.

Table 4 reports results from time-series regressions of subsequent real GDP growth on aggregate changes in accounting profitability drivers and stock market returns, as follows:

$$g_{q+1} = \alpha + \beta_1 \times \Delta ATO_q + \beta_2 \times \Delta OM_q + \beta_3 \times \Delta DEP_q + \beta_4 \times ret_{t-12\rightarrow t} + \varepsilon_{q+1}. \tag{4}$$

Equation (4) provides direct evidence on the marginal predictive content of accounting profitability drivers after controlling for annual stock market returns, $ret_{t-12\rightarrow t}$. We focus on annual stock market returns because our findings in Table 3 indicate that the predictive power of the stock market for quarter q+1 real GDP growth peaks when measuring returns over the 12 months preceding month t. Columns 1 and 2 of Table 4 report results using annual stock market returns based on the CRSP index and the S&P 500 index, respectively.

The key message from Table 4 is that financial statement analysis of firm profitability drivers applied at the aggregate level is relevant for forecasting real economic activity. More specifically, aggregate changes in operating margins and the depreciation-to-sales ratio contain leading information for subsequent real GDP growth *after* controlling for the predictive content of annual stock market returns. The estimated coefficients on ΔOM and ΔDEP remain significantly positive at the 1 percent level with t-statistics in excess of 3. The magnitudes of the estimated coefficients imply that a one-standard-deviation increase in ΔOM is associated with a 1.03 percentage point increase in subsequent real GDP growth, while a one-standard-deviation increase in ΔDEP is associated with a 0.59–0.61 percentage point increase in subsequent real GDP growth.

Clearly, the use of aggregate accounting profitability data leads to significant improvements in terms of explanatory power with the adjusted R^2 rising from 20 percent, when annual stock market returns are included as stand-alone predictors of subsequent real GDP growth, to 36 percent, when

TABLE 3

Predictive Content of Stock Market Returns for Subsequent Real GDP Growth

Panel A: Proxy for the Stock Market Portfolio is the CRSP Index

	Dependent Variable = g_{q+1}			
	1	**2**	**3**	**4**
Intercept	0.023	0.021	0.018	0.018
t-statistic	6.22	5.24	4.69	3.77
p-value	< 0.001	< 0.001	< 0.001	< 0.001
$ret_{t-3\rightarrow t}^{CRSP}$	0.09			
t-statistic	2.12			
p-value	0.04			
$ret_{t-6\rightarrow t}^{CRSP}$		0.08		
t-statistic		2.96		
p-value		< 0.001		
$ret_{t-12\rightarrow t}^{CRSP}$			0.06	
t-statistic			3.88	
p-value			< 0.001	
$ret_{t-24\rightarrow t}^{CRSP}$				0.03
t-statistic				2.20
p-value				0.03
Adjusted R^2	7%	15%	20%	7%

Panel B: Proxy for the Stock Market Portfolio is the S&P 500 Index

	Dependent Variable = g_{q+1}			
	1	**2**	**3**	**4**
Intercept	0.023	0.021	0.019	0.020
t-statistic	6.57	5.85	5.45	4.51
p-value	< 0.001	< 0.001	< 0.001	< 0.001
$ret_{t-3\rightarrow t}^{S\&P}$	0.09			
t-statistic	2.14			
p-value	0.03			
$ret_{t-6\rightarrow t}^{S\&P}$		0.09		
t-statistic		3.04		
p-value		< 0.001		
$ret_{t-12\rightarrow t}^{S\&P}$			0.06	
t-statistic			3.85	
p-value			< 0.001	
$ret_{t-24\rightarrow t}^{S\&P}$				0.03
t-statistic				2.46
p-value				0.02
Adjusted R^2	8%	16%	20%	8%

This table reports results from time-series regressions of subsequent real GDP growth (g_{q+1}) on buy-and-hold stock market returns (*ret*). Stock market returns are measured over the $\tau = 3$, 6, 12, and 24 months leading to the end of the first month, month t, after quarter q ends. We obtain data on annualized real GDP growth from the BEA's quarterly advance NIPA reports. Panel A reports results using the CRSP index (CRSP) as our proxy for the stock market portfolio. Panel B reports results using the S&P 500 index (S&P) as our proxy for the stock market portfolio. The sample period includes 120 quarters from 1981:Q3 to 2011:Q3.

