The Power of Aggregate Book-to-Market Innovations: Forecasting, Nowcasting, and Dating the Real Economy

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Abstract

Aggregate book-to-market (B/M) ratio reflects market-wide assessments of growth opportunities and productivity. In this paper, I find that aggregate B/M innovations predict time-series variations in the U.S. economy. More importantly, the predictive content of the innovations is incremental (or even superior in a long-horizon forecast) to that of the Survey of Professional Forecasters (SPF). A real-time dating algorithm that is based on the innovations accurately identifies the business cycle turning points for the last 40 years. Decomposing aggregate B/M into components of accounting conservatism and delayed recognition of growth reveals different implications for the macroeconomic information content of aggregate B/M.

Keywords: aggregate book-to-market, real GDP, recession, Dating algorithm, accounting conservatism, aggregate accounting earnings, NBER Business Cycle, peaks, troughs.

JEL Classification: E01, E32, E60, M41, M2

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1. Introduction

While there is considerable evidence on the role of book-to-market ratio (B/M hereafter) in predicting earnings growth and stock returns at the firm level, the association between aggregate B/M and the macroeconomy remains relatively unexplored. In this study, I analyze the informativeness of aggregate B/M innovations for the real economic activity in the United States. The study focuses on two aspects of the macroeconomy: aggregate growth in real output—incorporated in growth in real Gross Domestic Product (GDP)—and the comovement of real macroeconomic aggregates across sectors of the economy—incorporated in the business cycle transitions.

Real GDP growth is the most important variable in analyzing the macroeconomy (Henderson et al. 2012) and can represent an overall measure of a country’s welfare. The B/M ratio aggregated at the country level serves as a proxy for growth opportunities that are likely to lead to actual investments and realized economic growth. Given that B/M acts as a proxy for the inverse of Q, the standard Q-theory suggests that B/M reflects changes in both future productivity and future discount rates.\(^1\) Assuming a constant discount rate, current B/M is linked to future productivity.\(^2\) Therefore, aggregate information in B/M pools forward-looking expectations about the macroeconomy. While the Q-theory implication for the relation between B/M and real economic growth (the productivity path) is theoretically appealing, empirical research in financial economics and finance has mainly focused on the relation between B/M and equity returns (the discount rate path).\(^3\) Further, the aggregate information in B/M innovations summarizes the market-wide revised assessments of accounting earnings growth, which in turn proves to be a leading indicator of economic activity (Konchitchiki and Patatoukas 2014a, 2014b, Shivakumar and Urcan 2014). Moreover, while economic indicators reflect current realizations, the aggregate information in B/M innovations partly reflects revised expectations of future realizations and therefore is likely to

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1 The B/M has been usually used as a proxy for the inverse of Q in the Q-theory literature (see Xing 2008).
2 The Q-theory of investment was first outlined in Tobin (1969).
3 See Fama and French 1993 and Xing 2008 among others.
contain incremental useful macroeconomic content. Accordingly, I predict that aggregate B/M innovations contain information about future real GDP growth. To examine the extent to which information in aggregate B/M innovations is useful relative to leading indicators of the U.S. economy, I control for the quarter’s first release of real GDP growth and the quarter’s macroforecast of future real GDP growth conducted by the Survey of Professional Forecastsers (SPF) of the Federal Reserve Bank of Philadelphia. The first release represents a preliminary estimate of real GDP growth (i.e. current realization) whereas the SPF macroforecast represents expectations of future real GDP growth. The SPF is the most highly regarded macroforecast of GDP growth, and it subsumes the information content of well-known leading indicators (Konchitchiki and Patatoukas 2014a, 2016b). Using a sample of quarterly financial and macroeconomic data from Q3:1971 to Q3:2015, I find that aggregate B/M innovations forecast real GDP growth up to three quarters ahead—the horizon considered in this study. Importantly, after controlling for the SPF macroforecast, I find that the predictive content of aggregate B/M innovations is not subsumed by the SPF macroforecast when forecasting one-quarter-ahead real GDP growth and is even superior to the SPF macroforecast with respect to two- and three-quarter-ahead forecasts.

In the second test, I investigate the relation between aggregate B/M innovations and the U.S. business cycle. The business cycle reflects periodic fluctuations in real activity around its long-term historical trend (Brave and Butters 2014). Business cycle transitions reflect the aggregate comovement of

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4 The Bureau of Economic Analysis’s (BEA) “timely” estimates of GDP growth are: first estimate, second estimate, and third estimate released one month after the end of the quarter, two months after the end of the quarter, and three months after the end of the quarter, respectively. The third estimate is the official release that represents a more reliable representation of the economy, in real time, and is critical to real-time monetary policy decision making. Therefore, predicting the third (official) estimate has been a focus of research (Konchitchiki and Patatoukas 2014a, 2014b). I follow the same line of research and control for the contemporaneous quarter’s first estimate of GDP growth as it is released close to the time when accounting data become available.

5 The Survey of Professional Forecasters (SPF) is the oldest quarterly survey of macroforecasts in the United States. It was started in 1968 by the American Statistical Association (ASA) and the National Bureau of Economic Research (NBER). Starting from 1990, it was conducted by the Federal Reserve Bank of Philadelphia. The survey was known as the ASA-NBER in early academic research before it was taken over by the Federal Reserve Bank of Philadelphia. The documentation of the Federal Reserve Bank of Philadelphia’s Survey of Professional Forecasters can be accessed at https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/.
real macroeconomic indicators such as output, consumption, investment, and real wages (Jaimovich and Rebelo 2009) and the sectoral comovement of macroeconomic indicators across sectors of the economy. Therefore, finding a relation between aggregate B/M innovations and the business cycle suggests that the macroeconomic content embedded in aggregate B/M innovations is also informative about a broad range of real economic indicators and sectors of the economy. In forecasting the probability of future recessions, I control for the quarter’s first release of real GDP growth and the SPF macroforecast of recessions. In nowcasting (i.e. forecasting the present) the start and end of recessions as reflected by business cycle turning points: peaks and troughs, I also include an additional control for economic regime shifts based on the SPF macroforecast of real GDP growth.\(^6\) Using the standard National Bureau of Economic Research’s (NBER) official business cycle dates, I find that aggregate B/M innovations contain incremental useful information for forecasting future recessions and nowcasting the business cycle turning points.\(^7\)

Considering critics in the literature against the NBER dating committee for the delay in announcing the turning points and the lack of reproducibility of its dating methodology, the paper develops a real-time dating algorithm based on the aggregate B/M innovations. A real-time application of the B/M dating algorithm shows that the algorithm establishes most of the business cycle peaks and troughs in real time. Specifically, while the NBER announces peaks and troughs with no fixed timing rule, the algorithm recognizes six out of ten peaks and troughs in the sample period with no discrepancies between the NBER’s ex post-announcement date and the algorithm-identified date. Of the remaining four turning points, three have a one-quarter discrepancy, and one has a two-quarter discrepancy. Strikingly, these

\(^6\) Nowcasting is the assessment of the present, the very near future and the very recent past (Evans, 2005; and Giannone et al., 2008). The concept of nowcasting has been used by central banks for years but has only recently gained attention in accounting research (e.g. Carabias 2015, Konchitchiki and Patatoukas 2016b, Abdalla and Carabias 2016).

\(^7\) The National Bureau of Economic Research (NBER) is considered by most economists as the official source of the business cycle dates in the United States. The NBER’s Business Cycle Dating Committee, currently composed of nine academic economists, can be accessed at [http://www.nber.org/cycles/recessions.html](http://www.nber.org/cycles/recessions.html)
results based on a univariate financial ratio outperform the results from more sophisticated real-time dating methods in applied economics (e.g. Markov Switching Model).

To gain insights into the macroeconomic information content of aggregate B/M innovations, I distinguish two sources of B/M variations; a component of accounting conservatism and a component of delayed accounting recognition of growth. Using a decomposition approach developed by Beaver and Ryan (2000), I find that information in each firm-level component aggregates to provide useful and different implications for future macroeconomic conditions. The results show that the association between each component of aggregate B/M and real GDP growth is in the predicted direction and is statistically and economically significant. The results show that periods with low (high) B/M attributable to accounting conservatism are expected to be followed by periods of negative (positive) growth whereas periods with low (high) B/M attributable to untimely recognition of expected growth are expected to be followed by periods of positive (negative) growth. Nevertheless, the delayed accounting recognition tends to be the dominant source of macroeconomic information.

In additional analyses, I show in a horse-race forecast of future real GDP growth that information in aggregate B/M innovations is superior to aggregate accounting earnings innovations over short and long horizons. However, aggregate accounting earnings innovations appear to be superior to aggregate B/M innovations in forecasting aggregate investment in a short horizon. In another test, I also provide evidence that forecast errors of real GDP growth are predicted based on aggregate B/M innovations.

This study contributes to an incipient “macroaccounting” literature that investigates the relation between aggregate accounting data and the macroeconomy. So far, this literature has focused on the informativeness of aggregate accounting earnings (e.g. Konchitchiki and Patatoukas 2014a, 2016b, Shivakumar and Urcan 2014), components of aggregate earnings (Khan and Ozel 2016, Abdalla and Carabias 2016) and moments of earnings distribution (Nallareddy and Ogneva 2016). I extend this
literature by documenting that (i) aggregate B/M innovations are a leading indicator of the U.S. real economy and business cycle conditions, (ii) aggregate B/M innovations contain information that is incremental (and even superior in a long-horizon forecast) to professional macroforecasts. Therefore, forecast errors in future real GDP growth are predictable based on current aggregate B/M innovations, (iii) the accounting system properties (conservatism and recognition) have different implications for real activity forecast, (iii) the previously unexplored macroeconomic content of aggregate B/M is superior to the well-documented macroeconomic content of aggregate accounting earnings with respect to real GDP growth forecast. In addition, from a research perspective, the use of aggregate B/M innovations to date the turning points in real time adds another dimension to the growing macro research in accounting that has, so far, only considered forecasting and nowcasting.

