The Real-Time Macro Content of Corporate Financial Reports: A Dynamic Factor Model Approach

Ahmed M. Abdalla
ahmed.abdalla@monash.edu
Monash University

Jose M. Carabias
j.m.carabias-palmeiro@lse.ac.uk
London School of Economics

Panos N. Patatoukas
panos@haas.berkeley.edu
U. C. Berkeley

This Draft: January 20, 2021

Abstract

We use a standard dynamic factor model to extract new factors based on the real-time flow of accounting data from the corporate financial reports. The extracted accounting factors exploit across-sector comovements in corporate value creation drivers and can be used together with other closely watched economic indicators. We show that our weekly updated accounting factors are incrementally relevant for nowcasting and forecasting major components of economic output in the BEA's National Income and Product Accounts. Overall, our paper pioneers a new approach to incorporating the continuous flow of accounting data within the context of dynamic factor models.

Keywords: Corporate Financial Reports; Nowcasting; Forecasting; Macro Accounting.

JEL Codes: E01, E32, E60, M41.

Corresponding Author: Panos N. Patatoukas. Email: panos@haas.berkeley.edu. Phone: (510) 508-1362. Address: Berkeley Haas, 2220 Piedmont Ave, Berkeley, CA 94720.

Declarations of Interest: None.

Acknowledgements: We thank Domenico Giannone, Isaac Gross, Farshid Vahid, the PhD students at Berkeley Haas, and participants in BEA's Cross-Directorate Seminar for helpful discussions and comments. We also thank Dylan Rassier (BEA, Chief National Accounts Research Group) and Baoline Chen (BEA, Research Economist) for their advice on accounting measurement. Panos acknowledges the generous support of the Berkeley Haas Center for Financial Reporting and Management.

1. Introduction

What is the real-time macro content of corporate financial reports? This paper introduces a dynamic factor model approach to nowcasting and forecasting that exploits the flow of accounting data as it becomes available from the mandated reports of publicly traded firms. We construct real-time indicators of corporate value creation and exploit across-sector comovements to extract latent accounting factors that can be used alongside other closely watched indicators. We show that our continuously updated accounting factors are incrementally relevant for nowcasting and forecasting major components of economic output in the BEA's National Income and Product Accounts (NIPA).

Our starting point is the ground-breaking paper of Giannone, Reichlin, and Small (2008), henceforth GRS. In their paper, GRS develop a dynamic factor model that can handle mixed-frequency data and provide a formal method for updating estimates of economic output throughout the quarter. The model incorporates a large panel of about 200 time series of the U.S. economy, including industrial production, employment situation, inflation, financial variables, interest rates, money, and credit aggregates, along with other macro releases, such as housing market conditions and consumer confidence surveys. GRS show the incremental impact of different economic releases in terms of reducing estimation uncertainty in the months leading to the release of quarterly GDP. The GRS model has had a significant impact on macro forecasting, and it is widely used across a variety of platforms (for a survey see, e.g., Bok et al. 2018).[1]

GRS show that as more information becomes available, their dynamic factor model outperforms a naïve statistical model in terms of nowcasting current quarter GDP growth. The superior performance of the GRS model, however, kicks in only after the release of the employment situation report at the beginning of the second month of the quarter. In a follow-up paper, Bańbura et al. (2013) consider whether sectoral economic data can improve the performance of the GRS model. While their findings confirm the nowcasting relevance of the GRS model during the second and third months of the target quarter, Bańbura et al. (2013) do not find incremental improvements from expanding the information set with more disaggregated economic data.

Our paper synthesizes the bridge equation of the GRS model with a stylized weekly calendar of the real-time flow of accounting data from the corporate financial reports. Our research design builds on two key aspects of corporate financial reporting. First, U.S. federal securities laws require publicly traded firms to report their results at quarterly frequencies. Second, across publicly traded firms there is heterogeneity in the disclosure timing. Together, these two aspects of corporate financial reporting result in an incredibly rich flow of financial accounting data throughout the quarter.

The mandated quarterly reports provide a wealth of information from the corporate financial statements, including the income statement, the balance sheet, and the statement of cash flows. The financial statements allow capital providers to evaluate firm performance in terms of revenue growth and return on capital (e.g., Penman 2013). Indeed, corporate value creation hinges on the ability of the firm to grow its revenue while generating a return on invested capital that exceeds the cost of capital.

[1] To illustrate, the New York Fed and the Atlanta Fed provide nowcasts of GDP growth based on statistical filtering techniques applied to a dynamic factor model.

Our approach utilizes the cumulative flow of accounting data throughout the quarter to extract timely signals of economic activity. We have ex ante reasons to believe that accounting data aggregated across publicly traded firms in different sectors can be used for macro nowcasting and forecasting alongside the information set of the GRS model.

First, U.S. GAAP require companies to use accrual basis of accounting. While cash accounting recognizes transactions only when cash is exchanged, accrual accounting recognizes the effects of transactions in the period in which those effects occur, even if the resulting cash receipts and payments occur in a different period. Since accrual accounting is concerned with expected future cash receipts and payments, the mandated corporate reports contain information that is relevant not only for understanding past operating, investing, and financing activities but also for forecasting future business activities. Indeed, a longstanding line of capital markets research speaks to the forward-looking content of accounting data for anticipating firm-level performance (e.g., Bernard and Thomas 1990; Foster et al. 1984; Ball and Brown 1968).

Second, models on the granular origins of aggregate fluctuations show that individual firm shocks can explain an important part of aggregate shocks (e.g., Carvalho and Gabaix 2013; Acemoglu et al. 2012; Gabaix 2011; Gabaix et al. 2003). Dating back to Lucas (1977), the conventional argument is that individual firm shocks have a negligible aggregate effect because they are diversifiable. Gabaix (2011), however, shows that the diversification argument breaks down in an economy with a fat-tailed distribution of firms. A fat-tailed distribution implies that the largest firms have a disproportionate impact on overall economic activity so that individual firm shocks do not die out in the aggregate.

Following this lead, we note that publicly traded firms are typically much larger than privately held firms operating in the same sector and account for a disproportionate fraction of sectoral output. Moreover, leading bellwether firms in each industry disclose their quarterly results ahead of industry peers and typically within the first few weeks after the quarter ends (e.g., Foster 1981). Therefore, aggregating accounting data across publicly traded firms can provide timely insights into the micro-foundation of aggregate fluctuations.

As acknowledged by GRS, the flow of relevant data regardless of its frequency may enhance the precision of nowcasts and forecasts of quarterly GDP growth. Indeed, from the point of view of macro forecasters there is no reason to "throw away" any potentially relevant data, including accounting disclosures from the mandated corporate reports. In addition, BańBura et al. (2013) report that the timeliness of data is key to improving the accuracy of GDP estimates. Importantly, we observe that the bulk of the flow of accounting data coincides with the time when estimation uncertainty is high due to the lack of hard economic data relating to the current quarter.

Our paper adapts the GRS model to incorporate the real-time flow of accounting data as first reported. First, we divide each month into weekly blocks and create a stylized calendar of corporate financial reports throughout the quarter. Then, we use the Kalman filter to summarize information from the across-sector comovements of accounting indicators of corporate value creation into latent common factors. We then bridge the extracted factors with quarterly GDP growth to obtain weekly nowcasts and forecasts of economic output. As the information set expands every week with the addition of more accounting data from the corporate financial reports, we use the sequence of continuously updated nowcasts and forecasts of GDP growth to evaluate projection accuracy throughout the quarter.

Our main findings are as follows. First, the flow of accounting data helps reduce estimation uncertainty throughout the quarter. Expanding the GRS model to incorporate the real-time flow of accounting data in what we refer to as the GRS$^+$ model, we document incremental gains in terms of increasing the precision of GDP growth nowcasts and forecasts throughout the quarter. Decomposing GDP growth, we find that the real-time macro content of the accounting factors is mostly related to fluctuations in (a) personal consumption and (b) non-residential investment—two dominant drivers of real GDP fluctuations. Breaking down gross value added by sector, we find that the macro content of the accounting factors flows through business sector activity. This finding is important given that the business sector accounts for three-fourths of output and the publication lag is significantly longer for BEA's sector statistics compared to national GDP.

Second, the incremental gains in the performance of the GRS$^+$ model mostly accrue by week 4 of the current quarter, which corresponds to the peak of each accounting earnings season with leading bellwether firms in each industry releasing their reports. This is an important feature of our model because it implies that the cumulative flow of accounting data can be used to reduce estimation uncertainty during the first month of the quarter, when it is needed the most due to the lack of hard economic data for the current quarter. Another desirable feature of incorporating the cumulative flow of accounting data is that our dynamic factor model approach can be implemented at a low-cost using information from publicly traded firms. Those reports can be easily accessed, free of charge, from the U.S. Securities and Exchange Commission (SEC)'s EDGAR system.

Third, our analysis shows that the flow of accounting data contains relevant information for not only the product side but also the income side of the NIPA. While the product side features GDP as the sum of goods and services sold to final users, the income side features Gross Domestic Income (GDI) as the sum of income payments and other costs incurred in the production of goods and services. We find that the flow of accounting data is incrementally relevant for nowcasting and forecasting major GDI components from the income side of the BEA's NIPA. Our granular decomposition of GDI shows that the gains are especially pronounced for (a) employee compensation, which accounts for 56% of GDI, and (b) net operating surplus, which accounts for 23% of GDI and includes NIPA corporate profits from current production.

From a measurement perspective, a key implication is that accounting data could help mitigate the longer publication lag of the income side of the NIPA. Mitigating the publication lag is an important issue for the BEA in its mission to provide estimates of economic activity that are not only accurate, but also relevant, in terms of the time before those estimates can be used by decision makers.

Overall, our paper takes an important step towards incorporating accounting data in dynamic factor models. While consistent with evidence of a common component in the cross-section of accounting data that is relevant for gauging the prospects of the U.S. economy (e.g., Konchitchki and Patatoukas 2014a; 2014b; Patatoukas 2014; Patatoukas et al. 2020; Abdalla and Carabias 2020), this is the first paper to pioneer the use of the real-time flow of accounting data throughout the quarter within the context of the GRS dynamic factor model. Our adaptation of the GRS model shows that weekly updated accounting factors can be used alongside the information set of a large panel of economic releases to mitigate estimation uncertainty.

More broadly, our paper completements recent research by Bianchi et al. (2020) who develop a machine learning model that generates systematic gains in forecast accuracy relative to survey forecasts of GDP growth. Different from Bianchi et al. (2020), our focus is on incorporating the flow of accounting data in the GRS model and not necessarily to show improvements over survey forecasts.

Section 2 introduces the accounting factor model. Section 3 combines accounting with macro data. Section 4 introduces a stylized calendar of the flow of accounting data and evaluates the performance of the accounting factor model. Section 5 concludes.

2. The accounting factor model

2.1 Corporate value creation framework

Our accounting factor extraction combines two key ingredients. The first ingredient is the stylized fact in macroeconomics that business cycles are characterized by sectoral comovements in value-creation metrics (e.g., Hornstein and Praschnik 1997; Horvath 2000; Hornstein 2000). The second ingredient is the longstanding line of capital markets research using accounting disclosures from the corporate financial reports to gauge corporate value creation at the firm level.

A well-known framework for understanding corporate value creation is the residual income valuation model, which expresses the fundamental value of a corporation as the sum of the book value of capital invested plus the discounted sum of expected future income in excess of the opportunity cost of capital. The residual income model goes back to Edwards and Bell's (1961) theory of business income. In the context of the residual income model, the main drivers of corporate value creation are growth and profitability.

The key measure of firm growth is revenue growth ($growth$). This is because at steady state revenue growth is driving all dimensions of firm growth. From the point of view of equity and debt capital providers, the key measure of return on invested capital at the enterprise level is the return on net operating assets ($rnoa$), which measures net operating income per dollar of net operating assets. Net operating income is a measure of income available to equity and debt capital providers, and net operating assets is a measure of capital invested by the same group of capital providers (e.g., Penman 2013).

The two accounting measures have appealing economic interpretations. On the demand side, revenue growth captures fluctuations in the demand for goods and services offered. On the supply side, return on net operating assets captures the generation of income from invested capital and can be viewed as a measure of productivity.

2.2 Sector-level accounting aggregates

We utilize the continuous flow of accounting data to construct real-time vintages of sector-level aggregates of corporate value creation. To organize the continuous flow of accounting data, we divide each quarter into weekly blocks and use the quarterly earnings announcement dates to allocate firm-quarter observations to each week.

We construct our real-time sector-level vintages as follows. For each weekly block, we collect available firm-level accounting data and measure $growth$ as the year-over-year percentage change in quarterly revenue and $rnoa$ as the ratio of annualized net operating income divided by average net operating assets. Our measurement ensures that the accounting series are stationary. Appendix 1 provides the variable definitions.