TABLE 4

Incremental Predictive Content of Aggregate Changes in Accounting Profitability Drivers and Stock Market Returns for Subsequent Real GDP Growth

	Dependent Variable = g_{q+1}	
	1	**2**
Intercept	0.018	0.019
t-statistic	5.83	6.45
p-value	< 0.001	< 0.001
ΔATO_q	0.01	0.01
t-statistic	0.73	0.65
p-value	0.47	0.52
ΔOM_q	0.79	0.79
t-statistic	3.58	3.62
p-value	< 0.001	< 0.001
ΔDEP_q	1.01	0.98
t-statistic	3.12	3.03
p-value	< 0.001	< 0.001
$ret^{CRSP}_{t-12\rightarrow t}$	0.04	
t-statistic	3.63	
p-value	< 0.001	
$ret^{S\&P}_{t-12\rightarrow t}$		0.05
t-statistic		3.66
p-value		< 0.001
Adjusted R^2	36%	36%

This table reports results from time-series regressions of subsequent real GDP growth (g_{q+1}) on our quarterly indices of aggregate changes in profitability drivers and stock market returns. We obtain data on annualized real GDP growth from the BEA's quarterly advance NIPA reports. We measure quarterly changes in profitability drivers as year-over-year changes in asset turnover (ΔATO), operating margin (ΔOM), and the depreciation-to-sales ratio (ΔDEP). We construct the aggregate time-series using value-weighted cross-sectional averages based on the 100 largest U.S. listed firms in terms of lagged market capitalization with accounting data released by the end of the first month, month t, after quarter q ends. Stock market returns (ret) are measured over the 12 months leading to the end of the first month, month t, after quarter q ends. We proxy for the stock market portfolio using the CRSP index (CRSP) and the S&P 500 index (S&P). The sample period includes 120 quarters from 1981:Q3 to 2011:Q3.

annual stock market returns are included together with aggregate changes in accounting profitability drivers. Overall, the predictive content of aggregate accounting profitability data is incremental to that of stock market returns, suggesting that financial statement analysis applied at the aggregate level is *incrementally useful* for macro forecasting.

V. THE USE OF FINANCIAL STATEMENT ANALYSIS BY MACRO FORECASTERS

The analysis so far shows that aggregate changes in profitability drivers and stock market returns are *incrementally useful* for forecasting real economic activity. We now attempt to shed light on the *use* of financial statement analysis by professional macro forecasters.

Explaining Macro Forecasters' Revisions in Expectations

To begin, we test whether professional macro forecasters respond to aggregate changes in profitability drivers and stock market returns when revising their projections of quarter q+1 real

TABLE 5

Association of Revisions in Expectations about Subsequent Real GDP Growth with Aggregate Changes in Accounting Profitability Drivers and Stock Market Returns

	Dependent Variable $= E_q[g_{q+1}] - E_{q-1}[g_{q+1}]$	
	1	**2**
Intercept	-0.007	-0.006
t-statistic	-4.59	-4.30
p-value	< 0.001	< 0.001
ΔATO_q	0.00	0.00
t-statistic	0.24	0.20
p-value	0.81	0.84
ΔOM_q	0.29	0.29
t-statistic	3.51	3.65
p-value	< 0.001	< 0.001
ΔDEP_q	0.35	0.34
t-statistic	2.03	1.95
p-value	0.04	0.05
$ret^{CRSP}_{t-12\rightarrow t}$	0.02	
t-statistic	3.57	
p-value	< 0.001	
$ret^{S\&P}_{t-12\rightarrow t}$		0.02
t-statistic		3.37
p-value		< 0.001
Adjusted R^2	22%	22%

This table reports results from time-series regressions of the quarter q–1 to quarter q revision of the mean consensus forecast of quarter q+1 real GDP growth from the SPF, denoted $E_q[g_{q+1}] - E_{q\text{-}1}[g_{q+1}]$, on our quarterly indices of aggregate changes in profitability drivers and stock market returns. We obtain SPF mean consensus forecasts from the Federal Reserve Bank of Philadelphia. We measure quarterly changes in profitability drivers as year-over-year changes in asset turnover (ΔATO), operating margin (ΔOM), and the depreciation-to-sales ratio (ΔDEP). We construct the aggregate time-series using value-weighted cross-sectional averages based on the 100 largest U.S. listed firms in terms of lagged market capitalization with accounting data released by the end of the first month, month t, after quarter q ends. Stock market returns (*ret*) are measured over the 12 months leading to the end of the first month, month t, after quarter q ends. We proxy for the stock market portfolio using the CRSP index (CRSP) and the S&P 500 index (S&P). The sample period includes 120 quarters from 1981:Q3 to 2011:Q3.

