Tilting the Evidence: The Role of Firm-level Earnings Attributes in the Relation between Aggregated Earnings and Gross Domestic Product*

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Abstract

We examine whether the contribution of firm-level accounting earnings to the informativeness of the aggregate is tilted towards earnings with specific financial reporting characteristics. Specifically, we investigate whether considering the volatility of earnings relative to the volatility of cash flows at the firm level (smoothness) increases the informativeness of aggregate earnings for future real GDP, and if so, whether macroeconomic forecasters use this information efficiently. This study innovates on recently developed mixed data sampling methods in the construction of an aggregate earnings growth measure by allowing each firm's contribution to the aggregate to vary as a function of earnings smoothness. We find that the aggregate is tilted towards firms with smoother earnings and that this composition of aggregate earnings outperforms traditional weighting schemes in the association with future GDP growth. Further, this tilted aggregate has a stronger positive association with forecast revisions; in fact, analysts who utilize earnings the most in their forecasts appear to fully impound the informativeness of earnings smoothness. Our results synthesize and span parallel yet distinct streams of research on the role of accounting earnings in firm-level and macroeconomic outcomes and suggest an important role for financial reporting characteristics in the aggregate.

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1. Introduction

We examine whether considering financial reporting attributes enhances the overall informativeness of aggregate earnings for future real GDP growth and whether professional forecasters incorporate this information. Recent studies provide evidence that aggregate earnings contain information about future realizations of common macroeconomic indicators, such as GDP growth (Konchitchki and Patatoukas 2014a,b), inflation (Shivakumar and Urcan 2017), and the federal funds rate (Gallo et al. 2016). While the equal- and value-weighted aggregate earnings measures employed in these studies provide evidence about the average informativeness of earnings, they implicitly neglect differences in firm-level financial reporting attributes, even though firm-level evidence suggests that such attributes affect earnings informativeness (Kothari 2001; Dechow et al. 2010). Thus, we know relatively little about whether these firm-level earnings properties convey only idiosyncratic information or if there is a systematic component. We seek to bridge the gap between the micro (i.e., firm-level) and macro (i.e., aggregate earnings) literatures by exploiting these firm-level findings to investigate whether the relative contribution of firm-specific accounting earnings to the informativeness of the aggregate is tilted towards firms with specific financial reporting properties.

In general, it is not clear whether incorporating firm-level reporting attributes enhances earnings informativeness beyond equal- or value-weighted aggregate earnings measures. As Ball and Sadka (2015) suggest, random errors in the earnings generation process at the firm level would be greatly attenuated through diversification at the aggregate (i.e., portfolio) level. On the other hand, earnings properties that are correlated across firms (i.e., those inherent in the financial reporting system) will be reflected in the aggregate. If there is sufficient variation across firms in these

systematic earnings properties, this variation can potentially be exploited in constructing an informative aggregate. Even if such characteristics do survive in the aggregate, it is unclear whether professional macroeconomic forecasters understand that firms vary in their contribution to the aggregate informativeness of earnings. The goal of this study is to measure and test whether there is indeed a differentiating role for firm-level financial reporting attributes in the aggregate with respect to the informativeness of aggregate earnings for future real GDP growth, and whether professional forecasters efficiently incorporate such information. As a first step, we focus exclusively on the volatility of firm-level earnings relative to the volatility in underlying cash flows (hereafter, smoothness) as the financial reporting characteristic of interest; lower relative earnings volatility indicates *smoother* earnings.[1] We select earnings smoothness primarily because it reflects a basic premise of an accrual-based accounting system, specifically that earnings smooth transitory fluctuations in cash flows (Dechow et al. 2010). Therefore, finding that incorporating smoothness in the construction of the aggregate enhances informativeness provides a natural first step toward understanding the aggregate effects of an accrual-based financial reporting system.[2]

Underlying our tests is the hypothesis that the overall informativeness of aggregate earnings may be tilted more heavily toward some firms and away from others. We define tilt as the degree to which firm-level reporting attributes (smoothness in this study) shift the individual contribution of each firm away from a benchmark aggregation scheme. We measure and test whether the smoothness characteristic tilts the informativeness of firm-level earnings by permitting the possi-

[1] Smoothness is often considered a measure of a firm's "earnings quality" in other contexts. In this study, we do not take a position on whether smoother earnings reflects higher or lower earnings quality. Instead, our interest lies in simply understanding whether and to what extent smoothness influences the differential informativeness of firm-level earnings for aggregate outcomes.

[2] Although we focus on smoothness, the goal of this study is to measure, test, and report whether financial reporting characteristics can survive the aggregation process to enhance the aggregate informativeness of earnings, rather than attempting to identify the "best" financial reporting characteristic from a menu of options. We leave examinations of other firm-level reporting attributes to future research for which our empirical framework provides guidance.

bility that the association between individual firms' earnings and macroeconomic outcomes may differ across firms as a function of firm-level attributes.

In aggregate earnings time-series analyses, a challenge traditionally faced by researchers is the inability to exploit cross-sectional variation in firm-level attributes because the unit of observation is either aggregate quarterly or aggregate annual earnings within a given country. We circumvent this limitation using a novel mixed data sampling research design.[3] In our model, variation in each firm's influence on the information content of aggregate earnings for GDP is specified as a linear function of a flexible benchmark incorporating features of both equal and value weighting *and*, more importantly, the smoothness of a firm's earnings. We incorporate both equal and value weighting into our aggregation benchmark as these are the two commonly used weighting schemes in the aggregate earnings literature. The importance of smoothness in the cross-section is captured by a single parameter, which reflects the relative contribution (i.e., tilt) and is simultaneously estimated with the overall information content of the resulting tilted aggregate earnings. The ability to capture tilt with a single parameter maintains the advantage of diversifying away idiosyncratic components of firm-level earnings but permits an examination of how firm-level attributes tilt the informativeness of firm-level earnings for aggregate outcomes, which is not considered in other aggregate earnings studies.[4] Our method differs from existing aggregation approaches, such as value weighting, because our mixed data sampling model allows us to measure and test whether

[3]Mixed data sampling models, developed by Ghysels et al. (2006), have been applied almost exclusively to *temporal* differences in the frequency of observation among variables (e.g., quarterly versus daily). In our setting, mixed data sampling refers to *cross-sectional* differences in the frequency of observations because thousands of firm-level quarterly earnings are observed in the cross section for every one quarterly observation of real GDP. Along with Anderson et al. (2009) and Ball et al. (2018), our study is among the first to apply mixed data sampling methods in the cross-section.

[4]For example, an equal-weighted aggregate treats each dollar of (scaled) earnings the same (i.e., applies the same coefficient). In this study, we allow each firm's contribution to the aggregate to tilt away from the benchmark aggregate earnings as a function of firm-specific characteristics, which allows the coefficient to vary across firms in accordance with each firm's earnings smoothness parameter.

firm-level characteristics tilt the contribution significantly towards/away from a benchmark with minimal ex ante assumptions imposed on the relation.

