Another Look at the Macroeconomic Information Content of Aggregate Earnings: Evidence from the Labor Market

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Abstract

In this paper we examine the macroeconomic information content of aggregate earnings from the labor market's perspective. We use insights from the labor economics literature to characterize the information contained in aggregate GAAP earnings and its components that is relevant for predicting aggregate job creation and destruction, labor income, and unemployment. Our results suggest that not only does aggregate earnings news convey information about future labor market aggregates, but its information content is incremental to other macroeconomic variables at near-term horizons. Further, the source of this information stems primarily from two earnings components: aggregate core earnings and special items. Core earnings news signals persistent changes in economy-wide profitability that anticipate aggregate job creation and destruction up to four quarters ahead, while special items contain news only about job destruction at horizons of up to two quarters. Taken together, our results suggest that aggregate GAAP earnings contain useful information about future labor market conditions, with the nature of such information varying across earnings components.

1. Introduction

Prior research finds that aggregate GAAP earnings predict future GDP growth and attributes this finding to a "corporate profit" channel, whereby aggregate earnings predict the corporate profit component of future Gross Domestic Income (GDI), the income-based equivalent of GDP (e.g., Konchitchki and Patatoukas 2014a). Corporate profits, however, represent only a small portion of GDI (on average about 9% over the past 10 years).[1] Thus, if aggregate earnings convey macroeconomic information primarily through corporate profits, the role of accounting information for gauging the health of the macroeconomy is limited. Such a view is inconsistent with recent evidence that aggregate earnings news conveys important information about future inflation and monetary policy (Gallo et al. 2016; Shivakumar and Urcan 2017). In this paper, we focus on another aspect of the macroeconomic information contained in GAAP earnings—the link between aggregate GAAP earnings and the labor market.[2]

In neoclassical economics, a firm's demand for labor is determined by its product demand and the shape of its production function (e.g., Hicks 1963; Hamermesh 1993). To the extent that a firm's earnings news captures shocks to future profitability due to shifting product demand, positive earnings news should lead to additional investment and hiring, while negative earnings news should lead to downsizing and layoffs. However, despite a sound theoretical foundation that characterizes firms' employment decisions as a function of profitability shocks (e.g., Cooper, Haltiwanger and Willis 2007; Roys 2016), empirical evidence on this link is relatively scarce and limited mostly to layoffs associated with corporate downsizing preceded by periods of low profitability (John, Lang, and Netter 1992; Ofek 1993; Chen, Mehrotra, Sivakumar, and Yu

[1] For comparison, labor income is the largest component of GDI (on average around 43% over the last 10 years).
[2] Two recently published papers (Kalay, Nallareddy, and Sadka 2017; Nallareddy and Ogneva 2017) and a concurrent paper (Rouxelin, Wongusnai, and Yehuda 2017) investigate links between other accounting variables and the aggregate labor market. We discuss these papers later in the introduction and in Section 2.

2001). More recently, Nallareddy and Ogneva (2017) document a positive cross-sectional association between earnings news and future changes in firm-level employment for a broad sample of public companies. In this paper, we take it a step further and examine whether aggregate GAAP earnings news (i.e., shocks to aggregate net income) that reflect economy-wide profitability shocks can predict aggregate job growth and labor income.

To characterize earnings information that is relevant for predicting labor market conditions, we turn to prior literature on the mechanics of employment changes. Employment changes at the micro level are associated with non-trivial fixed (or quasi-fixed) adjustment costs (e.g., Hamermesh 1989; Caballero, Engel, and Haltiwanger 1997).[3] Firms therefore adjust the size of their workforce only when they face relatively large shocks, resulting in lumpy employment adjustment (e.g., Davis, Faberman, and Haltiwanger 2006; Cooper et al. 2007). Intuitively, profitability shocks that are more persistent are more likely to generate a revision in value that is sufficiently large to overcome these fixed adjustment costs. Roys (2016) formally models this intuition and shows that persistent shocks lead to changes in employment (i.e., hiring or firing of workers), while transitory shocks result in changes in wages. Given that core earnings are more persistent than the non-core components of earnings (e.g., Fairfield et al. 1996), we hypothesize that a shock to aggregate core earnings is a leading indicator of future aggregate job flows and labor income growth. Moreover, to the extent that there is a lag between the initial profitability shock and the subsequent shift in the firm's labor demand (e.g., Cooper et al. 2007), we expect this lead to extend over multiple quarters.

[3] Upward adjustment costs include hiring and training (e.g., Oi 1962; Barron, Berger and Black 1997), while downward adjustment costs include severance payments, union contract renegotiations, and unemployment insurance premiums (e.g., Anderson 1993; Serfling 2016). Until accumulated profitability shocks reach a threshold level, firms tend to adjust workers' hours without changing total employment (Cooper et al. 2007).

Although theory suggests that shocks to transitory non-core earnings are less likely to trigger significant employment adjustments, we expect one of the non-core components—special items—to convey information about future job flows despite its non-recurring nature. Special items are often recorded in anticipation of corporate restructuring and downsizing associated with layoffs (e.g., Donelson et al. 2011) and hence reflect actual (rather than expected) decisions to disinvest in response to sufficiently large past profitability shocks. Put differently, special items may convey a confirmatory or a more precise signal for abrupt changes in employment that occur shortly following their recognition. The precision of this signal depends on how well aggregate special items proxy for the events associated with workforce contraction (e.g., Capelli 2000; Kannan 2016).[4] Ultimately, whether decisions surrounding the recognition of special items are associated on average with significant near-term employment reduction and whether shocks to aggregate special items are a leading indicator of impending aggregate job losses are empirical questions that we test in the paper.

We test our hypotheses on a large sample of Compustat firms with quarterly observations between 1988 and 2015. To obtain news proxies for aggregate earnings series, we first employ a formal statistical process to select a time-series model for each aggregate earnings series considered. We then estimate the model parameters within a 10-year moving window using information available in real time. Our aggregate earnings news measures are the residuals from this estimation.[5] The first 10-year rolling estimation window starts in 1978, when the recognition

[4] Special items are not necessarily associated with restructuring or downsizing activities; for example, they can reflect litigation outcomes. Further, even when associated with downsizing, they may not always signal a workforce reduction. Capelli (2000) reports that 31% of firms surveyed by the American Management Association added workers at the time of downsizing, and in 6% of surveyed firms the workforce actually grew after downsizing. Kannan (2016) shows that 32% of layoffs announced by S&P 500 firms do not lead to employment downsizing.

[5] See Section 3 for a more detailed discussion.

of special items became sufficiently common (e.g., Elliot and Hanna 1996). Our sample period thus starts in 1988.

The results are consistent with our hypotheses. First, GAAP earnings can predict changes in job flows and labor income—aggregate net income news loads positively in time-series regressions that predict net job flows (i.e., the difference between aggregate job creation and job destruction) and labor income growth for up to four quarters. The results are similar when we use the wages and salaries of non-government employees or total wages and salaries of different vintages to measure labor income. Interestingly, despite accounting conservatism (i.e., the more timely recognition of bad news than good news in GAAP earnings), aggregate earnings news has similar predictive ability for aggregate job creation and destruction.

Second, aggregate core earnings news is positively associated with future job flows and labor income for up to four quarters, while aggregate special items news has significant predictive ability for only one or two quarters. Moreover, aggregate special items are associated with future mass layoffs, with their ability to predict future job flows concentrating in job destruction, while aggregate core earnings news predicts both job creation and job destruction. Untabulated results show that other components of non-core earnings are not consistently associated with future employment variables. Overall, our results suggest that aggregate GAAP earnings contain information about future labor market conditions, with the nature of such information varying across earnings components.

While predicting aggregate job flows and labor income is important for understanding the mechanism that links GAAP earnings to labor market outcomes, from a more practical standpoint it is useful to establish that our results carry over to unemployment prediction. As a primary macroeconomic indicator, the unemployment rate is followed by a broad range of economic agents and is embedded in various economic policy decisions, which brings it to the forefront of macroeconomists' agenda. Since unemployment rate is the ratio of unemployed individuals actively searching for a job to the total size of labor force, the link that we document between different GAAP earnings components and job flows should carry over to unemployment to the extent that laid-off workers remain in the workforce and newly hired workers were in the labor force prior to being hired. Our empirical results confirm this conjecture—aggregate GAAP earnings news is informative about future unemployment changes for up to four quarters. The horizons over which the different earnings components predict unemployment mirror the horizons over which they predict aggregate job flows and labor income, with core earnings news informative for up to four quarters and special items news for up to two quarters.

Of course, the ability of the different earnings components to forecast unemployment rates is of practical importance only if GAAP earnings contain information that is incremental to other available macroeconomic indicators. Conceptually, information about the labor market obtained from GAAP earnings may be more timely than that obtained from alternative sources: core earnings reflect shocks to profitability that precede hiring or firing decisions and special items reflect accrual charges that are recognized prior to layoffs or downsizing events, so both core earnings and special items may lead macroeconomic indicators that measure actual employment. However, given the wealth of macroeconomic information that is publicly available in real time, whether accounting earnings contain an incremental signal is an open question.

Our results show that both core earnings news and special items news continue to have a significant association with future changes in unemployment for up to two quarters after controlling for several macroeconomic indicators, including the aggregate book-to-market ratio, stock market returns, the inflation index, and a composite measure of economic activity, namely, the Chicago Fed National Activity Index. However, at horizons longer than two quarters the ability of earnings to predict unemployment is subsumed by other macroeconomic indicators. The incremental ability of earnings components to predict aggregate job flows and labor income remains statistically significant for up to four quarters. Additional analyses suggest that unemployment forecasts issued by macroeconomic forecasters do not fully impound the information contained in the aggregate earnings components. Overall, our results suggest that earnings news is incrementally informative about future labor market conditions. These findings are robust to using alternative aggregate earnings news estimates, different vintages of macroeconomic indicators, additional control variables, and mean versus median consensus unemployment forecasts, as well as to excluding recessionary quarters.

In contrast to our findings, concurrent research by Abdalla and Carabias (2017) shows that only aggregate special items, but not core earnings, predict future nominal GDP growth.[6] Although the focus of our study is quite different—we consider earnings components as predictors of labor market aggregates and unemployment, we perform additional tests to shed more light on the relation between these two sets of results. We first confirm that aggregate special items news but not core earnings news can predict future *real* GDP growth. We next show that neither core earnings nor special items predicts the corporate profits component of future GDI. Lastly, we show that the ability of aggregate special items to predict GDP growth is fully explained by future mass layoffs. Taken together, these findings suggest that the link between aggregate special items news and future GDP growth works primarily through the labor and unemployment channel. The lack of an association between core earnings news and GDP growth is puzzling in light of a strong link between core earnings and labor income growth. Explaining these contradictory results would require a more complete model that takes into

[6] A previous draft of our paper contained results that were similar to the findings in Abdalla and Carabias (2017).

account interlinkages between disposable personal income, consumption, and corporate profits. While such an analysis is outside the scope of our paper, the stylized facts that we document, combined with those in Abdalla and Carabias (2017), pave a fruitful avenue for future research.

Our paper makes three main contributions to the literature. First, our study complements a growing body of work that explores the macroeconomic information content of aggregate earnings.[7] While prior research finds that aggregate earnings convey information about future GDP growth, inflation, and monetary policy, we extend these findings by documenting the ability of aggregate earnings to predict labor market conditions. Our findings also add to the nascent thread of literature on the labor market information contained in GAAP earnings. Extant research shows that earnings-based variables, such as corporate earnings dispersion and cost stickiness, can explain unemployment and predict errors in unemployment forecasts or estimates (e.g., Kalay, Nallareddy, and Sadka 2017; Nallareddy and Ogneva 2017; Rouxelin, Wongusnai, and Yehuda 2017).[8] We complement these findings by establishing a direct link between aggregate GAAP earnings and the labor market that is grounded in microeconomic theory.

Second, our study takes a first step in examining the differential macroeconomic information contained in core earnings and non-core earnings, in particular, special items.[9] Understanding the extent to which macroeconomic information stems from core- or non-core

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[7] While the majority of the work in this literature explores various aspects of the aggregate earnings-return association (e.g., Kothari et al. 2006; Shivakumar 2007, 2010; Sadka and Sadka 2009; Hirshleifer et al. 2009; Jorgensen et al. 2011; Cready and Gurun 2010; Pakatokas 2014; Gallo et al. 2016), we contribute to a smaller but growing thread of research that benchmarks the information content of GAAP earnings against various macroeconomic aggregates, including real and nominal GDP growth, inflation, and unemployment (Konchitchki and Patatoukas 2014a, 2014b; Shivakumar and Urcan 2017; Nallareddy and Ogneva 2017; Kalay et al. 2017). See Ball and Sadka (2015) for a comprehensive review of this literature.