GDP growth. Table 5 reports results from time-series regressions of SPF consensus forecast revisions from quarter q–1 to quarter q of quarter q+1 real GDP growth, denoted $E_q[g_{q+1}] - E_{q-1}[g_{q+1}]$, on aggregate changes in accounting profitability drivers and annual stock market returns, as follows:

$$E_q[g_{q+1}] - E_{q-1}[g_{q+1}] = \alpha + \beta_1 \times \Delta ATO_q + \beta_2 \times \Delta OM_q + \beta_3 \times \Delta DEP_q + \beta_4 \times ret_{t-12\rightarrow t} + \varepsilon_q. \quad (5)$$

If macro forecasters revise their real GDP growth expectations in the direction of the predictive content of aggregate changes in *RNOA* drivers and stock market returns, then based on Equation (5) we conjecture that $\beta_1 = 0$, $\beta_2 > 0$, $\beta_3 > 0$, and $\beta_4 > 0$. This conjecture follows from the evidence in Table 4 that ΔATO has no incremental predictive content, while ΔOM, ΔDEP, and stock market returns are significantly positive predictors of real GDP growth.

The findings, presented in Table 5, are consistent with our conjectures. While unrelated to aggregate changes in asset turnover, macro forecasters' revisions in expectations are positively associated with aggregate changes in operating margins and the depreciation-to-sales ratio as well as with stock market returns. Taken together, aggregate changes in accounting profitability drivers and stock market returns explain 22 percent of the time-series variation in macro forecasters' revisions in expectations of quarter q+1 real GDP growth.

Interestingly, the estimated intercepts based on Equation (5) are significantly negative, suggesting that professional macro forecasters tend to revise their real GDP growth forecasts downward as the BEA's scheduled NIPA release dates approach. This result provides the first evidence of a "walk-down" in macro forecasts and extends results in firm-level accounting research that long-term optimism in analysts' earnings forecasts decreases as earnings announcement dates approach (Brown, Foster, and Noreen 1985; Richardson, Teoh, and Wysocki 2004).

Our inferences hold for both the CRSP index and the S&P 500 index and are consistent with the findings presented in Tables 2, 3, and 4, indicating that macro forecasters revise their expectations of quarter q+1 real GDP growth in the direction of the predictive content of aggregate accounting profitability drivers and stock market returns. In particular, macro forecasters interpret aggregate increases in operating margins and the depreciation-to-sales ratio as well as stock market returns as positive for future real GDP growth. These findings, however, do not necessarily imply that macro forecasters fully impound the predictive content of aggregate accounting profitability drivers and stock market returns when forecasting real economic activity.

Are Macro Forecasters' Errors Predictable?

Do professional macro forecasters fully impound the predictive content of aggregate accounting profitability drivers and stock market returns? To address this question, we estimate time-series regressions of subsequent real GDP growth forecast errors on aggregate changes in accounting profitability drivers and stock market returns, as follows:

$$g_{q+1} - E_q[g_{q+1}] = \alpha + \beta_1 \times \Delta ATO_q + \beta_2 \times \Delta OM_q + \beta_3 \times \Delta DEP_q + \beta_4 \times ret_{t-12 \rightarrow t} + \varepsilon_{q+1}. \quad (6)$$

If professional macro forecasters fully impound the predictive content of aggregate changes in *RNOA* drivers and stock market returns when revising their expectations about quarter q+1 real GDP growth, then their subsequent forecast errors, denoted $g_{q+1} - E_q[g_{q+1}]$, should not be predictable and the estimated slope coefficients based on Equation (6) should not be different from 0. As discussed in Section II, it is unclear whether professional macro forecasters are fully attuned to the idea that financial statement analysis of firm profitability drivers applied at the aggregate level can be useful for macro forecasting. In contrast, we have reasons to believe that they are attuned to the idea that stock market returns are useful for macro forecasting.

If macro forecasters are fully attuned to stock market return data but not to aggregate accounting profitability data, then based on Equation (6) we conjecture that $\beta_1 = 0$, $\beta_2 > 0$, $\beta_3 > 0$, and $\beta_4 = 0$. This conjecture also follows from the findings in Table 4 that show ΔATO has no incremental predictive content, while ΔOM and ΔDEP are significantly positive predictors of real GDP growth.