This study is also related to the economics literature that investigates the ability of formal rules to establish turning points in the business cycle in real time. This literature has mainly focused on the association of macroeconomic indicators with shifts in economic regimes (Stock and Watson 1989&1991, Chauvet and Piger 2008, Boldin 1994). Given that applied economics research has evolved independently from accounting and finance research, it has not previously considered the ability to date the turning points in real time using financial data. I contribute to this literature by showing that a simple dating algorithm that is based on aggregate B/M innovations outperforms popular dating methods in economics.

Further, the study contributes to the long stream of accounting and finance literature that studies the book-to-market ratio. This literature shows that firm-level B/M predicts future return on equity (e.g. Penman 1992, 1996, Bernard 1994) and future stock returns (Fama and French 1995), and that aggregate B/M forecasts market returns (e.g. Kothari and Shanken 1997, Pontiff and Schall 1998). My results extend the role of aggregate B/M ratio (and its aggregate components) and show that it forecasts, nowcasts, and dates in real time the overall macroeconomy.
The study is organized as follows. Section 2 explains the research design. Section 3 discusses the sample and presents descriptive statistics. Section 4 reports the empirical results. Section 5 provides additional analyses and robustness tests. Section 6 concludes.

2. Research Design
2.1 Forecasting the Real Economy

My first prediction is that aggregate B/M innovations contain information about economic growth. First, aggregate B/M serves as a proxy for \( Q^{-1} \) and the country’s growth opportunities that are likely to lead to actual investments and realized economic growth (Smith and Watts 1992, Booth et al. 2001). The Q-theory of investment suggests that B/M reflects changes in both future productivity and future discount rates. Assuming a constant discount rate, B/M is high (low) when the future marginal productivity is low (high). Therefore, aggregate information in B/M pools forward-looking expectations about the real economy. Second, aggregate B/M contains information derived from the market-wide assessments of future earnings, which in turn act as a proxy for the corporate profit component of GDP. In addition, while economic indicators reflect current realizations, aggregate information in B/M partly reflects expectations of future realizations and therefore is likely to contain incremental useful macroeconomic content.

To investigate the macroeconomic information content of aggregate B/M innovations, I start by testing the association between aggregate B/M innovations and future GDP growth. I use the following time-series regressions:

Model A: \( gdp_{q+n} = \alpha + \lambda btm_q + \epsilon_{q+n} \)
Model B: \( gdp_{q+n} = \alpha + \lambda btm_q + \kappa gdp_q + \epsilon_{q+n} \)
Model C: \( gdp_{q+n} = \alpha + \lambda btm_q + \kappa gdp_q + \delta SPF_q (gdp_{q+n}) + \epsilon_{q+n} \)
where $gdp_{qn}$ is real GDP growth in quarter $q+n$, $btm_q$ is aggregate B/M innovations in quarter $q$, $gdp_q$ is the first release of real GDP growth in quarter $q$, and $SPF_q(gdp_{qn})$ is mean SPF macroforecasts of real GDP growth for quarter $q+n$ as of quarter $q$.

Models A and B test whether aggregate B/M innovations contain information about future economic growth, and whether the macroeconomic information content of aggregate B/M innovations is incremental to that of contemporaneous GDP growth, respectively. Model C adds the SPF macroforecast of future GDP growth, which controls for the information set available for macroforecasters in quarter $q$. Konchitchki and Patatoukas (2014a & 2016b) find that controlling for the SPF macroforecast subsumes the information content of well-known leading indicators including treasury yield, term spread, and stock market return. Therefore, throughout the paper, I control for the information set in quarter $q$ by adding the relevant SPF macroforecast/macronowcast because it incorporates a wide set of macroeconomic information. A significant $\lambda$ coefficient in Model C implies that aggregate B/M innovations contain information that helps forecast the real economy and is beyond that captured in professional macroforecasts. The $\lambda$ coefficient is expected to be negative because higher aggregate B/M innovations represent expected lower future growth.\(^8\)

I estimate the time-series regressions using ordinary least squares (OLS) and report t-statistics with the Newey and West (1987) heteroscedasticity-and autocorrelation consistent standard errors with four lags.\(^9\) Throughout the paper, whenever applicable, I calculate the relative contribution of each explanatory variable toward the model adjusted R-squared using Shapley values (Shapley 1953).

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\(^8\) I show in additional analysis that the informativeness of aggregate B/M innovations is incremental to contemporaneous aggregate accounting earnings innovations.

\(^9\) The lag length for standard errors is determined by $T^{0.25}$, where $T$ is the number of observations used in the regression. Hence, the number of lags is set to four because $T$ is equal to 176 in most regressions (Greene 2011). The results are not sensitive to the lag length.
2.2 Forecasting the State of the Real Economy and Nowcasting the Business Cycle Turning Points

Real economic activity moves between periods of expansions, which represent the normal state of the economy, and periods of contractions, which are often rare and brief. During expansions, there is a broad economic growth. During recessions, there is a significant downturn in economic activity spread across the economy. These episodes collectively constitute the business cycle and the transitions between them are shaped by the business cycle turning points.

The Business Cycle Dating Committee of the NBER is considered by most economists as the official source of the U.S. business cycle dating (Chauvet and Piger 2003). The NBER’s definition of the business cycle is consistent with the definition of Burns and Mitchel (1946) as “expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle”. The turning points in the business cycle are peaks and troughs. A peak is a period that marks the end of an economic expansion and the onset of a recession whereas a trough is a period that marks the end of an economic recession and the transition to expansion. Consistently, an expansion runs between a trough and a peak and a recession runs between a peak and a trough.

It is unclear ex ante whether aggregate B/M innovations contain useful information that is significant enough to predict changes in the business cycle. This is because a shift in the state of the economy takes place when a broad range of economic indicators, which are not limited to real GDP growth, moves together to a regime, a concept referred to as comovement of economic activities in

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10 The NBER’s dates receive a great deal of attention from the media and economic community and prove to have intrinsic meaning. First, relations between economic variables vary with the state of the economy. For example, Gavin and Kliesen (2002) show that the relation between initial claims for unemployment insurance and employment growth is different conditional on the NBER-dated economy regime. Second, output has different patterns in different NBER regimes. For example Beaudry and Koop (1993) provide evidence of asymmetry in the persistence of fluctuations in the Gross National Product (GNP) such that these fluctuations are temporary during NBER recessions and permanent during NBER expansions.
macroeconomics (Chauvet and Piger 2008, Jaimovich and Rebelo 2009). Comovement involves aggregate comovement in macroeconomic indicators (e.g. output, consumption, investment, and real wages) and sectoral comovement of macroeconomic indicators in different sectors of the economy. Indeed, research shows that some leading indicators of real GDP growth report inconsistent signals of recessions (Stock and Watson 2003, Kauppi and Saikkonen 2008), and that well-known macroforecasts of real GDP growth that are efficient on average become systematically biased around turning points (Zarnowitz and Braun 1993, Konchitchiki and Patatoukas 2016a). Therefore, whether aggregate B/M innovations contain useful information about the future state of the economy and contemporaneous regime shifts is an empirical question.

To investigate whether aggregate B/M innovations help forecast the future state of the economy, I estimate the following time series regressions:

Model A: \[
\Pr(rcs_{q+n}) = \alpha + \lambda btm_q + \varepsilon_{q+n}
\]
Model B: \[
\Pr(rcs_{q+n}) = \alpha + \lambda btm_q + \kappa gdq_q + \varepsilon_{q+n}
\] 
Model C: \[
\Pr(rcs_{q+n}) = \alpha + \lambda btm_q + \kappa gdq_q + \delta SPF_q \Pr(rcs_{q+n}) + \varepsilon_{q+n}
\]

where \( rcs_{q+n} \) is a binary variable that equals 1 if there is a recession in quarter \( q+n \), and 0 otherwise. The standard NBER recession quarters are used to determine the values of \( rcs_{q+n} \). \( SPF_q \Pr(rcs_{q+n}) \) is the SPF macroforecast of the probability that real GDP will be negative in quarter \( q+n \) as of quarter \( q \). This survey is well known as the anxious index. 12

Model A tests whether aggregate B/M innovations help forecast the probability of an economic recession in quarter \( q+n \), whereas Model B tests whether the information content of aggregate B/M innovations is incremental to that of contemporaneous real GDP growth in forecasting the probability of

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11 For example, the NBER considers the economic series of employment, industrial production, real manufacturing and trade sales, real personal income less transfer payments and real GDP growth when dating the business cycle (See Chauvet and Piger 2008).
12 The term anxious index was first used in a New York Times article in 2002 by David Leonhardt (see Leonhardt 2002). The anxious index represents the SPF macroforecast of the probability that next quarter real GDP growth will be negative. The index is well-known for its ability to forecast most of recessions in the United States (Zarnowitz 1985).
future recessions. Model C adds the SPF macroforecast. Therefore, a significant $\lambda$ coefficient in Model C suggests that aggregate B/M innovations contain information that is incremental to the most well-known survey of professional macroforecasters on recessions (Stock and Watson 2003). The $\lambda$ coefficient is expected to be positive because higher aggregate B/M innovations represent expected lower future growth and hence a higher probability of future recession.