We begin by presenting a baseline model of the relationship between aggregate earnings and real GDP growth using a benchmark that incorporates properties of both equal- and value- weighted earnings. Consistent with prior research, we find a positive and significant association between our benchmark aggregate earnings and one-quarter-ahead real GDP growth. With this baseline result in mind, we next apply the mixed data sampling approach to test whether incorporating smoothness confers information content above the benchmark and, more specifically, the extent and direction of the tilt. At the firm level, smoothness has been empirically linked to earnings informativeness with results suggesting that smoothness in the fundamental earnings process leads to more persistent and predictable earnings (Dechow et al. 2010). Additionally, smoother earnings may be a result of managers credibly conveying private information on their firms' performance, thereby enhancing the informativeness of earnings (Dechow 1994). Therefore, there is reason to believe ex ante that smoother earnings are more informative about future economic outcomes. On the other hand, if the relatively low variance of earnings is driven by intentional manipulation, earnings may be a poor measure of the firm's underlying economics (e.g., Leuz et al. 2003). However, idiosyncratic earnings manipulation should be averaged out in the aggregate. Unless there is systematic earnings manipulation manifested as smoother earnings, we expect a significant tilt towards firms with smoother earnings.[5]

Consistent with this prediction, we find that there is a statistically significant tilt towards firms with smoother earnings when estimating the association between aggregate earnings and future

[5]Finding a significant tilt towards firms with smoother earnings in the association between aggregate earnings and future GDP does suggest that smoothness, on average, reflects either an attribute of the fundamental earnings process or management's communication of relevant private information, as opposed to nefarious earnings manipulation (which would not be expected to have a stronger relationship with real economic outcomes).

real GDP growth, which means that these firms contribute more to aggregate informativeness than firms with less smooth earnings. These results are robust to controlling for additional predictors of macroeconomic movements. Smoothness can be interpreted as partially capturing the effect of accruals in generating a difference in the relative volatility of earnings versus cash flows. If smoother earnings are more predictive of future economic outcomes such as GDP, this suggests that accruals play an important role in reflecting the persistent component of firm performance.

Next, we examine whether professional forecasters incorporate the information conveyed in smoothness-tilted aggregate earnings. We test whether aggregate earnings are tilted towards firms with smoother earnings when estimating the relationship between aggregate earnings and real GDP forecast revisions released by the Survey of Professional Forecasters (hereafter, SPF).[6] We find that aggregate earnings tilted towards firms with smoother earnings have a more significantly positive association with consensus SPF forecast revisions than our benchmark, which suggests that analysts do focus more on these earnings.

Even if smooth-tilted aggregate earnings are positively associated with forecast revisions, SPF forecasters may not impound the information content of aggregate earnings fully and/or efficiently. To ascertain whether earnings are used efficiently, we test whether smoothness-tilted aggregate earnings predict subsequent forecast errors. We find that although SPF respondents do fully incorporate whatever relevant information is contained in the benchmark aggregate earnings, forecast errors are still predictable using smoothness-tilted earnings. This finding suggests that there is room for improvement through better use of the information contained in smoother earnings.

[6]We do not assert whether or not forecasters explicitly use earnings smoothness in constructing their forecasts. It is possible that smoothness is associated with some other characteristic that makes these firms more relevant for their forecasts. Nevertheless, our findings do suggest that discriminating by earnings smoothing is a potentially fruitful approach.

Similar to the treatment of earnings in an equal-weighted aggregate, macroeconomic forecasters are treated equally when estimating the consensus (mean) forecast. Although we provide evidence that forecasters, *on average*, do not fully incorporate the information embedded in a firm's earnings smoothness, it is likely that some analysts are better than others. In additional analysis, we incorporate each forecaster's prior use of accounting information to create two competing consensus forecasts based on the (historical) sensitivity of forecast revisions to accounting information. By partitioning the sample along this dimension, we are able to test whether those analysts who do incorporate earnings information in their revisions *fully* incorporate the incremental informativeness of earnings properties. We document that smoothness has no incremental explanatory power (i.e., no significant tilt) for forecast errors within the high earnings-sensitivity cohort of analysts, and further, their forecasts are more accurate on average than those of the low-sensitivity cohort.

To our knowledge, this is the first study that considers specific earnings attributes in assessing a firm's contribution to aggregate informativeness. Our findings have important implications for how researchers think about aggregation. First, we document that firm-level findings in prior studies can provide guidance for assessing how individual firms differentially contribute to the aggregate information content of accounting earnings. Specifically, while idiosyncratic earnings information is averaged away in the aggregate, our results suggest that a substantial systematic component remains. Second, our results indicate that, in considering the ability of aggregate earnings to predict macroeconomic outcomes, researchers can potentially incorporate cross-sectional variation. Third, while prior studies find that macroeconomic forecasters do not fully incorporate the information conveyed by tilted aggregate earnings into their forecasts, our findings suggest that forecasters do use some of the information in revisions of their forecasts. However, once we condition on whether analysts incorporate earnings information into their forecasts, we find that some analysts

are perhaps more adept at using firm-level information than prior research would suggest. Finally, our study provides a road map for using mixed data sampling in an aggregate time-series setting.

The remainder of the paper proceeds as follows. Section 2 discusses related literature and motivation. Section 3 defines the sample and variables. Section 4 presents the research design and results from our analysis on the association between aggregate earnings and real GDP. Section 5 tests whether tilted aggregate earnings are associated with consensus and individual forecast revisions and forecast errors. Section 6 concludes.

2. Motivation

In the context of GDP, there are a number of potential reasons that aggregated earnings are informative. Earnings may be considered a timelier measure of corporate profits, which are a component of GDP. To the extent that smoother earnings convey more information about future cash flows, they would be positively associated with the future corporate profit component of GDP.[7] In addition to a direct relationship with corporate profits, earnings may also have explanatory power for other components and drivers of GDP growth, such as aggregate investment (Kothari et al. 2017) and producer prices (Shivakumar and Urcan 2017).

Konchitchki and Patatoukas (2014a,b) examine the association between aggregated earnings and future nominal and real GDP growth, respectively. They argue that accounting earnings offer a timelier measure of corporate profits and other GDP components and therefore can be considered a leading economic indicator that is useful in predicting future GDP. Their results suggest that aggregate earnings are associated with real GDP growth up to three quarters ahead, even after they

[7]Specifically, corporate profits are measured primarily using tax data, which are collected with a significant lag and then extrapolated to estimate corporate profits. In addition to tax returns, the BEA uses surveys as well as some financial statement information to measure corporate profits. This number is then revised over time.

control for contemporaneous GDP growth. Additionally, aggregate earnings growth is positively associated with future GDP forecast errors, consistent with economic forecasters not efficiently utilizing accounting earnings in their forecasts (Konchitchki and Patatoukas 2014a). The work of Konchitchki and Patatoukas (2014a) represents an important first step in understanding whether aggregate accounting earnings contain incremental information about macroeconomic outcomes. We expand on their findings—and speak to the aggregate earnings literature at large—by examining whether firm-level earnings attributes differentially influence the informativeness of aggregated earnings. If relatively smoother earnings better reflect the underlying economics of the firm, then we expect to see aggregate informativeness tilt towards such firms.

Few papers consider how individual firms' disclosures provide timely information about macroeconomic outcomes. Bonsall et al. (2013) find that the management forecasts of bellwether firms (defined by the proportion of earnings variation explained by macroeconomic factors) garner a greater aggregate market return. While Bonsall et al. (2013) classify firms based on their contemporaneous association with macro indicators, our focus is on the news contained in earnings about *future* realizations or their associated forecasts. Additionally, we are primarily interested in each firm's contribution to the aggregate information set of earnings, as opposed to considering each firm's earnings in isolation. Still, our findings provide evidence on the potential role of specific financial reporting attributes in the identification of bellwether firms.