The findings, presented in Table 6, are consistent with the above conjecture. Specifically, column 1 of Table 6 documents that, while unrelated to aggregate changes in asset turnover, real GDP growth forecast errors are predictable based on aggregate changes in operating margins and the depreciation-to-sales ratio. The estimated coefficients on ΔOM and ΔDEP are significantly different from zero. The positive signs of the estimated coefficients on ΔOM and ΔDEP are directionally consistent with the predictive content of these variables and imply that professional

TABLE 6

Predictive Content of Aggregate Changes in Accounting Profitability Drivers and Stock Market Returns for Subsequent Real GDP Growth Forecast Errors

	Dependent Variable $= g_{q+1} - E_q[g_{q+1}]$				
	1	**2**	**3**	**4**	**5**
Intercept	0.001	0.002	0.001	0.001	0.001
t-statistic	1.02	0.99	1.02	0.86	0.75
p-value	0.31	0.32	0.31	0.39	0.45
ΔATO_q	0.00			0.00	0.00
t-statistic	0.31			0.29	0.23
p-value	0.75			0.78	0.82
ΔOM_q	0.30			0.30	0.29
t-statistic	3.17			3.05	2.94
p-value	< 0.001			< 0.001	< 0.001
ΔDEP_q	0.78			0.77	0.76
t-statistic	2.34			2.25	2.15
p-value	0.02			0.03	0.03
$ret_{t-12\rightarrow t}^{CRSP}$		0.01		0.00	
t-statistic		1.07		0.24	
p-value		0.29		0.81	
$ret_{t-12\rightarrow t}^{S\&P}$			0.01		0.00
t-statistic			1.44		0.60
p-value			0.15		0.55
Adjusted R^2	8%	0%	1%	7%	7%

This table reports results from time-series regressions of subsequent real GDP growth forecast errors on our quarterly indices of aggregate changes in profitability drivers and stock market returns. We measure subsequent real GDP growth forecast errors as the difference between subsequent real GDP growth and the corresponding mean consensus forecast as of quarter q from the SPF, denoted $g_{q+1} - E_q[g_{q+1}]$. We obtain data on subsequent annualized real GDP growth from the BEA's quarterly advance NIPA reports. We obtain the SPF mean consensus forecasts of real GDP growth from the Federal Reserve Bank of Philadelphia. We measure quarterly changes in profitability drivers as year-over-year changes in asset turnover (ΔATO), operating margin (ΔOM), and the depreciation-to-sales ratio (ΔDEP). We construct the aggregate time-series using value-weighted cross-sectional averages based on the 100 largest U.S. listed firms in terms of lagged market capitalization with accounting data released by the end of the first month, month t, after quarter q ends. Stock market returns (*ret*) are measured over the 12 months leading to the end of the first month, month t, after quarter q ends. We proxy for the stock market portfolio using the CRSP index (CRSP) and the S&P 500 index (S&P). The sample period includes 120 quarters from 1981:Q3 to 2011:Q3.

macro forecasters do not fully impound the informativeness of aggregate changes in operating margins and the depreciation-to-sales ratio for subsequent real GDP growth.

The magnitudes of the estimated slope coefficients imply that real GDP growth forecasts can be improved in an economically significant way using aggregate accounting profitability drivers: a one-standard-deviation increase in ΔOM is associated with a 0.39 percentage point increase in subsequent real GDP growth forecast error, while a one-standard-deviation increase in ΔDEP is associated with a 0.47 percentage point increase in subsequent real GDP growth forecast error. Taken together, aggregate changes in accounting profitability drivers explain 8 percent of the time-series variation in one-quarter-ahead real GDP growth forecast errors.

In contrast, the results in columns 2 and 3 of Table 6 show that stock market returns lack predictive power for subsequent real GDP growth forecast errors. The lack of association between stock market returns and subsequent forecast errors implies that macro forecasters fully impound the predictive content of stock market returns when projecting real GDP growth. In line with this finding, columns 4 and 5 show that the predictive power of aggregate changes in operating margins and the depreciation-to-sales ratio for one-quarter-ahead real GDP growth forecast errors remain intact after controlling for stock market returns.

Viewed as a whole, our findings suggest that although professional macro forecasters are fully attuned to the predictive content of stock market returns, they do not fully impound the predictive content of aggregate accounting profitability drivers. Our evidence is consistent with the fact that stock market return data are known to have predictive ability for real economic activity (Fama 1981) and are readily available to macro forecasters, while aggregate accounting profitability data are not. Given that stock market returns do not subsume the predictive content of aggregate accounting profitability drivers for real GDP growth (Table 4) and real GDP growth forecast errors (Table 6), it follows that investors' projections of the real economy embedded in stock market prices can also be improved based on aggregate accounting profitability data.