[8] Kalay et al. (2017) and Nallareddy and Ogneva (2017) concentrate on unemployment resulting from the frictions associated with worker reallocation, where greater reallocation can be predicted by greater dispersion in earnings news across firms. In contrast, we focus on how *common* profitability shocks (captured by aggregate earnings) affect aggregate job creation and destruction. The papers also differ in terms of objectives. Our goal is to predict job flows, labor income, and unemployment, whereas Kalay et al. document contemporaneous associations between earnings dispersion and unemployment, and Nallareddy and Ogneva predict restatements in macroeconomic estimates.

[9] A concurrent study by Abdalla and Carabias (2017) examines aggregate earnings components as predictors of GDP growth.

earnings, which have vastly different persistence at the firm level, is particularly important in the context of the labor market due to the presence of significant employment adjustment costs. Our results suggest that despite their differential persistence, shocks to both core earnings and special items convey important information about the future state of the labor market, albeit through different channels.

Third, our study extends a large stream of research that examines trends in earnings quality. This research documents a general decrease in earnings persistence and reduced matching between revenues and expenses (e.g., Dichev and Tang 2008) due (in part) to a substantial increase in the frequency and magnitude of special items reporting (e.g., Elliott and Hanna 1996; Fairfield et al. 2009). Recent studies similarly argue that the proliferation of fair-value-related special items is behind a reduction in the use of GAAP earnings for valuation (Bradshaw and Sloan 2002) and contracting (Demerjian 2011). Our results suggest that the low information value of special items at the firm level does not extend to the macro setting—taken in aggregate, special items contain useful information about the macroeconomy.

The rest of the paper is organized as follows. Section 2 reviews the related literature and develops our ex ante predictions. Section 3 discusses our data and sample selection. Section 4 presents our research design and reports our main empirical results. Section 5 contains results of additional analyses and robustness checks. Section 6 concludes.

2. Related Literature and Hypotheses

2.1 GAAP Earnings as a Predictor of Aggregate Job Flows and Labor Income

In neoclassical economics, a firm's demand for labor is determined by the demand for its products and the shape of the production function that combines labor and capital (e.g., Hicks

1963; Hamermesh 1993). Although the shape of the production function (i.e., the degree of substitutability or complementarity of labor and capital) in modern economies is subject to extensive debate (e.g., Piketty 2014; Acemoglu and Robinson 2015), an expansion of firm operations typically requires an increase in the firm's workforce. To the extent that a firm's earnings signals its future profitability (perhaps due to changes in product demand), we expect positive earnings news to lead to additional investment and hiring and negative earnings news to lead to downsizing and layoffs.

While the lead-lag relationship between profitability (or cash flow) changes and future investment has been extensively documented—higher profits are followed by greater investment at both the firm level (e.g., Fazzari, Habbard and Petersen 1988) and the aggregate level (Kothari, Lewellen, and Shanken 2017), the link between changes in profitability and employment has received less attention in the literature.[10] Despite a sound theoretical foundation that characterizes firms' employment decisions as a function of profitability (e.g., Cooper et al. 2007; Roys 2016), the empirical evidence is limited mostly to downsizing-related layoffs that follow periods of low profitability (John et al. 1992; Ofek 1993; Chen et al. 2001). More recently, Nallareddy and Ogneva (2017) document a positive cross-sectional association between earnings news and future changes in a firm's total employment for a broad sample of public companies. In this paper, we take it a step further and hypothesize that aggregate GAAP earnings news (i.e., shocks to aggregate net income) that reflect economy-wide profitability shocks predict aggregate job growth.

[10] Research on investment sensitivity to cash flows is mixed as to whether earnings or cash flow shocks proxy for future investment opportunities or the availability of internal capital and financing constraints. While the early research favored the latter interpretation (Fazzari et al. 1988), more recent papers argue in favor of the former interpretation of a significant correlation between past earnings or cash flows and future investment Erickson and Whited (2000), Gomes (2001), Alti (2003), and Gala and Gomes (2016).

Labor income, i.e., total wages and salaries earned by the workers in the U.S. economy, is jointly determined by the number of employed, the number of hours worked by those employed, and hourly wages. In general, we expect that net job flows, i.e. the increase in the quantity of jobs created in the economy in a given quarter, should translate into the increase in labor income. This extrapolation is subject to two caveats. First, firms can adjust the number of hours worked by their employees more easily than the size of their workforce. Prior research shows that until accumulated profitability shocks reach a threshold level, workers' hours are adjusted without changing total employment (Cooper et al. 2007). Second, firms may adjust hourly wages (or worker salaries) in the direction that is opposite to the employment adjustment. Prior research, however, indicates that this is unlikely to happen. The accumulated body of evidence suggests that employment and hourly wages tend to move together, with wages being more rigid across the business cycles than total employment (Campbell and Kamlani 1997). Overall, we expect labor income to be at least as sensitive to aggregate earnings shocks as are aggregate job flows. Accordingly, our first hypothesis (formulated in alternative form) is as follows:

> *Hypothesis 1: Shocks to aggregate net income are positively associated with future aggregate net job growth (i.e., the difference between aggregate job creation and destruction) and labor income growth (i.e., growth in the wages and salaries component of GDI).*

This hypothesis is related to recent work by Kalay et al. (2017) and Nallareddy and Ogneva (2017) that links accounting earnings to worker flows. These papers focus on unemployment resulting from frictions that prevent the immediate reallocation of workers across firms. Such reallocation can be driven by disparate profitability shocks that cause some firms to hire and others to lay off workers, and hence both papers use earnings *dispersion* to measure such shocks. In contrast, the focus of our paper is to identify layoff and hiring decisions that are *correlated* across firms in the economy and that can have a significant effect on net job creation or destruction. We therefore use aggregate corporate earnings (where idiosyncratic profitability shocks are diversified away) to measure such shocks.

2.2 Earnings Components as Predictors of Aggregate Job Flows and Labor Income

We next investigate the ability of the components of GAAP earnings to predict future labor market conditions. We know from prior research that earnings components are heterogeneous in terms of the information they convey about firms' financial condition and operations (e.g., Lipe 1986; Fairfield et al. 1996; Bradshaw and Sloan 2002; Doyle et al. 2003; Curtis et al. 2014). We expect these components to retain the differences in their information content after aggregation, with core earnings and special items both signaling future aggregate job growth and labor income changes.

A large accounting literature examines the persistence of different earnings components and their implications at the firm level. This research shows that core and non-core earnings components have vastly different properties—core earnings tend to be fairly persistent, while non-core earnings are more transitory and have little ability to predict future earnings or cash flows (e.g., Fairfield et al. 1996). Consistent with their higher persistence, shocks to core earnings are associated with larger stock price revisions (e.g., Lipe 1986; Elliott and Hanna 1996; Burgstahler et al. 2002). We argue that such persistence drives the informativeness of aggregate core earnings in the labor market setting. Below we discuss the theory that motivates this hypothesis.

Employment changes at the micro level are associated with significant fixed adjustment costs: workforce expansions are associated with hiring and training costs (e.g., Oi 1962; Barron et al. 1997), while workforce contractions are associated with severance payments, union contract renegotiations, and unemployment insurance premiums (e.g., Anderson 1993; Serfling 2016; Hamermesh 1989). As a result of these fixed or quasi-fixed costs, employment changes are lumpy—the majority of firms experience little or no change in employment in any given quarter—with such lumpiness observed for both upward and downward adjustments (e.g., Hamemesh 1989; Davis et al. 2006).[11] In short, to compensate for the fixed or quasi-fixed employment adjustment costs, firms engage in hiring or layoffs only when shocks to profitability are sufficiently large.[12]

Given the above findings, we expect the information content of earnings with respect to future job growth to vary with the degree of earnings persistence—a \$1 shock that persists over a long horizon is more likely to induce a revision in value that is sufficiently large to compensate for the employment adjustment costs than a \$1 shock that is relatively transitory. Hence, persistent and transitory shocks should have different effects on firms' employment decisions. Formalizing this intuition, Roys (2016) models the effects of shocks' persistence on employment adjustment and shows that persistent shocks lead to changes in employment, while transitory shocks result in changes in wages. Accordingly, we predict that compared to non-core earnings components, core earnings' greater persistence should make them a better predictor of future hiring and layoffs. While the horizon over which core earnings can predict future job growth is less clear, prior research suggests that shifts in labor demand in response to a profitability shock occur at a significant lag (e.g., Cooper et al. 2007), which may spread core earnings' predictive

[11]The degree of lumpiness in employment adjustment is quite striking. Davis et al. (2006) report that in the third quarter of 2001, only 53% of surveyed establishments experienced a change in employment, with 68% of job destruction occurring at establishments that contracted their workforce by over 10%, while 63% of job creation occurred at establishments that expanded their workforce by over 10%.

[12] Firms tend to adjust workers' hours without changing total employment until accumulated profitability shocks reach a threshold level (Cooper et al. 2007).

ability over multiple quarters. Our hypothesis for aggregate core earnings (stated in alternative form) is therefore as follows:

Hypothesis 2a: Profitability shocks reflected in aggregate core earnings predict future aggregate job flows and labor income growth over multiple quarters.

Because non-core earnings are less persistent than core earnings, shocks to these earnings components may not generate revisions in value that are sufficiently large to drive labor adjustments. However, one of the components of non-core earnings, special items, may convey information about future job flows despite its transitory nature. Although by definition infrequent or unusual, special items are often recorded in anticipation of corporate restructuring and downsizing (e.g., Donelson et al. 2011) and hence reflect actual (rather than expected) decisions to disinvest in response to sufficiently large past profitability shocks. Special items can thus convey a confirmatory or a more precise signal for abrupt changes in employment that occur shortly following their recognition. Consistent with this view, Chen et al. (2001) find that layoff announcements are associated with a reduction in total employment in the year of the announcement, but this effect dissipates by the end of the second year following the announcement.

Despite these arguments, restructuring or downsizing activities may not always lead to a significant change in employment at the aggregate level. For instance, Capelli (2000) reports that 31% of firms surveyed by the American Management Association added workers while downsizing, and in 6% of surveyed firms the workforce grew after downsizing. Kannan (2016) similarly shows that 32% of layoffs announced by S&P 500 firms do not lead to a reduction in employment. Furthermore, special items are not always associated with restructuring or downsizing activities. While special items are typically associated with business events

(Donelson et al. 2011), they are recorded in relation to not only restructurings, but also mergers/acquisitions, litigation, and asset dispositions. They also encompass asset write-offs and goodwill impairment charges.[13] Accordingly, we first test whether all special items, in aggregate, are associated with mass layoffs (i.e., layoffs that involve more than fifty employees and hence are more likely to coincide with downsizing). Hence our first hypothesis pertaining to aggregate special items is the following (stated in alternative form):

Hypothesis 2b: Aggregate special items news is associated with future mass layoffs in the near term.

Overall, whether the recognition of special items is associated with a near-term change in aggregate employment is ultimately an empirical question. We test the following hypothesis with respect to aggregate special items (stated in alternative form):

Hypothesis 2c: Profitability shocks reflected in aggregate special items predict future aggregate job flows and labor income growth in the near term.

3. Sample Selection, Variable Measurement, and Research Design

3.1 Sample

To estimate aggregate earnings news, we rely on Compustat firms with quarterly observations between 1988 and 2015, which results in a sample that spans 112 quarters. Only firms with fiscal quarters ending in March, June, September, and December are included in the sample. Our procedure for constructing aggregate earnings news is based on 10-year moving windows ending in the quarter in which the news is estimated. The first 10-year window starts in 1978, when recognition of special items became sufficiently common (e.g., Elliot and Hanna

[13] It is difficult to address differences in the information contained in the various types of special items empirically, as data on special items type are not available in Compustat prior to 2002 (e.g., Cready, Lopez, and Sisneros 2012), and even when such data are available, they are not always precise (e.g., Frankel 2009).

1996), which results in our sample period starting in 1988.[14] In some of our tests, the sample period is limited by the availability of macroeconomic data; we describe these limitations in the next subsection and when we discuss the results in Section 4.