At the firm level, there is an abundance of evidence on the relationship between the informativeness of earnings and the characteristics of those earnings.[8] In the context of smoothing, it is unclear ex ante whether smoother earnings enhance or diminish the informativeness of earnings. Specifically, while one role of accruals is to smooth transitory fluctuations in cash flows, smoother

[8] See Dechow et al. (2010) for an overview of the earnings quality literature.

earnings can result from a fundamentally smoother economic earnings process or can occur if managers exercise discretion to artificially smooth earnings. Further, this discretion can be an effort by management either to conceal negative–but decision-useful–variance (e.g., DeFond and Park 1997; Leuz et al. 2003) *or* to convey relevant private information about a firm's underlying performance. Consistent with the latter, a number of studies document that smoothing enhances the information content of earnings, resulting in greater earnings persistence and predictability (e.g., Subramanyam 1996; Tucker and Zarowin 2006). Whether the increased informativeness is driven by managerial discretion and ability (e.g., Demerjian, Lewis-Western, and McVay 2017) or represents the fundamental earnings process, we would expect that smoother earnings better reflect the underlying economics of the respective firm and thus are more likely to contain information about macroeconomic outcomes. If the information in smoothing is purely idiosyncratic to the firm, then we would not expect it to survive in the aggregate.

Several studies have examined properties of aggregate earnings, such as conservatism, but have provided mixed evidence. For example, while Crawley (2014) finds that aggregate corporate profits and GDP growth are more sensitive to negative aggregate earnings news than positive aggregate earnings, Laurion and Patatoukas (2016) argue that this asymmetry is the result of countercyclical stock market volatility (i.e., economic downturns are associated with greater uncertainty) and does not reflect conditional conservatism in aggregate earnings. Dichev (2018) finds that aggregated GAAP earnings have become more volatile than the corporate profit component of GDP in recent years, which provides evidence that the properties of accounting information have changed over time. In contrast, our study examines how a *firm-level* financial reporting attribute (i.e., smoothing) can differentially influence the aggregate information content of earnings. The key difference between these prior studies and ours is that these studies examine the time-series properties of the

aggregate measure, while we take a step back and ask how these properties *at the firm level* may influence the *composition* of an informative aggregate earnings measure. To that end, our tests do not consider the smoothness of a predetermined equal- or value-weighted aggregate earnings number; rather, we empirically estimate the aggregate using individual firm attributes in the weighting scheme. Therefore, we can answer both *whether* these attributes survive in the aggregate and *to what extent* they influence the composition of aggregate earnings when we estimate the relationship between aggregate earnings and our macroeconomic outcome of interest (in our case, real GDP growth).

3. Variables and Sample

Our sample of firms comes from the intersection of Compustat and CRSP over the period 1984–2016. We require that observations have non-missing values for earnings, earnings announcement date, and lagged values of market value of equity and book value of debt. In order to estimate smoothness, we require a minimum of sixteen quarters of available quarterly earnings and cash flows over the prior twenty quarters. Macroeconomic forecasts are from the Philadelphia Fed's Survey of Professional Forecasters, and realizations of GDP come from the Philadelphia Fed's Real-Time Economic Database.

3.1. Firm-Level Variables

Earnings, $earn_{n,q}$, is the quarterly earnings growth of firm n for the fiscal quarter ending in calendar quarter q. We measure quarterly earnings growth by computing the difference between firm n's quarterly net income before extraordinary items in q and $q-1$. We then scale this difference by the market value of n's assets (i.e., market value of equity plus book value of liabilities) at the

beginning of the fiscal quarter.[9] We examine quarterly earnings changes, rather than year-over-year changes, to maintain consistency with the quarterly growth rate reflected in GDP_{q+1}. We classify earnings as being measured in quarter q if the fiscal quarter ends any time during quarter q. We include only quarter q earnings that are announced before the end of the first month following the end of quarter q in order to ensure that these earnings are in the available information set of the macroeconomic forecasters, who make their forecasts in the middle of the second month of the quarter.[10]

The smoothness attribute ($smth_{n,q}$) captures the volatility of firm n's earnings growth relative to its volatility of growth in cash flow from operations. Specifically, we measure $smth_{n,q}$ as the standard deviation of $earn_{n,q}$ divided by the standard deviation of the quarterly growth in cash from operations, $cfo_{n,q}$. We then multiply this measure by negative one such that higher values represent smoother earnings. Cash from operations is net income before extraordinary items minus the change in working capital accruals, which is equal to the change in the book value of current assets net of changes in cash, minus the change in book value current liabilities net of changes in the current portion of long-term debt. We estimate standard deviations for $earn_{n,q}$ and $cfo_{n,q}$ using available data from the 20 fiscal quarters immediately preceding quarter q, requiring a minimum of 16 observations. Finally, in each quarter q we normalize the cross-sectional distribution of our smoothness measure, $smth_{n,q}$, so that it has a mean of zero and a standard deviation of one in order to facilitate an economic interpretation of the effect on the information content of aggregate earnings. We winsorize both $earn_{n,q}$ and $smth_{n,q}$ at the top and bottom 1%.

[9] We choose market value of assets as our scaling variable in an effort to abstract away from the firm's financing choice. Scaling by sales or market value of equity—two common approaches in the aggregate earnings literature—yields qualitatively similar results.

[10] For example, firms with a fiscal quarter ending in January, February or March of 2014 would all be included in our aggregate of 2014 Q1 earnings, so long as the earnings are announced before the end of April 2014.

3.2. Macro Variables

Real GDP growth estimates are released by the Bureau of Economic Analysis (BEA) in the quarter following its measurement. The advance (or first) estimate, GDP_q, is released at the end of the month following the end of quarter q, with two formal revisions at the end of each of the two subsequent months. Although GDP is subject to further revisions—sometimes years later—we follow prior literature and use the final (or third) revision (i.e., the revision occurring at the end of the third month following the measurement quarter) when estimating the relationship between aggregate earnings and future real GDP growth, GDP_{q+1}.[11]

The consensus forecast of GDP growth from the Philadelphia Fed's Survey of Professional Forecasters, $E_{q+1}[GDP_{q+1}]$, is the average forecast of GDP growth for quarter $q+1$ made in the middle of quarter $q+1$ (i.e., after the release of quarter q earnings).[12] The forecast revision of GDP growth in quarter $q+1$, REV_{q+1}, is $E_{q+1}[GDP_{q+1}] - E_q[GDP_{q+1}]$, while the forecast error for quarter $q+1$, FE_{q+1}, is measured as $GDP_{q+1} - E_{q+1}[GDP_{q+1}]$, where GDP_{q+1} is the final real GDP growth estimate of quarter $q+1$ released at the end of the third month following quarter $q+1$. The appendix presents a timeline of our variable measurement that highlights the importance of timing in determining the information set available to both forecasters and the BEA.

[11] Konchitchki and Patatoukas (2014a, pg. 80) state that "according to Thomas Stark, Assistant Director and Manager of the Real-Time Data Research Center, 'almost no one uses the advance estimate' when measuring GDP growth forecast errors."

[12] The Philadelphia Fed sends the questionnaire to its panel of forecasters at the end of the first month of the calendar quarter, after the advance release of GDP. The deadline for responses is set for the second or third week of the middle month of the calendar quarter. The results are always released before the second report is released by the BEA at the end of the middle month of the quarter. For example, in the first quarter, the questionnaire is sent to panelists at the end of January and is due back in the middle of February, with results released in mid- to late-February. In our sample, the average number of forecasters is 36.

3.3. Control Variables

We follow prior literature and control for several measures of the overall macroeconomic environment (Konchitchki and Patatoukas 2014a). YLD_q is the yield on the one-year Treasury bill, and $SPRD_q$ is the yield on the ten-year Treasury bond minus the yield on the one-year Treasury bill; both are measured as of the end of the first month following quarter q. RET_q is the cumulative three-month return beginning one month after the start of quarter q (i.e., aligned with the earnings announcement window). We also add four lags of real GDP growth to control for any potential influence of serial correlation on our results.