Monetary policy decisions depend not only on the expectations of the future state of the real economy but also on the present shifts in real economic activity. To investigate whether aggregate B/M innovations help provide current nowcasting signals of regime shifts, I estimate the following time series regressions:

Model A: $\Pr(cyc_q) = \alpha + \lambda btm_q + \varepsilon_{q+1}$
Model B: $\Pr(cyc_q) = \alpha + \lambda btm_q + \kappa gdp_q + \varepsilon_{q+1}$
Model C: $\Pr(cyc_q) = \alpha + \lambda btm_q + \kappa gdp_q + \delta_i E_q[Pr(cyc_q)] + \delta_2 SPF_q[Pr(rcs_q)] + \varepsilon_q$ (3)

where $cyc_q$ represents the NBER’s turning points in quarter $q$ measured alternatively as $peak_q$ or $trough_q$. I measure $peak_q$ ($trough_q$) as a binary variable that equals one if the current quarter is officially dated by the NBER as a peak (a trough) and zero otherwise. The SPF does not provide a macronowcast of the business cycle turning points. The closest available macronowcast control is the anxious index macronowcast that represents the probability that real GDP growth will be negative in quarter $q$ as of quarter $q$. Given that the anxious index macronowcast does not ask the SPF panelists about the probability of a regime shift but rather a probability of a decline in real GDP growth, I also consider an additional macronowcast control in the regression. I construct an indicator variable for turning points, $E_q[Pr(cyc_q)]$, that proxies for potential regime shifts. $E_q[Pr(cyc_q)]$ is measured as $E_q[Pr(peak_q)]$ or $E_q[Pr(trough_q)]$ consistently with the turning point dependent variable. $E_q[Pr(peak_q)]$ is equal to one if the first release of real GDP growth in quarter $q$ is positive but the SPF macroforecast of real GDP growth for quarter $q+1$ as of quarter $q$ is negative, and zero otherwise. $E_q[Pr(trough_q)]$ is equal to one
if the first release of real GDP growth in quarter $q$ is negative but the SPF macroforecast of real GDP growth for quarter $q+1$ as of quarter $q$ is positive, and zero otherwise. Therefore, $E_q[\Pr(\text{cyc}_q)]$ can be seen as a modification of $SPF_q(gdp_{q+1})$ to proxy for the probability of contemporaneous regime shifts.

Model A tests if aggregate B/M innovations contain *timely* information about the probability that the current quarter is subsequently announced as a peak (a trough) by the NBER whereas Model B tests if this information content is beyond that of real GDP growth. Model C adds the macronowcasts. Therefore, a significant $\lambda$ coefficient in Model C suggests that aggregate B/M innovations contain timely information about the probability of a regime shift that is not contained in the most well-known surveys of professional macroforecasters. The $\lambda$ coefficient is expected to be positive (negative) when the model nowcasts the peaks (the troughs) because peaks (troughs) represent the onset of recessions (expansions).

Since the dependent variables are dichotomous, I estimate the time-series regressions using a probit model and report t-statistics with the Newey and West (1987) heteroscedasticity-and autocorrelation-consistent standard errors with four lags.

2.3 Dating the Real Economy in Real-Time: A Book-to-Market Dating Algorithm

Real economic agents, policy-makers, and businesses need real-time estimates of the state of the economy and regime shifts to make real decisions in real time. However, the NBER dating announcements are made long after the actual turning point. According to the NBER, the dating committee does not make real-time judgments, but rather weighs accuracy over timing. Additionally, there is no fixed timing rule for announcing that a regime shift has taken place. For example, the July 1990 peak was announced in April 1991, and the March 1991 trough was announced in November 1992. Although the cautious approach of the NBER is likely to avoid premature calls, the lack of timeliness makes the official NBER dates less useful to real economic agents. For example, policy makers seek real-
time information to design public policy that is likely to reduce the impact and duration of economic slowdowns (Boldin 1993, Chauvet and Piger 2003 & 2008).

Another criticism of the NBER dating approach is that it is neither transparent nor replicable. According to the NBER, the dating committee members use different techniques to analyze macroeconomic conditions as well as their own judgments to arrive at consensus dates of peaks and troughs. In fact, the committee appears to rely on judgment more than formal rules.

Given the importance to real economic agents of the speed in identifying turning points, economics research has developed different methods for dating the business cycle in real time. The dating methods have different levels of technical sophistication and cost-effectiveness. Additionally, when simulating the models in real time, the identified dates show large discrepancies with the official NBER dates. In his review of different methods to date the business cycle, Boldin (1994) notes that dating is elusive and no single method can efficiently identify the NBER peaks and troughs. Indeed, some methods are very time-consuming and cannot be easily replicated (e.g. Stock and Watson 1989&1991). Other techniques identify some peaks and troughs with a reasonable degree of accuracy but fail to recognize others. For example, Chauvet and Piger (2003) use a Markov-switching dynamic factor model in real time and manage to recognize four of 11 correct turning points. Their largest discrepancy is up to four quarters. Moreover, these methods use economic variables such as real GDP growth, employment and industrial production that are all subject to major revisions, whereas the NBER dating committee is reluctant to change its official turning points.  

Noting the problems in dating turning points, research in accounting and finance has not addressed this issue so far. In developing a useful dating method, accuracy, timeliness, and ease of replication are important considerations. As for accuracy, the NBER dates are considered the standard for accuracy.  

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13 According to the NBER, there has been no change in the dates of turning points since the dating committee was formed in 1978. Additionally, the NBER reports that it would only change a date if it thought that date to be incorrect.
Therefore, the accuracy of a given dating method is measured by its ability to replicate the NBER dates. Considering timeliness, the out-of-sample performance of the dating method determines its ability to recognize turning points before their official announcements by the NBER. Further, the use of a formal algorithm that requires less sophistication facilitates the replication of the dating method.

Thus, I consider developing a dating algorithm based on aggregate B/M innovations. The proposed algorithm tackles some problems associated with the dating approaches in applied economics. First, in contrast to the dating methods that use economic indicators subject to major data revisions, the algorithm uses only aggregate B/M—a financial ratio that is not subject to similar revisions. Second, given that revisions of the economic variables can be substantial, some dating methods require the completion of early data revisions, which makes them less timely. On the other hand, aggregate B/M is available in real time. Third, the algorithm applies formal rules that are fundamental to the NBER definitions of peaks and troughs. Therefore, while the NBER dating approach is not replicable, the B/M algorithm is. Fourth, the B/M algorithm avoids ad hoc rules and arbitrary designations of benchmarks for a regime shift assumed by other dating methods. For example, Hamilton (1989) and Chauvet and Piger (2003) impose a rule that a move in the probability of the state of the economy below (above) 50 percent to above (below) 50 percent indicates that a turning point has taken place. Chauvet and Piger (2008) use a two-step approach that involves 80 percent and 50 percent benchmarks. In contrast, the B/M algorithm calls for regime shifts based on whether the change in the economy is “significant”, which is fundamental to the NBER definition of recessions.

The B/M algorithm has the following steps. First, aggregate B/M innovations are estimated in-sample using recursively increasing samples of data. The first estimation window is ten quarters.

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14 Using Compustat as the main source of information on accounting book value of equity in the B/M ratio, I note that earnings can also be restated. These earnings restatements affect book value of equity. However, Konchitchiki (2014) finds that restated earnings in the Compustat Fundamentals dataset occur in less than two percent of firms and are close to the unrestated amounts in the Preliminary History Compustat dataset. Moreover, the revision in an economic variable is much severe than a restatement in the very few firms that may constitute a small fraction of the aggregate BM innovations index.
Innovations are estimated for the last observation in the recursive samples. That is, in my sample that extends from Q3: 1971 to Q3: 2015, I start with data that extend from Q3: 1971 to Q4: 1973, and calculate the innovations for Q4: 1973. I expand the window by one data point and estimate the innovations for Q1: 1974. The routine is repeated until the final sample is reached. Second, a binary time series of recessions on the lagged aggregate B/M innovations is estimated recursively using a probit model and out-of-sample predicted probabilities are estimated. A similar window length is used. That is, the first recursive sample extends from Q1: 1974 to Q2: 1976 to estimate the predicted probability for quarter Q3:1976 as of Q2:1976. Third, the means and standard deviations of the resulting predicted probabilities are estimated recursively for each sample window. That is, the first recursive sample extends from Q2: 1976 to Q3: 1978 for the mean and standard deviation on Q3: 1978. Fourth, the following score is derived:

$$E_q(S_{q+1}) = \frac{E_q(e_{q+1}) - \mu_{e_q}}{sd_{e_q}}$$

where $E_q(S_{q+1})$ represents the standardized probability of the state of the economy (herein recession) in quarter $q+1$ as of quarter $q$, $E_q(e_{q+1})$ is the probit predicted probability in quarter $q+1$ as of quarter $q$, $\mu_{e_q}$ is the mean of the probit predicted probability in quarter $q$, and $sd_{e_q}$ is the standard deviation of the probit predicted probability in quarter $q$.

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15 I use NBER recession quarters. The business cycle analyst at quarter $q$ would have sufficient information about the prior state of the economy in his estimated window. For sensitivity, considering that recent states of the economy are not timely available, I use another recession indicator based on the Fed’s anxious index nowcast. Following Konchitchiki and Patatoukas (2016a), the indicator variable for recession is equal to one if the anxious index nowcast is above 0.25 and zero otherwise. Inferences do not change when this alternative definition of recession is used. For brevity, I report only those based on the NBER classification of recessions.

16 The literature does not require an optimal number of observations (see Konchitchiki and Patatoukas 2016a). Results are also not sensitive to a recursive rolling window of 8 to 20 quarters. However, given that the recursive routine in my algorithm involves more than one recursive process where the output of one process is used in the subsequent step, the choice of an initial expanding window of 10 observations leads to less loss of observations than an initial window of 20 observations. For example, an initial 10 observations window for the three recursive processes results in a loss of 28 observations whereas an initial 20 observations window would have resulted in a loss of 58 observations. More importantly, the remaining observations after the recursive routine estimation period would have fewer turning points to test the performance of the dating algorithm, should longer initial windows have been used.
Limiting the window to a domain \( \{q-2, q\} \) to obtain real-time estimates of the turning points, the following rule is applied:

\[
\text{Peak Rule: } P_q = S_{q-1} < 3^*sd_{q-1} + \mu_{q-1}, \quad E_q(S_{q+1}) > 3^*sd_{q} + \mu_{q} \\
\text{Trough Rule: } T_q = S_{q-2} > 3^*sd_{q-2} + \mu_{q-2}, \quad S_{q-1} < 3^*sd_{q-1} + \mu_{q-1}
\]  

(5)

Where \( P_q (T_q) \) is an estimated peak (trough) in quarter \( q \).