Separately for each sector, we compute the weighted average values of $growth$ and $rnoa$ using the cumulative flow of accounting data at the end of each week. For the weights, we use the product of the firm's lagged enterprise value multiplied by its cyclicality. We measure firm-level cyclicality from firm-level time-series regressions of firm profitability on real GDP growth. These regressions are estimated point-in-time and are free from look-ahead bias. In effect, the weighting scheme places more weight on large and procyclical firms while it places less weight on small and countercyclical firms.

Throughout the quarter, we update the sector-level aggregate series as more firms publish their accounting reports. The sector-level aggregates evolve from one week to the next as the later week's aggregate incorporates the incremental flow of information from newly available accounting data releases. We then use a dynamic factor model to extract weekly latent factors from the sector-level aggregates.[2]

2.3 Common factor extraction

Our model extracts weekly latent factors from the comovements of $growth$ and $rnoa$ across sectors. To model comovements across our panel of sector-level accounting aggregates, we adapt the GRS model assuming that these sector-level series are driven by a latent variable. Formally, we use the following state-space model:

$$A_{i,t} = \mu_i + \varphi_i F_t + \xi_{i,t} \qquad i = 1, \dots, n \tag{1a}$$

where $A_{i,t}$ represents the accounting aggregate series of growth or profitability for sector i at end of week t, μ_i and φ_i are the series-specific constant and factor loading, F_t is the series' latent common dynamic factor, and $\xi_{i,t}$ are the idiosyncratic components.

Equation (1a) links the observable accounting variables $A_{i,t}$ to the unobservable factor F_t and requires the additional assumption that the idiosyncratic components are cross-sectionally uncorrelated white noise processes:

$$E(\xi_t \xi_t') = \ diag\ (\psi_1, \dots, \psi_n) \tag{1b}$$

$$E(\xi_t \xi_{t-s}') = \ 0, \quad s > 0 \tag{1c}$$

In addition, we allow the latent common dynamic factor to vary through time by parameterizing its dynamics as an AR(1) process:

$$F_t = \lambda F_{t-1} + e_t \tag{2a}$$

$$e_t \sim N(0, I) \text{ and } E(\xi_t e_{t-s}') = 0 \text{ for all } s \tag{2b}$$

Within the context of our forecasting framework, there will be missing observations at the end of the sample due to the non-synchronous releases of accounting and economic data. To deal with this "jagged" edge structure of the panels, we assume that $\psi_{i,t} = \psi_i$ if $A_{i,t}$ is available, and $\psi_{i,t} = \infty$ if $A_{i,t}$ is missing. Given this assumption on the variance of the idiosyncratic component, the Kalman filter will place a zero weight on missing observations and the series with missing values will be disregarded when estimating the factors.

Using the above framework, we extract weekly latent accounting factors using the cumulative flow of accounting information throughout the quarter. We label the extracted accounting factors of growth and profitability as F_t^{growt} and F_t^{rnoa}, respectively. Similarly, we use this framework to extract a weekly latent factor akin to that in GRS by replacing our sector-level accounting aggregates in equation (1a) with a panel of economic indicators

[2] We note that consistent with standard practice in financial statement analysis, we use year-over-year (YoY) changes in quarterly revenue to control for seasonal effects. In additional analysis, we use quarter-over-quarter (QoQ) changes in trailing twelve-month (TTM) revenue. We find that the YoY factor is 99% correlated with the QoQ factor and, therefore, our results are not sensitive to the seasonal adjustment choice. While we consider two commonly used seasonal adjustments, future research could develop alternative procedures.

typically used by macro forecasters. We label the extracted factor using macro information available as F_t^{GRS}.

2.4 Bridge regressions

After we extract the weekly latent factors, we proceed by examining the relative nowcasting and forecasting content of these factors using bridge regressions at different horizons. We bridge the extracted factors with quarterly GDP growth (or its components) to obtain weekly nowcasts and forecasts of economic output conditioning on our continuously updated factors.

Specifically, we estimate bridge regressions of the following form:

$$GDP_{q+h} = \mu + \theta F_{q-k|q,t} + e_{q+h} \tag{3}$$

where GDP_{q+h} is the quarterly GDP growth in the current quarter q $(h = 0)$ or the subsequent quarter $q + 1$ $(h = 1)$, and $F_{q-k|q,t}$ is the estimate of factor F_{q-k} conditioning on information available in week t of quarter q.

As we detail in Section 3.1 and Appendix 2, since accounting periods do not always coincide with calendar periods, we realign off-calendar accounting data prior to constructing the sector-level accounting aggregate series. The data realignment ensures that all accounting information released in the current quarter q refers to the prior quarter $q - 1$ $(k = 1)$. With respect to the panel of economic releases used to extract the GRS factor, the employment situation report at the beginning of the second month of the quarter is the first in the string of releases containing information for the current quarter $(k = 0)$.

We estimate three regression model specifications based on the bridge equation in (3). The first model specification, which we label "ACC" model, considers the information in the latent growth and profitability factors obtained from the flow of financial accounting data. The second model specification, which we label "GRS" model, considers the information in the latent factor obtained from the GRS panel of closely watched indicators. The third model specification, which we label "GRS$^+$" model, combines our accounting factors with the GRS macro factor.

For each week in the quarter, we produce conditional projections of GDP growth, and its components, for the current and subsequent quarter based on the ACC, GRS, and GRS$^+$ factor models. We estimate the bridge equation (3) for two horizons $(h = 0$ and $h = 1)$ recursively starting with an initial sample period from 1987:Q1 to 1994:Q4. We iterate expanding the estimation sample period by adding one quarter at a time until the end of the sample in 2015:Q4. In each iteration, we estimate the parameters of the bridge regression by week using lagged information. We then apply the estimated parameters on the current values of the weekly latent factors to produce out-of-sample projections of economic activity throughout the quarter.

We evaluate model performance using mean squared forecast errors (MSFE). For model comparison, we benchmark the MSFE from each factor model against the MSFE from a random-walk model over the evaluation sample. If the ratio of the MSFE from a factor model to the MSFE from the random-walk model is below one, the factor model outperforms the statistical benchmark.[3]

[3] In additional analysis, we expand the flow of accounting data to include sell-side analysts' projections of quarterly accounting data. We find only small incremental nowcasting and forecasting benefits from incorporating such data.

3. Combining accounting data with macroeconomic data

3.1 Accounting data

We collect stock market data from the CRSP database and accounting data "as first reported" from the Compustat Unrestated Quarterly database for the period between 1987:Q1 and 2015:Q4. By using the as first reported accounting data, we ensure that the extracted accounting factors are based on information as originally seen by market participants, untainted by future accounting restatements.

In the context of quarterly financial reporting, the accounting period does not always align with the calendar quarter. For the general population, the frequency of misalignment between the accounting period and the calendar quarter is 16%. For 84% of the general population, the accounting period is aligned with the calendar quarter. To avoid mixing data with different accounting periods, we realign off-calendar observations prior to constructing the sector-level aggregate series of growth and profitability. Specifically, we first decompose (interpolate) off-calendar quarterly accounting series into their unobservable monthly components and then combine the monthly components into "synthetic" calendar quarter series. For the time-series disaggregation, we use the first difference smoothing procedure of Boot, Feibes, and Lisman (1967). Appendix 2 provides the details.

To derive our sample, we impose the following filters: (i) a minimum of 20 consecutive quarterly observations; (ii) non-missing values for all necessary accounting data to measure revenue growth and return on net operating assets; (iii) revenue and net operating assets of at least $1 million so that we avoid small or negative denominators in the ratios. To mitigate the effect of extreme values, we trim the top and bottom 0.5% of $growth$ and $rnoa$ based on the distributional cutoffs of each quarterly cross-section. We organize the data in 24 industry groups using the Global Industry Classification Standard (GICS).

3.2 Macroeconomic data

Following GRS, we consider a large panel of economic series, including surveys (such as the Purchasing Managers' Survey, the Consumer Confidence Survey index, and the Michigan Survey of Consumers), real variables (such as industrial production and the employment situation), GDP and income releases, producer and consumer prices, financial variables, interest rates, money and credit aggregates, and housing market conditions. The panel captures the bulk of closely watched indicators of the macroeconomy. We collect key macroeconomic releases from Datastream between 1987:Q1 and 2015:Q4. All series are transformed to induce stationarity.

To align macro data with accounting data, we use the calendar of data releases within the month and allocate macroeconomic series into weekly blocks. We then use the weekly sequence to capture the flow of macroeconomic data throughout the quarter. We refer the readers to Table 3 in Giannone et al. (2008) for details about the calendar of data releases and Appendix 2 in Carabias (2018) for details about specific series.

Consistent with GRS, we evaluate the GRS factor in a pseudo real-time setting using the most recent vintages of the economic series. This is because real-time vintages are not available for all economic series. Liebermann (2014), however, confirms the usefulness of the GRS model in a fully real-time setting. With respect to our evaluation of the accounting factor, we use the as first reported accounting data from the original corporate financial reports, untainted by future restatements in the underlying data.

3.2 Research design timeline

Figure 1 presents the research design timeline using the second calendar quarter of 2015 as an illustrative example. Our dynamic factor model generates nowcasts for the current quarter (2015:Q2) and forecasts for the subsequent quarter (2015:Q3). Starting with the current quarter, the BEA released the advance estimate of GDP growth for 2015:Q2 on July 30, 2015, which is one month after the end of the quarter. The timeline illustrates that while the advance estimate of GDP growth is released one month after the end of the quarter, the publication lag is even longer for GDI growth. The BEA released the preliminary NIPA estimate of GDI growth for 2015:Q2 on August 27, 2015, which is nearly two months after the end of the quarter. With respect to economic output for 2015:Q3, the BEA released the advance estimate of GDP growth on October 29, 2015 and the preliminary estimate of GDI growth on November 24, 2015.

Our dynamic factor model approach utilizes the weekly flow of accounting data released throughout the quarter; that is, from the first week of April (week 1) to the last week of June (week 12). In our stylized calendar, the disclosure gap, which is the time between the fiscal quarter end and the accounting disclosure date, ranges from 1 to 6 weeks. This is because publicly traded firms file their quarterly reports within 45 days after the end of the fiscal quarter.

Since accounting periods do not always coincide with calendar periods, as we explain in Section 3.1 and Appendix 2, we realign off-calendar accounting data prior to constructing the sector-level aggregate series of growth and profitability. The realignment ensures that all accounting data released in the current calendar quarter refers to the prior calendar quarter (the reference quarter). In our illustrative example, the announcement quarter is 2015:Q2 and the reference quarter is 2015:Q1.

4. Empirical results

In this section, we first describe the flow of accounting data. We then evaluate the nowcasting and forecasting gains from incorporating the flow of accounting data within the context of the GRS dynamic factor model. Our granular analysis evaluates the incremental macro content of the flow of accounting data with respect to nowcasting and forecasting product-side and income-side measures of economic output in the national accounts.

4.1 Flow of accounting data

Figure 2, Panel A, shows the flow of accounting data at weekly frequencies separately for each calendar quarter. The top panels correspond to quarters one (January, February, March) and two (April, May, June), and the bottom panels correspond to quarters three (July, August September) and four (October, November, December). The following observations are in order. First, nearly half of all firms disclose their accounting data between weeks 1 and 4 of the current quarter, with a disproportionate fraction of firms releasing their data in week 4. Indeed, for all calendar quarters, the flow of accounting data spikes in week 4 and subsequently tapers off with most firms releasing by week 6.

We note that the flow of accounting data is very consistent across quarters two, three, and four, with the cumulative frequency of reporting companies reaching >50% by week 4 and >70% by week 6. In the first calendar quarter, however, we observe that while the flow of accounting data also spikes in week 4, the frequency of reporting companies is more spread out with the cumulative flow of accounting data reaching >50% by week 6. This is because the majority of firms have calendar fiscal year-ends for which the first calendar quarter coincides with the release of annual accounting data for the previous year that typically takes more time to prepare relative to the accounting data for interim quarters.

Figure 2, Panel B, presents the weekly flow of accounting data across the 24 GICS industry groups and offers a visualization of how the industry accounting data enter our model. We find that the weekly flow of accounting data across different sectors is consistent with the pooled evidence in Figure 2, Panel A. Indeed, looking across industry groups, we observe that the flow of accounting data spikes in week 4. Sorting industry groups based on the frequency of reporting companies in week 4, we find that banks, semiconductors, utilities, transport, and materials consistently rank at the top five.

Figure 2, Panel C, shows the revisions of the profitability and growth factors throughout the quarter. We measure the revision of each factor component as the absolute difference between each weekly value and the ending value in week 12 of the quarter. The top (bottom) two panels report the mean values (standard deviation) of the profitability and growth factor revisions throughout the quarter. The solid lines correspond to the dynamics of the aggregate-level components, and the dots correspond to the dynamics of the industry-level components.