3.2 Aggregate Earnings News and Earnings Components

Our earnings news estimates are based on aggregate earnings series (GAAP net income or its components), with each quarterly observation equal to the cross-sectional sum of sample firms' quarterly earnings scaled by the sum of their lagged book values:

$$AGGX_t = \frac{\sum_{i=1}^{N}(X_{i,t})}{\sum_{i=1}^{N} BV_{i,t-1}}, \tag{1}$$

where $X_{i,t}$ is quarter t GAAP net income (*NI*; Compustat item NIQ), core earnings (*EBIT*; Compustat item *OIADQ*, operating income after depreciation), or special items (*SPI*; Compustat item *SPIQ*), $BV_{i,t\text{-}1}$ is quarter t-1 book value of equity, and N is the number of firms with earnings information available in Compustat.

We use a two-step process to select a time-series model for each aggregate earnings series considered. In the first step, we test the stationarity of each series using the augmented Dickey-Fuller test (with one lag and a time trend). The null hypothesis under the Dickey-Fuller test is a unit-root autoregressive process, so a significant Dicker-Fuller statistic would indicate stationarity. Panel A of Table 1 reports p-values for the Dicker-Fuller statistics for two periods—the full sample period (1978-2015), which we use to estimate aggregate earnings news, and the subperiod (1988-2015) constrained by out-of-sample news estimation, as discussed in Section

[14] Based on Elliot and Hanna (1996, Figure 1), 1978 is the first year in which the percentage of firms reporting large positive and negative special items reaches a threshold that is close to 5%.

3.1. For both periods, the *p*-values associated with the Dickey-Fuller test are below 10%, suggesting that each earnings series is stationary.

In the second step, we select the time-series model that best describes each earnings series. Because the null of a unit root is rejected for all measures, series differencing is unnecessary. We compare the following three time-series models: AR(1), ARIMA $(0,0,0)x(1,0,0)_4$, and ARIMA $(1,0,0)x(1,0,0)_4$. These models imply autocorrelation with a one-quarter lag, a four-quarter lag, and both one- and four-quarter lags, respectively. We do not consider series with moving-average terms for the sake of simplicity. Model selection is based on two tests: Akaike information criterion (AIC) and Schwarz Bayesian information criterion (BIC). Smaller values of each criterion indicate better model fit. Panel B of Table 1 reports the AICs and BICs of the three models for each earnings series. Both the AIC and the BIC favor the ARIMA $(1,0,0)x(1,0,0)_4$ model for each earnings series, and thus this is the model we adopt to estimate aggregate earnings news.

Having selected the time-series model, we next estimate aggregate earnings news. To ensure that the news estimates are available to economic agents in real time, we estimate the parameters of the time-series process within a 10-year moving-window hold-out period. The news estimates are the differences between actual aggregate earnings for a quarter and expectations based on the previously estimated parameters. For instance, for the first aggregate news observation in our sample, 1988:1, we estimate the model parameters from the initial 10-year estimation window, 1978:1 to 1987:4. We then use these parameters to obtain the expectation for 1988:1, which we subtract from the actual value to get the news component of aggregate earnings. The 1988:2 news estimate is based on the window 1978:2 to 1988:1, and so on, so that the parameters of the time-series process are always based on 40 quarterly observations. We employ this procedure to obtain out-of-sample aggregate earnings news estimates for aggregate GAAP net income news (NI_NEWS_t), core earnings news ($EBIT\_NEWS_t$), and special items news (SPI_NEWS_t).

3.3 Labor Market Variables: Job Flows, Labor Income, Mass Layoffs, and Unemployment

We use three job flow variables in our tests: aggregate job destruction (*LOSS*), aggregate job creation (*GAIN*), and their difference, net job flows (*NETGAIN*). All three variables are expressed as a fraction of total employment (i.e., job flow levels are divided by average employment across the current and previous quarters). The data are from the Business Employment Dynamics dataset maintained by the Bureau of Labor Statistics (BLS). Job flows are estimated for the total private sector and are available from 1992 onwards. The aggregate flows represent net changes in employment at the establishment level. Job creation is positive when establishments open or expand. Job destruction is positive when establishments close or contract.[15]

To measure labor income, we use two measures. We first use the wages and salaries of employees in the private sector (*WAGE_PRIVATE*), which we obtain from Federal Reserve Economic Data (FRED) maintained by the Federal Reserve Bank of St. Louis. The advantage of this measure is that it is well aligned with our arguments for a link between aggregate profitability shocks and total employment and compensation. The disadvantage is that FRED contains only latest-revision data, so private sector wages and salaries are not available in real-time vintages. Moreover, the series are cut short, with the latest available observation corresponding to the second quarter of 2015. We therefore also use the wages and salaries of all employees in the U.S. economy (*WAGE_ALL*), which we obtain from the Philadelphia Federal

[15] A detailed description of the job flow data can be found at https://www.bls.gov/bdm/bdmover.htm#concepts.

Reserve's Real Time Data Set for Macroeconomists. These data are available in real time, but include compensation of government workers, which introduces noise in the measurement. We use *WAGE_ALL* estimates from two vintages, the initially available mid-quarter estimates and the revised estimates available one quarter later, but most of our *WAGE_ALL* tests use the initially available estimates, which helps differentiate our results from restatement predictability (e.g., Nallareddy and Ogneva 2017). Both labor income series are seasonally adjusted, converted to growth rates, and exclude supplements such as employer contributions to employee pensions and insurance funds and government social insurance.

Some of our analyses use mass layoff statistics from the BLS' Mass Layoff Statistics program, which started in 1996 and was discontinued in 2013. This program collected mass layoff numbers from establishments with at least 50 initial claims for unemployment insurance (UI) filed against them during a 5-week period. We convert the monthly data to quarterly and then estimate the seasonal growth in the number of mass layoffs relative to the same quarter in the previous year. Data availability for this series results in a restricted sample of 64 to 67 quarters depending on the forecast horizon considered.

Our measures of unemployment come from the Philadelphia Federal Reserve's Real Time Data Set for Macroeconomists. We use the seasonally adjusted civilian unemployment rate. As is the case with other macroeconomic indicators, unemployment figures are revised over time as more information becomes available to government statistical agencies, and the revisions may be economically significant in magnitude (e.g., Nallareddy and Ogneva 2017). Our analyses employ vintages that correspond to the vintages of our labor income estimates. In particular, we use *UNEMP1,* the initially available mid-quarter estimate, and *UNEMP2,* a revised estimate available one quarter later. Because unemployment rates are highly persistent, we convert them into quarter-over-quarter changes.

3.4 Real GDP Growth and Corporate Profits

Our measures of real GDP growth and NIPA (National Income and Production Accounts) corporate profits (*CP*)—corporate profits after tax, inventory valuation, and capital consumption adjustments—come from the Philadelphia Federal Reserve's Real Time Data Set for Macroeconomists. We use the *CP* vintage that corresponds to the middle of the second quarter following the quarter in which profits were earned, which is the earliest vintage for which *CP* data are continuously available. We convert the *CP* data to growth rates. To match the vintage of corporate profits, we use GDP growth estimates that correspond to the GDP revision issued by the Bureau of Economic Analysis (BEA) about three months after the quarter-end, which is referred to as the "third estimate". In robustness tests we use the advanced (i.e., initially announced) real GDP growth estimates.

3.5 Other Macroeconomic and Stock Market Variables

We control for several macroeconomic and stock market variables in our tests on the incremental information content of aggregate earnings news. First, we control for the aggregate stock market return (*RET*), which we estimate as the quarterly value-weighted return of sample firms. Our main specification controls for the aggregate return earned over the same quarter in which we estimate aggregate earnings. In robustness tests we also include returns earned over the previous one to four quarters to account for the possibility that the stock market may lead aggregate earnings. Second, we control for the aggregate book-to-market ratio (*AGGBM*), which we estimate as the sum of firms' quarterly book values scaled by the sum of their market values. Third, we control for inflation as proxied by the GDP deflator (*PGDP*), which we obtain from the Philadelphia Federal Reserve's Real Time Data Set for Macroeconomists (we use the first available quarterly vintage that corresponds to *WAGE_ALL* and *UNEMP1*). Finally, we control for the Chicago Fed National Activity Index (*CFNAI*), a composite index of economic activity that gauges the overall state of the U.S. economy based on a variety of factors, including industrial production, personal income, and employment. In our main analyses, all macroeconomic variables are based on information that is publicly available as of the middle of quarter *t*+1, which coincides approximately with when aggregate earnings news for quarter *t* can be estimated using reported earnings.[16] In additional analyses related to unemployment forecast efficiency, we estimate aggregate earnings news using earnings announced in the first month of quarter *t*+1.

3.6 Research Design

Our analyses are based on time-series regressions of various macroeconomic variables on lagged aggregate earnings news. In all analyses, we control for seasonality and time trends. In particular, we estimate the following regression specification, where a subscript *t* indicates quarters:

$$MACRO_{t+n} = a + b_1\, MACRO_t + b_2\, AGGX\_NEWS_t + \boldsymbol{b_3\,'CONTROL_{jt}} + \boldsymbol{b_4\,'QTR_t} + b_5\, TIME\_TREND_t + e_{t+n}, \tag{2}$$

where $MACRO_{t+n}$ is the macro variable of interest (n = 1 to 4), AGG_NEWS_t is aggregate earnings news, $\boldsymbol{CONTROL_{jt}}$ is a vector of control variables, $\boldsymbol{QTR_t}$ is a vector of dummy variables indicating the first through third calendar quarters, and $TIME\_TREND_t$ is a trend variable.

To determine whether the standard errors in the time-series regressions need to be adjusted for autocorrelation in residuals, we use the Durbin-Watson test. In all specifications we

[16] The book values used in the estimation of the aggregate book-to-market ratio may not be available until later, when the 10-Qs and 10-Ks are filed.

find that the Durbin-Watson test statistic is greater than one, which indicates that autocorrelation is not high enough to warrant the Newey-West (1987) correction. We therefore make no adjustments to the reported *t*-statistics.

4. Main Results

4.1 Descriptive Statistics

Panel A of Table 2 presents descriptive statistics for aggregate GAAP earnings news (*NI_NEWS*), core earnings news (*EBIT_NEWS*), and special items news (*SPI_NEWS*). While on average *NI_NEWS* is close to zero, mean *EBIT_NEWS* and *SPI_NEWS* are negative and statistically significant. Since our estimation procedure does not restrict earnings news to be zero on average, the negative average earnings component news estimates suggest that our sample period is associated with a disproportionate share of adverse macro shocks. The financial crisis of 2007-2008 and subsequent Great Recession of 2008-2009 represent one such shock. To examine whether our results are unduly impacted by economic downturns, in robustness tests we exclude all recessionary periods from our analysis and find that our main results are qualitatively similar.

Table 2, Panel A further presents descriptive statistics for the labor market variables, including aggregate job flows, labor income, mass layoffs, and unemployment. The three job flow variables—aggregate job destruction (*LOSS*), aggregate job creation (*GAIN*), and the difference between them, net job flows (*NETGAIN*)—are expressed as a percent of average labor force size. The averages for these variables reveal constant turnover of workers in the economy: the gross job flows (*GAIN* and *LOSS*) are an order of magnitude higher than the net growth in the number of jobs (*NETGAIN*). The reported statistics for labor income growth indicate that on average it does not vary much between the private sector (*WAGE_PRIVATE*) and the entire U.S.

economy (*WAGE_ALL*), although *WAGE_PRIVATE* is significantly more volatile than *WAGE_ALL*. The mass layoff growth series is highly skewed, with an average of 3.6% and a median of -13%, which is likely a result of the disproportionate number of severe downturn quarters in the sample period considered. Turning to the unemployment figures, *UNEMP1* and *UNEMP2*, which are expressed in percentage points, we find that the mean unemployment changes are negative but not statistically significant (p-values untabulated). The summary statistics vary only slightly with the vintage of our unemployment estimates, suggesting that one-quarter restatements are not likely to affect our inferences.

Panel A of Table 2 also presents descriptive statistics for two additional variables used in our supplementary analyses, namely, real GDP growth (*RGDP*) and growth in corporate profits (*CP*). Average growth in corporate profits is about two times greater than average real GDP growth, which is due to the fact that corporate profits are measured in nominal dollars, unadjusted for inflation.