Fundamental to this definition of peaks and troughs is the idea that the NBER considers only “a significant decline in activity” to identify the state of the economy. Therefore, my benchmark is also based on the significance of the standardized probability. Hence, the algorithm recognizes a regime shift when the standardized probability moves below to above its significance level and vice versa. This avoids the use of ad hoc benchmarks employed by other dating algorithms. In addition, my peak and trough rules mimic the NBER procedure, which identifies a month when the economy reaches a peak of activity and a “later” month when the economy reaches a trough.\(^{17}\)

2.4 Components of Aggregate Book-to-Market: Accounting Conservatism versus Delayed Recognition of Growth

The B/M ratio has a component that reflects accounting conservatism and another component that reflects delayed accounting recognition of expected growth opportunities (Ryan 1995, Beaver and Ryan 2000, Billings and Morton 2001). To elaborate, the book value incorporates the value of assets-in-place whereas the market value includes expectations of the value of assets-in-place and future growth opportunities. Accounting conservatism implies asymmetric timeliness of earnings because expected negative shocks to the value of assets-in-place are reflected in earnings immediately whereas positive shocks are only reflected when realized. This asymmetric timelines in earnings produces an

\(^{17}\) Since my dating algorithm is quarterly rather than monthly, this “later” month might fall within the same quarter or the next quarter. Therefore, in my analysis, I alter the trough rule so that a trough is the quarter in which a transition takes place rather than the next quarter after the transition. Untabulated results show that the troughs that my algorithm recognizes with one-quarter’s delay are identified with no delay in this case, and those identified with no delay are identified with one quarter’s delay. Therefore, the overall performance of the dating algorithm is qualitatively similar under both alternatives. For brevity, these alternative results are not tabulated.
understatement in the book value of assets-in-place relative to their market value and hence a smaller B/M ratio (Roychowdhury and Watts 2007). On the other hand, the delayed accounting recognition of growth opportunities implies that a temporary difference exists between the book value and the market value. Therefore, market expectations of positive (negative) future growth opportunities result in a currently lower (higher) B/M ratio (Ryan 1995, Beaver and Ryan 2000, Caskey and Peterson 2014).

At the aggregate level, in relation to GDP growth, the conservative accounting element of B/M implies that low B/M reflects an anticipation of future negative shocks to the economy. On the other hand, the low B/M that is attributable to the untimely recognition of growth implies an anticipation of future positive growth. This suggests that the decomposition of aggregate B/M provides different implications for forecasting economic growth.\textsuperscript{18} To test this, I consider the following time-series regression:

\[ gdp_{q+1} = \alpha + \lambda_1 chtm_q + \lambda_r rbm_q + \kappa gdp_q + SPF_{q} (gdp_{q+1}) + \epsilon_{q+1} \]  

(6)

where \( chtm_q \) and \( rbm_q \) are the aggregate B/M components (measured as innovations) driven by accounting conservatism and delayed recognition of growth opportunities, respectively. Henceforth, I refer to \( chtm_q \) as the conservatism component and to \( rbm_q \) as the recognition component. The measurement of these components is described in the appendix.

Insofar as \( chtm_q \) and \( rbm_q \) capture an “inverse” measure of conservatism and delayed recognition of growth, respectively, the coefficient \( \lambda_1 \) is expected to be positive whereas the coefficient \( \lambda_r \) is expected to be negative. Ceteris paribus, periods with low B/M ratio attributable to accounting conservatism are expected to be followed by periods of negative growth whereas periods with low B/M

\textsuperscript{18} I note that both components of B/M are negatively associated with future accounting earnings at the firm level. Conservatism implies immediate reporting of expected future losses, which leads to higher accounting earnings in future periods. At the macro level, this “pseudo” growth in accounting earnings has no economic justification (Penman 1996). Nevertheless, accounting conservatism provides forward-looking information about negative shocks to the economy via anticipating these shocks immediately.
ratio attributable to untimely recognition of expected growth are expected to be followed by periods of positive growth.

I estimate the time-series regressions using OLS and report t-statistics with the Newey and West (1987) heteroscedasticity-and autocorrelation-consistent standard errors with four lags.

3. Sample and Descriptive Statistics

The sample contains financial and macroeconomic data. I collect financial data from Wharton Research Data Services (WRDS). Specifically, I use Compustat quarterly dataset to obtain accounting data and the Centre for Research in Security Prices (CRSP) to obtain market capitalization. For a firm-quarter to be included in the sample, it must have available market value of equity, lagged market value of equity, book value of equity, earnings before extraordinary items, and sales. In each quarter, I exclude observations with negative book value of equity or book value of equity less than $1 million. To mitigate the effect of outliers, I exclude firm-quarter observations that fall in the top and bottom 1% of book-to-market ratio, growth in market value and growth in accounting earnings. In order to align financial data with macroeconomic data, the sample is restricted to firms with a December fiscal year-end and those with a reporting date no later than 45 days after the fiscal quarter-end. All aggregate financial variables are value-weighted cross-sectional averages, with weights based on market capitalization as of the beginning of the quarter. Variable innovations are estimated as residuals of the AR (1) process.\(^{19}\)

I collect Macroeconomic data from Real-Time Data Research Center, Federal Reserve Bank of Philadelphia. Specifically, I use the Real-Time Data Set for Macroeconomists (RTDS) to obtain the BEA’s releases of real GDP growth, and the Survey of Professional Forecasts (SPF) to obtain mean macroforecasts of real GDP growth and mean macroforecasts of the probability of a contraction in real

\(^{19}\) As an additional sensitivity test, I construct the aggregate BM index using the year-over-year change in the BM ratio. Inferences do not change using this alternative change specification.
GDP growth. The recession dates are the standard NBER recession dates.\textsuperscript{20} The merged sample consists of quarterly data over the period Q3:1971 to Q3:2015, a total of 177 quarters, among which there are 27 recession-quarters.

Table 1 reports descriptive statistics for the key continuous variables in the analysis. The mean of value-weighted aggregate B/M ratio in my sample is less than one (0.62), which is consistent with prior B/M research. Mean aggregate B/M innovations is zero by construction with a standard deviation of 0.068. Mean official release of real GDP growth and Mean SPF macroforecast of real GDP growth are 0.026 and 0.023, with standard deviations of 0.033 and 0.022, respectively. Interestingly, the mean of aggregate B/M innovations is positive during the quarters preceding the NBER-designated recession quarter (0.072) and negative during the quarters preceding the NBER-designated expansion quarter (−0.011). Additionally, values of aggregate B/M innovations are positive at the NBER-designated peak dates and negative at the NBER-designated trough dates.

Figure 1 displays the time series of the value-weighted aggregate B/M ratio and the aggregate B/M innovations. Value-weighted aggregate B/M ratio is non-stationary from a causal inspection, and hence aggregate B/M innovations are used in all regressions. Aggregate B/M innovations are the residuals of an AR (1) process.\textsuperscript{21}

\[\text{Insert Table 1}\]
\[\text{Insert Figure 1}\]

4. Empirical Results
4.1 Forecasting the Real Economy

Table 2 reports the results of the univariate and multivariate time-series regressions on the forecasting of real GDP growth as described in 2.1 Model A shows that aggregate B/M innovations have a significantly negative relation with future real GDP growth up to three quarters ahead. For example,

\textsuperscript{20} The NBER recession dates are available at http://www.nber.org/cycles.html
\textsuperscript{21} The AR (1) coefficient for aggregate B/M is 0.959 and is statistically significant whereas an AR (2) process shows that a second lag of aggregate B/M is statistically insignificant. Hence, the AR (1) process isolates the innovation component.
when predicting real GDP growth, the coefficient estimates are $-0.154$, $-0.196$, and $-0.147$ with t-statistics of $-3.55$, $-3.17$, and $-3.33$ for one, two, and three quarters ahead, respectively.

Model B shows that aggregate B/M innovations contain incrementally more information than the first release of real GDP growth. Including the first release does not affect the coefficient estimates of aggregate B/M innovations. Additionally, for the one-quarter-ahead forecast, the relative contribution of aggregate B/M innovations to the R-squared of the model is lower than that of the first release. However, when the forecast horizon increases, the relative contribution of the first release of GDP growth decays whereas the relative contribution of aggregate B/M innovations improves and exceeds that of the first release.\footnote{As mentioned earlier, I follow previous research (Konchitchki and Patatoukas 2014a) and control for the quarter’s first estimate of real GDP growth, because it is released close to the time when accounting data are available. However, results are not sensitive to controlling for the quarter’s second and third releases of real GDP growth.}

Model C shows that aggregate B/M innovations contain information beyond the SPF macroforecast and the first release of GDP growth. Consistent with prior research findings (Konchitchki and Patatoukas 2014, Abdalla and Carabias 2016), the inclusion of the SPF macroforecast eliminates the predictive content of the first release except for the one-quarter-ahead forecast. Interestingly, as the horizon increases, aggregate B/M innovations explain more variations in real GDP growth relative to the first release and the macroforecast.\footnote{As a robustness check, I re-consider an innovations-to-innovations analysis by estimating the regressions using real GDP growth innovations of the third release (the dependent variable), the first release and the SPF macroforecast (the independent variables). Untabulated results support the findings that aggregate B/M innovations contain macroeconomic information incremental to the first release and the SPF macroforecast. Indeed, the innovations-to-innovations results even show more superiority for aggregate B/M innovations relative to other GDP variables in the regression.} To further compare the relative effects of the variables without the problem of scale, I estimate standardized regression coefficients. Interpreted in standard deviation change, the standardized coefficients show that the effect of aggregate B/M innovations is lower than that of the SPF macroforecast with respect to the one-quarter-ahead forecast whereas aggregate B/M innovations beat the SPF macroforecast with respect to two- or three-quarter-ahead forecasts. A one standard deviation-increase in aggregate B/M innovations (the SPF macroforecast) results in 0.317, 0.380, and
0.293 (0.418, 0.338, and 0.149) standard deviation-decreases (-increases) in future real GDP growth in quarters one, two, and three, respectively.

These findings suggest that aggregate B/M innovations contain substantial macroeconomic information that helps predict the real economy and is incremental to the information in the contemporaneous real GDP growth and the SPF macroforecast. A comparison shows that the aggregate B/M innovations explain relatively higher variations in the future real economy.