The evidence shows that the absolute deviation of the accounting factor components from their ending quarterly values converges to zero by week 4 of the quarter. This is true both at the aggregate level and across GICS industry groups. In addition, while the variability of the profitability and growth factor revisions drops throughout the quarter, most of the action is concentrated in the first four weeks of the quarter. These findings are consistent with the fact that the flow of accounting data spikes in week 4 of the quarter.[4]

Figure 3 plots the ACC nowcast in week 4 of each quarter versus the realized GDP growth between 1987:Q1 and 2015:Q4. The plot shows that the ACC nowcast tracks variation in GDP growth. The plot also shows that the ACC nowcast is effective in capturing the recessions of the early 1990s, the early 2000s, as well as the Great Recession of 2008. Downturns of economic activity have generally not been predicted before their occurrence and recessions were not recognized even as they occurred (e.g., Fintzen and Stekler 1999; Culbertson and Sinclair 2014). Furthermore, downturns have been associated with large spikes in uncertainty (e.g., Bloom 2014). A key implication is that the flow of accounting data might be particularly relevant in downturns of economic activity and, more generally, in periods of high aggregate uncertainty.

Figure 3 also shows that the ACC nowcast comoves with the consensus projection available from Philadelphia Fed's Survey of Professional Forecasters (SPF). Regarding the SPF timeline, we note that the panelists receive the questionnaires at the end of the 1st month of each quarter; that is, week 4 in our stylized calendar. The SPF panelists submit their responses by the mid of the 2nd month of each quarter, which corresponds to weekly block 6 in our stylized calendar. As an illustrative example, Figure 1 shows that in 2015:Q2 the SPF panelists submitted their responses by mid-May 2015, which corresponds to week 6 relative to the beginning of the quarter. From the SPF timeline, it follows that the consensus nowcast

[4] We note that an alternative approach to extracting the systematic content of corporate financial reports would be to use the pooled cross-sectional average values of the accounting series. A key advantage of the factor-model approach is that it exploits across-sector and time-series dynamics. Such dynamics, however, are muted when using pooled cross-sectional averages. Brave et al. (2014) show that a dynamic approach is superior to simple averages for the purpose of constructing indexes aimed at nowcasting business cycles.

becomes available only after the peak of the accounting earnings season and, therefore, the panelists can inform their projections using available accounting data.

4.2 Accounting factor model performance

Figure 4 shows the weekly evolution of %MSFEs from the ACC model projections. We provide out-of-sample results for current quarter nowcasts and next quarter forecasts of real and nominal GDP growth.

Starting with real GDP growth, Figure 4, Panel A, shows that the ACC model reduces estimation uncertainty throughout the quarter and offers significant gains relative to the random-walk model. Indeed, the %MSFE is consistently less than one across all weekly blocks. By week 4, the %MSFE is 0.86 for current quarter nowcasts and 0.89 for next quarter forecasts. Cumulating more accounting data beyond week 4 does not add further to the ACC model's out-of-sample performance. This finding is consistent with the fact that the flow of accounting data spikes in week 4, as illustrated in our stylized calendar of the flow of corporate financial reports.

Turning to nominal GDP growth, Figure 4, Panel B, provides consistent evidence that the ACC model reduces estimation uncertainty throughout the quarter and offers significant improvements relative to the random-walk model. The %MSFE is consistently less than one across all weekly blocks. By week, 4 the %MSFE of the ACC model is 0.84 for both the current quarter nowcast and the next quarter forecast of nominal GDP growth. Again, we observe that adding more accounting data to the ACC factor model beyond what is cumulated by week 4 leads to small incremental MSFE gains.

Taken together, the evidence establishes that the real-time flow of accounting data, is relevant for nowcasting and forecasting nominal and real GDP growth. Next, we assess the incremental nowcasting and forecasting gains from incorporating the flow of accounting data alongside the information set of the GRS model.

4.3 Incremental gains from incorporating the flow of accounting data

Panels A and B of Table 1 report out-of-sample %MSFEs of nominal and real GDP growth projections for the current and subsequent quarter based on the ACC model, the GRS model, and the GRS^+ model. Across the weekly data blocks, we find evidence of improvements in the out-of-sample performance of the GRS^+ model with most of the incremental gains accruing within the first four weeks from the beginning of the current quarter. This is consistent with the fact that the frequency of corporate financial reports across industry groups spikes in week 4 after the quarter ends, when the accounting earnings season is in full swing.

The incremental gains from incorporating the flow of accounting data are more pronounced when forecasting nominal GDP growth for the subsequent quarter. Focusing on week 4, the %MSFE for the next quarter forecast of nominal GDP growth is 0.84 for the ACC model, 0.91 for the GRS model, and 0.87 for the GRS^+ model. At the same time, the %MSFE for next quarter forecast of real GDP growth is 0.89 for the ACC model, 1.02 for the GRS model, and 0.97 for the GRS^+ model.

Clearly, the evidence highlights that the real-time flow of accounting data embeds forward-looking information that is incrementally relevant for anticipating fluctuations in GDP growth. We further observe that the incremental gains from incorporating the flow of accounting data are even more pronounced for anticipating fluctuations in nominal GDP growth. This observation is consistent with the fact that the corporate financial reports are expressed in nominal terms.

To shed light on the incremental gains from incorporating the flow of accounting data, Figure 5 presents the relative contribution of the GRS factor and the ACC factor towards the total R^2 of the GRS$^+$ bridge equations. The R^2 decomposition is based on the Shapley value (e.g., Shapley 1953; Shorrocks 1982). Given that the ACC and GRS factors have overlapping content, the decomposition of R^2 shows the marginal contribution of each factor towards the GRS$^+$ model's explanatory power.

Focusing on the nowcasting bridge equation, Figure 5, Panel A, shows that the total R^2 increases throughout the quarter from 28% in week 1 to 53% in week 12. The marginal contribution of the ACC factor is highest in week 4, though the GRS factor contributes more to the model's explanatory power. Turning to the forecasting bridge equation, Figure 5, Panel B, shows that the R^2 also increases throughout the quarter from 8% in week 1 to 30% in week 12. We observe that the spread between the relative contribution of the GRS factor and the ACC factor to the R^2 of the GRS$^+$ model is lower for the forecasting bridge equation relative to the nowcasting bridge equation. In fact, for weeks 3 and 4 of the quarter we observe that the relative contribution of the ACC factor is in line with that of the GRS factor.

Taken together, the evidence suggests that incorporating the flow of accounting data within the context of the GRS model can help reduce estimation uncertainty throughout the quarter. The fact that most of the incremental gains from the cumulative flow of accounting data accrue by week 4 implies that the accounting factors can be used to reduce estimation uncertainty during the first month of the quarter, which is the time when it is needed the most. Indeed, GRS point out that factor model estimates become more accurate than benchmark estimates only after the release of the employment situation report at the beginning of the second month of the quarter, which is effectively the first release that contains hard economic data for the current quarter.

Another desirable feature of the accounting factor extraction is that it helps improve the GRS model performance beyond the current quarter projection. Thus, our paper has implications for prior evidence of limited GDP predictability (e.g., d'Agostino et al. 2006).

4.4 GDP component analysis

Why is accounting information relevant for macro nowcasting and forecasting? With this question in mind, we decompose real GDP growth into its major components as identified by the BEA, including consumption, non-residential and residential investment, government spending, plus net exports. Panels C through G of Table 1 present the out-of-sample %MSFEs of the nowcasts and forecasts of GDP components for the ACC model, the GRS model, and the GRS$^+$ model.

Focusing on personal consumption, which historically accounts for 70% of GDP, we observe that by week 4 the ACC model beats the out-of-sample nowcasting and forecasting performance of the GRS model. This result is especially striking considering that the GRS model incorporates the information set of a large panel of macroeconomic releases while the ACC model is purely based on financial accounting data from the corporate financial reports. In addition, the GRS$^+$ model offers incremental gains from incorporating the flow of accounting data with most of these gains accruing within the first month of the current quarter. Focusing on week 4, the %MSFE for the current quarter nowcast of consumption growth is 0.64 for the ACC model, 0.67 for the GRS model, and 0.63 for the GRS$^+$ model. Turning to the next quarter forecast of consumption growth, the %MSFE in week 4 is 0.67 for the ACC model, 0.70 for the GRS model, and 0.65 for the GRS$^+$ model.

With respect to non-residential investment, which is known to be the most important component of gross private domestic investment, we find evidence of incremental nowcasting and forecasting gains from incorporating the flow of accounting data with most of the gains accruing within the first month of the current quarter. By week 4, the %MSFE for the current quarter nowcast of non-residential investment growth is 0.79 for the ACC model, 0.54 for the GRS model, and 0.49 for the GRS$^+$ model. At the same time, the %MSFE for the next quarter forecast of non-residential investment growth is 0.99 for the ACC model, 1.00 for the GRS model, and 0.94 for the GRS$^+$ model. With respect to the remaining GDP components, we find that incorporating the flow of accounting data does not improve the performance of the GRS$^+$ model relative to the GRS model.

Overall, the GDP component analysis provides evidence that the real-time flow of accounting data is especially relevant for projecting personal consumption and non-residential investment—the two most dominant components of NIPA's product side measure of GDP growth. The evidence provides new insights into why accounting information is relevant for macro nowcasting and forecasting.

4.5 Gross value added by sector

What is the relevance of accounting data for projecting economic activity across sectors? The BEA disaggregates GDP into (a) gross value added of business (77% of GDP), (b) gross value added of households and non-profit institutions serving households (10% of GDP), and (c) gross value added of the general government (13% of GDP).[5]

Table 2 presents the out-of-sample %MSFEs for the nowcasts and forecasts of growth in the gross value added by sector. Starting with the business sector, Panel A of Table 2 shows that the factor model projections outperform the random-walk benchmark. Across weekly data blocks, the ACC factor model performance improves with the cumulation of accounting data and the incremental MSFE gains plateau within the first month of the quarter. The MSFE comparisons show that there are incremental forecasting gains from incorporating the flow of accounting data in the GRS$^+$ model. The %MSFE for the next quarter forecast is 0.87 for the GRS model and 0.82 for the GRS$^+$ model. Turning to growth in gross value added by households and the general government, which together account for the remaining of 23% of GDP, we find that the factor model projections underperform the random-walk benchmark with no evidence of gains from incorporating the flow of accounting data.

Overall, the key finding here is that the macro content of the accounting factors flows through business sector activity. This is an important finding for two reasons. First, the gross value added of the business sector accounts for as much as 77% of GDP. Second, BEA's publication lag is significantly longer for the sector-level statistics compared to national GDP. Specifically, the BEA releases the sector-level statistics after the third release of GDP, typically, more than 100 days after the end of the quarter. It follows that our approach to incorporating the real-time flow of financial accounting data could help mitigate the publication lag of the BEA releases of sector-level statistics.

---

[5] The historical data on gross value added by sector (in chained dollars) is available from BEA's Table 1.3.6. Starting on April 25, 2014, the BEA also issues quarterly GDP statistics across industry groups. The historical GDP-by-industry statistics are available from the BEA only from 2005:Q1 onward. Due to the short history of GDP-by-industry data, we focus our efforts on projecting BEA's sector-level statistics. For more information, see BEA's May 2014 briefing on "New Quarterly Gross Domestic Product by Industry Statistics" available online.

4.6 From the product side to the income side of the national accounts

There are two sides in the measurement of economic output. The product side of the NIPA measures GDP as the value of the goods and services produced by the nation's economy less the value of the goods and services used in production and is equal to consumption, investment, government spending, plus net exports. The income side of the NIPA features GDI as the sum of incomes earned and costs incurred in the production of GDP. While conceptually the product and income sides should articulate, GDI and GDP differ in practice because they are based on different estimation methods and largely independent data sources. Over time, the two series are highly correlated and the average deviation between GDP and GDI, known as statistical discrepancy, is 0.36% of GDP. Prior work on the measurement of economic output makes the case that GDI deserves significant attention and may even better reflect business cycle fluctuations than GDP (e.g., Nalewaik 2010).

A key difference between the product and the income side of the NIPA is the BEA's publication lag. While the BEA releases the advance estimate of GDP growth near the end of the first month following the quarter end, the publication lag is longer for income-side measures of output. For the first, second, and third quarters of the year, the BEA releases the initial estimates of GDI and other income-side series, including NIPA corporate profits, nearly two months after the quarter end together with the second GDP estimate.[6] For the fourth quarter, the income-side estimates are released almost three months after the quarter end along with the third GDP estimate. According to the NIPA Handbook, the BEA does not prepare advance income-side estimates because of a lag in the availability of source data.

Panels A and B of Table 3 report the out-of-sample %MSFEs of nowcasts and forecasts of GDI growth for the ACC model, the GRS model, and the GRS^{+} model. The evidence shows that the flow of accounting data is incrementally relevant for nowcasting and forecasting GDI growth. Consistent with our evidence from the product side of the NIPA, the incremental gains from incorporating accounting data plateau by week 4 of the current quarter and are especially pronounced for nowcasting nominal GDI growth. By week 4, the %MSFE for the current quarter nowcast of nominal GDI growth is 0.77 for the GRS model and 0.68 for the GRS^{+} model. At the same time, the %MSFE for the next quarter forecast of nominal GDI growth is 1.09 for the GRS model and 0.97 for the GRS^{+} model.