Implications for Stock Valuation

We now examine the association between stock market returns and the portion of quarter q+1 real GDP growth that is predictable based on our indices of aggregate accounting profitability data but that is not anticipated by stock market investors. Specifically, we estimate the following time-series regression:

$$ret_{t+1\rightarrow t+3} = \alpha + \beta \times g_{q+1}^{ACC} + \varepsilon_{t+1\rightarrow t+3}. \tag{7}$$

The left-hand-side variable in Equation (7) is the buy-and-hold stock market return measured over the three-month period from the end of month t to the end of month t+3. The return measurement window allows us to capture information flows leading to the BEA's advance release of real GDP growth for quarter q+1, which occurs by the end of the first month after quarter q+1 ends, i.e., end of month t+3. Figure 1, Panel B illustrates the measurement of $ret_{t+1\rightarrow t+3}$.

The right-hand-side variable in Equation (7) is measured in two stages. In the first stage, we obtain the fitted values from the following time-series regression of subsequent real GDP growth on aggregate changes in accounting profitability drivers:

$$g_{q+1} = \alpha + \beta_1 \times \Delta ATO_q + \beta_2 \times \Delta OM_q + \beta_3 \times \Delta DEP_q + \varepsilon_{q+1}. \tag{8}$$

In the second stage, we regress the fitted values from Equation (8) on annual stock market returns measured over the 12 months leading to the end of month t and obtain the residuals. The residuals from this second-stage regression, denoted g_{q+1}^{ACC}, capture the portion of subsequent real GDP growth that is predictable based on our indices of aggregate accounting profitability drivers but that is not anticipated by stock market investors.

Table 7 reports results based on Equation (8).[11] Columns 1 and 3 document a significantly positive association between stock market returns and the predictable portion of real GDP growth for the CRSP index and the S&P index, respectively. Columns 2 and 4 expand the right-hand side of Equation (8) to include the portions of aggregate changes in *RNOA* drivers that are unrelated to g_{q+1}^{ACC}, denoted ΔATO^{res}, ΔOM^{res}, and ΔDEP^{res}. The estimated coefficients on g_{q+1}^{ACC} remain intact, while the estimated coefficients on ΔATO^{res}, ΔOM^{res}, and ΔDEP^{res} are insignificantly different from zero. This finding suggests that aggregate accounting profitability drivers flow into stock

[11] To ease interpretation of the estimated coefficients, we standardize the right-hand-side variables in Table 7 to have a mean of 0 and a standard deviation of 1. Our inferences are identical using the raw values of the regressors.

TABLE 7

Association between Stock Market Returns and Predictable Real GDP Growth

	Dependent Variable = $ret^{CRSP}_{t+1\rightarrow t+3}$		Dependent Variable = $ret^{S\&P}_{t+1\rightarrow t+3}$	
	1	**2**	**3**	**4**
Intercept	0.028	0.028	0.021	0.021
t-statistic	3.64	3.42	2.80	2.67
p-value	$<$ 0.001	$<$ 0.001	0.01	0.01
g_{q+1}^{ACC}	0.02	0.02	0.01	0.01
t-statistic	2.18	2.18	2.24	2.28
p-value	0.03	0.03	0.03	0.02
ΔATO_q^{res}		−0.002		−0.003
t-statistic		−0.12		−0.22
p-value		0.91		0.82
ΔOM_q^{res}		−0.014		−0.008
t-statistic		−1.06		−0.61
p-value		0.29		0.54
ΔDEP_q^{res}		−0.002		0.002
t-statistic		−0.21		0.22
p-value		0.83		0.83
Adjusted R^2	3%	4%	3%	3%

This table reports results from time-series regressions of the three-month buy-and-hold stock market return (*ret*) measured after the end of the first month, month *t*, after quarter *q* ends on the following variables: (i) $g_{q+1}{}^{ACC}$, the predictable portion of subsequent real GDP growth measured in two stages. In the first stage, we obtain the fitted values from a time-series regression of subsequent real GDP growth on aggregate changes in asset turnover (ΔATO), aggregate changes in operating margins (ΔOM), and aggregate changes in the depreciation-to-sales ratio (ΔDEP). We construct the aggregate time-series using value-weighted cross-sectional averages based on the 100 largest U.S. listed firms in terms of lagged market capitalization with accounting data released by the end of the first month, month *t*, after quarter *q* ends. In the second stage, we orthogonalize these fitted values on stock market returns measured over the 12 months leading to the end of month *t*; (ii) ΔATO^{res}, the residual from a regression of ΔATO on the predictable portion of subsequent GDP growth; (iii) ΔOM^{res}, the residual from a regression of ΔOM on the predictable portion of subsequent GDP growth; and (iv) ΔDEP^{res}, the residual from a regression of ΔDEP on the predictable portion of subsequent GDP growth. Variables (i) through (iv) are standardized to have a mean of 0 and a standard deviation of 1. We proxy for the stock market portfolio using the CRSP index (CRSP) and the S&P 500 index (S&P). The sample period includes 120 quarters from 1981:Q3 to 2011:Q3.