[Insert Table 2]

4.2 Forecasting the State of the Real Economy and Nowcasting the Turning Points

Figure 2 displays the full sample probabilities of a one-quarter-ahead recession from a probit time-series regression of a recession binary on the lagged aggregate B/M innovations. The shaded areas denote the NBER recession quarters. The predicted probabilities tend to increase during recession quarters and decrease during non-recession quarters. Untabulated analysis shows that the mean of the predicted probabilities is approximately three times higher during recessions (31% during recession quarters and 11% during non-recession quarters).

Table 3 reports the results from the univariate and multivariate probit time-series regressions on the forecasting of the state of the economy as described in 2.2. Model A confirms a significantly positive association between the probability of a future recession and aggregate B/M innovations, with t-statistic of 5.57, 4.20, and 2.82 for one, two, and three quarters ahead. Model B shows that controlling for the first

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24 With the passage of time, the BEA provides a sequence of revised estimates of its current quarter-official release of GDP growth to reflect updated data and changes in economic definitions and statistical conventions. Late July, every year, quarterly estimates of the three preceding years (or sometimes more) are revised. The BEA revises its official GDP estimate in a sequence of “vintages” and hence the “latest vintage” release represents a revised picture of the economy. As a robustness check, I test if the results change when the latest vintage real GDP growth is used as a dependent variable instead of the official (third) release of real GDP growth. Untabulated results as of vintage 2015:Q3—the most recent vintage at the time of the study—show qualitatively consistent results. The only observations are (i) the results are relatively attenuated, as the models explain relatively less variations in the GDP variable (e.g., the adjusted R-squared in Model C decreases from 39% to 31%), and (ii) aggregate B/M innovations are only superior to the SPF macroforecast (i.e., higher Shapley value and higher standardized regression coefficients) in a three-quarter-ahead forecast instead of two-and three-quarter-ahead forecasts. All test results in this paper are qualitatively similar using the most recent vintage real GDP growth.
release of real GDP growth does not affect the results. The real GDP growth variable has a negative coefficient that confirms that higher real GDP growth is less likely to be associated with the probability of recession in the next two quarters. Strikingly, Model C shows that adding the SPF macroforecast for recession does not subsume the information in the innovations. Given that, the coefficients in the probit models are inherently standardized, and hence can be meaningfully compared without the problem of scaling (Williams 2009), the larger size of the coefficient on the B/M innovations relative to the SPF macroforecast suggests superior macroeconomic information content. Indeed, the coefficient on the SPF macroforecast becomes insignificant when the horizon expands to three quarters whereas the coefficient on the innovations remains significant in all quarters.

[Insert Figure 2]
[Insert Table 3]

Figure 3 displays the behavior of aggregate B/M innovations around the business cycle turning points. Interestingly, the figure shows that aggregate B/M innovations are negative around troughs and positive around peaks. Before most troughs (peaks), aggregate B/M innovations are relatively large (small) and then show a downward (an upward) spike around the trough (peak). Afterwards, they increase (decrease) as the economy shifts to an expansion (a recession). Only a few episodes show less than an ideal performance for the innovations, namely trough Q3: 1980, peak Q1: 2001 and peak Q4: 2007. The downward spike in the innovations around the trough precedes the upturn in the economy whereas the upward spike in the innovations around the peak precedes the onset of the recession.

Table 4 reports the results from the univariate and multivariate probit time-series regressions on the nowcasting of the regime shifts as described in 2.2. The model predicts a positive (negative) coefficient for the innovations when the model nowcasts the peaks (troughs). Model A confirms a significantly positive (negative) association between the probability of a peak (trough) in quarter \( q \) and aggregate B/M innovations in quarter \( q \). Model B shows that controlling for the quarter’s first release of real GDP
growth does not affect the ability of the innovations to nowcast. Indeed, the coefficient on the GDP variable is only significantly negative when the model nowcasts the troughs. Model C shows that the innovations’ ability to nowcast a regime shift is incremental to the SPF macroforecasts. In addition, the coefficient on the B/M innovations is larger than each of the two SPF macroforecasts. Moreover, the coefficient on the SPF macronowcast of recessions is only significant when the model nowcasts the troughs whereas the coefficient on the modified SPF macronowcast of the relevant regime shift is only significant when the model nowcasts the peaks.

These full sample results suggest that aggregate B/M innovations have information on the future state of the real economy and contemporaneous regime shifts. These results confirms that aggregate B/M innovations capture the comovement of aggregate economic output, investment and consumption across sectors of the economy as reflected in business cycle transitions.

4.3 Dating the Real Economy in Real time: The Book-to-Market Algorithm Performance

Figure 4 displays the real-time standardized probabilities of recession for the contemporaneous quarter using lagged aggregate B/M innovations consistent with the B/M dating algorithm. The shaded areas denote the NBER recession quarters. The values on the graph at quarter $q$ are the standardized probabilities of recession that are based on data up to quarter $q-1$. The real-time probabilities show consistency with the NBER recessions as they tend to increase substantially in periods of recession. To get more insights on the performance of the B/M dating algorithm, I tabulate the official business cycle dates from the NBER and those recognized by the algorithm and report the discrepancies between both dates. I also report the NBER announcement dates for each turning point. Table 5 reports these results.
Table 5 reveals that the B/M algorithm dates the peaks and troughs consistently with the NBER chronology. Specifically, for the five peaks in my sample period, the algorithm identifies three peaks with no discrepancy, one peak with a one-quarter discrepancy, and one peak with a two-quarter discrepancy. For the five troughs, the dating algorithm identifies three troughs with no discrepancy and two troughs with a one-quarter discrepancy. The average discrepancy is only a half of a quarter for all peaks and troughs. Moreover, the algorithm does not call for many false turning points because type II error (i.e. classifying a non-turning point as a turning point) represents 12 percent. These results show a relatively high level of accuracy because the algorithm dates are close to the official NBER dates. Additionally, while the NBER announcement dates show delays, my algorithm accurately identifies the official NBER dates in real time before they are announced.

These results show improvement over other sophisticated methods in economics. For example, Boldin (1994) find that dating methods in economics, such as the Stock and Watson’s (1989, 1991) indicator model and the Markov switching model of unemployment rate, as well as informal judgmental approaches could not accurately recognize the Q3: 1990 peak and the Q1: 1991 trough. The Stock and Watson’s procedure and the Markov switching model missed the peak by three months and more than one year, respectively. However, my dating algorithm identifies both turning points with no discrepancy. As for timeliness, while my dating algorithm identifies the turning points in real time, Chauvet and Piger (2008) find that two common dating methods in economics, namely the Harding and Pegan’s (2006) algorithm and the Markov switching model, do not show substantial improvement over the NBER in the speed at which they identify the turning points. In some cases, the identified turning points are even after the NBER announcement, making them less timely.

Another remarkable result is the performance of the algorithm during the 2001 great recession. While the algorithm shows relatively lower performance during this recession, it proves to be better than macroforecasts, real-time economic indicators, and dating models. Specifically, the algorithm identifies
the Q1: 2001 peak with a two-quarter discrepancy and calls its end in Q4: 2001 with a one-quarter discrepancy whereas the SPF and the Blue Chip Economic Indicators (BCEI) macroforecasters failed to predict a change in the economic regime until long after it had taken place. More so, the real-time (official) real GDP releases were only negative in one quarter during this recession, which was Q3: 2001. Afterwards, in Q3: 2002, the BEA made substantial revisions in real GDP, which showed estimates of the revised real GDP growth as negative for Q1: 2001, Q2: 2001 and Q3: 2001 (Kliesen 2003, Stock and Watson 2003). Chauvet and Piger (2003) note that the Markov switching model identified different peaks and troughs for the 2001 recession depending on whether it was applied to early releases or subsequent revisions of the data.

To summarize, the performance of the B/M dating algorithm is impressive given its ease of replication, accuracy and timeliness. Moreover, it is based on a univariate financial ratio that does not include economic indicators, which are subject to large revisions.

[Insert Figure 4]
[Insert Table 5]

4.4 Components of Aggregate Book-to-Market: Accounting Conservatism versus Delayed Recognition of Growth

Table 6 Panel A reports the results of the mean coefficients for the B/M decomposition at the firm level and the descriptive statistics of the aggregate components of B/M (measured as innovations). Table 6 Panel B reports the results from the time-series regression on the forecasting ability of the aggregate components’ innovations for future real GDP growth. Panel A shows that the mean coefficients are consistent with previous research (Beaver and Ryan 2000, Billings and Morton 2001). The coefficients on the changes in current and lagged market values are significantly negative consistent with unrecognized positive (negative) growth decreases (increases) the B/M ratio. The coefficients monotonically rise with

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25 Stock and Watson (2003) note that the stock market provides a reliable signal of the 2001 recession. My dating algorithm captures this market effect also.
the lag as further lagged unrecognized growth is more fully recognized. After aggregation, as described in
the appendix, the descriptive statistics show that the aggregate components’ innovations have means of
zero by construction and standard deviations of 0.020 and 0.064 for the aggregate conservatism
component and the aggregate recognition component, respectively.