In the BEA's NIPA (see NIPA Table 1.10), GDI is equal to net operating surplus (23% of GDI), which measures business income before subtracting financing costs and business transfer payments, plus compensation of employees (56% of GDI), which measures the income accruing to employees as remuneration for their work for domestic production, plus the consumption of fixed capital (14% of GDI), which measures the change in the value of the stock of fixed assets due to wear and tear, obsolescence, accidental damage, and aging, plus taxes on production and imports less subsidies (7% of GDI).

From our earlier GDP component analysis (Section 4.4), we note that the flow of accounting data is especially relevant for projecting personal consumption and non-residential investment. We also note that personal consumption comoves with the employee compensation component of GDI, while non-residential investment is closely related to the net operating surplus (NOS) component of GDI. Thus, we predict that the gains from

[6] To illustrate, while the advance estimate of GDP growth for 2015:Q2 was released on July 30, 2015, the preliminary estimates of GDI and corporate profits were released on August 27, 2015, nearly two months after the end of the quarter.

incorporating the flow of accounting data should be especially pronounced when projecting the employee compensation and NOS components of GDI.

Panels C through F of Table 3 present the out-of-sample %MSFEs of the factor model projections of real GDI components. Except for the consumption of fixed capital, the factor models outperform the random-walk benchmark when projecting GDI components. Importantly, we find that the flow of accounting data is especially relevant for projecting NOS and employee compensation—the two most dominant components of GDI.

Focusing on the NOS component of GDI, we find that within the first month of the current quarter the ACC factor model beats the out-of-sample performance of the GRS model. By week 4, the %MSFE for the current quarter nowcast of NOS growth is 0.62 for the ACC model and 0.66 for the GRS model. At the same time, the %MSFE for the next quarter forecast of NOS growth is 0.64 for the ACC model and 0.69 for the GRS model. Turning to employee compensation, we find that there are incremental gains from incorporating the flow of accounting data in the GRS^+ model especially when forecasting the next quarter. By week 4, the %MSFE for the current quarter nowcast of employee compensation growth is 0.57 for the ACC model, 0.51 for the GRS model, and 0.49 for the GRS^+ model. At the same time, the %MSFE for the next quarter forecast of NOS growth is 0.62 for the ACC model, 0.63 for the GRS model, and 0.55 for the GRS^+ model.

We observe that the NOS component of GDI consists of the NOS of private enterprises (99.98% of NOS) and the current surplus of government enterprises (0.02% of NOS). In turn, the NOS of private enterprises consists of (a) corporate profits from current production (35% of NOS), (b) proprietors' income (32% of NOS), which measures current-production income of sole proprietorships, partnerships, and tax-exempt cooperatives, (c) net interest and miscellaneous payments (22% of NOS), (d) rental income (8% of NOS), and (e) business transfer payments (3% of NOS). To gain further insights into the macro content of accounting data, we next break down NOS of private enterprises.

Table 4 reports the out-of-sample %MSFEs for nowcasts and forecasts of NOS components. With the exception for corporate profits and business transfer payments, the dynamic factor models underperform the random-walk benchmark when nowcasting and forecasting other NOS components, including proprietors' income, net interest and miscellaneous payments, and rental income. Focusing on the corporate profit component of NOS, the evidence shows that the ACC factor model is very effective in reducing nowcasting uncertainty throughout the quarter and offers significant improvements relative to the GRS model. Again, we find that most of the gains from incorporating the real-time flow of financial accounting data are realized within the first month of the current quarter. Indeed, cumulating accounting data beyond the first month does not lead to incremental MSFE gains. By week 4, the %MSFE for the current quarter nowcast of corporate profit growth is 0.49 for the ACC model, 0.60 for the GRS model, and 0.54 for the GRS^+ model.

While incorporating accounting data within the GRS model leads to incremental MSFE gains, the ACC factor performs better on a stand-alone basis with respect to nowcasting the corporate profit component of NOS. This is an important result given that the ACC factor model does not incorporate any other economic indicators beyond the flow of accounting data. To be clear, however, this result does not reflect a mechanical link between accounting data and NIPA corporate profits. In Appendix 3, we explain in detail that financial accounting earnings reported by public companies differ from BEA's NIPA corporate profits along several dimensions, including the purpose, coverage, and underlying source data.

Overall, our evidence shows that the cumulative flow of accounting data contains relevant information for both the product side and the income side of the national accounts. Furthermore, our approach to incorporating the real-time flow of accounting data has the potential to mitigate the longer publication lag of the income side of the national accounts. To illustrate, for the second quarter of 2015, the BEA released the preliminary estimate of NIPA corporate profits along with the second estimate of GDP growth on August 27, 2015, which is nearly two months after the end of the quarter.

5. Conclusion

Our paper pioneers a new approach to incorporating the continuous flow of accounting data in the GRS dynamic factor model. Our extracted accounting factors exploit across-sector comovements in corporate value creation drivers and can be used together with other closely watched economic indicators. The evidence shows that our weekly updated accounting factors are incrementally relevant for nowcasting and forecasting GDP growth within the context of the GRS model.

When we decompose GDP, we find that the accounting factor content is mostly related to personal consumption and non-residential investment—two dominant components of the product side of the NIPA. Breaking down gross value added by sector, we further uncover that the macro content of the accounting factors flows through business sector activity, which accounts for three-fourths of output. Our analysis shows that the flow of accounting data is also relevant for the income side of the NIPA. A granular decomposition of GDI reveals that the accounting factor content is especially relevant for projecting employee compensation and net operating surplus—two dominant components of GDI.

Overall, our paper highlights the need for cross-disciplines fertilization through the synthesis of ideas in macro-accounting. An interesting direction would be to explore the origins of the macro content of financial accounting data back to first principles. One such principle is the accrual basis of accounting, whereby revenues are reported when earned rather than when cash is received, and expenses are matched with the related revenues as incurred rather than when cash is paid. Separating cash flows from accruals and breaking down accrual accounts could lead to a more granular understanding of the macro content of corporate financial reports.

References

Abdalla, A. M. and Carabias, J. M., 2020. From accounting to economics: The role of aggregate special items in gauging the state of the economy. Working Paper.

Acemoglu, D., Carvalho, V.M., Ozdaglar, A. and Tahbaz-Salehi, A., 2012. The network origins of aggregate fluctuations. *Econometrica*, 80(5), pp.1977-2016.

Ball, R. and Brown, P., 1968. An empirical evaluation of accounting income numbers. *Journal of Accounting Research*, pp.159-178.

Bańbura, M., Giannone, D., Modugno, M. and Reichlin, L., 2013. Now-casting and the real-time data flow. In Handbook of economic forecasting (Vol. 2, pp. 195-237). Elsevier.

Bernard, V.L. and Thomas, J.K., 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics*, 13(4), pp.305-340.

Bianchi, F., Ludvigson, S.C. and Ma, S., 2020. Belief distortions and macroeconomic fluctuations (No. w27406). National Bureau of Economic Research.

Bloom, N., 2014. Fluctuations in uncertainty. *Journal of Economic Perspectives*, 28(2), pp.153-76.

Bok, B., Caratelli, D., Giannone, D., Sbordone, A.M. and Tambalotti, A., 2018. Macroeconomic nowcasting and forecasting with big data. *Annual Review of Economics*, 10, pp.615-643.

Boot, J. C., Feibes, W., and Lisman, J. H. C., 1967. Further methods of derivation of quarterly figures from annual data. *Applied Statistics*, 16(1), pp.65-75.

Brave, S.A. and Butters, R., 2014. Nowcasting using the Chicago FED national activity index. *Economic Perspectives*, 38(1): 19-37.

Carabias, J.M., 2018. The real-time information content of macroeconomic news: implications for firm-level earnings expectations. *Review of Accounting Studies*, 23(1), pp.136-166.

Carvalho, V. and Gabaix, X., 2013. The great diversification and its undoing. *American Economic Review*, 103(5), pp.1697-1727.

Chen, B., 2007. An empirical comparison of methods for temporal disaggregation at the national accounts. Office of Directors Bureau of Economic Analysis, Washington, DC.

Chen, B., and Andrews, S.H., 2008. Research spotlight: An empirical review of methods for temporal distribution and interpolation in the national accounts. *Survey of Current Business*, 88, pp. 31-37

Cholette, P.A., 1984. Adjusting sub-annual series to yearly benchmarks. *Survey Methodology*, 10 (1), pp. 35–49.

Culbertson, D.S., and Sinclair, T.M., 2014. The failure of forecasts in the Great Recession. *Challenge*, 57(6), pp.34-45.

d'Agostino, A., Giannone, D. and Surico, P., 2006. (Un) predictability and macroeconomic stability. SSRN Working Paper 890990.

Dagum, E.B. and Cholette, P.A., 2006. Benchmarking, temporal distribution, and reconciliation methods for time series (Vol. 186). Springer Science & Business Media.

Denton, F.T., 1971. Adjustment of monthly or quarterly series to annual totals: An approach based on quadratic minimization. *Journal of the American Statistical Association*, 66 (333), pp. 99–102.

Dutta, S., Patatoukas, P.N. and Wang, A.Y., 2017. Identifying the roles of accounting accruals in corporate financial reporting. SSRN Working Paper 3279895.

Edwards, E., and P. Bell. 1961. The theory and management of business income. University of California Press, California.

Fintzen, D. and Stekler, H.O., 1999. Why did forecasters fail to predict the 1990 recession? *International Journal of Forecasting*, 15(3), pp.309-323.

Foster, G., 1981. Intra-industry information transfers associated with earnings releases. *Journal of Accounting and Economics*, 3(3), pp.201-232.

Foster, G., Olsen, C. and Shevlin, T., 1984. Earnings releases, anomalies, and the behavior of security returns. *The Accounting Review*, pp.574-603.

Gabaix, X., Gopikrishnan, P., Plerou, V. and Stanley, H.E., 2003. A theory of power-law distributions in financial market fluctuations. *Nature*, 423(6937), pp.267-270.

Gabaix, X., 2011. The granular origins of aggregate fluctuations. *Econometrica*, 79(3), pp.733-772.

Giannone, D., Reichlin, L. and Small, D., 2008. Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics*, 55(4), pp.665-676.

Hornstein, A., 2000. The business cycle and industry comovement. F*RB Richmond Economic Quarterly*, 86(1), pp.27-48.

Hornstein, A. and Praschnik, J., 1997. Intermediate inputs and sectoral comovement in the business cycle. *Journal of Monetary Economics*, 40(3), pp.573-595.

Horvath, M., 2000. Sectoral shocks and aggregate fluctuations. *Journal of Monetary Economics*, 45(1), pp.69-106.

Konchitchki, Y. and Patatoukas, P.N., 2014. Accounting earnings and gross domestic product. *Journal of Accounting and Economics*, 57(1), pp.76-88.

Konchitchki, Y. and Patatoukas, P.N., 2014. Taking the pulse of the real economy using financial statement analysis: Implications for macro forecasting and stock valuation. *The Accounting Review*, 89(2), pp.669-694.

Laurion, H. and Patatoukas, P.N., 2016. From micro to macro: Does conditional conservatism aggregate up in the National Income and Product Accounts? *Journal of Financial Reporting*, 1(2), pp.21-45.

Liebermann, J., 2014. Real-time nowcasting of GDP: A factor model vs. professional forecasters. *Oxford Bulletin of Economics and Statistics*, 76(6), pp.783-811.

Lucas Jr, R.E., 1977, January. Understanding business cycles. In Carnegie-Rochester Conference Series on Public Policy (Vol. 5, pp. 7-29). North-Holland.

Nalewaik, J.J., 2010. The income-and expenditure-side estimates of U.S. output growth [with comments and discussion]. Brookings Papers on Economic Activity, pp.71-127.

Patatoukas, P.N., 2014. Detecting news in aggregate accounting earnings: Implications for stock market valuation. *Review of Accounting Studies*, 19(1), pp.134-160.

Patatoukas, P.N., Yezegel, A. and Zeng, J., 2020. On the origins of forecast walk-downs: A macro-to-micro perspective. SSRN Working Paper 3222884.

Penman, S.H., 2013. Financial statement analysis and security valuation. McGraw-Hill.

Shapley, L.S., 1953. A value for n-person games. *Contributions to the Theory of Games*, 2(28), pp.307-317.