Table 1 presents descriptive statistics for the key variables. Mean real GDP growth (using the final estimate) is 2.6% with a standard deviation of 2.2%. Forecast revisions are -0.002 on average, while the average forecast error is 0.002—consistent with macroeconomic forecasters being relatively accurate. The standard deviation of 0.017 suggests significant variation in accuracy over the time series.

4. Smoothness Tilt and Future Real GDP Growth

In this section, we test whether aggregate earnings is tilted towards firms with smoother earnings in estimating the relationship between aggregate earnings and one-quarter-ahead real GDP growth. Section 4.1 develops our research design based on a novel mixed data sampling model. Section 4.2 presents the results from this analysis.

4.1. Empirical Model

Our main objective in this section is to measure and test whether a firm-level attribute (in this case, smoothing) can differentially influence, or tilt, the information content of aggregate earnings

for future real GDP growth. A key challenge in our pursuit is the need to incorporate data that are observed at significantly different frequencies while parsimoniously integrating cross-sectional data on firm-level attributes, which are typically discarded in the process of aggregation.[13] Our analysis employs the following two simultaneously estimated equations:

$$GDP_{q+1} = \alpha + \beta_{EARN} \sum_{n=1}^{N_q} \omega_{n,q} \cdot earn_{n,q} + \sum \beta_k \cdot CONTROLS_q^k + \varepsilon_{q+1}, \quad (1)$$

$$\text{subject to:} \quad \omega_{n,q} = \underbrace{ew_{n,q} \cdot (1-\theta) + vw_{n,q} \cdot \theta}_{\text{Benchmark component}} + \underbrace{\tau_{smth} \cdot smth_{n,q}}_{\text{Tilt component}}. \quad (2)$$

The regression coefficient β_{EARN} in (1) measures the information content of aggregated firm-level earnings for future real GDP growth in the spirit of prior studies (e.g., Konchitchki and Patatoukas 2014a). The key innovation in our mixed data sampling model is the inclusion of equation (2), which specifies the weight $\omega_{n,q}$ applied to each firm's earnings growth ($earn_{n,q}$) as a linear function of two distinct components: a benchmark component and a tilt component.[14]

The benchmark component provides a rejectable null from which we measure and test whether the smoothness of firm-level earnings incrementally tilts the weight applied to each firm away from the benchmark weight. We rely on a linear combination of equal weighting, $ew_{n,q}$, and value-weighting, $vw_{n,q}$, for the benchmark component of $\omega_{n,q}$ because they are the two most common aggregation methods employed in prior studies. This specification is motivated by the absence of theoretical or empirical guidance that exclusively favors one weighting scheme over the other. The

[13] In our setting, we observe firm-level quarterly earnings growth for hundreds of firms every calendar quarter for every one quarterly observation of real GDP growth.

[14] Using a predetermined representative agent utility function, Brandt et al. (2009) formulate approximated portfolio allocations using a similar weighting scheme. Their analysis does not involve the estimation of regression models with purpose of aggregating cross-sectional data as we do in our analysis.

parameter θ determines the relative importance of $ew_{n,q}$ and $vw_{n,q}$ and is simultaneously estimated with the regression coefficients in (1) and (2).[15]

The tilt component, $\tau_{smth} \cdot smth_{n,q}$, in (2) measures the degree to which firm-level weights deviate from the benchmark weights. The parameter τ_{smth} measures the incremental change in the weight, $\omega_{n,q}$, applied to a given firm's earnings growth, $earn_{n,q}$, in response to a unit change in firm-level smoothing, $smth_{n,q}$. The parameter τ_{smth} is simultaneously estimated with θ and the regression coefficients included in (1). We refer to this parameter as tilt, which is the focus of our study.

Modeling $\omega_{n,q}$ as a linear function of firm-level attributes in equation (2) embeds several important features. First, the benchmark weight serves as a natural null that permits a formal test of the hypothesis that $smth_{n,q}$ significantly tilts the aggregate information content of firm-level earnings (i.e., $\tau_{smth} \neq 0$). In other words, the parameter τ_{smth} can be measured and tested for statistical and economic significance in a manner similar to that used for other regression coefficients. Second, the linear function is described by two data-driven parameters (θ and τ_{smth}) that are estimated as part of maximizing the explanatory power of the mixed data sampling model (i.e., minimizing the sum of squared error terms). The addition of these two parameters increases the flexibility of our model relative to those used in prior studies, but it maintains a degree of a parsimony necessary for our empirical tests based on a small sample of 131 time-series observations. Third, we impose only linearity (as in most reduced-form regression models), which allows our data to determine whether, and in which direction, firm-level smoothing tilts the weight applied to each firm. Lastly, τ_{smth} has a convenient economic interpretation. Its values can be directly interpreted as the percentage dif-

[15]For example, the benchmark component is equivalent to applying an equal weight to all observations if the estimated value of $\theta = 0$. Conversely, the benchmark component is equivalent to applying a value weight to all observations if the estimated value of $\theta = 1$. We allow θ to take on a range of values, which increases the flexibility of the benchmark component.

ference between the weight applied to the earnings growth of two observations with the mean size, but a one-standard-deviation difference in $smth_{n,q}$.

We expect τ_{smth} to be positive if firms with smoother earnings have earnings growth that is more informative for one-quarter-ahead GDP than the earnings growth of firms with less smooth earnings. The positive sign implies that increasing smoothness increases the weight applied to a given firm, which is redistributed from firms with lower values of smoothness. If we find a significant τ_{smth}, we also expect the magnitude of the resulting aggregate earnings information content, measured by β_{EARN}, to increase as more (less) weight is given to more (less) informative firms, which makes the resulting tilted aggregate earnings more informative.[16]

4.2. Results

Table 2 presents coefficients and tilt parameter values estimated from the mixed data sampling regressions in equations (1) and (2). The first two columns report results for a version of the model that excludes all control variables except lagged real GDP growth variables, while the last two columns include all control variables. Because the results including control variables are qualitatively similar, for brevity we limit our discussion to results in the first two columns excluding controls. The first column presents results from a baseline model that excludes the tilt component, which implicitly assumes $\tau_{smth} = 0$. The estimated value of the information content of equal-weighted aggregate earnings, β_{EARN}, is positive and equal to 2.552, which is statistical significant at the 1% level.

[16]Technically speaking, the estimated smoothness-weighted aggregate earnings presumably reduces the measurement error that results from imposing an equal weight when constructing aggregate earnings, which ultimately biases the coefficient β_{EARN}.

The second column reports results for the model that includes the tilt parameter, which allows the estimated weights, and therefore aggregate earnings, to tilt away from the benchmark aggregation scheme employed in the first column as a function of earnings smoothness. Two results are striking. First, the tilt parameter has a positive estimated value equal to 0.586, which is significant at the 1% level. This implies that within a given calendar quarter q, the contribution of firm-level earnings to the aggregate information content is tilted towards (away from) firms with higher (lower) smoothness. The magnitude of this tilt is economically significant as well. Specifically, firms with smoothness one standard deviation above the cross-sectional mean (equal to zero) contribute 58.6% more to the aggregate information content of earnings relative to that implied by the benchmark specification. In contrast, firms one standard deviation below have their contribution reduced by 58.6%, which indicates that the earnings characterized by lower smoothness are less informative than smoother earnings.

The second striking result is the large increase in the estimated information content of the tilted aggregate earnings reported in the second column compared to that in the baseline model reported in the first column. Specifically, the estimated coefficient on the smoothness-tilted aggregate earnings, β_{EARN}, is 6.627, which is statistically significant at the 1% level (versus an insignificantly positive β_{EARN} in the baseline model). Thus, incorporating smoothness not only tilts the aggregate towards smoother earnings but also improves the informativeness of aggregate earnings. These two results together are also reflected in a 29% increase in the adjusted R^2 from 0.219 when we use the benchmark weighting scheme to 0.282 when we consider titled aggregate earnings.