Panel B shows that each aggregate component has a unique relation with future GDP growth. As
predicted, the aggregate conservatism (aggregate recognition) component is positively (negatively)
associated with future real GDP growth. In particular, the coefficient on the aggregate conservatism
component is significant at the 5% level for one- and two-quarter-ahead GDP growth and only significant
at the 10% level for three-quarter-ahead GDP growth. The coefficient on the aggregate recognition
component is significant at the 1% level for one- and two-quarter-ahead GDP growth and significant at
the 5% level for three-quarter-ahead GDP growth. The Shapley R-squared decomposition shows that the
marginal contribution of each aggregate component toward explaining variations in future GDP growth
increases as the horizon expands whereas that of each GDP growth variable decreases. In addition, the
aggregate recognition component explains more variations in future real GDP growth relative to the
aggregate conservatism component. Interpreted in standard deviation change, the standardized
coefficients show that the effect of the aggregate recognition component is relatively higher than the
aggregate conservatism component. A one standard deviation-increase in aggregate recognition
(aggregate conservatism) results in 0.287, 0.325, and 0.187 (0.172, 0.230, and 0.135) standard deviation-
decreases (-increases) in real GDP growth in quarters one, two, and three, respectively.\textsuperscript{26}

\textsuperscript{26} I note that the conservatism and recognition component of B/M do not represent a complete decomposition of the B/M ratio. A full decomposition would also include a time component as well as a residual component from the B/M decomposition regression. The time component represents the relative impact of a specific quarter. Beaver and Ryan (2000) report that, at the firm level, the time fixed effect incorporates similar properties as the recognition component and is also associated with unrecognized economic growth. Billings and Morton (2001) find that the residual component is negatively associated with future earnings. At the aggregate level, I find that both time and residual components of aggregate B/M have negative relations with future real GDP growth. This further clarifies the “overall” negative coefficient on aggregate B/M. Given the main accounting constructs that both aggregate conservatism and aggregate recognition components represent, I focus on these two components of aggregate B/M.
These results show some role of the accounting system in capturing future economic activity via conservatism. This role is broadly consistent with the results in Abdalla and Carabias (2016) who find that accounting conservatism represents one of the mechanisms through which accounting earnings forecast the macroeconomy. Nevertheless, the expectations of future growth that are incorporated in the aggregate B/M ratio but rather untimely recognized by the accounting system appear to be the main driver of the aggregate B/M association with future economic activity.

[Insert Table 6]

5. Additional analyses and robustness tests
5.1 Horse Race with Aggregate Earnings Growth Innovations

A growing literature on the information content of aggregate accounting earnings argues that aggregate accounting earnings convey macroeconomic information. Extant evidence shows that aggregate earnings growth help predict GDP growth (Konchitchiki and Patatoukas 2014) and specifically the aggregate investment component of GDP (Shivakumar and Urcan 2014). To examine whether aggregate B/M innovations contain macroeconomic information beyond aggregate accounting earnings growth, I run the following horse races between aggregate B/M innovations and aggregate earnings growth innovations:

\[
\text{Model A: } gdp_{q+n} = \alpha + \lambda btm_{q} + \omega \Delta ern_{q} + \epsilon_{q+n} \\
\text{Model B: } inv_{q+n} = \alpha + \lambda btm_{q} + \omega \Delta ern_{q} + \epsilon_{q+n}
\]

(7)

where \( inv_{q+n} \) is aggregate (seasonally-adjusted) real investment growth in quarter \( q + n \) and \( \Delta ern_{q} \) is aggregate earnings growth innovations in quarter \( q \).\textsuperscript{27} Aggregate earnings growth is measured as the value-weighted average of the year-over-year change in scaled quarterly earnings before extraordinary items. To avoid negative denominator problems, accounting earnings are scaled by sales (Konchitchki

\textsuperscript{27} Given that the focus is on horse races between the informativeness of aggregate B/M innovations and aggregate earnings growth innovations, adding SPF controls would induce another benchmarks of whether the information in the innovations are incorporated in the macroforecasts. Nevertheless, in untabulated results I find that inferences do not change when the first release of GDP growth (first release of aggregate investment growth) in quarter \( q \) and the SPF macroforecast of GDP growth (the SPF macroforecast of aggregate investment growth) are added to the GDP growth (aggregate investment growth) regression.
and Patatoukas 2014). Aggregate earnings growth innovations are the residuals of an AR (1) process. The results of the forecast horse races of the real GDP growth and the real investment growth are reported in Table 7 Panel A and Panel B, respectively.

Table 7 Panel A reveals that aggregate B/M innovations dominate aggregate earnings growth innovations in forecasting real GDP growth in all horizons considered. Both standardized regression coefficients and Shapley values of the aggregate B/M innovations are higher than those of the aggregate earnings growth innovations. Moreover, the power of the B/M innovations is greatest as the horizon expands.

Table 7 panel B reveals that aggregate earnings growth innovations dominate aggregate B/M innovations in forecasting real investment growth in a short horizon but not in a long horizon of three quarters ahead. More specifically, both the standardized regression coefficient and the Shapley value of aggregate earnings growth innovations are higher than those of aggregate B/M innovations in the one-quarter horizon. As the horizon increases, both the standardized regression coefficient and the Shapley value of aggregate earnings growth innovations decrease whereas those of aggregate B/M innovations increase. Aggregate B/M innovations have superiority in the three-quarter horizon.

In sum, the evidence indicates that in forecast horse races of the future macroeconomy between aggregate B/M innovations and aggregate earnings growth innovations, the former is superior in gauging the overall real economy. Nevertheless, aggregate earnings growth innovations are superior to aggregate B/M innovations in forecasting short-term aggregate investment but not long-term aggregate investment.

[Insert Table 7]

5.2 GDP Growth Forecast Error specification

As a robustness check, I also estimate alternative forecast error specifications to test whether forecast errors in real GDP growth are predicted by aggregate B/M innovations. Specifically, I estimate the following time-series regressions:
Model A: \( gdp_{q+n} - SPF_q (gdp_{q+n}) = \alpha + \lambda btm_q + \kappa gdp_q + \epsilon_{q+n} \)

Model B: \( gdp_{q+n} - SPF_q (gdp_{q+n}) = \alpha + \lambda btm_q + \kappa gdp_q + \theta [gdp_q - SPF_q (gdp_q)] + \epsilon_{q+n} \)

where \( gdp_{q+n} - SPF_q (gdp_{q+n}) \) is real GDP growth forecast error in quarter \( q+n \) based on the SPF macroforecast as of quarter \( q \), and \( gdp_q - SPF_q (gdp_q) \) is real GDP growth forecast error in quarter \( q \) based on the SPF macroforecast as of quarter \( q-n \).

The difference between Model A and Model B is that the latter controls for the possibility of serial correlation in the SPF macroforecast errors of future GDP growth. A significant \( \lambda \) coefficient suggests that real GDP growth forecast errors are predictable based on aggregate B/M innovations.

Table 8 reports the results of these regressions. Consistent with the results in Table 2 that aggregate B/M innovations have information that is incremental to the SPF macroforecast, the results in Table 8 reveal that real GDP growth forecast errors are predictable based on the innovations. The results also show systematic errors in the SPF macroforecast. This suggests that SPF panelists underestimate the presence of past forecast errors when forecasting future real GDP growth. This result documents the first evidence of the presence of systematic forecast errors of future real GDP growth. Nevertheless, even after controlling for past forecast errors, aggregate B/M innovations incrementally predict future forecast errors of real GDP growth.

[Insert Table 8]

6. Conclusion

I investigate whether aggregate B/M innovations contain macroeconomic information content with respect to future real GDP growth and the business cycle. I find that aggregate B/M innovations predict variations in real GDP growth up to three quarters ahead. The information content of aggregate B/M innovations is not subsumed by the SPF macroforecast when forecasting one-quarter-ahead real GDP growth and is even superior to the SPF macroforecast with respect to two- and three-quarter-ahead forecasts. I also find that aggregate B/M innovations are a leading indicator of the business cycle
conditions. Consistent with this finding, I develop a dating algorithm of the business cycle turning points. A practical application of the algorithm shows that it calls for peaks and troughs, in real time, with a relatively high level of accuracy. The dating algorithm performance exceeds that of sophisticated dating methods in applied economics.

I also show that two components of the aggregate B/M ratio have different implications for the source of macroeconomic information in the aggregate B/M innovations: an aggregate accounting conservatism component and an aggregate delayed recognition of growth component. However, on average, the delayed recognition component represents the dominating source of information. In additional tests, I show that the macroeconomic information in aggregate B/M innovations outperforms that of aggregate earnings growth innovations in forecasting future real GDP growth and real investment growth, but not for the one-quarter-ahead real investment forecast. In another test, I also show that real GDP growth forecast errors are predictable based on aggregate B/M innovations even after controlling for serial correlation in the SPF forecast errors of future real GDP growth.

The results can be viewed either as documenting a substantial macroeconomic information content of aggregate B/M innovations or, more ambitiously, as reflecting a casual association between the innovations and the U.S. macroeconomy. That is, expectations about the future can influence (and drive) real activity (Stock and Watson 2003). Businesses respond to aggregated revised expectations embedded in B/M innovations by cutting their investments, which in turn lead to declines in manufacturing output and shifts in the economy. Indeed, the Q-theory implies that expectations of future productivity transmitted through B/M are a significant determinant of the investment rate. While I do not take a stance on whether B/M innovations causally influence the overall economy, the results revive a question that goes back to the early economics literature on business cycles (Beveridge 1909, Clark 1934) on whether the revised expectations about the future merely predict the economy or rather drive it?
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APPENDIX
Estimating Conservatism and Recognition Components of Aggregate Book-to-Market

The aggregate components of B/M, \( cbtm_q \) and \( rbtm_q \), are measured as following. First, I estimate the components at the firm level consistent with Beaver and Ryan (2000) and Billings and Morton (2001). Henceforth, for ease of exposition, I add firm subscripts to variables at the firm level without changing notations. The firm-level regression is: \( btm_{i,q} = \eta_i + \eta_q + \sum_{\tau=0}^{5} \kappa_{\tau} \Delta m_{i,q-\tau} + \zeta_{i,q} \), where \( btm_{i,q} \) is book-to-market ratio for firm \( i \) measured at the end of quarter \( q \). \( \Delta m_{i,q-\tau} \) is the change in market value for firm \( i \) at quarter \( q-\tau \). The terms \( \eta_i \) and \( \eta_q \) are the firm fixed effects and quarter fixed effects, respectively.