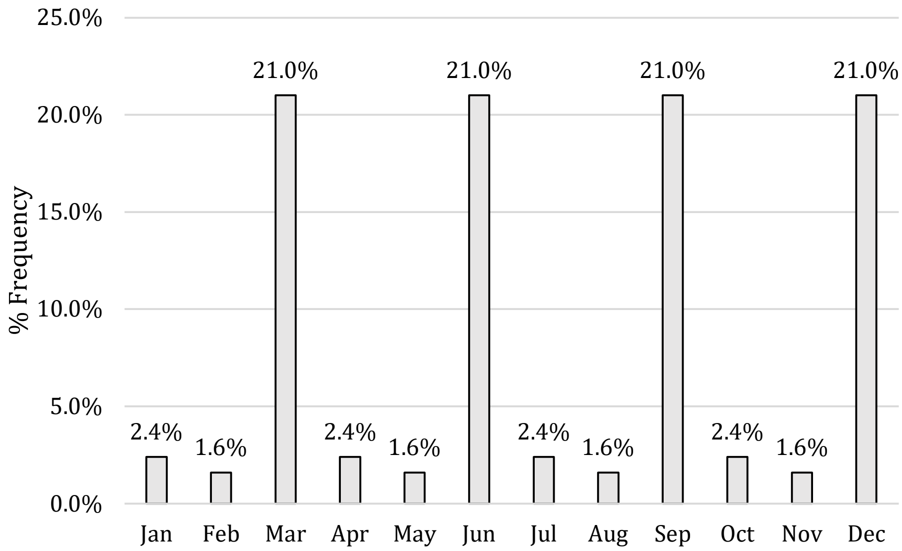
Shorrocks, A.F., 1982. Inequality decomposition by factor components. *Econometrica*, 50 (1), pp.193-211.

Appendix 1
Variable definitions

Description	Variable	Definition
Weighting parameters	Enterprise value	We measure enterprise value as the sum of market value of equity plus the book value of current and non-current debt obligations.
	Firm cyclicality	We measure firm cyclicality as the slope coefficients from firm-level time-series regressions of firm profitability on real GDP growth. We use expanding windows and require a minimum of twenty consecutive observations to estimate these regressions.
Accounting series	$rnoa$	We measure return on net operating assets as the ratio of annualized net operating income divided by average net operating assets: $rnoa_q = \left(4 \times noi_q\right) / \left(\left(noa_q + noa_{q-4}\right)/2\right)$. We measure net operating income (noi) as net income plus the after-tax interest expense. We measure net operating assets (noa) as the book value of equity plus the book value of current and non-current debt obligations. The sector-level $rnoa$ series is a weighted average of firm-level $rnoa$ using accounting data cumulated from the beginning of the quarter to the end of each week. For the weights, we use the product of the total enterprise value multiplied by firm-level cyclicality. We define sectors using the 24 GICS industry groups.
	$growth$	We measure sales growth as the year-over-year percentage change in quarterly revenue; that is, $growth_q = (saleq_q / saleq_{q-4}) - 1$. The sector-level $growth$ series is a weighted average of firm-level $growth$ using accounting data cumulated from the beginning of the quarter to the end of each week. For the weights, we use the product of the total enterprise value multiplied by firm-level cyclicality. We define sectors using the 24 GICS industry groups.

Appendix 2
Realigning accounting data

Accounting periods do not always coincide with calendar periods. To document the prevalence of the misalignment issue, the figure below reports the frequency of fiscal quarter-end dates by month. We note that all accounting periods always cover whole months.



The evidence shows that the accounting period coincides with the calendar quarter for most listed firms. Specifically, we find that 84% of observations in our sample have calendar fiscal quarter-end dates ending on the last day of March, June, September, and December. Misaligned observations account for 16% of our sample. More specifically, 9.6% of observations have fiscal quarter-end dates ending on the last day of January, April, July, and October. The remaining 6.4% of observations have fiscal quarter-end dates ending on the last day of February, May, August, and November. The prevalence of misalignment is somewhat lower on a value-weighted basis with misaligned observations accounting for 15% of aggregate revenues and 11% of enterprise value.

Due to heterogeneity in accounting periods, it would be incorrect to aggregate accounting data over different accounting periods for a given calendar quarter. To avoid mixing calendar with off-calendar observations, we realign accounting data items at the individual firm level prior to constructing the sector-level aggregate series of growth and profitability. Specifically, we first decompose (interpolate) off-calendar quarterly accounting series into their unobservable monthly components and then combine the monthly components into "synthetic" calendar quarter series.

For the time-series disaggregation, we use the first difference smoothing procedure of Boot, Feibes, and Lisman (1967), henceforth BFL. The BFL constrained optimization procedure minimizes the sum of squared first differences in the interpolated series subject to the temporal aggregation constraint. The BFL procedure is a special case of the Denton-Cholette procedure for temporal disaggregation without high frequency indicator series (e.g., Denton 1971; Cholette 1984; Dagum and Cholette 2006).

We note that the BEA routinely uses the BFL procedure for temporal disaggregation of low frequency time series with no indicators (e.g., Chen 2007; Chen and Andrews 2008). While the BFL procedure allows the temporal disaggregation of quarterly accounting data into monthly series, we acknowledge that there is no way to perfectly make up for the absence of monthly accounting data since companies are only mandated to report at quarterly frequencies. When compared to a linear intrapolation procedure, also known as fractional calendarization, the BFL procedure results in smoother intrapolated series since it accounts for the trend between consecutive quarters (e.g., Dagum and Cholette 2006). In additional analysis, we find consistent results using the fractional calendarization procedure to realign accounting data.

Appendix 3
Accounting earnings and NIPA corporate profits

In this appendix, we discuss the purpose, coverage, and source data of accounting earnings from the corporate financial reports and corporate profits in the BEA's NIPA. Our discussion is based on the FASB Concepts Statements and the NIPA Handbook. In sum, the discussion highlights that accounting earnings differ from NIPA corporate profits along several dimensions, including the purpose, coverage, and source data.

Accounting earnings

Accounting earnings are produced based on Generally Accepted Accounting Principles (GAAP) by public companies filing their reports with the SEC. The Financial Accounting Standards Board (FASB), an independent, private-sector, not-for-profit organization, is recognized by the SEC as the designated accounting standard setter for public companies. The FASB promulgates accounting standards through an open process and its mission is to promote financial reporting that provides useful information to investors and other users of corporate financial reports.

According to FASB's Concepts Statement No. 1, the primary focus of financial reporting is to provide information about earnings. The accrual accounting system records the financial effects of transactions that have consequences on firm performance in the periods in which those transactions occur rather than only in the period in which cash is received or paid by the firm. When there is a timing mismatch between the occurrence of the economic transaction and the associated cash transaction, the accounting system records accruals to recognize revenues and associated expenses in the period of the economic transaction. Accruals align cash flows and the economic activities generating the cash flows. Accrual accounting is concerned with expected future cash receipts and payments and provides information about a firm's assets and liabilities and changes in them that cannot be obtained by accounting for only cash receipts and outlays.

As defined in FASB's Concepts Statement No. 6, "…*by accounting for noncash assets, liabilities, revenues, expenses, gains, losses, accrual accounting links an entity's operations and other transactions, events, and circumstances that affect it with its cash receipts and outlays*." Common examples of accruals include changes in accounts receivable and payable, changes in inventory, changes in accrued income taxes, depreciation, and amortization accruals, and other, as well as asset write-downs and impairments. See Dutta et al. (2020) for a detailed breakdown of accruals.

NIPA corporate profits

Different from GAAP accounting earnings, NIPA corporate profits are prepared by the BEA and measure income from current production, defined as "receipts arising from current production less associated expenses." The domestic portion of NIPA corporate profits is a component of Gross Domestic Income (GDI) featured in the income side of Account 1 in the BEA's NIPA.

While accounting earnings are reported in the SEC filings of public firms, NIPA corporate profits cover all publicly traded as well as privately held corporations required to file federal corporate tax returns. NIPA earnings are derived from tax corporate profits after several adjustments. The BEA uses data from aggregate corporate tax returns as the primary input for the annual estimates of NIPA corporate profits. This is because the aggregated corporate tax return data cover the entire corporate universe, while financial accounting data covers only the subset of publicly traded corporations. In addition, the concepts and definitions underlying the corporate tax return data closely parallel the framework underlying BEA's measurement of NIPA corporate profits. Laurion and Patatoukas (2016) show that due to measurement differences, key properties of accrual accounting do not aggregate up from the firm-level corporate reports to NIPA measure of corporate profits.

Regarding higher frequency estimates of NIPA corporate profits, we note that the BEA obtains quarterly estimates by interpolation between annual estimates and for more recent quarters by extrapolation. For the first three quarters of the calendar year, the preliminary estimates of NIPA corporate profits are released approximately 55 days after the end of the quarter along with the second revised estimates of GDP for the quarter. For the fourth quarter of the calendar year, the publication lag is even longer, with the estimate released approximately 85 days after the end of the quarter.

Table 1
Out-of-sample nowcasts and forecasts of GDP growth and components

Panel A: Nominal GDP growth.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	0.88	0.74	0.70	0.91	1.02	1.04
2	0.89	0.69	0.70	0.84	0.96	0.96
3	0.88	0.69	0.66	0.85	0.95	0.90
4	0.84	0.67	0.62	0.84	0.91	0.87
5	0.84	0.66	0.58	0.84	0.87	0.78
6	0.85	0.58	0.52	0.85	0.82	0.81
7	0.85	0.58	0.52	0.86	0.82	0.80
8	0.84	0.58	0.53	0.86	0.80	0.78
9	0.85	0.58	0.52	0.86	0.77	0.72
10	0.84	0.51	0.46	0.85	0.75	0.75
11	0.84	0.51	0.47	0.85	0.75	0.75
12	0.83	0.51	0.47	0.85	0.73	0.72

Panel B: Real GDP growth.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	0.91	0.78	0.80	0.93	1.20	1.25
2	0.87	0.70	0.72	0.89	1.08	1.09
3	0.87	0.69	0.69	0.89	1.07	1.02
4	0.86	0.65	0.64	0.89	1.02	0.97
5	0.86	0.66	0.65	0.89	1.01	0.95
6	0.86	0.54	0.52	0.89	0.89	0.86
7	0.86	0.53	0.52	0.89	0.89	0.85
8	0.86	0.53	0.51	0.90	0.87	0.84
9	0.86	0.56	0.56	0.90	0.88	0.83
10	0.85	0.47	0.46	0.90	0.78	0.77
11	0.85	0.46	0.46	0.90	0.77	0.76
12	0.85	0.46	0.46	0.89	0.76	0.73

Panel C: Real personal consumption.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	0.72	0.67	0.71	0.68	0.74	0.73
2	0.70	0.66	0.67	0.68	0.71	0.69
3	0.70	0.66	0.65	0.70	0.71	0.69
4	0.64	0.67	0.63	0.67	0.70	0.65
5	0.65	0.67	0.63	0.68	0.70	0.68
6	0.64	0.66	0.61	0.69	0.68	0.66
7	0.64	0.67	0.62	0.69	0.68	0.65
8	0.64	0.68	0.64	0.70	0.68	0.66
9	0.64	0.66	0.62	0.70	0.68	0.67
10	0.64	0.64	0.61	0.69	0.67	0.67
11	0.64	0.64	0.61	0.69	0.67	0.67
12	0.64	0.64	0.61	0.69	0.67	0.65

Panel D: Real gross non-residential domestic investment.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	1.02	0.66	0.69	1.04	1.19	1.21
2	0.83	0.62	0.63	0.99	1.06	1.06
3	0.79	0.61	0.57	1.00	1.05	0.98
4	0.79	0.54	0.49	0.99	1.00	0.94
5	0.78	0.53	0.50	0.99	0.95	0.87
6	0.79	0.47	0.44	0.99	0.80	0.74
7	0.79	0.48	0.44	0.98	0.80	0.73
8	0.78	0.46	0.42	0.99	0.82	0.76
9	0.78	0.49	0.46	0.99	0.78	0.74
10	0.77	0.48	0.43	0.98	0.66	0.64
11	0.77	0.49	0.43	0.98	0.66	0.64
12	0.76	0.48	0.42	0.97	0.65	0.62

Panel E: Real gross residential domestic investment.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	1.05	0.87	0.99	0.98	1.02	1.06
2	0.96	0.86	0.90	0.97	1.05	1.05
3	0.96	0.85	0.88	0.96	1.04	0.97
4	0.99	0.85	0.87	0.99	1.03	0.99
5	0.98	0.80	0.79	1.00	1.00	0.97
6	0.98	0.80	0.82	1.01	1.00	0.98
7	0.99	0.80	0.82	1.01	1.00	0.99
8	0.98	0.79	0.82	1.01	1.00	0.99
9	0.99	0.70	0.71	1.02	0.97	0.98
10	0.98	0.73	0.76	1.02	0.96	0.97
11	0.98	0.72	0.76	1.02	0.96	0.98
12	0.98	0.72	0.75	1.02	0.96	0.97

Panel F: Real government consumption and gross investment.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	0.65	0.63	0.68	0.61	0.62	0.63
2	0.66	0.62	0.69	0.62	0.61	0.62
3	0.63	0.62	0.67	0.64	0.61	0.64
4	0.64	0.64	0.69	0.67	0.61	0.65
5	0.66	0.63	0.68	0.68	0.61	0.65
6	0.65	0.63	0.69	0.69	0.61	0.67
7	0.64	0.63	0.68	0.67	0.61	0.66
8	0.64	0.64	0.70	0.67	0.61	0.66
9	0.65	0.63	0.70	0.67	0.61	0.66
10	0.64	0.63	0.69	0.67	0.63	0.68
11	0.65	0.63	0.69	0.66	0.63	0.67
12	0.64	0.63	0.68	0.66	0.63	0.68

Panel G: Real net exports of goods and services.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	0.60	0.55	0.59	0.54	0.55	0.56
2	0.58	0.56	0.57	0.56	0.60	0.64
3	0.58	0.56	0.57	0.57	0.60	0.66
4	0.57	0.56	0.56	0.57	0.60	0.64
5	0.57	0.54	0.56	0.57	0.55	0.57
6	0.57	0.54	0.56	0.57	0.60	0.64
7	0.57	0.54	0.56	0.58	0.60	0.65
8	0.57	0.54	0.57	0.58	0.60	0.65
9	0.57	0.54	0.57	0.59	0.55	0.60
10	0.57	0.53	0.57	0.59	0.59	0.64
11	0.57	0.53	0.57	0.59	0.59	0.64
12	0.57	0.54	0.57	0.59	0.59	0.64

This table reports the out-of-sample MSFEs for nowcasts and forecasts of GDP growth and its components based on the ACC model, the GRS model, and the GRS+ model. The MSFEs are expressed as a percentage of the MSFE of the benchmark random-walk model.