In Panel B of Table 2 we regress real GDP growth on corporate profits and our measures of labor income to shed light on their relative contribution to aggregate output. For the purpose of this analysis, we use *WAGE_ALL* vintage that matches the *CP* vintage (i.e. estimates that are available in the middle of the second quarter following the quarter in which wages and profits were earned). The results suggest that GDP growth exhibits a stronger association with labor income than corporate profits: the R-squared in regressions of GDP growth on labor income is an order of magnitude higher than the R-squared in regressions of GDP growth on corporate profits. While both labor income and corporate profits load with statistically significant coefficients when they are included together in the regression, the coefficient on labor income growth is significantly higher than that on corporate profits. These results are perhaps not surprising, given that labor income accounts for a significantly larger share of GDI compared to corporate profits. Nevertheless, the results underscore the importance of understanding how GAAP earnings are linked to the macroeconomy through labor markets.

4.2 Earnings News, Aggregate Job Flows, and Labor Income

In this section, we test our hypothesis on the information content of aggregate GAAP earnings.

We start by examining the ability of aggregate earnings news to forecast economy-wide job flows at horizons of up to four quarters. In particular, we regress aggregate job losses, gains, and net flows (the net change in the number of jobs as a percentage of labor force size) on our measure of aggregate net income news (*NI_NEWS*). In these tests, the sample period (1992 to 2015, or 94 quarters) is constrained by the availability of job flow data.

Table 3, Panel A reports the results. Columns (1) to (4) correspond to net job flows (*NETGAIN*) over forecast horizons of one to four quarters, respectively. Consistent with Hypothesis 1, which posits that profitability shocks reflected in aggregate net income are positively associated with future net job growth, the coefficient on *NI_NEWS* is positive and statistically significant at all forecast horizons. When we separately consider aggregate job destruction (*LOSS*) (columns (5) to (8)) and aggregate job creation (*GAIN*) (columns (9) to (12)), we find that aggregate net income news is informative about both job destruction and job creation. These results have interesting implications. Concurrent research suggests that the primary channel through which aggregate earnings is informative about the macroeconomy is accounting conservatism, the more timely recognition of bad news compared to good news (e.g., Abdalla and Carabias 2017). Our finding that aggregate earnings news is informative about both job creation and job destruction is perhaps inconsistent with this notion.

Next, we turn to the ability of aggregate earnings news to predict labor income. We regress future labor income growth as measured by the quarterly growth in labor income earned in the private sector (*WAGE_PRIVATE*) and the quarterly growth in total labor income in the U.S. economy (*WAGE_ALL*) on aggregate net income news. Panel B of Table 3 reports the regression results. Columns (1) to (4) are based on *WAGE_PRIVATE*, while columns (5) to (6) are based on *WAGE_ALL*. The results suggest that, irrespective of the labor income measure used, aggregate net income news is a significant predictor of labor income growth for up to four quarters ahead. These results support our first hypothesis, which posits that aggregate net income news predicts future labor income. Since labor income is part of GDI—an income-based equivalent of GDP—these results suggest a channel through which aggregate GAAP earnings are linked to future GDP growth. We further explore the implications of these findings for GDP prediction in Section 5.2 below.

4.3 Earnings Components, Aggregate Job Flows, and Labor Income

In this section, we test our hypotheses pertaining to the components of aggregate earnings. We expect two components of aggregate net income to predict future aggregate job growth and labor income—core earnings and special items. As discussed in Section 3, we proxy for core earnings using earnings before interest and taxes (EBIT), and we derive the news components of both core earnings (*EBIT_NEWS*) and special items (*SPI_NEWS*) by estimating parameters of the time-series process in real time.

Table 4 reports results of regressions that test an association between *SPI_NEWS* and the seasonal growth in the number of mass layoffs over horizons of one to four quarters. EBIT_NEWS is included in the regressions for comparison purposes. The results suggest that aggregate special items news, but not core earnings news, predict mass layoffs. The predictive ability of aggregate special items is significant over one to two quarters ahead and then tapers off. These results suggest that aggregate special items do indeed signal impending restructuring- or downsizing-related layoffs, while core earnings shocks, if they predict future job flows, are associated with more gradual changes in employment.

In our next set of regressions we examine the ability of *EBIT_NEWS* and *SPI_NEWS* to predict aggregate job flows and labor income over horizons of one to four quarters. We first focus on aggregate job flows. Panel A of Table 5 reports regressions of net job flows (*NETGAIN*), aggregate job destruction (*LOSS*), and aggregate job creation (*GAIN*) on core earnings news and special items news. The results in columns (1) through (4) suggest that while both earnings components are informative about future net job flows, their information content is different. In particular, while the coefficients are statistically significant for *EBIT_NEWS* for up to four quarters, they are significant for *SPI_NEWS* for only one to two quarters. These findings are consistent with firms' hiring and firing decisions following profitability shocks with a lag of up to several quarters (Cooper et al. 2007): the lag (which may differ across firms) between the profitability signal conveyed via core earnings news and the actual employment decision extends the predictability horizon for future job flows, whereas special items reflect layoff decisions that have already been made, which makes them a powerful signal of employment changes at a short horizon.

When we decompose net job flows into job destruction (columns (5) to (8)) and job creation (columns (9) to (12)), the results show that shocks to aggregate core earnings are informative about both future job destruction and future job creation, with predictability extending up to four quarters, while aggregate special items news is informative only about future job destruction for up to two quarters. These results lend further support to the arguments that underpin our hypotheses. In particular, aggregate core earnings news predicts future changes in employment because it reflects persistent shocks that result in revisions to NPV that are large enough to overcome employment adjustment costs, while aggregate special items are informative about changes in employment because they reflect actual decisions to lay off workers, decisions that may have been made in response to sufficiently large past profitability shocks.

Turning to the results pertaining to labor income prediction, Panel B of Table 5 shows that aggregate core earnings news (*EBIT_NEWS*) is significantly associated with growth in wages and salaries for up to four quarters, regardless of whether we consider labor income of the private sector or labor income of the overall economy. Special items news (*SPI_NEWS*) is significantly associated with private sector labor income at the one-quarter horizon and with the overall economy's labor income at the two-quarter horizon. Overall, the results in Table 5 are consistent with our second set of hypotheses.

In additional (untabulated) results we find that other components of non-core earnings are not consistently able to predict future job flows or labor income changes. The component closest in its transitory nature to special items—discontinued operations and extraordinary items—does not predict future employment aggregates, which further highlights the importance of earnings persistence in predicting labor market outcomes.

4.3 Unemployment Prediction

In this section we examine whether core earnings and special items news help predict unemployment and whether the ability of these aggregate earnings components to predict unemployment is incremental to that of other macroeconomic indicators.

As we discuss in the introduction, while predicting labor income and job flows is important for understanding business cycle dynamics and the role that corporate earnings play in the macroeconomy, unemployment is the main labor market indicator followed by policy makers, economists, and investors. Because the unemployment rate captures the ratio of unemployed individuals actively searching for a job to the total size of active labor force, we expect the link between the different GAAP earnings components and aggregate job flows to carry over to unemployment to the extent that laid-off workers remain in the workforce and newly hired workers were in the labor force prior to being hired.

Table 6 reports results of regressions of our unemployment measures on core earnings news and special items news. Columns (1) through (4) correspond to the first-quarter-vintage unemployment estimates (*UNEMP1*), while columns (5) through (8) are based on the second-quarter-vintage unemployment estimates (*UNEMP2*). Establishing that the results are robust to different vintages of data is important for drawing inferences about the usefulness of accounting information for real-time unemployment forecasting. The results suggest that both aggregate core earnings news and aggregate special items news are informative about future unemployment changes. As expected, the horizons over which the earnings components predict unemployment mirror the horizons over which they predict aggregate job flows. In particular, core earnings news is informative about unemployment changes for up to four quarters, whereas the predictive ability of special items news is limited to two quarters. The results are not sensitive to the vintage of unemployment estimates used.

As we also discuss in the introduction, the ability of different earnings components to forecast unemployment rates is of practical importance only if GAAP earnings contain information that is incremental to other macroeconomic sources. To test for the incremental ability of aggregate earnings components to predict future unemployment, we regress future unemployment changes on aggregate earnings component news and several macroeconomic indicators. We first control for the aggregate stock market return (*RET*); the stock market responds to changes in the health of the corporate sector more quickly than accounting earnings and thus may supersede the information contained in aggregate GAAP earnings components. We also include the aggregate book-to-market ratio (*AGGBM*); to the extent it captures the availability of positive-NPV investment opportunities in the economy, it may subsume information about future business downsizing or expansion contained in aggregate earnings news. We include the GDP deflator (*PGDP*), which controls for inflation-related signals conveyed by aggregate earnings news (Shivakumar and Urcan 2017). Finally, we control for a composite index of economic activity, the Chicago Fed National Activity Index (*CFNAI*), which gauges the overall state of the U.S. economy based on a number of information sources, including industrial production, personal income, and employment.

Panel A of Table 7 reports the regression results. The last two rows of the panel include F-test statistics that compare the R-squared of models including the aggregate earnings components to models that include only the macroeconomic control variables. We find that the aggregate earnings components contain a signal about future unemployment rates that is incremental to other macroeconomic indicators at the one- and two-quarter horizons for core earnings and the two-year horizon for special items, but the information embedded in aggregate earnings is fully subsumed by other macroeconomic indicators at longer horizons. These results are not sensitive to the vintage of unemployment data used. Overall, we find that both the core earnings and the special items components of GAAP net income represent sources of information that are useful for predicting unemployment at shorter horizons.

For completeness, we also examine the incremental predictive ability of the aggregate earnings components for aggregate job flows and labor income. The results, reported in Panels B and C of Table 7, are consistent with those in Panel A: both aggregate core earnings news and aggregate special items news contain information that is incrementally useful for predicting job flows and labor income, though their predictive ability is subsumed in part by other macroeconomic indicators at longer horizons. When we decompose job flows into job creation and job destruction, we find that the incremental predictive ability of core earnings is restricted to job creation, while the incremental predictive ability of special items remains restricted to job destruction.

Overall, our results suggest that the information conveyed through the aggregate earnings components is not only relevant for unemployment forecasting at short horizons, but also contains information that is incremental to other contemporaneously available macroeconomic sources.

5. Additional Tests and Robustness Checks

5.1 Unemployment Forecast Efficiency

In this section, we investigate whether the information contained in aggregate GAAP earnings, core earnings, and special items is fully impounded in economists' unemployment forecasts. Prior research suggests that macroeconomists' forecasts of GDP growth (Konchitchki and Patatoukas 2014b), inflation, and aggregate investment (Shivakumar and Urcan 2017) can be improved by incorporating information from aggregate earnings news, and Rouxelin et al. (2017) suggest that unemployment forecasts can be improved by incorporating information about cost stickiness, that is, the asymmetry with which changes in costs respond to changes in sales. More relevant to our paper, Abdalla and Carabias (2017) suggest that the information contained in special items, but not core earnings, is not fully incorporated in GDP forecasts. Given overwhelming evidence that professional macro forecasters do not fully impound accounting information in macroeconomic forecasts, we expect the unemployment predictability results to carry over to macro forecast inefficiency.

To evaluate the degree of economists' forecast efficiency, we regress future changes in the unemployment rate on aggregate earnings news and unemployment forecasts from the Survey of Professional Forecasters (SPF) maintained by the Philadelphia Federal Reserve. If economists impound all earnings information, then earnings news should have no ability to predict future unemployment rates after controlling for economists' forecasts. In particular, we estimate the following regression:[17]

$$UNEMP_{t+n} = a + b_1\, UNEMP_t + b_2\, EBIT\_NEWS^{1Month}{}_t + b_3\, SPI\_\, NEWS^{1Month}{}_t$$
$$+\; b_4\, FUNEMP_{t+n,\, t+1} + e_{t+n}, \qquad (3)$$

[17] Note that equation (3) is equivalent to a regression that predicts a forecast error, that is, $UNEMP_{t+n}$ - $FUNEMP_{t+n,\, t}$ = $Intercept + b_1\, UNEMP_{t+n} + b_2\, EBIT\_NEWS_{t.} + b_3\, SPI\_NEWS_{t.} + \; b_4\, FUNEMP_{t+n,\, t} \; + e_{t+1}$. The coefficients on $UNEMP_{t+n}$, $EBIT\_NEWS_t$, and SPI_NEWS_t are identical in both specifications as long as the regression includes unemployment forecasts. Omitting $FUNEMP_{t+n,\, t}$ from the forecast error regression is equivalent to restricting the slope on $FUNEMP_{t+n,\, t}$ in equation (3) to one.

where $UNEMP_{t+n}$ is the change in unemployment rate between quarters $t+n$ and $t+n$-1, $EBIT\_NEWS^{1Month}_{t}$ and $SPI\_ NEWS^{1Month}_{t}$ are aggregate core earnings news and special items news constructed based on earnings announced by the end of the first month of quarter t+1, and $FUNEMP_{t+n,\ t+1}$ is the SPF median consensus forecast of the unemployment rate for quarter $t+n$ issued in quarter t+1 minus the realized unemployment rate for quarter $t+n$-1. Unemployment rate actuals are from the first available quarterly vintage, which ensures that our results are not picking up predictability in unemployment estimate restatements (Nallareddy and Ogneva 2017). All other variables are as defined before.