market returns through subsequent real GDP growth. In additional month-by-month analysis, we find that the link between the predictable portion of subsequent real GDP growth and stock market returns flows evenly over the three months leading to the BEA's advance release of real GDP growth for quarter $q+1$.

There are at least two potential explanations for our finding of a positive association between stock market returns and the portion of real GDP growth that is predictable based on aggregate accounting profitability data. First, it may be due to delayed assimilation of aggregate accounting profitability drivers. Second, it may be due to a positive link between investors' expectations about discount rates and investors' expectations about growth. Indeed, prior research suggests that there is a common component between revisions in expectations about discount rates and revisions in expectations about growth.[12] We remain agnostic about the appropriate explanation. Nevertheless, the evidence we document suggests that the link between aggregate accounting profitability drivers and subsequent real GDP growth is relevant for stock valuation.

VI. CONCLUSION

Our study investigates the usefulness of financial statement analysis of firm profitability drivers for forecasting real economic activity. We first document that focusing on the 100 largest firms offers a cost-effective way to extract information in accounting profitability data of the entire stock market portfolio. We then show that accounting profitability data aggregated across the 100 largest firms have predictive ability for subsequent real GDP growth. We also show that stock market returns predict subsequent real GDP growth, while their predictive power varies with the length of the measurement window with annual stock market returns being the most powerful. Importantly, we find that the predictive content of our indices of aggregate accounting profitability drivers is not subsumed by that of stock market returns, suggesting that financial statement analysis of firm profitability at the aggregate level is *incrementally useful* for macro forecasting.

An in-depth investigation of consensus forecasts from the SPF shows that professional macro forecasters revise their expectations of real economic activity in the direction of the predictive content of aggregate accounting profitability drivers and stock market returns. Although macro forecasters are fully attuned to stock market return data, their forecasts of real GDP growth can be improved in a statistically and economically significant way using our indices of aggregate accounting profitability drivers. Overall, our findings suggest that professional macro forecasters and stock market investors do not fully impound the predictive content of aggregate accounting profitability drivers for real economic activity. In additional analysis, we examine the association between stock market returns and the portion of subsequent real GDP growth that is predictable based on our indices of aggregate accounting profitability drivers but that is not anticipated by stock market investors. We find that this portion is positively related to stock market returns, suggesting that the predictive content of aggregate accounting profitability drivers for real economic activity is relevant for stock valuation.

Notwithstanding our evidence that financial statement analysis of firm profitability drivers applied at the aggregate level is an incrementally useful tool for taking the pulse of the U.S. real economy, we acknowledge that collecting and aggregating income statement and balance sheet data impose non-trivial information acquisition and processing costs on macro forecasters. Our indices of aggregate firm profitability drivers, however, are based on the 100 largest firms with accounting data released within one month after the quarter ends. Our study highlights that focusing on this set of firms can offer insights into the performance of the entire stock market portfolio, limiting the practical costs associated with collecting and aggregating data from corporate financial reports. We also acknowledge that aggregate indices mask heterogeneity across firms. Future research may find cross-sectional variation in the usefulness of financial statement analysis for macro forecasting.

[12] Campbell and Shiller (1988) and Campbell (1991) decompose stock returns into expected returns, cash flow news, and discount rate news. With this decomposition in mind, prior research shows that there is a common component between cash flow news and discount rate news. Lettau and Ludvigson (2005) provide evidence of common variation in discount rates and expected growth rates. Cochrane (2011) notes that discount rates and expected growth rates are likely to covary positively over the business cycle. Konchitchki, Lou, G. Sadka, and R. Sadka (2014), motivated by investment-based asset pricing models, argue that high expected earnings can be obtained by undertaking risky projects, suggesting a positive relation at the firm level between expected returns and expected growth. Patatoukas (2013) finds that cash flow news and discount rate news in aggregate changes in accounting profitability covary positively over time and have offsetting impacts on stock market prices.

Such research would further broaden our knowledge of the link between accounting profitability drivers and the aggregate economy.[13]

REFERENCES

Abarbanell, J. S., and B. J. Bushee. 1998. Abnormal returns to a fundamental analysis strategy. *The Accounting Review* 73 (1): 19–45.