Table 2
Out-of-sample nowcasts and forecasts of real gross value added by sector

Panel A: Business sector.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	0.80	0.70	0.72	0.86	0.95	1.00
2	0.76	0.67	0.70	0.76	0.90	0.83
3	0.77	0.67	0.67	0.79	0.89	0.77
4	0.76	0.65	0.64	0.82	0.87	0.82
5	0.77	0.62	0.60	0.81	0.85	0.78
6	0.77	0.55	0.53	0.82	0.80	0.75
7	0.77	0.55	0.53	0.81	0.80	0.75
8	0.76	0.57	0.54	0.82	0.80	0.76
9	0.77	0.53	0.49	0.82	0.77	0.71
10	0.76	0.47	0.45	0.81	0.74	0.72
11	0.76	0.46	0.45	0.82	0.74	0.72
12	0.75	0.47	0.45	0.81	0.74	0.70

Panel B: Households and non-profit institutions serving households.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	1.16	1.13	1.13	1.26	1.18	1.29
2	1.20	1.13	1.18	1.20	1.17	1.22
3	1.19	1.12	1.16	1.18	1.17	1.20
4	1.15	1.13	1.13	1.22	1.16	1.20
5	1.15	1.12	1.12	1.23	1.14	1.17
6	1.16	1.12	1.12	1.23	1.13	1.17
7	1.17	1.12	1.14	1.24	1.13	1.17
8	1.19	1.13	1.17	1.25	1.13	1.19
9	1.20	1.10	1.15	1.26	1.12	1.18
10	1.19	1.13	1.17	1.25	1.11	1.18
11	1.18	1.12	1.16	1.25	1.11	1.18
12	1.18	1.13	1.15	1.25	1.11	1.18

Panel C: General government.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS^{+}	ACC	GRS	GRS^{+}
1	1.17	1.07	1.10	1.22	1.22	1.23
2	1.17	1.06	1.10	1.25	1.20	1.25
3	1.17	1.06	1.12	1.29	1.19	1.28
4	1.15	1.06	1.11	1.25	1.19	1.23
5	1.16	1.05	1.09	1.28	1.19	1.23
6	1.15	1.05	1.12	1.28	1.16	1.21
7	1.16	1.05	1.14	1.28	1.16	1.23
8	1.16	1.06	1.15	1.29	1.16	1.24
9	1.16	1.03	1.13	1.29	1.15	1.22
10	1.16	1.05	1.15	1.29	1.13	1.21
11	1.17	1.05	1.16	1.30	1.13	1.22
12	1.16	1.05	1.15	1.30	1.13	1.23

This table reports the MSFEs for nowcasts and forecasts of nominal and real gross value added by sector based on the ACC mode, the GRS model, and the GRS^{+} model. The MSFEs are expressed as a percentage of the MSFE of the benchmark random-walk model.

Table 3
Out-of-sample nowcasts and forecasts of GDI growth and components

Panel A: Nominal GDI growth.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	1.00	0.83	0.82	1.12	1.21	1.24
2	0.92	0.81	0.78	1.03	1.12	1.11
3	0.94	0.80	0.71	1.04	1.12	1.02
4	0.94	0.77	0.68	1.00	1.09	0.97
5	0.93	0.69	0.57	1.00	1.05	0.91
6	0.96	0.66	0.57	1.00	0.97	0.85
7	0.96	0.66	0.58	1.00	0.97	0.85
8	0.95	0.65	0.57	1.01	0.98	0.87
9	0.95	0.60	0.50	1.01	0.93	0.79
10	0.94	0.57	0.51	1.01	0.87	0.79
11	0.94	0.57	0.51	1.01	0.87	0.78
12	0.94	0.56	0.50	1.00	0.87	0.77

Panel B: Real GDI growth.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	0.97	0.88	0.90	1.08	1.30	1.37
2	0.89	0.84	0.82	0.99	1.20	1.20
3	0.91	0.83	0.75	1.00	1.20	1.10
4	0.91	0.79	0.71	0.98	1.17	1.07
5	0.90	0.73	0.63	0.98	1.15	1.03
6	0.91	0.66	0.58	0.97	1.04	0.91
7	0.91	0.66	0.58	0.96	1.04	0.91
8	0.91	0.66	0.57	0.98	1.06	0.94
9	0.90	0.62	0.53	0.97	1.04	0.89
10	0.90	0.58	0.51	0.97	0.94	0.84
11	0.90	0.58	0.51	0.97	0.94	0.83
12	0.90	0.57	0.50	0.96	0.93	0.81

Panel C: Net operating surplus.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	0.63	0.68	0.71	0.66	0.72	0.75
2	0.64	0.65	0.68	0.64	0.69	0.71
3	0.63	0.65	0.63	0.63	0.69	0.69
4	0.62	0.66	0.62	0.64	0.69	0.70
5	0.62	0.69	0.63	0.64	0.69	0.71
6	0.61	0.64	0.58	0.64	0.67	0.68
7	0.62	0.64	0.59	0.64	0.67	0.68
8	0.62	0.66	0.61	0.64	0.67	0.69
9	0.62	0.67	0.61	0.64	0.69	0.70
10	0.62	0.62	0.57	0.64	0.66	0.68
11	0.62	0.61	0.57	0.64	0.66	0.67
12	0.62	0.62	0.57	0.64	0.66	0.67

Panel D: Compensation of employees.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	0.62	0.52	0.52	0.70	0.65	0.66
2	0.57	0.55	0.53	0.67	0.64	0.64
3	0.58	0.55	0.51	0.68	0.64	0.60
4	0.57	0.51	0.49	0.62	0.63	0.55
5	0.55	0.44	0.42	0.63	0.59	0.50
6	0.58	0.47	0.46	0.63	0.58	0.51
7	0.57	0.47	0.45	0.62	0.58	0.51
8	0.56	0.45	0.43	0.63	0.58	0.52
9	0.57	0.41	0.41	0.63	0.53	0.46
10	0.56	0.46	0.43	0.63	0.54	0.50
11	0.56	0.46	0.43	0.62	0.54	0.50
12	0.56	0.45	0.42	0.62	0.54	0.50

Panel E: Taxes on production and imports less subsidies.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	0.66	0.63	0.66	0.62	0.63	0.62
2	0.67	0.62	0.63	0.62	0.66	0.62
3	0.68	0.62	0.62	0.64	0.66	0.63
4	0.68	0.61	0.60	0.64	0.65	0.64
5	0.69	0.61	0.61	0.65	0.62	0.58
6	0.69	0.58	0.58	0.64	0.64	0.61
7	0.69	0.58	0.58	0.64	0.64	0.61
8	0.69	0.57	0.56	0.64	0.62	0.59
9	0.69	0.59	0.59	0.64	0.61	0.56
10	0.69	0.54	0.55	0.64	0.63	0.60
11	0.69	0.54	0.55	0.65	0.63	0.60
12	0.69	0.54	0.54	0.65	0.62	0.58

Panel F: Consumption of fixed capital.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	2.71	2.01	1.79	3.05	2.01	1.91
2	2.33	2.44	2.17	2.50	2.37	2.22
3	2.40	2.45	2.16	2.67	2.38	2.23
4	2.26	2.44	2.12	2.28	2.31	1.93
5	2.33	2.19	2.00	2.37	1.92	1.63
6	2.39	2.61	2.31	2.45	2.43	2.17
7	2.42	2.63	2.35	2.49	2.44	2.22
8	2.42	2.62	2.35	2.50	2.36	2.17
9	2.44	2.44	2.28	2.54	1.96	1.86
10	2.44	2.80	2.45	2.52	2.51	2.30
11	2.44	2.82	2.45	2.53	2.52	2.30
12	2.42	2.80	2.42	2.51	2.47	2.22

This table reports the out-of-sample MSFEs for nowcasts and forecasts of GDI and its components based on the ACC model, the GRS model, and the GRS+ model. The MSFEs are expressed as a percentage of the MSFE of the benchmark random-walk model.

Table 4
Out-of-sample nowcasts and forecasts of net operating surplus components

Panel A: Corporate profits.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	0.54	0.58	0.59	0.57	0.55	0.58
2	0.53	0.59	0.59	0.55	0.55	0.56
3	0.51	0.59	0.55	0.55	0.55	0.56
4	0.49	0.60	0.54	0.54	0.55	0.57
5	0.49	0.60	0.53	0.54	0.55	0.57
6	0.49	0.61	0.51	0.54	0.55	0.57
7	0.49	0.62	0.52	0.54	0.55	0.57
8	0.50	0.63	0.55	0.54	0.55	0.57
9	0.49	0.63	0.53	0.54	0.55	0.57
10	0.50	0.62	0.51	0.54	0.56	0.57
11	0.50	0.62	0.51	0.54	0.56	0.57
12	0.50	0.62	0.51	0.54	0.56	0.57

Panel B: Proprietors' income.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	1.11	1.01	1.08	1.15	1.19	1.29
2	1.05	1.00	1.05	1.05	1.16	1.15
3	1.08	0.99	1.07	1.04	1.16	1.08
4	1.06	0.98	1.01	1.04	1.13	1.06
5	1.06	0.97	1.03	1.03	1.12	1.06
6	1.06	0.94	0.97	1.04	1.08	1.02
7	1.06	0.93	0.97	1.04	1.07	1.01
8	1.07	0.93	0.98	1.04	1.05	0.99
9	1.06	0.94	1.01	1.04	1.06	1.02
10	1.06	0.91	0.97	1.04	1.01	0.97
11	1.06	0.91	0.96	1.06	1.00	0.98
12	1.06	0.91	0.96	1.06	0.99	0.97

Panel C: Net interest and miscellaneous payments.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	1.33	1.06	1.06	1.37	1.19	1.19
2	1.13	1.17	1.08	1.24	1.15	1.08
3	1.17	1.17	1.11	1.32	1.16	1.12
4	1.07	1.16	1.04	1.20	1.15	1.09
5	1.06	1.06	0.99	1.21	1.09	1.04
6	1.06	1.20	1.05	1.21	1.11	1.05
7	1.07	1.21	1.05	1.22	1.12	1.07
8	1.07	1.20	1.06	1.23	1.14	1.09
9	1.08	1.12	1.03	1.23	1.08	1.04
10	1.07	1.25	1.07	1.22	1.13	1.09
11	1.07	1.26	1.07	1.21	1.14	1.09
12	1.06	1.25	1.06	1.20	1.15	1.08

Panel D: Rental income.

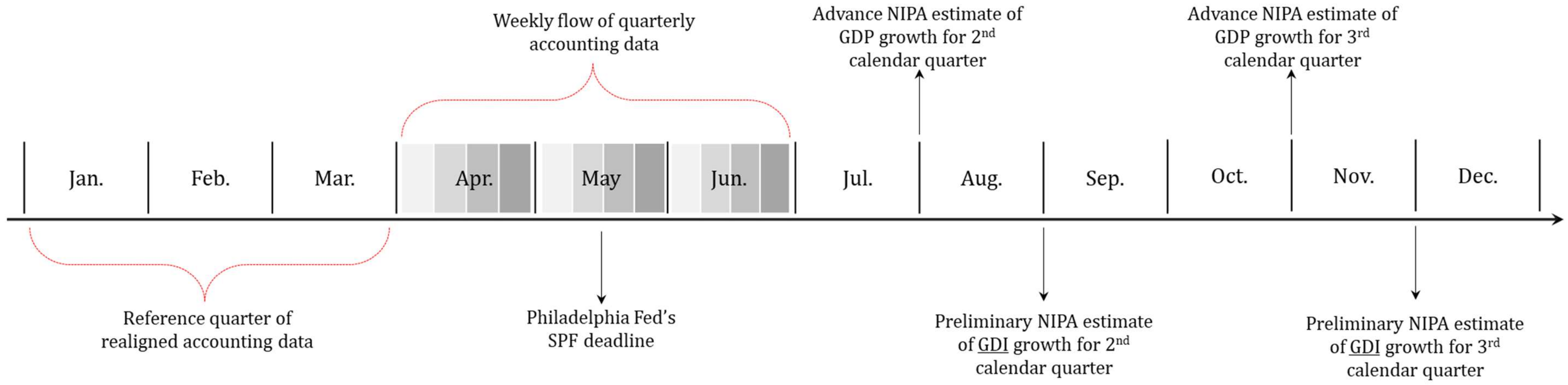
	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	3.27	2.89	3.32	3.27	3.14	4.06
2	2.95	2.93	3.10	3.13	3.07	3.36
3	2.93	2.93	3.03	2.95	3.07	3.17
4	2.97	2.94	3.09	3.23	3.10	3.41
5	2.95	2.88	2.99	3.34	3.02	3.51
6	2.95	3.01	3.17	3.21	2.98	3.37
7	3.04	3.02	3.29	3.13	2.98	3.29
8	3.04	3.02	3.31	3.10	3.01	3.27
9	3.06	2.89	3.15	3.03	2.99	3.20
10	3.06	3.13	3.56	3.03	2.95	3.23
11	3.18	3.15	3.73	3.02	2.94	3.22
12	3.08	3.13	3.55	2.99	2.95	3.18

Panel E: Business current transfer payments.