The results are reported in Table 8. The regressions reported in columns (1) through (4) do not control for other macroeconomic information sources. For the current-quarter forecast, $FUNEMP_{t+1,t+1}$, we observe no inefficiency with respect to accounting information. Beyond the current quarter, aggregate core earnings news (*EBIT_NEWS*) predicts up to four quarters of future unemployment, while aggregate special items news (*SPI_NEWS*) is incrementally predictive only up to two quarters. The regressions in columns (5) through (8) include the additional macroeconomic variables as controls. The results for core earnings are weaker when other macroeconomic indicators are incorporated into the analysis, with core earnings news significant only up to the three-quarter horizon. The last two rows include F-test statistics that compare the coefficients on economists' unemployment forecasts to one and compare the R-squared of models including the aggregate earnings components to models that include only the control variables. While economists' forecasts are significantly biased in most regressions specifications (i.e., the coefficients on unemployment forecasts are significantly different from one), the inefficiency with respect to earnings components is subsumed by other macroeconomic indicators at longer horizons. In particular, aggregate core earnings news and special items news jointly lead to a significant increase in the R-squared at only the two-quarter horizon. These results suggest that while the efficiency of economists' forecasts can be improved by incorporating information contained in GAAP earnings components, much of the information contained in these components is available from other macroeconomic sources.

Our conclusions are further tempered by the fact that aggregate earnings component information may not be publicly available when unemployment forecasts are issued. SPF forecasts are typically solicited by the end of the first month of quarter t+1. Although in the analysis above we restrict the sample to firms that have announced earnings in the first month of the quarter, economists may not have access to detailed income statement information until firms file their 10-Qs, and on average less than 20% (10%) of 10-Q (10-K) filings in our sample occur by the end of the first month. Thus, while on the surface our results suggest that macroeconomic forecasters do not fully utilize the information available in aggregate earnings components, these results should be interpreted with caution.

5.2 Earnings Components, GDP Growth, and Corporate Profits

In this section, we investigate the implications of our findings for research that considers aggregate special items and core earnings as predictors of GDP growth. In particular, Abdalla and Carabias (2017) document that aggregate special items dominate core earnings as predictors of future nominal GDP growth. In their analyses, special items aggregated over firms with both zero and non-zero special items represent the only earnings component that is associated with future nominal GDP growth.

These findings differ from our results, in that our results emphasize the importance of persistent core earnings in predicting labor market aggregates and unemployment. To shed more light on how these two sets of results are related, in Table 9 we conduct three additional tests. First, we replicate the GDP forecasting results within our sample period using our GAAP earnings component measures and real, rather than nominal, GDP growth. Panel A of Table 9 reports regressions of future real GDP growth rates on aggregate core earnings news (*EBIT_NEWS*) and special items news (*SPI_NEWS*). The results are consistent with the findings in Abdalla and Carabias (2017): both before and after controlling for other macroeconomic information sources, special items news is significantly positively associated with real GDP growth up to two quarters ahead, while core earnings news is not significant at any forecasting horizon.

Second, we investigate whether aggregate special items are associated with future GDP growth through the corporate profits channel. While at the firm level special items have a less significant association with future net income than core earnings (e.g., Fairfield et al. 1996), aggregation might emphasize special items that are recorded in anticipation of adverse economy-wide events. In this case aggregate special items news would signal a reduction in corporate profits' slice of GDI. To provide evidence on this channel, we regress future NIPA corporate profit growth (*CP*) on aggregate earnings component news with or without controls for other macroeconomic variables. The results, reported in Panel B of Table 9, provide no evidence that either special items or core earnings are associated with future NIPA corporate profits at any horizon that we consider.

Finally, we investigate whether aggregate special items are associated with future GDP growth by signaling future layoffs coupled with a reduction in labor income. To do so, we rerun the regressions of future GDP growth on the earnings components after controlling for future mass layoffs. Since the results reported in Table 4 suggest that aggregate special items are significantly associated with mass layoffs up to two quarters in the future, we include both quarters' mass layoff data in the regression. The results are reported in Panel C of Table 9. For comparison purposes, the table includes regressions with and without controls for mass layoff frequencies, which are available only for a limited period (1995 to 2012). The results suggest that the ability of aggregate special items to predict GDP growth is fully explained by future mass layoffs—the coefficients on aggregate special items news turn statistically insignificant after controlling for the mass layoff variables.

Taken together, our findings suggest that the link between aggregate special items news and future GDP growth operates primarily through the labor and unemployment channel. The lack of an association between core earnings news and GDP growth is puzzling in light of a strong link between core earnings and labor income growth. Explaining these contradictory results would require a more complete model that takes into account feedback loops between disposable personal income, consumption, and corporate profits. While further investigation in this direction is outside the scope of our paper, the documented stylized facts combined with the facts documented in Abdalla and Carabias (2017) pave a fruitful avenue for future research.

5.3 Robustness Tests

Alternative Estimation of Aggregate Earnings News

We perform two tests to evaluate the sensitivity of our results to changes in the specification of our aggregate earnings news measure. First, we examine whether our results are sensitive to changes in sample composition. Our main analyses are based on aggregate earnings series constructed for a sample of firms with fiscal quarters ending in March, June, September, and December. In a robustness test, we do not exclude firms with fiscal quarter-ends in the remaining calendar months. Our results (untabulated) are qualitatively unchanged.

Second, we consider alternative procedures for extracting earnings component news from aggregate earnings series. Our main specification employs a ten-year rolling window to estimate the parameters of a time-series process for aggregate earnings and the earnings components. In robustness tests we replicate these tests using windows of eight or six years. The results (untabulated) are again qualitatively unchanged.

Alternative Regression Specifications

Our main regressions include one lag of the predicted macro variable to control for persistence in the macro series. In robustness tests we formally estimate the optimal number of lags based on the Akaike Information Criterion. The results (untabulated) are robust to including additional lags as controls.

We also add the prior one to four quarters of aggregate stock market returns to our regressions, to control for the fact that the stock market may lead the macroeconomy by more than one quarter. We find that the aggregate earnings components remain significant predictors of labor market aggregates at horizons of one to two quarters.

Finally, we investigate whether our inferences are affected by using standard errors that are not adjusted autocorrelation, as discussed in Section 3.6. For this purpose, we re-evaluate the significance of the regression coefficients using Newey and West (1987) standard errors with three lags. The number of lags is determined by a rule of thumb specified in Green (2002, p. 200) that sets it equal to approximately $T^{1/4}$, where T is the number of periods in the sample. The results (untabulated) are qualitatively similar.

Alternative Vintages for Predicted Macro Variables

We next rerun our tests using different vintages of the macroeconomic variables. In particular, we consider labor income estimates (*WAGES_ALL*) available one quarter after the vintage used in our main specification and the real GDP growth estimate (*RGDP*) in the initially announced vintage (i.e., advanced estimates) instead of the third-revision estimates. The results (untabulated) are qualitatively similar to those reported in our main analysis.

Sub-period Analysis

Given the changing economic and regulatory landscape, it is important to investigate how the relations between earnings components and macroeconomic activities change over time. For this purpose, we perform a sub-period analysis. Specifically, we split our sample into the following two sub-periods: 1981-2001 and 2002-2015, and we investigate whether the ability to predict labor market outcomes changes over time for either aggregate core earnings news or aggregate special items news.

The (untabulated) results are generally quite similar to those in the full sample analysis—both aggregate earnings news components remain significant predictors of aggregate job flows and labor income in both sub-periods. Two results are worth noting. First, despite the upward trend in the frequency of special items over time, the information content of aggregate special items does not vary significantly across the two sub-periods. This is perhaps not surprising, since our sample period starts in 1988 and the upward trend in the reporting of special items is not as stark as it is in the earlier decade. Second, the information content of aggregate core earnings news with respect to job flows does change. In the first sub-period, the ability of aggregate core earnings news to predict job growth (*NETGAIN*) stems exclusively from the association with job gains (*GAIN*). In the second sub-period, aggregate core earnings news is not only significantly associated with future job losses (*LOSS*), but the horizon at which the association remains statistically significant is longer than for future job gains (*GAIN*). However, these results should be interpreted with caution because sub-periods are relatively short (the number of quarters in the earlier sub-period is as low as 38 for the job flow analysis due to data availability constraints), which significantly reduces the statistical power of the tests.

We have also replicated our analyses after excluding recessionary quarters from our sample and the results (untabulated) remain qualitatively similar.

6. Conclusion

A growing body of research aims to shed light on the information content of various corporate disclosures for macroeconomic outcomes. While these studies suggest that aggregate earnings contain significant information about the macroeconomy, we know little about the nature of this information. In this study, we provide evidence on the source of the macroeconomic information contained in aggregate earnings by studying the predictive content of aggregate earnings and its core and non-core components for the labor market.

Drawing from labor economics theory, we develop predictions that link aggregate GAAP earnings and its components to aggregate job creation and destruction, aggregate labor income, and unemployment. We find that aggregate earnings news is associated with future labor market conditions, and that it conveys information that is incremental to other macroeconomic indicators over near-term horizons. We further find that core earnings and special items are the primary sources of the labor market information contained in aggregate earnings, but that these two earnings components vary in the signals they deliver. In particular, while core earnings news is informative about persistent changes in economy-wide profitability that anticipate aggregate job creation and destruction over multiple future quarters, special items news contains predictive information content only about job destruction and only for horizons of up to two quarters.

Taken together, our findings offer several new insights about the macroeconomic information contained in GAAP earnings. First, our findings extend prior research (e.g., Konchitchki and Patatoukas 2014a) that suggests aggregate earnings contain macroeconomic information because they proxy for corporate profits, which is a component of GDI. In particular, we show that aggregate earnings are also linked to aggregate labor income, which is another component of GDI. Second, our findings add to emerging research on the labor market information contained in GAAP earnings (e.g., Kalay, Nallareddy, and Sadka 2017; Nallareddy and Ogneva 2017; Rouxelin, Wongusnai, and Yehuda 2017). To date, this literature focuses on the information contained in variables derived from GAAP earnings, such as earnings dispersion and cost stickiness. We complement this work by focusing directly on aggregate GAAP earnings. Third, our results expand the literature in accounting on the different properties of core and non-core earnings by documenting that these properties have significant implications for the ability of earnings to predict labor market conditions at the macro level.

We note that our finding that core earnings has significant ability to predict labor market outcomes differs from the finding in Abdalla and Carabias (2017) that core earnings is not associated with future GDP growth. This divergence in results poses an interesting challenge for future research, which can perhaps be addressed with a more complete representation of the interconnections among various macroeconomic aggregates.