5. Smoothness Tilt and SPF Forecasts of Future Real GDP Growth

5.1. Do SPF Forecasters Incorporate Information in Tilt?

The results in section 4 point towards a significant increase in the informativeness of tilted aggregate earnings for future real GDP growth compared to our benchmark. Next, we consider whether macroeconomic forecasters incorporate the information in earnings smoothness when generating their *contemporaneous* forecast revisions for one-quarter-ahead real GDP growth. To this end, we estimate equations (1) and (2) substituting the contemporaneous forecast revision, REV_{q+1}, as the dependent variable. The regression coefficient β_{EARN} in equation (1) measures the information content of the aggregate of firm-level earnings for contemporaneous forecast revisions subject to equation (2), which specifies the weight, $\omega_{n,q}$, applied to each firm's earnings growth, $earn_{n,q}$, as a linear function of two distinct components: a benchmark component and a tilt component. As in section 4, the benchmark is a linear combination of equal weighting, $ew_{n,q}$, and value weighting, $vw_{n,q}$. The parameter of interest is the tilt component, τ_{smth}, in equation (2), which measures the degree to which firm-level weights deviate from the benchmark.

We expect τ_{smth} to be positive if forecasters incorporate the information content in the earnings growth of firms with smoother earnings, $smth_{n,q}$, to a greater degree than that of firms with less smooth earnings when contemporaneously revising their forecasts. If we find a significant τ_{smth}, then we expect the magnitude of the resulting aggregate earnings information content, measured by β_{EARN}, to change as more (less) weight is given to more (less) informative firms, which increases the association between aggregate earnings growth and forecast revisions.

Table 3 presents the results of this analysis. The first two (last two) columns exclude (include) control variables with the exception of GDP_q. Because the results including control variables are

qualitatively similar, for brevity we limit our discussion to results in the first two columns excluding controls. The first column reports results from the baseline model excluding the tilt component in equation (2). We find that our benchmark aggregate earnings measure is positively associated with forecast revisions: β_{EARN} is 1.493 and significant at the 1% level, which suggests that forecasters do incorporate aggregate earnings news in their forecast revisions.

The second column reports results for the model including the tilt parameter in equation (2). First, the tilt parameter, τ_{smth}, is equal to 0.371 and is significant at the 1% level, consistent with the contribution of firm-level earnings to the aggregate being tilted *towards* firms with smoother earnings when forecasters revise their forecasts of real GDP growth. Second, the coefficient on aggregate earnings growth, β_{EARN}, has increased from 1.493 in the first column to 2.350 (significant at the 1% level) in the second column, pointing to a more positive association between the tilted aggregate earnings and forecast revisions than between the benchmark aggregate earnings growth and forecast revisions. Taken together, the results in Table 3 are consistent with forecasters, on average, incorporating the information contained in earnings smoothness when issuing contemporaneous forecast revisions.

5.2. Do SPF Forecasters Fully Incorporate Information in Tilt?

Even if tilted aggregate earnings are more positively associated with contemporaneous forecast revisions than are benchmark earnings, this does not necessarily indicate that forecasters are impounding the information content of aggregate earnings fully and/or efficiently. Next, we examine whether forecast errors are predictable using smoothness-tilted aggregate earnings growth. Again, we re-estimate equations (1) and (2) substituting forecast error, FE_{q+1}, as the dependent variable in (1). The coefficient β_{EARN} measures the association between aggregate earnings growth and

forecast errors, with a significant value indicating that forecast errors are predictable (i.e., forecasters do not fully incorporate the information content of aggregate earnings). The parameter τ_{smth} measures the degree to which firm-level weights deviate from the benchmark. A positive value indicates that the aggregate is tilted towards firms with smoother earnings when we estimate the relation between aggregate earnings and forecast errors.

Table 4 reports the results of this analysis. The first two (last two) columns exclude (include) control variables. Again, we limit our discussion to results in the first two columns excluding controls for brevity. The first column reports results from the baseline model excluding the tilt component in equation (2). The statistically insignificant value for β_{EARN} in the first column suggests that any relevant information contained in our benchmark aggregate earnings measure is incorporated into the consensus forecast (i.e., the forecast error is not predictable). In the second column, when the tilt parameter is included in equation (2), we find a positive and statistically significant value for τ_{smth} (0.623, significant at the 1% level), along with a positive and significant β_{EARN} coefficient (1.667, significant at the 5% level). Taken together, the estimates in the second column demonstrate that forecasters do not fully impound the information content of smoothness-tilted aggregate earnings for future real GDP growth (i.e., the forecast errors are predictable).

5.3. Do Some SPF Forecasters Incorporate Information in Tilt?

While the results in Table 4 indicate that *on average* forecasters do not efficiently utilize the information in earnings smoothness, it is possible that some forecasters are more adept than others. To address this possibility, we investigate whether forecasters who historically incorporate earnings properties in their forecast revisions also more efficiently utilize the information contained in smoothness-tilted aggregate earnings. For each forecaster, we estimate a rolling regression akin to

that of Table 3, using a window of eight quarters prior to the revision measure. We then partition the forecasters with available data into high and low earnings-sensitivity cohorts each quarter based on the median value of β_{EARN}. Within each cohort we estimate equations (1) and (2) including the tilt parameter, τ_{smth}. If the forecasters who utilize smoothness the most also utilize the information most efficiently, then we expect that the high (low) sensitivity cohort will have less (more) predictable forecast errors.

Table 5 reports the results of this analysis. The first (second) column reports results for the high (low) sensitivity group of forecasters, while the third column represents the sample of forecaster-quarters with insufficient observations to estimate the rolling regressions (the "all other" sample). Consistent with our prediction, forecast errors in the high-sensitivity group are not predictable. Both β_{EARN} and τ_{smth} in the first column are insignificantly different from zero, which means that the information embedded in earnings smoothness is fully impounded into the forecasts of real GDP within this group. For the low-sensitivity group, β_{EARN} is positive (2.197) and significant at the 5% level, indicating that these forecasters do *not* fully incorporate the information in smoothness into their forecasts of real GDP growth. That we also obtain a positive and significant coefficient on β_{EARN} in the "all other" group is further evidence that the results for the high-sensitivity group are not spurious and represent a clear difference in the ability to discern earnings informativeness. We also note that the mean squared forecast error is smaller for the high-sensitivity cohort than for the low-sensitivity cohort of forecasters, which suggests that the high-sensitivity group not only impounds the information content of smoothness-tilted aggregate earnings but also is more accurate on average.

Overall, the results of our SPF forecast analyses impart important insights about the way macroeconomic forecasters use accounting information. First, forecasters do appear to impound

the information content of earnings properties when revising their forecasts of future real GDP. Second, *on average*, forecasters do not fully incorporate the information content of smoothness-tilted aggregate earnings. However, when we partition on the forecaster's historical sensitivity of revisions to smoothness-tilted earnings, we find that the high-sensitivity cohort does appear to fully impound the information in aggregate earnings. This final result has particularly important implications for studies that look at forecast revisions and forecast errors in the context of earnings. Specifically, studies that document that forecasters do not use aggregate earnings information efficiently can benefit from incorporating firm-level attributes in the aggregation process and incorporating variation in forecaster ability when constructing the consensus forecast.

6. Conclusions

Prior literature examines the information content of earnings at the aggregate level for macroeconomic outcomes such as market returns, real and nominal GDP growth, inflation, unemployment and interest rates (e.g., Kothari et al. 2006; Konchitchki and Patatoukas 2014a,b; Shivakumar and Urcan 2017; Nallareddy and Ogneva 2016; Gallo et al. 2016). While these studies are an important first step in understanding the role of aggregate earnings as a leading economic indicator, they are limited in their ability to incorporate firm-level attributes in the measurement of aggregate earnings. In this paper, we attempt to bridge the gap between firm-level findings and these aggregate earnings studies by considering the role of a firm-level attribute, earnings smoothness, in generating a more informative aggregate measure.