	MSFE comparisons across weekly data blocks					
	Factor-based nowcasts			Factor-based forecasts		
Week	ACC	GRS	GRS+	ACC	GRS	GRS+
1	0.60	0.59	0.61	0.59	0.59	0.59
2	0.59	0.59	0.59	0.60	0.59	0.60
3	0.59	0.59	0.60	0.59	0.59	0.59
4	0.59	0.59	0.59	0.59	0.59	0.60
5	0.59	0.59	0.59	0.59	0.59	0.60
6	0.59	0.59	0.60	0.59	0.59	0.60
7	0.59	0.59	0.60	0.60	0.59	0.60
8	0.59	0.59	0.60	0.60	0.59	0.60
9	0.60	0.59	0.60	0.60	0.59	0.60
10	0.60	0.59	0.60	0.60	0.59	0.60
11	0.60	0.59	0.60	0.60	0.59	0.60
12	0.60	0.59	0.60	0.59	0.59	0.60

This table reports the out-of-sample MSFEs for nowcasts and forecasts of net operating surplus components based on the ACC model, the GRS model, and the GRS+ model. The MSFEs are expressed as a percentage of the MSFE of the benchmark random-walk model.

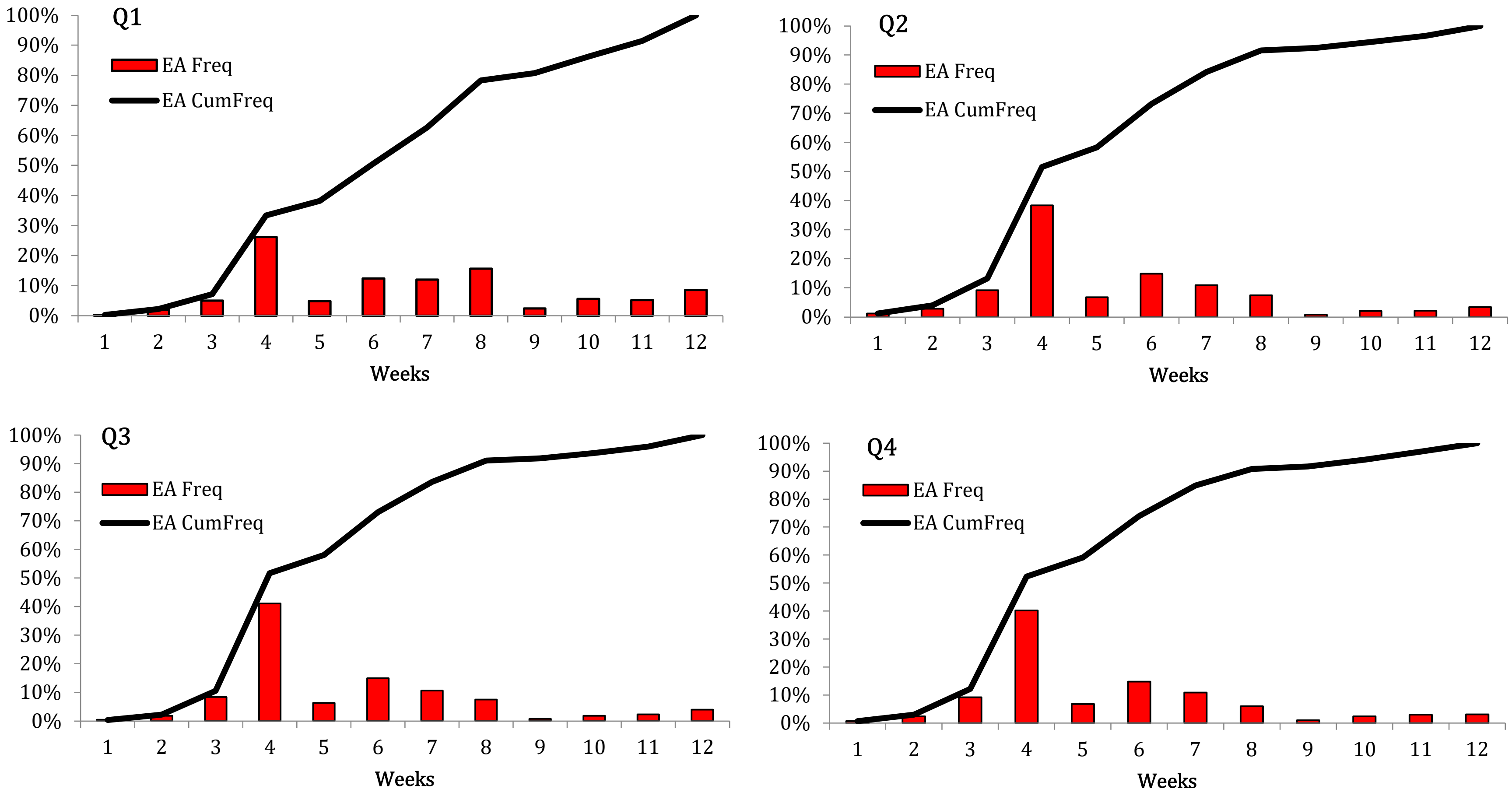
Figure 1
Research design timeline



This figure illustrates the research design timeline for the second calendar quarter of 2015

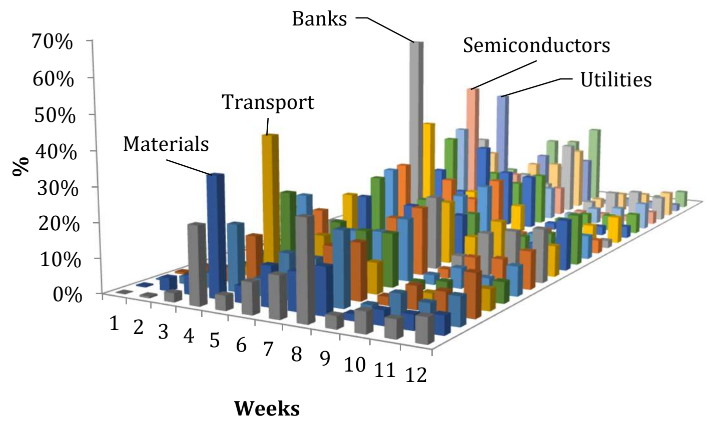
Figure 2
Flow of accounting data throughout the quarter

Panel A: Weekly flow of accounting data across calendar quarters.

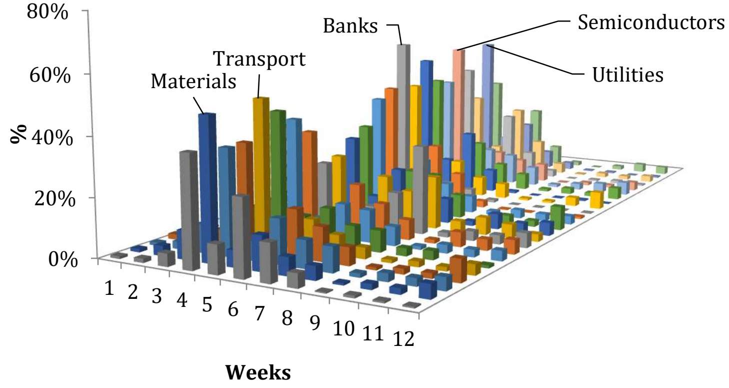


Panel B: Weekly flow of accounting data across calendar quarters and industries.