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Appendix. Variable Definitions

Variable	Definition
NI_NEWS_t	The innovation in the cross-sectional sum of sample firms' quarterly earnings scaled by aggregate lagged equity, where earnings are defined as net income from Compustat. The innovation is the residual estimated for quarter *t* based on the parameters from an ARIMA(1,0,0)x$(1,0,0)_4$ model estimated between *t*-40 and *t*-1.
$EBIT\_NEWS_t$	The innovation in the cross-sectional sum of sample firms' quarterly EBIT scaled by aggregate lagged equity, where EBIT is defined as operating income after depreciation from Compustat. The innovation is the residual estimated for quarter *t* based on the parameters from an ARIMA(1,0,0)x$(1,0,0)_4$ model estimated between *t*-40 and *t*-1.
SPI_NEWS_t	The innovation in the cross-sectional sum of sample firms' quarterly special items scaled by aggregate lagged equity. The innovation is the residual estimated for quarter *t* based on the parameters from an ARIMA(1,0,0)x$(1,0,0)_4$ model estimated between *t*-40 and *t*-1.
$WAGE\_PRIVATE_t$	The growth rate of the wages and salaries of employees in the private sector for quarter *t*. *WAGE_PRIVATE* data come from Federal Reserve Economic Data (FRED) maintained by the Federal Reserve Bank of St. Louis.
$WAGE\_ALL_t$	The growth rate of the wages and salaries of all employees in the U.S. economy for quarter *t*. *WAGE_ALL* is initially available mid-quarter estimate from the Philadelphia Federal Reserve's Real Time Data Set for Macroeconomists.
$GAIN_t$	Aggregate job creation for quarter *t* divided by average employment across the current and previous quarters. Data come from the Business Employment Dynamics dataset maintained by the Bureau of Labor Statistics.
$LOSS_t$	Aggregate job destruction for quarter *t* divided by average employment across the current and previous quarters. Data come from the Business Employment Dynamics dataset maintained by the Bureau of Labor Statistics.
$NETGAIN_t$	Net job flows for quarter *t* divided by average employment across the current and previous quarters. Data come from the Business Employment Dynamics dataset maintained by the Bureau of Labor Statistics.
MLS_t	Seasonal growth in the number of mass layoffs from the Bureau of Labor Statistics' Mass Layoff Statistics (MLS) program.
$UNEMP1_t$	The change in the initially available mid-quarter estimate of the unemployment rate from quarter *t*-1 to quarter *t*. Data come from the Philadelphia Federal Reserve's Real Time Data Set for Macroeconomists.
$UNEMP2_t$	The change in the revised estimate, available one quarter after the initial estimate, of the unemployment rate from quarter *t*-1 to quarter *t*. Data come from the Philadelphia Federal Reserve's Real Time Data Set for Macroeconomists.
$RGDP_t$	The third revised estimate of real GDP growth for quarter *t*. Data come from the Bureau of Economic Analysis.
CP_t	Growth in NIPA corporate profits after tax, inventory valuation, and capital consumption adjustments for quarter *t*; the estimate's vintage is the middle of the second quarter following quarter *t*. Data come from the Philadelphia Federal Reserve's Real Time Data Set for Macroeconomists.
$FUNEMP_{t+n,\ t+1}$	The forecast for the change in unemployment rate, estimated as Survey of Professional Forecasters' median consensus forecast of the unemployment rate for quarter *t*+*n* issued in quarter *t*+1 minus the realized unemployment rate for quarter *t*+*n*-1.

RET_t	The value-weighted return of sample firms for quarter *t*.
$CFNAI_t$	Chicago Fed National Activity index for quarter *t*.
$AGGBM_t$	The cross-sectional sum of sample firms' quarterly book values of equity scaled by the sum of their market values of equity at the end of quarter *t*.
$PGDP_t$	The initially available GDP deflator (*PGDP*) estimate for quarter *t* from the Philadelphia Federal Reserve's Real Time Data Set for Macroeconomists.

Table 1: Selecting a Time-Series Model for Aggregate Earnings

Table 1 summarizes the procedure used to select a time-series model for estimating the innovation in aggregate earnings (net income, NI) and the two earnings components of interest (core earnings, EBIT, and special items, SPI). Panel A reports *p*-values from Dickey-Fuller tests for each earnings variable. Panel B reports the Akaike information criterion (AIC) and Schwarz Bayesian information criterion (BIC) for three time-series models: AR(1), ARIMA(0,0,0)x$(1,0,0)_4$, and ARIMA (1,0,0)x$(1,0,0)_4$.

Panel A. P-Values of Dickey-Fuller Test

	NI	EBIT	SPI
1988-2015	0.002	0.097	0.000
1978-2015	0.000	0.074	0.000

Panel B. Time-Series Process Diagnostic Tests

	NI	EBIT	SPI
Akaike information criterion			
AR(1)	-823.36	-938.29	-986.60
ARIMA(0,0,0)x$(1,0,0)_4$	-769.75	-820.63	-981.20
ARIMA(1,0,0)x$(1,0,0)_4$	-829.40	-966.20	-998.40
Schwarz Bayesian information criterion			
AR(1)	-817.92	-932.85	-981.20
ARIMA(0,0,0)x$(1,0,0)_4$	-761.60	-812.47	-973.00
ARIMA(1,0,0)x$(1,0,0)_4$	-818.53	-955.32	-987.60

Table 2. Descriptive Results

Panel A presents descriptive statistics for the variables used in our analyses. Panel B compares the relative importance of labor income and corporate profits for real GDP growth. Variables are defined in the Appendix. The sample comprises 112 quarters over the period 1988Q1 to 2015Q4.

Panel A. Summary Statistics

	NO.	Mean	StdDev	25%	Med	75%
Aggregate Earnings						
NI_NEWS_t	112	-0.0005	0.0071	-0.0031	0.0011	0.0039
$EBIT\_NEWS_t$	112	-0.0023	0.0060	-0.0062	-0.0028	0.0022
SPI_NEWS_t	112	-0.0006	0.0029	-0.0016	-0.0001	0.0010
Labor Market Aggregates						
$WAGE\_PRIVATE_t$	110	0.0113	0.0119	0.0056	0.0129	0.0184
$WAGE\_ALL_t$	112	0.0112	0.0060	0.0083	0.0109	0.0150
$GAIN_t$	94	0.0717	0.0081	0.0640	0.0705	0.0800
$LOSS_t$	94	0.0686	0.0072	0.0620	0.0705	0.0740
$NETGAIN_t$	94	0.0031	0.0062	0.0020	0.0050	0.0070
MLS_t	68	0.0363	0.2741	-0.0100	-0.1272	0.1043
$UNEMP1_t$	112	-0.0019	0.0724	-0.0402	-0.0120	0.0239
$UNEMP2_t$	112	-0.0019	0.0715	-0.0402	-0.0081	0.0201
Other Macro Variables						
$RGDP_t$	112	0.0059	0.0050	0.0035	0.0060	0.0087
CP_t	112	0.0163	0.0602	-0.0096	0.0128	0.0427
RET_t	112	0.0509	0.0807	0.0088	0.0536	0.1004
$CFNAI_t$	112	-0.2203	0.6842	-0.4817	-0.0140	0.1642
$AGGBM_t$	112	0.4304	0.0928	0.3803	0.4209	0.4910
$PGDP_t$	112	0.0051	0.0029	0.0031	0.0047	0.0067

Table 2 continued

Panel B. Relative Importance of Labor Income and Corporate Profits for GDP growth

	(1)	(2)	(3)	(4)	(5)
	$RGDP_t$	$RGDP_t$	$RGDP_t$	$RGDP_t$	$RGDP_t$
CP_t	0.029***			0.026***	0.032***
	(3.371)			(3.289)	(4.323)
$WAGE\_PRIVATE_t$		0.211***		0.202***	
		(5.150)		(5.135)	
$WAGE\_ALL_t$			0.316***		0.338***
			(4.995)		(5.742)
Intercept	0.006***	0.004***	0.003***	0.004***	0.002**
	(10.965)	(5.808)	(2.993)	(5.447)	(2.196)
Nobs	112	110	112	110	112
Adj. R^2	0.085	0.190	0.177	0.257	0.291
F-test: $b_{WAGEt} = b_{CPt}$				18.82	27.14
P-value				<0.001	<0.001

Table 3: Aggregate Net Income News and Future Job Flows and Labor Income

This table presents regressions of job flows (Panel A) and labor income (Panel B) on aggregate earnings. Regressions in both panels control for the first through third calendar quarter indicators, and a trend variable; coefficients on these variables are suppressed. Variables are defined in the Appendix. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. In Panel A the sample comprises 94 quarters over the period 1992Q3 to 2015Q4; in Panel B the sample comprises 112 quarters over the period 1988Q1 to 2015Q4.

Panel A. Job Flows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$NETGAIN_{t+n}$				$LOSS_{t+n}$				$GAIN_{t+n}$			
	n=1	*n=2*	*n=3*	*n=4*	*n=1*	*n=2*	*n=3*	*n=4*	*n=1*	*n=2*	*n=3*	*n=4*
NI_NEWS_t	0.339***	0.305***	0.297***	0.233**	-0.190***	-0.224***	-0.156**	-0.116	0.129***	0.081**	0.108**	0.069
	(5.084)	(3.751)	(3.018)	(2.185)	(-4.511)	(-3.906)	(-2.241)	(-1.546)	(2.897)	(2.053)	(2.212)	(1.624)
$NETGAIN_t$	0.544***	0.463***	0.278**	0.245**								
	(7.313)	(5.093)	(2.533)	(2.049)								
$LOSS_t$					0.610***	0.409***	0.330***	0.244*				
					(8.487)	(4.179)	(2.778)	(1.905)				
$GAIN_t$									0.496***	0.629***	0.381***	0.607***
									(5.677)	(8.101)	(3.972)	(7.102)
Intercept	0.004	0.006*	0.007*	0.007*	0.043***	0.064***	0.073***	0.083***	0.059***	0.044***	0.073***	0.046***
	(1.406)	(1.822)	(1.840)	(1.694)	(5.372)	(5.916)	(5.527)	(5.826)	(5.615)	(4.718)	(6.312)	(4.427)
Nobs	94	94	94	93	94	94	94	93	94	94	94	93
Adj. R^2	0.668	0.504	0.278	0.181	0.920	0.853	0.784	0.752	0.882	0.908	0.858	0.893

Table 3 continued

Panel B. Labor Income

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	WAGE_PRIVATE$_{t+n}$				*WAGE_ALL*$_{t+n}$			
	n=1	*n=2*	*n=3*	*n=4*	*n=1*	*n=2*	*n=3*	*n=4*
NI_NEWS$_t$	1.076***	0.496***	0.557***	0.497***	0.280***	0.390***	0.310***	0.305***
	(7.255)	(2.907)	(3.186)	(2.789)	(4.838)	(5.903)	(4.189)	(3.960)
WAGE_PRIVATE$_t$	-0.061	0.188*	0.062	0.042				
	(-0.721)	(1.936)	(0.623)	(0.414)				
WAGE_ALL$_t$					0.553***	0.288***	0.212**	0.068
					(7.925)	(3.604)	(2.372)	(0.730)
Intercept	0.029***	0.019***	0.024***	0.021***	0.010***	0.016***	0.017***	0.021***
	(5.101)	(2.986)	(3.507)	(3.001)	(3.742)	(5.282)	(5.105)	(5.947)
Nobs	109	108	107	106	112	112	112	112
Adj. R^2	0.344	0.132	0.096	0.064	0.600	0.468	0.315	0.230

Table 4: Aggregate Earnings Components and Mass Layoffs

This table presents regressions of seasonal growth in the number of mass layoffs on the aggregate earnings components. Regressions control for the first through third calendar quarter indicators, and a trend variable; coefficients on these variables are suppressed. Variables are defined in the Appendix. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample comprises 67 quarters over the period 1996Q2 to 2012Q4.

	(1) MSL_{t+1}	(2) MSL_{t+2}	(3) MSL_{t+3}	(4) MSL_{t+4}
$EBIT\_NEWS_t$	-0.949	-2.418	-5.246	-7.631
	(-0.203)	(-0.367)	(-0.664)	(-0.929)
SPI_NEWS_t	-39.863***	-39.257***	-22.386	5.164
	(-4.768)	(-3.325)	(-1.577)	(0.350)
MLS_t	0.514***	0.224*	-0.028	-0.189
	(5.633)	(1.738)	(-0.182)	(-1.177)
Intercept	-0.129	-0.126	0.015	0.233
	(-0.648)	(-0.439)	(0.042)	(0.626)
Nobs	67	66	65	64
Adj. R^2	0.628	0.270	-0.022	-0.084

Table 5: Aggregate Earnings Component News and Future Job Flows and Labor Income

This table presents regressions of job flows (Panel A) and labor income (Panel B) on the aggregate earnings components. Regressions in all panels control for the first through third calendar quarter indicators, and a trend variable; coefficients on these variables are suppressed. Variables are defined in the Appendix. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. In Panel A the sample comprises 94 quarters over the period 1992Q3 to 2015Q4; in Panel B the sample comprises 112 quarters over the period 1988Q1 to 2015Q4.