Specifically, we examine whether and to what extent cross-sectional differences in earnings smoothness influence the contribution of individual firms to the information content of aggregate earnings for future real GDP growth. Further, we test whether forecasters efficiently incorporate

this variation across firms when formulating their forecasts. We document three important results. First, when we estimate the relation between aggregate earnings and future real GDP growth, the aggregate is significantly tilted towards smoother earnings and away from our benchmark. Additionally, smoothness-tilted earnings are more informative for future real GDP growth than are benchmark aggregate earnings. Second, forecasters do use the incremental information in smoothness-tilted earnings when issuing forecasts revisions for real GDP growth, although, on average, forecast errors are still predictable. Finally, forecasters whose revisions are historically more sensitive to smoothness-tilted earnings do in fact fully incorporate the information content of aggregate earnings into their forecasts and have more accurate forecasts, on average.

Our study makes an important contribution to the literature examining the information content of aggregate earnings by exploring the role of firm-level earnings attributes in augmenting the informativeness of aggregate earnings. Our findings also suggest that smoothing is not an idiosyncratic attribute that is diversified away. Rather, the systematic component varies across firms in a way that can be exploited to enhance the relationship between aggregate earnings and future GDP. Specifically, our mixed data sampling approach provides a foundation for future research to test whether other cross-sectional properties are useful in estimating the relationship between aggregate earnings and other macroeconomic outcomes.

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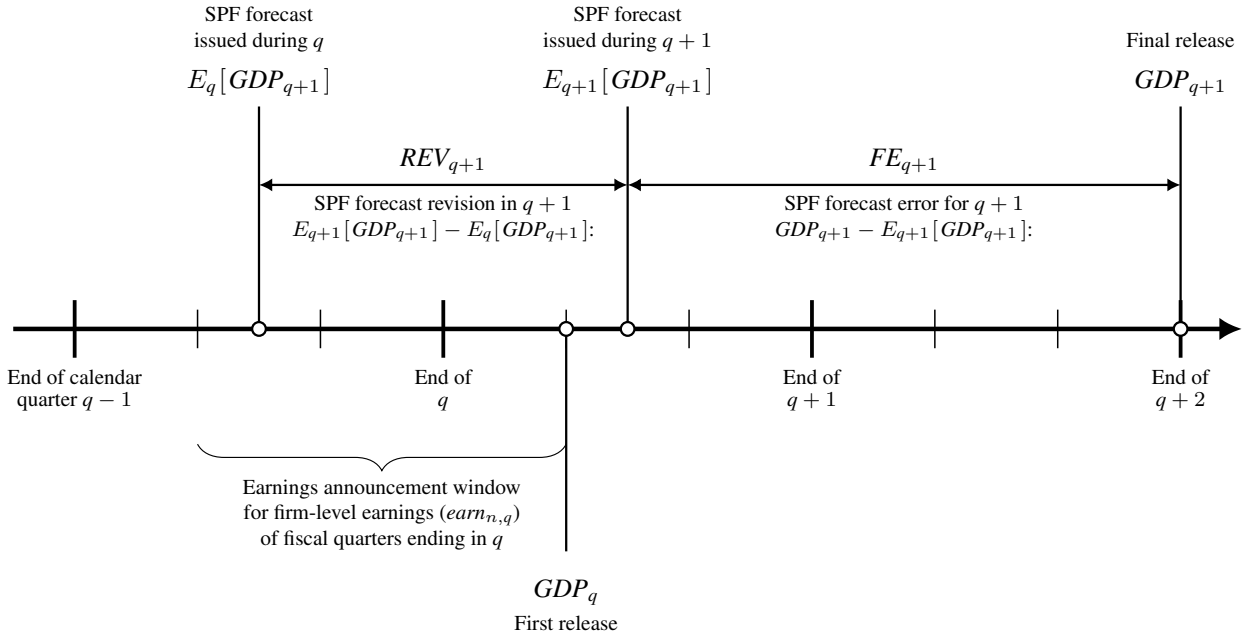
Appendix: Timeline and Variable Descriptions

A.1. Timeline



A.2. Macro-level Variables

GDP_{q+1} Third (or final) estimate of real GDP growth for calendar quarter $q+1$ (released approximately 3 months after the end of quarter $q+1$) obtained from the Real-Time Data Set for Macroeconomists provided by the Federal Reserve Bank of Philadelphia.

REV_{q+1} SPF forecast revision of real GDP growth for calendar quarter $q+1$ defined as the difference between the mean of individual SPF forecasts issued during $q+1$ ($E_{q+1}[GDP_{q+1}]$) and the mean of individual SPF forecasts issued during q ($E_q[GDP_{q+1}]$).

FE_{q+1} Real GDP growth forecast error defined as the difference between the third estimate of real GDP growth in calendar quarter $q+1$ (GDP_{q+1}) and the mean of the most recent SPF individual forecasts of real GDP growth in $q+1$ ($E_{q+1}[GDP_{q+1}]$) issued approximately 45 days prior to the end of $q+1$.

A.2. Macro-level Variables (continued)

GDP_q The first estimate of real GDP growth for quarter q (released approximately one month after the end of calendar quarter q) obtained from the Real-Time Data Set for Macroeconomists provided by the Federal Reserve Bank of Philadelphia.

GDP_{q-k} Third (or final) estimate of real GDP growth for calendar quarter $q-k$ (released approximately 3 months after the end of quarter $q-k$) obtained from the Real-Time Data Set for Macroeconomists provided by the Federal Reserve Bank of Philadelphia.

YLD_q Yield on the one-year Treasury bill with constant maturity measured one month after the end of calendar quarter q retrieved from the Federal Reserve Bank of St. Louis (FRED).

$SPRD_q$ Difference between the yields, measured one month after the end of calendar quarter q, on the 10-year Treasury bond with constant maturity and the one-year Treasury bill with constant maturity, which are both retrieved from FRED.

RET_q Buy-and-hold market return, including distributions, on the value-weighted market portfolio over a three-month window that ends one month after the end of calendar quarter q.

N_q Number of firms with a fiscal quarter ending in calendar quarter q that report earnings no later than one month after the end of calendar quarter q and have non-missing data for all required variables.

A.3. Firm-level Variables

$earn_{n,q}$ Quarterly earnings growth of firm n for the fiscal quarter ending in calendar quarter q defined as the difference between n's quarterly net income before extraordinary items in q and $q-1$ scaled by the market value of assets (i.e., market value of equity plus book value of liabilities) at the beginning of the fiscal quarter.

$cfo_{n,q}$ Quarterly growth of cash from operations of firm n for the fiscal quarter ending in calendar quarter q, which is equal to the difference between n's quarterly cash from operations in q and $q-1$ scaled by the market value of assets (i.e., market value of equity plus book value of liabilities) at the beginning of the fiscal quarter. Cash from operations is net income before extraordinary items minus the change in working capital accruals, which is defined as the change in the book value of current assets net of changes in cash minus the change in book value current liabilities net of changes in the current portion of long-term debt.

$smth_{n,q}$ Firm n's earnings smoothness measured as the standard deviation of quarterly earnings growth, $\sigma(earn_{n,q})$, divided by the standard deviation of quarterly growth in cash from operations, $\sigma(cfo_{n,q})$, where standard deviations are estimated over a 20-quarter rolling window ending with calendar quarter $q-1$.