The regression is estimated in an iterative fashion (expanding window-rolling regressions) using successive eight quarter panels of data. The current and lagged changes in market value serve as a proxy for the currently unrecognized economic shocks whereas the firm-fixed effect is the firm-specific variation in the book-to-market that is not explained by the delay in recognizing economic growth (Beaver and Ryan 2000). Therefore, \( cbtm_i \) is estimated as the firm effect (\( \eta_i \)) whereas \( rbtm_{i,q} \) is estimated as the \( \kappa_{\tau} \) coefficients multiplied by the market value change variables \( \sum_{\tau=0}^{5} \kappa_{\tau} \Delta m_{i,q-\tau} \).

For each eight-quarter panel, \( cbtm_i \) is constant across the panel (the \( q \) subscript is omitted), whereas \( rbtm_{i,q} \) is quarter-specific and is therefore estimated for the last quarter of the panel. As the rolling regression moves one quarter, both \( cbtm_i \) and \( rbtm_{i,q} \) are updated.

Second, similar to aggregate B/M, I compute the value-weighted aggregate conservatism component, \( cbtm_q \), and the value-weighted aggregate recognition component, \( rbtm_q \), and estimate innovations in each aggregate component as the residual of an AR (1) model.
Table 1
Descriptive Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>SD</th>
<th>1%</th>
<th>5%</th>
<th>25%</th>
<th>Median</th>
<th>75%</th>
<th>95%</th>
<th>99%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$btm_q^*$</td>
<td>0.620</td>
<td>0.243</td>
<td>0.266</td>
<td>0.316</td>
<td>0.417</td>
<td>0.553</td>
<td>0.823</td>
<td>1.064</td>
<td>1.232</td>
</tr>
<tr>
<td>$btm_q$</td>
<td>0.000</td>
<td>0.068</td>
<td>−0.206</td>
<td>−0.090</td>
<td>−0.033</td>
<td>−0.008</td>
<td>0.022</td>
<td>0.144</td>
<td>0.255</td>
</tr>
<tr>
<td>$\Delta ern_q^*$</td>
<td>−0.001</td>
<td>0.020</td>
<td>−0.076</td>
<td>−0.028</td>
<td>−0.007</td>
<td>−0.000</td>
<td>0.006</td>
<td>0.019</td>
<td>0.050</td>
</tr>
<tr>
<td>$\Delta ern_q$</td>
<td>0.000</td>
<td>0.017</td>
<td>−0.046</td>
<td>−0.016</td>
<td>−0.005</td>
<td>0.000</td>
<td>0.006</td>
<td>0.019</td>
<td>0.041</td>
</tr>
<tr>
<td>$gdp_q$ (Official)</td>
<td>0.026</td>
<td>0.033</td>
<td>−0.096</td>
<td>−0.029</td>
<td>0.013</td>
<td>0.027</td>
<td>0.043</td>
<td>0.080</td>
<td>0.097</td>
</tr>
<tr>
<td>$SPF_q (gdp_q)$</td>
<td>0.023</td>
<td>0.022</td>
<td>−0.049</td>
<td>−0.023</td>
<td>0.017</td>
<td>0.025</td>
<td>0.033</td>
<td>0.055</td>
<td>0.067</td>
</tr>
<tr>
<td>$SPF_q (rcs_q)$</td>
<td>0.188</td>
<td>0.228</td>
<td>0.015</td>
<td>0.021</td>
<td>0.050</td>
<td>0.094</td>
<td>0.203</td>
<td>0.818</td>
<td>0.901</td>
</tr>
<tr>
<td>$(btm_q</td>
<td>rcs_{q+1} = 1)$</td>
<td>0.072</td>
<td>0.092</td>
<td>−0.074</td>
<td>−0.017</td>
<td>0.002</td>
<td>0.051</td>
<td>0.145</td>
<td>0.255</td>
</tr>
<tr>
<td>$(btm_q</td>
<td>rcs_{q+1} = 0)$</td>
<td>−0.011</td>
<td>0.058</td>
<td>−0.206</td>
<td>−0.092</td>
<td>−0.036</td>
<td>−0.014</td>
<td>0.015</td>
<td>0.093</td>
</tr>
</tbody>
</table>

Mean | SD  | Values of aggregate B/M innovations at NBER turning points

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$btm_q$</td>
<td>0.105</td>
<td>0.082</td>
<td>0.173</td>
<td>0.114</td>
<td>0.173</td>
<td>0.161</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$btm_q$</td>
<td>−0.114</td>
<td>0.065</td>
<td>−0.206</td>
<td>−0.030</td>
<td>−0.111</td>
<td>−0.084</td>
</tr>
</tbody>
</table>

This table reports descriptive statistics for the key variables. Financial data is from Wharton Research Data Services (WRDS) and GDP data is from Real-Time Data Research Center, Federal Reserve Bank of Philadelphia. For every firm-quarter, the book-to-market ratio, is measured as the book value of equity (seqq) divided by market value. Aggregate book-to-market, $btm_q^*$, is value-weighted cross-sectional averages, with weights based on market capitalization as of the beginning of the quarter. Aggregate book-to-market innovations, $btm_q$, are the residuals of the AR (1) process. Aggregate earnings growth, $\Delta ern_q^*$, is measured as the value weighted average of year-over-year change in scaled quarterly earnings before extraordinary items. Accounting earnings are scaled by sales. Aggregate earnings growth innovations, $\Delta ern_q$, are the residuals of an AR (1) process. GDP growth variable, $gdp_q$ (official) is the third estimate of quarter-over-quarter annual real GDP growth rates. $SPF_q (gdp_q)$ and $SPF_q (rcs_q)$ are the mean consensus GDP growth forecast and the mean consensus probability of negative GDP growth from the Survey of Professional Forecasters (SPF) of the Federal Reserve Bank of Philadelphia.
Table 2
Aggregate Book-to-Market Innovations as Predictors of the Real Economy:
Univariate and Multivariate Analysis

Model A: $gdp_{q+n} = \alpha + \lambda btm_{q} + \epsilon_{q+n}$

Model B: $gdp_{q+n} = \alpha + \lambda btm_{q} + \kappa gdp_{q} + \epsilon_{q+n}$

Model C: $gdp_{q+n} = \alpha + \lambda btm_{q} + \kappa gdp_{q} + \delta SPF_{q} (gdp_{q+n}) + \epsilon_{q+n}$

<table>
<thead>
<tr>
<th>Variables</th>
<th>$n = 1$</th>
<th>$n = 2$</th>
<th>$n = 3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Int.</td>
<td>0.026*** (8.05) 0.014*** (4.77) Shapley</td>
<td>0.026*** (8.53) 0.020*** (6.00) Shapley</td>
<td>0.026*** (8.09) 0.024*** (5.23) Shapley</td>
</tr>
<tr>
<td>$btm_{q}$</td>
<td>-0.154*** (-3.55) -0.157*** (-3.90) [44%]</td>
<td>-0.196*** (-3.17) -0.197*** (-3.22) [79%]</td>
<td>-0.147*** (-3.33) -0.148*** (-3.40) [95%]</td>
</tr>
<tr>
<td>$gdp_{q}$</td>
<td>0.482*** (6.12)</td>
<td>0.225*** (3.05) [21%]</td>
<td>0.079 (0.75) [5%]</td>
</tr>
<tr>
<td>Adj.R²</td>
<td>10% 29% 16%</td>
<td>20% 9%</td>
<td>9%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variables</th>
<th>$n = 1$</th>
<th>$n = 2$</th>
<th>$n = 3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Int.</td>
<td>0.000 (0.09)</td>
<td>0.000 (0.04)</td>
<td>0.009 (1.11)</td>
</tr>
<tr>
<td>$btm_{q}$</td>
<td>-0.155*** (-4.11)</td>
<td>-0.183*** (-2.91) [51%]</td>
<td>-0.141*** (-3.15) [74%]</td>
</tr>
<tr>
<td>$gdp_{q}$</td>
<td>0.179** (2.09)</td>
<td>0.070 (0.89) [8%]</td>
<td>0.048 (0.44) [3%]</td>
</tr>
<tr>
<td>$SPF_{q} (gdp_{q+n})$</td>
<td>0.821*** (4.75) [48%]</td>
<td>0.852*** (5.41) [41%]</td>
<td>0.523* (1.90) [23%]</td>
</tr>
<tr>
<td>Adj.R²</td>
<td>39% 29% 11%</td>
<td>29%</td>
<td>11%</td>
</tr>
</tbody>
</table>

The table reports results from time-series regressions of future real GDP growth on current-quarter aggregate book-to-market ratio innovations. Financial data is from Wharton Research Data Services (WRDS) and GDP data is from Real-Time Data Research Center, Federal Reserve Bank of Philadelphia. For every firm-quarter, the book-to-market ratio, is measured as the book value of equity (seqq) divided by market value. Aggregate book-to-market, is value-weighted cross-sectional averages, with weights based on market capitalization as of the beginning of the quarter. Aggregate book-to-market innovations, $btm_{q}$, are the residuals of the AR (1) process. GDP growth variables, $gdp_{q+n}$ and $gdp_{q}$, are the quarter-over-quarter annual real GDP growth rates, where the former is the official release of GDP growth in quarter $q + n$ and latter is the first release of GDP growth in quarter $q$. $SPF_{q} (gdp_{q+n})$ is the mean consensus GDP
growth forecast from the Survey of Professional Forecasters (SPF). Reported t-statistics are based on Newey and West –HAC standard errors with a lag length of four. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively, using two-tailed tests. Shapley values are additive decompositions of the total adjusted $R^2$ of the model and show the contribution of each independent variable to the total adjusted $R^2$ (See Shapley 1953). “Standardized” are standardized regression coefficients presented in italic.
Table 3
Aggregate Book-to-Market Innovations as Predictors of the State of the Economy:
Univariate and Multivariate Analysis

Pr(rcs_{q+n}) = \alpha + \lambda btm_{q} + \epsilon_{q+n}
Pr(rcs_{q+n}) = \alpha + \lambda btm_{q} + \kappa gdp_{q} + \epsilon_{q+n}
Pr(rcs_{q+n}) = \alpha + \lambda btm_{q} + \kappa gdp_{q} + \delta SPF_{q}[Pr(rcs_{q+n})] + \epsilon_{q+n}