Panel A. Job Flows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$NETGAIN_{t+n}$				$LOSS_{t+n}$				$GAIN_{t+n}$			
	n=1	*n=2*	*n=3*	*n=4*	*n=1*	*n=2*	*n=3*	*n=4*	*n=1*	*n=2*	*n=3*	*n=4*
$EBIT\_NEWS_t$	0.286***	0.275***	0.447***	0.436***	-0.122**	-0.168**	-0.174**	-0.172*	0.138**	0.109**	0.223***	0.196***
	(3.454)	(2.660)	(3.674)	(3.357)	(-2.351)	(-2.391)	(-2.025)	(-1.854)	(2.341)	(2.059)	(3.546)	(3.648)
SPI_NEWS_t	0.523***	0.393*	0.062	-0.181	-0.349***	-0.413***	-0.172	-0.002	0.146	0.008	-0.133	-0.203*
	(3.295)	(1.984)	(0.266)	(-0.721)	(-3.634)	(-3.183)	(-1.079)	(-0.013)	(1.165)	(0.068)	(-0.995)	(-1.762)
$NETGAIN_t$	0.522***	0.445***	0.215*	0.187								
	(7.006)	(4.795)	(1.961)	(1.577)								
$LOSS_t$					0.598***	0.372***	0.285**	0.210				
					(7.934)	(3.659)	(2.280)	(1.557)				
$GAIN_t$									0.489***	0.622***	0.351***	0.579***
									(5.642)	(8.003)	(3.790)	(7.133)
Intercept	0.004	0.006*	0.005	0.004	0.043***	0.067***	0.078***	0.087***	0.060***	0.044***	0.075***	0.047***
	(1.641)	(1.799)	(1.335)	(0.983)	(5.131)	(5.921)	(5.568)	(5.794)	(5.739)	(4.753)	(6.711)	(4.811)
Nobs	94	94	94	93	94	94	94	93	94	94	94	93
Adj. R^2	0.683	0.507	0.316	0.228	0.921	0.857	0.785	0.752	0.884	0.908	0.868	0.904

Table 5 continued

Panel B. Labor Income

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$WAGE\_PRIVATE_{t+n}$				$WAGE\_ALL_{t+n}$			
	n=1	*n=2*	*n=3*	*n=4*	*n=1*	*n=2*	*n=3*	*n=4*
$EBIT\_NEWS_t$	0.604***	0.490**	0.525**	0.616**	0.167**	0.183**	0.258**	0.356***
	(3.065)	(2.110)	(2.214)	(2.539)	(2.111)	(1.992)	(2.532)	(3.381)
SPI_NEWS_t	2.137***	0.138	0.415	-0.416	0.481***	0.708***	0.309	-0.042
	(5.000)	(0.274)	(0.806)	(-0.792)	(2.862)	(3.626)	(1.424)	(-0.186)
$WAGE\_PRIVATE_t$	-0.024	0.211**	0.082	0.075				
	(-0.286)	(2.171)	(0.829)	(0.735)				
$WAGE\_ALL_t$					0.588***	0.346***	0.246***	0.097
					(8.445)	(4.282)	(2.740)	(1.049)
Intercept	0.023***	0.013*	0.017**	0.011	0.008***	0.013***	0.014***	0.016***
	(3.968)	(1.861)	(2.390)	(1.539)	(2.908)	(4.260)	(4.072)	(4.593)
Nobs	109	108	107	106	112	112	112	112
Adj. R^2	0.354	0.104	0.073	0.044	0.589	0.434	0.286	0.206

Table 6: Aggregate Earnings Component News and Future Unemployment

This table presents regressions of unemployment on the aggregate earnings components. Regressions control for the first through third calendar quarter indicators, and a trend variable; coefficients on these variables are suppressed. Variables are defined in the Appendix. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample comprises 112 quarters over the period 1988Q1 to 2015Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$UNEMP1_{t+n}$				$UNEMP2_{t+n}$			
	n=1	*n=2*	*n=3*	*n=4*	*n=1*	*n=2*	*n=3*	*n=4*
$EBIT\_NEWS_t$	-0.031**	-0.028**	-0.034**	-0.037**	-0.029**	-0.029**	-0.034**	-0.037**
	(-2.473)	(-2.227)	(-2.280)	(-2.431)	(-2.372)	(-2.337)	(-2.326)	(-2.479)
SPI_NEWS_t	-0.065**	-0.077***	-0.019	-0.001	-0.067***	-0.075***	-0.015	-0.003
	(-2.622)	(-3.100)	(-0.647)	(-0.040)	(-2.760)	(-3.086)	(-0.527)	(-0.111)
$UNEMP1_t$	0.382***	0.351***	0.199*	0.150	0.387***	0.349***	0.201*	0.145
	(4.376)	(3.998)	(1.917)	(1.415)	(4.534)	(4.049)	(1.967)	(1.379)
Intercept	0.000	0.000	0.001	0.001	0.000	0.000	0.001	0.001
	(1.347)	(1.252)	(1.343)	(1.545)	(1.309)	(1.356)	(1.366)	(1.486)
Nobs	112	112	112	112	112	112	112	111
Adj. R^2	0.397	0.384	0.139	0.101	0.407	0.394	0.142	0.105

Table 7: Incremental Information in Aggregate Earnings Component News

This table presents regressions of unemployment (Panel A), job flows (Panel B), and labor income (Panel C) on the aggregate earnings components controlling for other macro information sources. Regressions in all panels control for the first through third calendar quarter indicators, and a trend variable; coefficients on these variables are suppressed. Variables are defined in the Appendix. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The last two rows of each panel report results of an F-test for the increase in R^2 achieved by adding *EBIT_NEWS* and *SPI_NEWS* to a model based on the control variables alone. In Panels A and C the sample comprises 112 quarters over the period 1988Q1 to 2015Q4; in Panel B the sample comprises 94 quarters over the period 1992Q3 to 2015Q4.

Panel A. Unemployment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$UNEMP1_{t+n}$				$UNEMP2_{t+n}$			
	n=1	*n=2*	*n=3*	*n=4*	*n=1*	*n=2*	*n=3*	*n=4*
$EBIT\_NEWS_t$	-0.028**	-0.028**	-0.021	-0.023	-0.027**	-0.028**	-0.020	-0.023
	(-2.513)	(-2.055)	(-1.371)	(-1.416)	(-2.407)	(-2.107)	(-1.390)	(-1.478)
SPI_NEWS_t	-0.021	-0.074**	-0.012	-0.004	-0.027	-0.069**	-0.008	-0.005
	(-0.862)	(-2.558)	(-0.377)	(-0.112)	(-1.147)	(-2.455)	(-0.243)	(-0.136)
$UNEMP1_t$	-0.073	0.219*	0.067	0.151	-0.044	0.206*	0.069	0.142
	(-0.749)	(1.859)	(0.512)	(1.079)	(-0.458)	(1.796)	(0.537)	(1.027)
RET_t	-0.000	-0.000	-0.001	-0.001	-0.000	-0.001	-0.001	-0.001
	(-0.474)	(-0.446)	(-1.392)	(-0.998)	(-0.311)	(-0.669)	(-1.418)	(-1.004)
$CFNAI_t$	-0.001***	-0.000	-0.000*	-0.000	-0.001***	-0.000	-0.000**	-0.000
	(-6.509)	(-1.294)	(-1.978)	(-0.744)	(-6.158)	(-1.519)	(-2.042)	(-0.757)
$AGGBM_t$	-0.000	0.000	-0.001	-0.002*	-0.000	0.000	-0.001*	-0.002*
	(-0.157)	(0.380)	(-1.602)	(-1.926)	(-0.066)	(0.279)	(-1.684)	(-1.864)
$PGDP_t$	0.012	0.033	0.089***	0.082***	0.015	0.033	0.088***	0.077**
	(0.563)	(1.314)	(3.229)	(2.765)	(0.713)	(1.371)	(3.256)	(2.618)
Intercept	0.001	-0.000	0.000	0.000	0.000	-0.000	0.000	0.000
	(1.221)	(-0.153)	(0.108)	(0.515)	(0.994)	(-0.022)	(0.164)	(0.535)
Nobs	112	112	112	112	112	112	112	111
Adj. R^2	0.594	0.403	0.266	0.166	0.589	0.421	0.272	0.164
F-test for R^2 *increase*	3.99	6.41	1.13	1.06	4.12	6.25	1.08	1.16
F-test p-value	0.022	0.002	0.329	0.349	0.019	0.003	0.344	0.317

Table 7 continued

Panel B. Job Flows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$NETGAIN_{t+n}$				$LOSS_{t+n}$				$GAIN_{t+n}$			
	n=1	*n=2*	*n=3*	*n=4*	*n=1*	*n=2*	*n=3*	*n=4*	*n=1*	*n=2*	*n=3*	*n=4*
$EBIT\_NEWS_t$	0.382***	0.223*	0.336**	0.154	-0.079	-0.095	-0.054	-0.015	0.268***	0.127**	0.271***	0.108*
	(4.493)	(1.914)	(2.469)	(1.096)	(-1.575)	(-1.337)	(-0.656)	(-0.181)	(4.761)	(2.126)	(3.878)	(1.784)
SPI_NEWS_t	0.417**	0.375	-0.252	-0.415	-0.374***	-0.334**	-0.020	0.147	0.018	0.052	-0.277*	-0.227*
	(2.477)	(1.629)	(-0.934)	(-1.484)	(-3.653)	(-2.300)	(-0.117)	(0.858)	(0.144)	(0.403)	(-1.827)	(-1.725)
RET_t	-0.004	-0.000	0.012	0.020**	0.003	-0.004	-0.007	-0.012**	-0.002	-0.003	0.004	0.011***
	(-0.824)	(-0.052)	(1.503)	(2.466)	(1.121)	(-0.874)	(-1.579)	(-2.423)	(-0.537)	(-0.928)	(0.885)	(2.812)
$CFNAI_t$	0.003***	0.002	0.003**	0.001	-0.001**	-0.001*	-0.002**	-0.002*	0.001*	0.001	0.001	-0.000
	(3.551)	(1.573)	(2.443)	(0.958)	(-2.339)	(-1.783)	(-2.412)	(-1.722)	(1.958)	(1.064)	(1.590)	(-0.237)
$AGGBM_t$	-0.012**	0.004	0.014	0.032***	-0.008**	-0.016***	-0.028***	-0.033***	-0.031***	-0.009	-0.017***	0.013**
	(-2.117)	(0.559)	(1.489)	(3.348)	(-2.237)	(-3.220)	(-4.822)	(-5.607)	(-6.186)	(-1.604)	(-2.681)	(2.459)
$PGDP_t$	-0.298*	-0.542**	-0.227	-0.413	0.312***	0.114	0.104	0.129	-0.107	-0.405***	-0.158	-0.208
	(-1.794)	(-2.384)	(-0.854)	(-1.507)	(2.981)	(0.769)	(0.613)	(0.741)	(-0.908)	(-3.238)	(-1.080)	(-1.649)
$NETGAIN_t$	0.193*	0.350**	0.065	0.351**								
	(1.942)	(2.574)	(0.410)	(2.101)								
$LOSS_t$					0.517***	0.291**	0.160	0.170				
					(5.755)	(2.291)	(1.096)	(1.138)				
$GAIN_t$									-0.059	0.437***	0.002	0.772***
									(-0.574)	(3.981)	(0.017)	(6.771)
Intercept	0.010***	0.009**	0.002	-0.003	0.052***	0.080***	0.098***	0.099***	0.131***	0.071***	0.119***	0.023
	(2.905)	(2.019)	(0.313)	(-0.503)	(4.774)	(5.216)	(5.594)	(5.520)	(10.087)	(5.210)	(7.418)	(1.590)
Nobs	94	94	94	93	94	94	94	93	94	94	94	93
Adj. R^2	0.758	0.545	0.378	0.342	0.935	0.870	0.829	0.823	0.927	0.919	0.889	0.917
F-test for R^2 increase	15.17	3.71	3.21	1.51	8.66	3.93	0.23	0.37	11.68	2.52	8.34	2.72
F-test p-value	0.000	0.029	0.045	0.228	0.000	0.023	0.793	0.691	0.000	0.087	0.001	0.072