Table 1
Sample Summary Statistics

			Percentile				
Variable	Mean	Std. Dev.	5th	25th	50th	75th	95th
GDP_{q+1}	0.026	0.022	−0.007	0.014	0.026	0.039	0.059
REV_{q+1}	−0.002	0.009	−0.015	−0.007	−0.002	0.004	0.010
FE_{q+1}	0.002	0.017	−0.024	−0.009	0.001	0.014	0.034
GDP_q	0.025	0.020	−0.003	0.015	0.025	0.037	0.057
YLD_q	0.040	0.029	0.001	0.008	0.043	0.060	0.085
$SPRD_q$	0.015	0.010	−0.001	0.007	0.016	0.024	0.031
RET_q	0.028	0.072	−0.112	−0.015	0.038	0.077	0.123

This table reports descriptive statistics for all macro-level variables. GDP_{q+1} is the final estimate of real GDP growth for calendar quarter $q+1$. REV_{q+1} is the mean SPF forecast revision of real GDP growth for calendar quarter $q+1$. FE_{q+1} is the mean SPF forecast error of real GDP growth for calendar quarter $q+1$. GDP_q is the initial estimate of real GDP growth in quarter q. YLD_q is the yield on the one-year Treasury bill measured one month after the end of quarter q. $SPRD_q$ is the yield on the 10-year Treasury bill minus the yield on the one-year Treasury bill measured one month after the end of quarter q. RET_q is the buy-and-hold market return over a three-month period ending one month after the end of quarter q. The appendix provides a description of all variables.

Table 2
Aggregate Earnings Tilt and Future Real GDP Growth

	(1)	(2)	(3)	(4)
Panel A: Estimated tilt parameter				
τ_{smth}		0.586^{***}		0.581^{***}
		(0.057)		(0.064)
Panel B: Estimated regression coefficients				
β_{EARN}	2.552^{***}	6.027^{***}	2.305^{***}	5.579^{***}
	(0.558)	(0.906)	(0.548)	(0.919)
β_{GDP}	0.402^{***}	0.220^{**}	0.390^{***}	0.228^{**}
	(0.150)	(0.101)	(0.130)	(0.112)
$\beta_{GDP_{q-1}}$	0.006	-0.050	0.001	-0.049
	(0.074)	(0.075)	(0.077)	(0.077)
$\beta_{GDP_{q-2}}$	0.036	0.083	0.065	0.102
	(0.084)	(0.075)	(0.084)	(0.079)
$\beta_{GDP_{q-3}}$	0.159^{*}	0.200^{*}	0.192^{*}	0.220^{*}
	(0.089)	(0.113)	(0.103)	(0.127)
β_{YLD}			-0.071	-0.054
			(0.055)	(0.065)
β_{SPRD}			-0.045	-0.023
			(0.144)	(0.146)
β_{RET}			0.039^{*}	0.026^{*}
			(0.023)	(0.014)
Panel C: Other model estimates				
θ	0.621	0.271	0.774	0.317
	(0.518)	(0.188)	(0.597)	(0.215)
Adj. R^2	0.219	0.282	0.225	0.275

This table reports tilt parameter and regression coefficient values estimated from the following mixed data sampling model using a sample of 131 calendar quarter observations between 1984:Q1 and 2016:Q4:

$$GDP_{q+1} = \alpha + \beta_{EARN} \sum_{n=1}^{N_q} \omega_{n,q} \cdot earn_{n,q} + \beta_{GDP}\, GDP_q + \sum_{k=1}^{3} \beta_{GDP_{q-k}} \cdot GDP_{q-k} + \beta_{YLD}\, YLD_q + \beta_{SPRD}\, SPRD_q + \beta_{RET} RET_q + \varepsilon_{q+1},$$

subject to: $\omega_{n,q} = \theta \cdot vw_{n,q} + (1-\theta) \cdot ew_{n,q} + \tau_{smth} \cdot smth_{n,q}$.

The dependent variable GDP_{q+1} is the final estimate of real GDP growth for calendar quarter $q+1$. The explanatory variable $earn_{n,q}$ is firm n's quarterly earnings growth for the fiscal quarter ending in calendar quarter q. $vw_{n,q}$ ($ew_{n,q}$) is the weight applied to $earn_{n,q}$ used to construct value-weighted (equal-weighted) aggregate earnings growth for calendar quarter q. $smth_{n,q}$ is firm n's earnings smoothness. Additional control variables include GDP_q, the initial estimate of real GDP growth in quarter q; GDP_{q-k}, the third estimate of real GDP growth in quarter $q-k$; YLD_q, the yield on the one-year Treasury bill measured one month after the end of quarter q; $SPRD_q$, the yield on the 10-year Treasury bill minus the yield on the one-year Treasury bill measured one month after the end of quarter q; and RET_q, the buy-and-hold market return over a three-month period ending one month after the end of quarter q. Standard errors based on a Newey and West (1987) correction for autocorrelation with four lags are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3
Aggregate Earnings Tilt and Mean SPF Forecast Revisions

	(1)	(2)	(3)	(4)
Panel A: Estimated tilt parameter				
τ_{smth}		0.371^{***}		0.280^{***}
		(0.064)		(0.072)
Panel B: Estimated regression coefficients				
β_{EARN}	1.493^{***}	2.350^{***}	1.216^{***}	1.696^{***}
	(0.283)	(0.423)	(0.231)	(0.311)
β_{GDP}	0.141^{***}	0.096^{**}	0.121^{***}	0.098^{**}
	(0.048)	(0.041)	(0.039)	(0.041)
$\beta_{GDP_{q-1}}$	0.021	0.007	0.010	0.003
	(0.030)	(0.031)	(0.034)	(0.034)
$\beta_{GDP_{q-2}}$	-0.016	-0.006	0.012	0.016
	(0.031)	(0.030)	(0.024)	(0.025)
$\beta_{GDP_{q-3}}$	0.046^{**}	0.058^{***}	0.066^{***}	0.072^{***}
	(0.019)	(0.022)	(0.021)	(0.022)
β_{YLD}			-0.043^{***}	-0.040^{***}
			(0.016)	(0.015)
β_{SPRD}			-0.053	-0.050
			(0.047)	(0.047)
β_{RET}			0.040^{***}	0.039^{***}
			(0.011)	(0.010)
Panel C: Other model estimates				
θ	0.501	0.323	0.750	0.537
	(0.386)	(0.236)	(0.511)	(0.355)
Adj. R^2	0.260	0.318	0.337	0.390

This table reports tilt parameter and regression coefficient values estimated from the following mixed data sampling model using a sample of 131 calendar quarter observations between 1984:Q1 and 2016:Q4:

$$REV_{q+1} = \alpha + \beta_{EARN} \sum_{n=1}^{N_q} \omega_{n,q} \cdot earn_{n,q} + \beta_{GDP} GDP_q + \sum_{k=1}^{3} \beta_{GDP_{q-k}} \cdot GDP_{q-k} + \beta_{YLD} YLD_q + \beta_{SPRD} SPRD_q + \beta_{RET} RET_q + \varepsilon_{q+1},$$

subject to: $\omega_{n,q} = \theta \cdot vw_{n,q} + (1-\theta) \cdot ew_{n,q} + \tau_{smth} \cdot smth_{n,q}$.