Baghestani, H., and A. M. Kianian. 1993. On the rationality of US macroeconomic forecasts: Evidence from a panel of professional forecasters. *Applied Economics* 25 (7): 869–878.

Barro, R. J. 1990. The stock market and investment. *Review of Financial Studies* 3 (1): 115–131.

Barth, M. E., D. P. Cram, and K. K. Nelson. 2001. Accruals and the prediction of future cash flows. *The Accounting Review* 76 (1): 27–58.

Basu, S., S. Markov, and L. Shivakumar. 2010. Inflation, earnings forecasts, and post-earnings announcement drift. *Review of Accounting Studies* 15 (2): 403–440.

Brown, L., G. Foster, and E. Noreen. 1985. *Security Analyst Multi-Year Earnings Forecasts and the Capital Market*. Studies in Accounting Research No. 23. Sarasota, FL: American Accounting Association.

Bureau of Economic Analysis (BEA). 2007. *Measuring the Economy: A Primer on GDP and the National Income and Product Accounts*. United States Department of Commerce: Economics and Statistics Administration, Bureau of Economic Analysis.

Campbell, J. Y. 1991. A variance decomposition for stock returns. *Economic Journal* 101 (405): 157–179.

Campbell, J. Y., and R. J. Shiller. 1988. The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies* 1 (3): 195–228.

Cheng, Q. 2005. What determines residual income? *The Accounting Review* 80 (1): 85–112.

Cochrane, J. H. 2011. Presidential address: Discount rates. *Journal of Finance* 66 (4): 1047–1108.

Cready, W. M., and U. G. Gurun. 2010. Aggregate market reaction to earnings announcements. *Journal of Accounting Research* 48 (2): 289–334.

Croushore, D. 2002. Comments on: The state of macroeconomic forecasting. *Journal of Macroeconomics* 24 (4): 483–489.

Croushore, D. 2011. Real-time forecasting. In *Advances in Economic Forecasting*, 7–24. Kalamazoo, MI: Upjohn Institute.

Fairfield, P. M., and T. L. Yohn. 2001. Using asset turnover and profit margin to forecast changes in profitability. *Review of Accounting Studies* 6 (4): 371–385.

Fama, E. F. 1981. Stock returns, real activity, inflation, and money. *American Economic Review* 71 (4): 545–565.

Fama, E. F. 1990. Stock returns, expected returns, and real activity. *The Journal of Finance* 45 (4): 1089–1108.

Fildes, R., and H. Stekler. 2002. The state of macroeconomic forecasting. *Journal of Macroeconomics* 24 (4): 435–468.

Fischer, S., and R. C. Merton. 1984. *Macroeconomics and Finance: The Role of the Stock Market*. Working Paper No. 1291. Cambridge, MA: National Bureau of Economic Research.

Fixler, D. J., and B. T. Grimm. 2005. Reliability of the NIPA estimates of U.S. economic activity. *Survey of Current Business* 85 (2): 8–19.

Graham, J. R. 1996. Is a group of economists better than one? Than none? *Journal of Business* 69 (2): 193–232.

Konchitchki, Y. 2011. Inflation and nominal financial reporting: Implications for performance and stock prices. *The Accounting Review* 86 (3): 1045–1085.

[13] In a follow-up study, we find evidence that macro forecasters can further enhance their projections of future real economic activity by paying closer attention to accounting data from bellwether firms and cyclical industries.

Konchitchki, Y., X. Lou, G. Sadka, and R. Sadka. 2014. *Expected Earnings and the Post-Earnings-Announcement Drift*. Working paper.

Konchitchki, Y., and P. N. Patatoukas. 2013. Accounting earnings and gross domestic product. *Journal of Accounting and Economics* (forthcoming). DOI: 10.1016/j.jacceco.2013.10.001. Available at: http://www.sciencedirect.com/science/article/pii/S016541011300058X

Kothari, S. P. 2001. Capital markets research in accounting. *Journal of Accounting and Economics* 31 (1-3): 105–231.

Kothari, S. P., J. Lewellen, and J. B. Warner. 2006. Stock returns, aggregate earnings surprises, and behavioral finance. *Journal of Financial Economics* 79 (3): 537–568.

Kothari, S. P., L. Shivakumar, and O. Urcan. 2013. *Aggregate Earnings Surprises and Inflation Forecasts*. Working paper.