Table 7 continued

Panel C. Labor Income

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$WAGE\_PRIVATE_{t+n}$				$WAGE\_ALL_{t+n}$			
	n=1	*n=2*	*n=3*	*n=4*	*n=1*	*n=2*	*n=3*	*n=4*
$EBIT\_NEWS_t$	0.665***	0.433*	0.525**	0.415	0.130*	0.187*	0.209*	0.338***
	(3.608)	(1.738)	(1.996)	(1.582)	(1.661)	(1.984)	(1.964)	(2.979)
SPI_NEWS_t	1.726***	0.412	0.189	-0.756	0.166	0.581***	0.183	-0.048
	(4.028)	(0.711)	(0.310)	(-1.241)	(0.947)	(2.740)	(0.767)	(-0.190)
RET_t	0.017	-0.006	0.011	0.032*	0.009*	0.002	0.005	0.006
	(1.506)	(-0.409)	(0.702)	(1.979)	(1.830)	(0.353)	(0.774)	(0.839)
$CFNAI_t$	0.004**	0.002	0.002	0.003	0.003***	0.002**	0.002**	0.001
	(2.428)	(0.998)	(0.906)	(1.328)	(3.765)	(2.415)	(2.313)	(0.954)
$AGGBM_t$	-0.047***	-0.012	-0.019	0.007	-0.010**	-0.016***	-0.010	-0.010
	(-4.373)	(-0.839)	(-1.258)	(0.467)	(-2.169)	(-2.723)	(-1.487)	(-1.530)
$PGDP_t$	0.446	-1.146**	0.133	-0.621	0.220	-0.000	-0.215	-0.307
	(1.221)	(-2.297)	(0.252)	(-1.180)	(1.339)	(-0.002)	(-0.960)	(-1.286)
$WAGE\_PRIVATE_t$	-0.276***	0.108	-0.036	-0.001				
	(-3.354)	(0.975)	(-0.307)	(-0.005)				
$WAGE\_ALL_t$					0.348***	0.110	0.067	0.002
					(4.027)	(1.053)	(0.566)	(0.013)
Intercept	0.043***	0.037***	0.026**	0.015	0.014***	0.026***	0.025***	0.027***
	(4.930)	(3.192)	(2.085)	(1.240)	(3.663)	(5.468)	(4.727)	(4.792)
Nobs	109	108	107	106	112	112	112	112
Adj. R^2	0.548	0.172	0.0851	0.101	0.688	0.537	0.396	0.288
F-test for R^2 *increase*	16.17	1.99	2.18	1.76	2.99	6.46	2.36	4.28
F-test p-value	0.000	0.142	0.119	0.178	0.055	0.002	0.099	0.017

Table 8: Unemployment Forecast Efficiency

This table contains regressions of unemployment rates on economists' forecasts and aggregate earnings components. Regressions control for the first through third calendar quarter indicators, and a trend variable; coefficients on these variables are suppressed. Variables are defined in the Appendix. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The last two rows report results of an F-test for the coefficient on unemployment forecast equal to one and an F-test for the increase in R^2 achieved by adding *EBIT_NEWS* and *SPI_NEWS* to a model based on the control variables alone. The sample comprises 112 quarters over the period 1988Q1 to 2015Q4.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				$UNEMP1_{t+n}$				
	n=1	*n=2*	*n=3*	*n=4*	*n=1*	*n=2*	*n=3*	*n=4*
$EBIT\_NEWS_t$	-0.007	-0.023**	-0.030**	-0.026*	-0.009	-0.025**	-0.025*	-0.020
	(-0.974)	(-2.004)	(-2.340)	(-1.783)	(-1.314)	(-2.033)	(-1.903)	(-1.316)
SPI_NEWS_t	0.001	-0.055*	0.026	0.043	0.004	-0.075**	-0.004	0.025
	(0.048)	(-1.806)	(0.771)	(1.138)	(0.196)	(-2.120)	(-0.105)	(0.579)
$UNEMP1_t$	-0.191***	0.081	-0.122	-0.015	-0.281***	0.101	-0.052	0.097
	(-3.254)	(0.839)	(-1.165)	(-0.137)	(-4.433)	(0.904)	(-0.425)	(0.706)
RET_t					0.001	-0.000	-0.001	-0.001
					(1.244)	(-0.085)	(-0.650)	(-0.689)
$CFNAI_t$					-0.000**	0.000	0.000	0.000
					(-2.310)	(0.719)	(0.131)	(0.308)
$AGGBM_t$					0.000	0.001	-0.000	-0.001
					(0.849)	(1.057)	(-0.588)	(-1.289)
$PGDP_t$					-0.013	0.014	0.064**	0.055*
					(-1.009)	(0.612)	(2.419)	(1.847)
$FUNEMP_{t+1,\ t+1}$	0.922***				0.860***			
	(16.838)				(12.902)			
$FUNEMP_{t+2,\ t+1}$		0.343***				0.351***		
		(4.929)				(4.090)		
$FUNEMP_{t+3,\ t+1}$			0.397***				0.333***	
			(6.063)				(4.252)	
$FUNEMP_{t+4,\ t+1}$				0.273***				0.220***
				(4.249)				(2.872)
Intercept	-0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	0.000
	(-0.747)	(0.780)	(0.945)	(0.957)	(-0.173)	(-0.577)	(-0.455)	(0.317)
Nobs	112	112	112	112	112	112	112	112
Adj. R^2	0.831	0.494	0.360	0.204	0.841	0.484	0.378	0.213
F-test: $b_{FUNEMP}=1$	4.21**	48.67***	77.00***	114.13***	4.41**	57.06***	72.59***	103.95***
F-test: increm. R^2					0.86	4.93***	1.88	0.94

Table 9. Aggregate Earnings Components and Future Real GDP Growth

This table presents regressions of real GDP growth (Panel A) and corporate profits (Panel B) on the aggregate earnings components controlling for other macro information sources. This table also presents regressions predicting real GDP growth after controlling for the seasonal growth in mass layoff numbers (Panel C). Variables are defined in the Appendix. *t*-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. In Panels A and B the sample comprises 112 quarters over the period 1988Q1 to 2015Q4; in Panel C the sample comprises 94 quarters over the period 1992Q3 to 2015Q4.

Panel A. Real GDP Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$RGDP_{t+1}$	$RGDP_{t+1}$	$RGDP_{t+2}$	$RGDP_{t+2}$	$RGDP_{t+3}$	$RGDP_{t+3}$	$RGDP_{t+4}$	$RGDP_{t+4}$
$EBIT\_NEWS_t$	0.002	-0.051	-0.023	-0.022	0.059	0.042	0.067	0.067
	(0.024)	(-0.496)	(-0.238)	(-0.184)	(0.518)	(0.339)	(0.611)	(0.541)
SPI_NEWS_t	0.472**	0.607**	0.408*	0.641**	-0.133	0.025	-0.778***	-0.617**
	(2.079)	(2.569)	(1.868)	(2.367)	(-0.523)	(0.087)	(-3.174)	(-2.137)
RET_t		0.002		0.000		0.008		-0.001
		(0.319)		(0.037)		(1.043)		(-0.167)
$CFNAI_t$		0.003***		0.001		0.001		0.000
		(3.210)		(1.243)		(1.000)		(0.120)
$AGGBM_t$		-0.013**		-0.016**		-0.009		-0.002
		(-2.062)		(-2.267)		(-1.254)		(-0.327)
$PGDP_t$		-0.474**		-0.549**		-0.513**		-0.371
		(-2.351)		(-2.375)		(-2.125)		(-1.519)
$RGDP_t$	0.407***	-0.083	0.163	-0.180	0.175	-0.123	0.255**	0.165
	(3.862)	(-0.621)	(1.604)	(-1.179)	(1.483)	(-0.774)	(2.251)	(1.018)
Intercept	0.006**	0.023***	0.009***	0.028***	0.007**	0.020***	0.004	0.011*
	(2.042)	(4.445)	(3.213)	(4.799)	(2.014)	(3.282)	(1.289)	(1.833)
Nobs	112	112	112	112	112	112	111	111
Adj. R^2	0.252	0.356	0.049	0.154	-0.005	0.079	0.079	0.069

Table 9 continued

Panel B. Corporate Profits

	(1) CP_{t+1}	(2) CP_{t+1}	(3) CP_{t+2}	(4) CP_{t+2}	(5) CP_{t+3}	(6) CP_{t+3}	(7) CP_{t+4}	(8) CP_{t+4}
$EBIT\_NEWS_t$	-1.045	-1.146	-1.392	-1.135	-0.828	-1.484	-1.748	-0.279
	(-0.858)	(-0.821)	(-1.143)	(-0.822)	(-0.680)	(-1.056)	(-1.436)	(-0.204)
SPI_NEWS_t	2.048	3.369	2.469	4.474	-2.714	-3.686	-1.098	2.185
	(0.740)	(1.042)	(0.892)	(1.398)	(-0.981)	(-1.131)	(-0.397)	(0.684)
RET_t		0.059		0.066		-0.013		-0.146*
		(0.672)		(0.761)		(-0.148)		(-1.677)
$CFNAI_t$		-0.006		-0.015		0.010		-0.025**
		(-0.487)		(-1.285)		(0.813)		(-2.147)
$AGGBM_t$		0.025		0.034		0.103		-0.069
		(0.306)		(0.430)		(1.270)		(-0.879)
$PGDP_t$		-4.106		-4.314		-0.263		-0.544
		(-1.506)		(-1.599)		(-0.096)		(-0.203)
CP_t	-0.061	-0.093	-0.018	-0.044	0.021	0.040	0.095	0.154
	(-0.597)	(-0.862)	(-0.174)	(-0.410)	(0.200)	(0.371)	(0.914)	(1.433)
Intercept	0.044	0.085	0.043	0.080	0.043	-0.003	0.024	0.077
	(1.281)	(1.346)	(1.231)	(1.278)	(1.238)	(-0.042)	(0.683)	(1.218)
Nobs	112	112	112	112	112	112	111	111
Adj. R^2	-0.024	-0.029	-0.021	-0.005	-0.014	-0.035	-0.005	0.024

Table 9 continued

Panel C. Controlling for Future Mass Layoffs

	(1) $RGDP_{t+1}$	(2) $RGDP_{t+1}$	(3) $RGDP_{t+2}$	(4) $RGDP_{t+2}$	(5) $RGDP_{t+3}$	(6) $RGDP_{t+3}$	(7) $RGDP_{t+4}$	(8) $RGDP_{t+4}$
$EBIT\_NEWS_t$	-0.071	-0.073	-0.079	-0.002	0.014	0.082	-0.038	-0.049
	(-0.548)	(-0.645)	(-0.517)	(-0.018)	(0.088)	(0.545)	(-0.250)	(-0.320)
SPI_NEWS_t	0.758***	0.209	0.771**	0.170	0.121	-0.099	-0.726**	-1.022***
	(2.737)	(0.779)	(2.362)	(0.626)	(0.355)	(-0.276)	(-2.232)	(-2.827)
RET_t	0.003	0.001	0.005	-0.007	0.015	0.006	0.002	0.002
	(0.323)	(0.087)	(0.549)	(-0.918)	(1.593)	(0.634)	(0.253)	(0.255)
$CFNAI_t$	0.004**	0.001	0.002	-0.001	0.001	-0.000	0.003	0.001
	(2.505)	(0.849)	(1.307)	(-0.384)	(0.546)	(-0.037)	(1.454)	(0.623)
$AGGBM_t$	0.008	-0.012	0.011	-0.019	0.028	0.013	0.054***	0.044**
	(0.571)	(-0.960)	(0.647)	(-1.426)	(1.603)	(0.773)	(3.279)	(2.519)
$PGDP_t$	-0.481*	0.005	-0.451	0.249	-0.327	0.014	0.060	0.302
	(-1.687)	(0.019)	(-1.342)	(0.917)	(-0.936)	(0.039)	(0.179)	(0.836)
$RGDP_t$	-0.148	-0.249	-0.345	-0.345**	-0.129	-0.073	0.171	0.103
	(-0.810)	(-1.533)	(-1.601)	(-2.094)	(-0.576)	(-0.336)	(0.797)	(0.469)
MSL_{t+1}		-0.008**		0.001		0.006		-0.006
		(-2.266)		(0.380)		(1.201)		(-1.167)
MSL_{t+2}		-0.008**		-0.020***		-0.013***		-0.003
		(-2.581)		(-6.334)		(-3.130)		(-0.712)
Intercept	0.031***	0.029***	0.039***	0.035***	0.033***	0.031***	0.023***	0.023***
	(4.214)	(4.647)	(4.564)	(5.534)	(3.744)	(3.675)	(2.726)	(2.689)
Nobs	67	67	67	67	67	67	67	67
Adj. R^2	0.419	0.568	0.186	0.553	0.118	0.228	0.194	0.211