The dependent variable REV_{q+1} is the mean SPF forecast revision of real GDP growth for calendar quarter $q+1$. The explanatory variable $earn_{n,q}$ is firm n's quarterly earnings growth for the fiscal quarter ending in calendar quarter q. $vw_{n,q}$ ($ew_{n,q}$) is the weight applied to $earn_{n,q}$ used to construct value-weighted (equal-weighted) aggregate earnings growth for calendar quarter q. $smth_{n,q}$ is firm n's earnings smoothness. Additional control variables include GDP_q, the initial estimate of real GDP growth in quarter q; GDP_{q-k}, the third estimate of real GDP growth in quarter $q-k$; YLD_q, the yield on the one-year Treasury bill measured one month after the end of quarter q; $SPRD_q$, the yield on the 10-year Treasury bill minus the yield on the one-year Treasury bill measured one month after the end of quarter q; and RET_q, the buy-and-hold market return over a three-month period ending one month after the end of quarter q. Standard errors based on a Newey and West (1987) correction for autocorrelation with four lags are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4
Aggregate Earnings Tilt and Mean SPF Forecast Errors

	(1)	(2)	(3)	(4)
Panel A: Estimated tilt parameter				
τ_{smth}		0.623^{***}		0.602^{***}
		(0.146)		(0.137)
Panel B: Estimated regression coefficients				
β_{EARN}	0.644	1.667^{**}	0.735	1.873^{**}
	(0.454)	(0.804)	(0.520)	(0.943)
β_{GDP}	0.071	0.017	0.074	0.018
	(0.088)	(0.100)	(0.084)	(0.098)
$\beta_{GDP_{q-1}}$	−0.124	−0.141	−0.127	−0.144
	(0.082)	(0.088)	(0.086)	(0.089)
$\beta_{GDP_{q-2}}$	0.128	0.140	0.117	0.127
	(0.080)	(0.086)	(0.091)	(0.084)
$\beta_{GDP_{q-3}}$	−0.027	−0.013	−0.043	−0.030
	(0.082)	(0.079)	(0.081)	(0.079)
β_{YLD}			−0.001	0.005
			(0.067)	(0.069)
β_{SPRD}			−0.136	−0.129
			(0.198)	(0.200)
β_{RET}			−0.006	−0.011
			(0.016)	(0.016)
Panel C: Other model estimates				
θ	2.395	0.934	2.094	0.819
	(2.775)	(0.960)	(2.431)	(0.856)
Adj. R^2	0.002	0.011	0.007	0.017

This table reports tilt parameter and regression coefficient values estimated from the following mixed data sampling model using a sample of 131 calendar quarter observations between 1984:Q1 and 2016:Q4:

$$FE_{q+1} = \alpha + \beta_{EARN} \sum_{n=1}^{N_q} \omega_{n,q} \cdot earn_{n,q} + \beta_{GDP} GDP_q + \sum_{k=1}^{3} \beta_{GDP_{q-k}} \cdot GDP_{q-k} + \beta_{YLD} YLD_q + \beta_{SPRD} SPRD_q + \beta_{RET} RET_q + \varepsilon_{q+1},$$

subject to: $\omega_{n,q} = \theta \cdot vw_{n,q} + (1-\theta) \cdot ew_{n,q} + \tau_{smth} \cdot smth_{n,q}.$

The dependent variable FE_{q+1} is the mean SPF forecast error of real GDP growth for calendar quarter $q+1$. The explanatory variable $earn_{n,q}$ is firm n's quarterly earnings growth for the fiscal quarter ending in calendar quarter q. $vw_{n,q}$ ($ew_{n,q}$) is the weight applied to $earn_{n,q}$ used to construct value-weighted (equal-weighted) aggregate earnings growth for calendar quarter q. $smth_{n,q}$ is firm n's earnings smoothness. Additional control variables include GDP_q, the initial estimate of real GDP growth in quarter q; GDP_{q-k}, the third estimate of real GDP growth in quarter $q-k$; YLD_q, the yield on the one-year Treasury bill measured one month after the end of quarter q; $SPRD_q$, the yield on the 10-year Treasury bill minus the yield on the one-year Treasury bill measured one month after the end of quarter q; and RET_q, the buy-and-hold market return over a three-month period ending one month after the end of quarter q. Standard errors based on a Newey and West (1987) correction for autocorrelation with four lags are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5

Aggregate Earnings Tilt and Mean Forecast Errors of Individual SPF Analysts Grouped by Forecast Revision Sensitivity to Aggregate Earnings

	Forecast Revision/Aggregate Earnings Sensitivity		
	High	Low	All Other
Panel A: Estimated tilt parameter			
τ_{smth}	0.682	0.433**	0.629***
	(0.610)	(0.169)	(0.137)
Panel B: Estimated regression coefficients			
β_{EARN}	1.792	2.197**	1.840**
	(1.938)	(1.098)	(0.852)
β_{GDP}	0.030	−0.002	0.021
	(0.097)	(0.101)	(0.100)
$\beta_{GDP_{q-1}}$	−0.138	−0.162	−0.150
	(0.084)	(0.098)	(0.093)
$\beta_{GDP_{q-2}}$	0.151	0.106	0.128
	(0.093)	(0.077)	(0.089)
$\beta_{GDP_{q-3}}$	−0.034	−0.035	−0.029
	(0.080)	(0.083)	(0.081)
β_{YLD}	0.000	−0.027	0.011
	(0.071)	(0.093)	(0.065)
β_{SPRD}	−0.136	−0.202	−0.121
	(0.197)	(0.257)	(0.194)
β_{RET}	−0.009	−0.005	−0.013
	(0.014)	(0.020)	(0.016)
Panel C: Other model estimates			
θ	0.618	0.578	0.921
	(0.736)	(0.785)	(0.913)
Adj. R^2	0.002	0.023	0.018
Mean$[(FE_{q+1})^2]$	0.291	0.371	0.312

This table reports tilt parameter and regression coefficient values estimated from the following mixed data sampling model using a sample of 131 calendar quarter observations between 1984:Q1 and 2016:Q4:

$$FE_{q+1} = \alpha + \beta_{EARN} \sum_{n=1}^{N_q} \omega_{n,q} \cdot earn_{n,q} + \beta_{GDP} GDP_q + \sum_{k=1}^{3} \beta_{GDP_{q-k}} \cdot GDP_{q-k} + \beta_{YLD} YLD_q + \beta_{SPRD} SPRD_q + \beta_{RET} RET_q + \varepsilon_{q+1},$$

$$\text{subject to:} \quad \omega_{n,q} = \theta \cdot vw_{n,q} + (1-\theta) \cdot ew_{n,q} \quad + \quad \tau_{smth} \cdot smth_{n,q}.$$

The dependent variable FE_{q+1} is the mean of individual SPF forecast errors of real GDP growth for calendar quarter $q+1$. FE_{q+1} is based on individual SPF forecasters with high and low forecast revision sensitivities to aggregate earnings growth in the first and second columns, respectively. In the third column, FE_{q+1} is based on all other individual SPF forecasters with fewer than eight historical revisions (required to estimate the forecast revision sensitivity to aggregate earnings growth). The explanatory variable $earn_{n,q}$ is firm n's quarterly earnings growth for the fiscal quarter ending in calendar quarter q. $vw_{n,q}$ ($ew_{n,q}$) is the weight applied to $earn_{n,q}$ used to construct value-weighted (equal-weighted) aggregate earnings growth for calendar quarter q. $smth_{n,q}$ is firm n's earnings smoothness. Additional control variables include GDP_q, the initial estimate of real GDP growth in quarter q; GDP_{q-k}, the third estimate of real GDP growth in quarter $q-k$; YLD_q, the yield on the one-year Treasury bill measured one month after the end of quarter q; $SPRD_q$, the yield on the 10-year Treasury bill minus the yield on the one-year Treasury bill measured one month after the end of quarter q; and RET_q, the buy-and-hold market return over a three-month period ending one month after the end of quarter q. Standard errors based on a Newey and West (1987) correction for autocorrelation with four lags are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.