Krane, S. 2003. An evaluation of real GDP forecasts: 1996–2001. *Federal Reserve Bank of Chicago Economic Perspectives* (Q1): 2–21.

Lahiri, K., and J. G. Wang. 2006. Subjective probability forecasts for recessions: Evaluations and guidelines for use. *Business Economics* 41 (2): 26–37.

Landefeld, J. S., E. P. Seskin, and B. M. Fraumeni. 2008. Taking the pulse of the economy: Measuring GDP. *Journal of Economic Perspectives* 22 (2): 193–216.

Lettau, M., and S. C. Ludvigson. 2005. Expected returns and expected dividend growth. *Journal of Financial Economics* 76 (3): 583–626.

Lev, B. 1983. Some economic determinants of time-series properties of earnings. *Journal of Accounting and Economics* 5 (1): 31–48.

Lev, B., and R. Thiagarajan. 1993. Fundamental information analysis. *Journal of Accounting Research* 31 (2): 190–215.

McNees, S. K. 1992. How large are economic forecast errors? *New England Economic Review* (July/August): 25–42.

Merchant, K. A. 2012. Making management accounting more useful. *Pacific Accounting Review* 24 (3): 334–356.

Moehrle, S. R., K. Anderson, F. L. Ayres, C. E. Bolt-Lett, R. S. Debreceny, M. T. Dugan, C. E. Hogan, M. W. Maher, and E. Plummer. 2009. The impact of academic accounting research on professional practice: An analysis by the AAA Research Impact Task Force. *Accounting Horizons* 23 (4): 411–456.

Newey, W. K., and K. D. West. 1987. A simple, positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55 (3): 703–708.

Nissim, D., and S. H. Penman. 2001. Ratio analysis and equity valuation: From research to practice. *Review of Accounting Studies* 6 (1): 109–154.

Ou, J. A., and S. H. Penman. 1989. Financial statement analysis and the prediction of stock returns. *Journal of Accounting and Economics* 11 (4): 295–329.

Patatoukas, P. N. 2012. Customer-base concentration: Implications for firm performance and capital markets. *The Accounting Review* 87 (2): 363–392.

Patatoukas, P. N. 2013. Detecting news in aggregate accounting earnings: Implications for stock market valuation. *The Review of Accounting Studies* (forthcoming). DOI: 10.1007/S11142-013-9221-3. Available at: http://link.springer.com/article/10.1007%2Fs11142-013-9221-3

Penman, S. H. 1992. Return to fundamentals. *Journal of Accounting, Auditing and Finance* 7 (Fall): 465–483.

Penman, S. H. 2001. *Financial Statement Analysis and Security Valuation*. 1st edition. New York, NY: McGraw-Hill.

Richardson, S., S. H. Teoh, and P. D. Wysocki. 2004. The walk-down to beatable analyst forecasts: The role of equity issuance and insider trading incentives. *Contemporary Accounting Research* 21 (4): 885–924.

Schuh, S. 2001. An evaluation of recent macroeconomic forecast errors. *New England Economic Review* (January/February): 35–56.

Shivakumar, L. 2010. Discussion of aggregate market reaction to earnings announcements. *Journal of Accounting Research* 48 (2): 335–342.

Sims, C. A. 2002. The role of models and probabilities in the monetary policy process. *Brookings Papers on Economic Activity, Economic Studies Program, the Brookings Institution* 33 (2): 1–62.

Soliman, M. T. 2008. The use of DuPont analysis by market participants. *The Accounting Review* 83 (3): 823–853.

Stark, T. 2010. Realistic evaluation of real-time forecasts in the survey of professional forecasters. Federal Reserve Bank of Philadelphia, Special Report. Available at: http://www.phil.frb.org/research-and-data/publications/research-rap/2010/realistic-evaluation-of-real-time-forecasts.pdf

Stock, J. H., and M. W. Watson. 2003. How did the leading indicator forecasts perform during the 2001 recession? *Federal Reserve Bank of Richmond*, *Economic Quarterly* 89 (3): 71–90.

White, H. 1980. A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity. *Econometrica* 48 (4): 817–838.

Wieland, V., and M. H. Wolters. 2011. The diversity of forecasts from macroeconomic models of the U.S. economy. *Economic Theory* 47 (2): 247–292.

Zarnowitz, V., and P. Braun. 1993. Twenty-two years of the NBER-ASA quarterly economic outlook surveys: Aspects and comparisons of forecasting performance. In *Business Cycles, Indicators, and Forecasting*, edited by J. Stock, and M. Watson. Chicago, IL: University of Chicago Press.