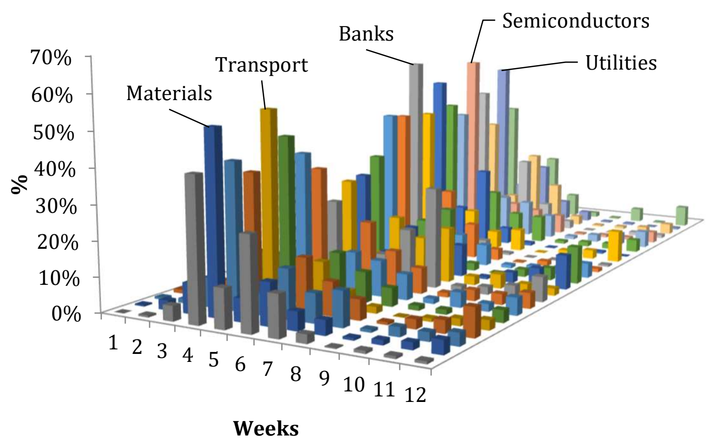
Q1



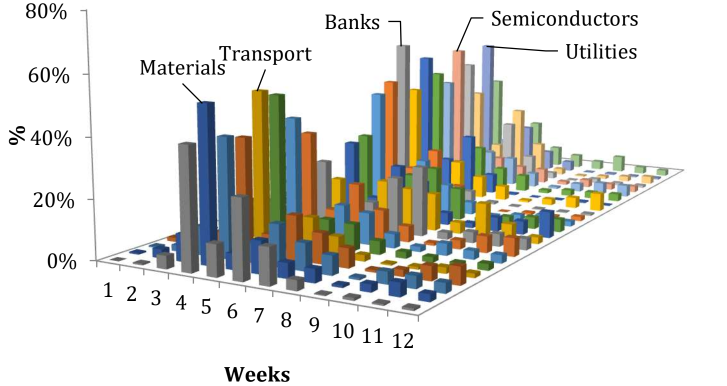
Q2



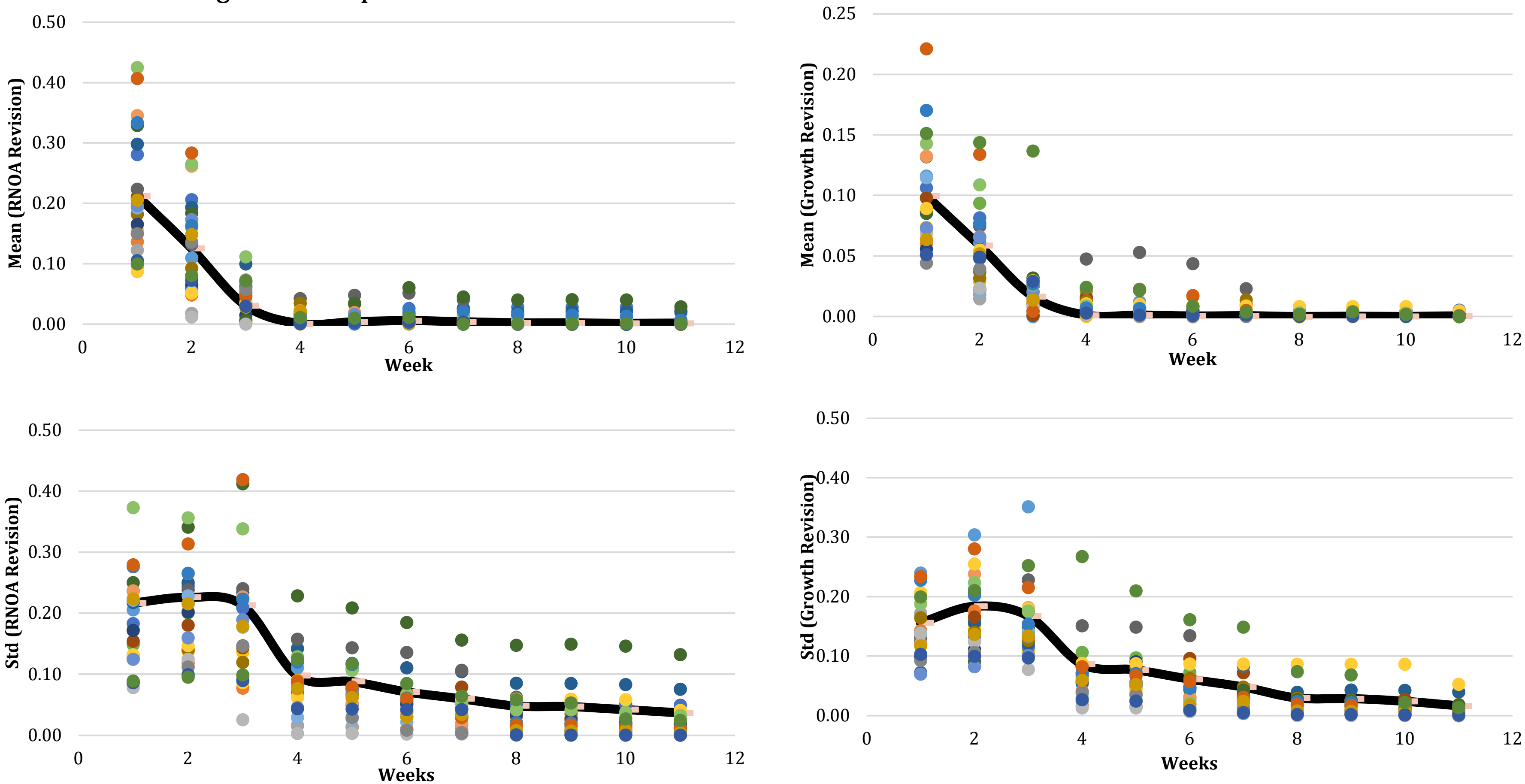
Q3



Q4



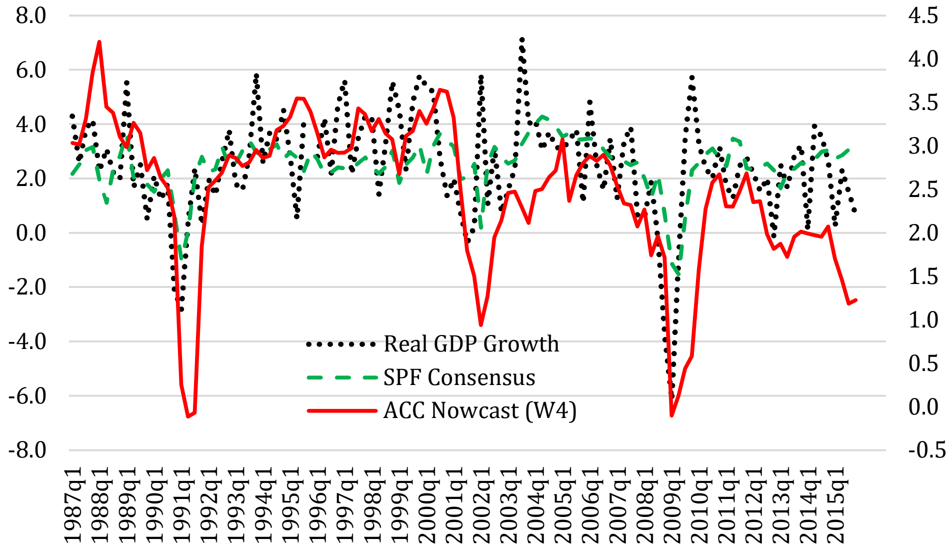
Panel C: Accounting factor component revisions.



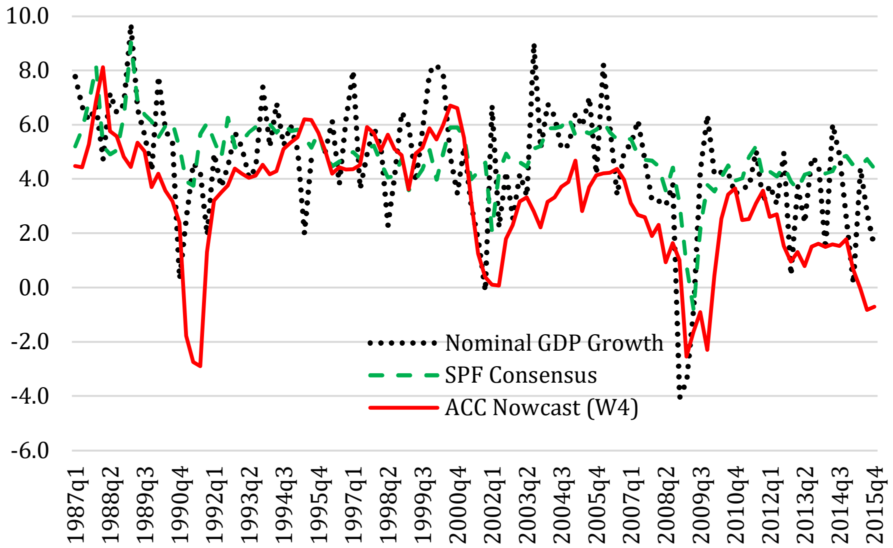
This figure provides evidence on the flow of accounting data at weekly frequencies throughout calendar quarters. Panel A reports the flow of accounting data for the pooled sample. Panel B reports the flow of accounting data across GICS industry groups. Panel C reports accounting factor component revisions throughout the quarter.

Figure 3
Accounting factor model nowcast versus realized GDP growth

Panel A: Real GDP growth ACC nowcast.



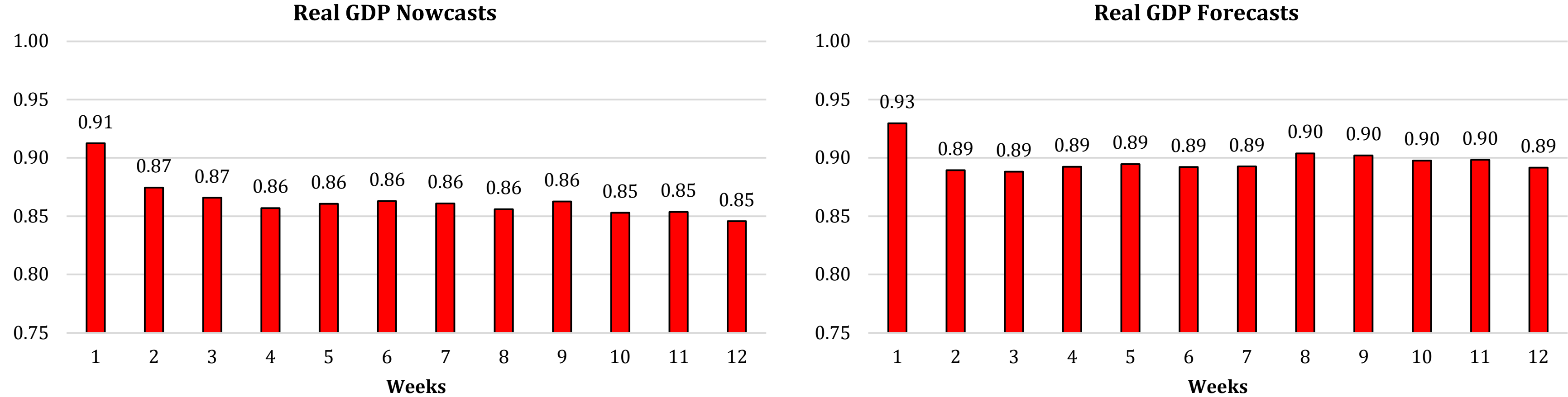
Panel B: Nominal GDP growth ACC nowcast.



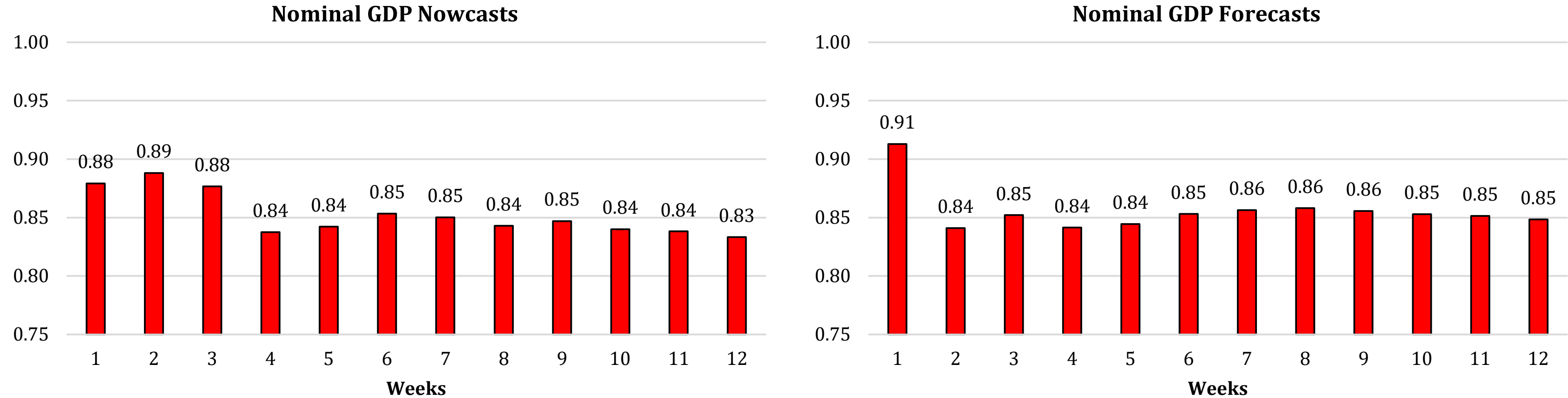
This figure plots the accounting factor model nowcast in week 4 of each quarter (ACC nowcast) along with Philadelphia Fed's SPF consensus forecast versus the realized GDP growth between 1987:Q1 and 2015:Q4.

Figure 4
Accounting factor model out-of-sample performance

Panel A: Nowcasting and forecasting real GDP growth.



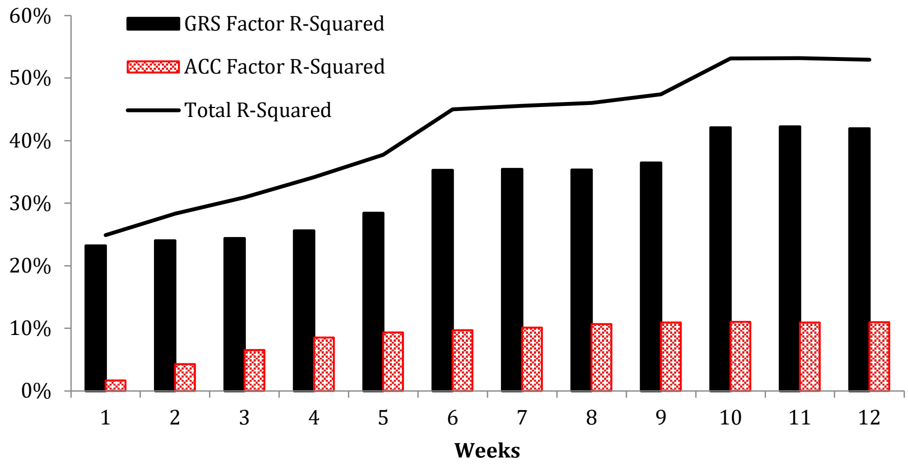
Panel B: Nowcasting and forecasting nominal GDP growth.



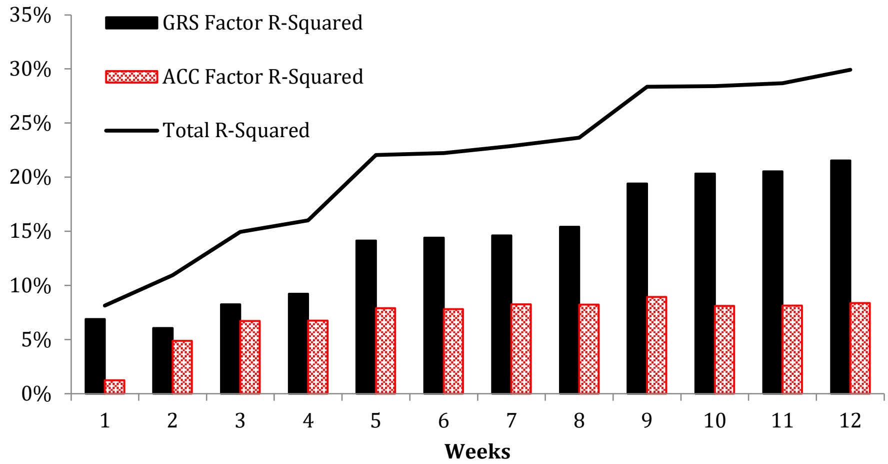
This figure provides a weekly breakdown of the evolution of the MSFE of the ACC nowcasts and forecasts of nominal and real GDP growth. We express the MSFE from each model as a percentage of the MSFE from the random-walk benchmark.

Figure 5
Breaking down the total R^2 of the GRS$^+$ bridge equations

Panel A: GRS$^+$ nowcasting bridge equation.



Panel B: GRS$^+$ forecasting bridge equation.



This figure provides a weekly breakdown of the relative contributions of the ACC and the GRS factors to the total R^2 of the GRS$^+$ nowcasting and forecasting bridge equations.