<table>
<thead>
<tr>
<th>Variables</th>
<th>Int.</th>
<th>btm_{q}</th>
<th>gdp_{q}</th>
<th>E[Pr(rcs_{q+n})]</th>
</tr>
</thead>
<tbody>
<tr>
<td>n = 1</td>
<td>-1.284*** (-6.20)</td>
<td>9.321*** (5.57)</td>
<td>-17.377*** (-4.55)</td>
<td>2.173*** (3.00)</td>
</tr>
<tr>
<td>n = 2</td>
<td>-0.968*** (-4.55)</td>
<td>9.538*** (4.41)</td>
<td>-8.084* (-1.703)</td>
<td>2.823*** (2.73)</td>
</tr>
<tr>
<td>n = 3</td>
<td>-1.162*** (-5.94)</td>
<td>5.182*** (4.16)</td>
<td>-9.830*** (-2.84)</td>
<td>2.115</td>
</tr>
</tbody>
</table>

Pseudo. R^2 | 19% | 31% | 34% | 7% | 11% | 15% | 2% | 4% | 12%

The table reports results from probit time-series regressions of future recessions on current-quarter aggregate book-to-market ratio innovations. Financial data is from Wharton Research Data Services (WRDS) and GDP data is from Real-Time Data Research Center, Federal Reserve Bank of Philadelphia. For every firm-quarter, the book-to-market ratio, is measured as the book value of equity (seqq) divided by market value. Aggregate book-to-market, is value-weighted cross-sectional averages, with weights based on market capitalization as of the beginning of the quarter. Aggregate book-to-market innovations, btm_{q}, are the residuals of the AR (1) process. GDP growth variables, gdp_{q+n} and gdp_{q}, are the quarter-over-quarter annual real GDP growth rates, where the former is the third release of GDP growth in quarter q + n and latter is the first release of GDP growth in quarter q. rcs_{q+n} is a binary variable that equals 1 if there is a recession in quarter q + n, and 0 otherwise. The standard NBER recession quarters are used to determine the values of rcs_{q+n}. SPF_q[Pr(rcs_{q+n})] is the mean SPF macroforecast of the probability that real GDP growth is negative in quarter q + n as of quarter q from the Survey of Professional Forecasters (SPF). This survey is well known as the anxious index. Reported t-statistics are based on Newey and West -HAC standard errors with a lag length of four. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively, using two-tailed tests. Shapley values are additive decompositions of the total adjusted R^2 of the model and show the contribution of each independent variable to the total adjusted R^2 (See Shapley 1953).
Table 4
Aggregate Book-to-Market Innovations and nowcasting the NBER Business Cycle Dates: Univariate and Multivariate Analysis

Model A:  Pr\(\text{cyc}_q\) = \(\alpha + \lambda btm_q + \varepsilon_q\)
Model B:  Pr\(\text{cyc}_q\) = \(\alpha + \lambda btm_q + \kappa \text{gdp}_q + \varepsilon_q\)
Model C:  Pr\(\text{cyc}_q\) = \(\alpha + \lambda btm_q + \kappa \text{gdp}_q + \delta \text{E}_q[\text{Pr}\text{cyc}_{q-n}] + \delta \text{SPF}_q[\text{Pr}\text{rcs}_q] + \varepsilon_q\)

<table>
<thead>
<tr>
<th>Variables</th>
<th>(cyc_q = \text{peak}_q)</th>
<th>(cyc_q = \text{trough}_q)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Int.</td>
<td>-2.133***</td>
<td>-2.352***</td>
</tr>
<tr>
<td></td>
<td>(-9.30)</td>
<td>(-6.99)</td>
</tr>
<tr>
<td>(btm_q)</td>
<td>8.053***</td>
<td>16.148***</td>
</tr>
<tr>
<td></td>
<td>(3.15)</td>
<td>(-3.36)</td>
</tr>
<tr>
<td>(gdp_q)</td>
<td>-4.369</td>
<td>-15.643**</td>
</tr>
<tr>
<td></td>
<td>(-1.33)</td>
<td>(-2.38)</td>
</tr>
<tr>
<td>(E_q[\text{Pr}\text{cyc}_{q-n}])</td>
<td>1.545***</td>
<td>1.376</td>
</tr>
<tr>
<td></td>
<td>(3.04)</td>
<td>(0.96)</td>
</tr>
<tr>
<td>(E_q[\text{Pr}\text{rcs}_q])</td>
<td>-0.277</td>
<td>5.719**</td>
</tr>
<tr>
<td></td>
<td>(-0.26)</td>
<td>(2.47)</td>
</tr>
</tbody>
</table>

Pseudo. R\(^2\)  
22%  22%  31%  39%  50%  76%

The table reports results from probit time-series regressions of contemporaneous turning points peaks and troughs on current-quarter aggregate book-to-market ratio innovations. Financial data is from Wharton Research Data Services (WRDS) and GDP data is from Real-Time Data Research Center, Federal Reserve Bank of Philadelphia. For every firm-quarter, the book-to-market ratio, is measured as the book value of equity (seqq) divided by market value. Aggregate book-to-market, is value-weighted cross-sectional averages, with weights based on market capitalization as of the beginning of the quarter. Aggregate book-to-market innovations, \(btm_q\), are the residuals of the AR (1) process. GDP growth, \(gdp_q\), is first release of GDP growth measured as the quarter-over-quarter annual real GDP growth rate. \(cyc_q\) is the NBER’s business cycle turning points measured alternatively as peaks, \(\text{peak}_q\), or troughs, \(\text{trough}_q\). \(\text{peak}_q\) (\(\text{trough}_q\)) is a binary variable that equals 1 if the current quarter is officially dated by the NBER as a peak (a trough). \(\text{SPF}_q[\text{Pr}\text{rcs}_{q+n}]\) is the mean SPF macroforecast of the probability that real GDP growth is negative in quarter \(q+n\) as of quarter \(q\) from the Survey of Professional Forecasters (SPF). This survey is well known as the anxious index. \(E_q[\text{Pr}\text{cyc}_{q-n}]\) is measured as \(E_q[\text{Pr}\text{peak}_q]\) or \(E_q[\text{Pr}\text{trough}_q]\) consistently with the turning point dependent variable. \(E_q[\text{Pr}\text{peak}_q]\) (\(E_q[\text{Pr}\text{trough}_q]\)) is equal to 1 if the first release of GDP
growth in quarter \( q \) is positive (negative) but the mean SPF macroforecast of GDP growth for quarter \( q + 1 \) as of quarter \( q \) is negative (positive), and zero otherwise. Reported t-statistics are based on Newey and West -HAC standard errors with a lag length of four. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively, using two-tailed tests. Shapley values are additive decompositions of the total adjusted R\(^2\) of the model and show the contribution of each independent variable to the total adjusted R\(^2\) (See Shapley 1953).
Table 5
Dating Business Cycle Turning Points in Real-Time

<table>
<thead>
<tr>
<th>Type</th>
<th>Date</th>
<th>NBER Chronology Announcement</th>
<th>Delay</th>
<th>B/M Dating Algorithm Date</th>
<th>Discrepancy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak</td>
<td>Q1: 1980</td>
<td>Q2: 1980</td>
<td>+1Q</td>
<td>Q1: 1980</td>
<td>0</td>
</tr>
<tr>
<td>Peak</td>
<td>Q4: 1982</td>
<td>Q1: 1982</td>
<td>+2Q</td>
<td>Q4: 1982</td>
<td>0</td>
</tr>
<tr>
<td>Trough</td>
<td>Q1: 1991</td>
<td>Q4: 1992</td>
<td>+7Q</td>
<td>Q1: 1991</td>
<td>0</td>
</tr>
<tr>
<td>Peak</td>
<td>Q1: 2001</td>
<td>Q4: 2001</td>
<td>+3Q</td>
<td>Q3: 2001</td>
<td>+2</td>
</tr>
<tr>
<td>Trough</td>
<td>Q4: 2001</td>
<td>Q3: 2003</td>
<td>+7Q</td>
<td>Q1: 2002</td>
<td>+1</td>
</tr>
<tr>
<td>Peak</td>
<td>Q4: 2007</td>
<td>Q4: 2008</td>
<td>+4Q</td>
<td>Q1: 2008</td>
<td>+1</td>
</tr>
<tr>
<td>Trough</td>
<td>Q2: 2009</td>
<td>Q3: 2010</td>
<td>+5Q</td>
<td>Q3: 2009</td>
<td>+1</td>
</tr>
</tbody>
</table>

Mean Discrepancy          0.5 Quarter
Type II error             0.12

This table reports results of the book-to-market innovations dating algorithm. The algorithm has the following steps. First, aggregate book-to-market innovations are estimated in-sample using recursively increasing samples of data. The first estimation window includes 10 quarters. Innovations are estimated for the last observation in the recursive samples. Second, a binary time series of recessions on the lagged aggregate book-to-market innovations is estimated recursively using a probit model and out-of-sample predicted probabilities are estimated. Similar window length is used. Third, means and standard deviations of the resulting predicted probabilities are estimated recursively for each sample window. Finally, the following score is derived:

\[ E(S_{q+1}) = \frac{E(e_{q+1}) - \mu_{e_q}}{sd_{e_q}}, \]

where \( E(S_{q+1}) \) represents the standardized probability of the state of the economy (herein recession) in quarter \( q+1 \) as of quarter \( q \), \( \mu_{e_q} \) is the mean of the probit predicted probability in quarter \( q \), and \( sd_{e_q} \) is the standard deviation of the probit predicted probability in quarter \( q \). The algorithm applies following rule for peaks and troughs:

Peak Rule: \( P_q = S_{q-1} < 3*sd_{e_{q-1}} + \mu_{e_{q-1}}, E(S_{q-1}) > 3*sd_{e_{q-1}} + \mu_{e_{q-1}} \)

Trough Rule: \( T_q = S_{q-2} > 3*sd_{e_{q-2}} + \mu_{e_{q-2}}, S_{q-2} < 3*sd_{e_{q-1}} + \mu_{e_{q-1}} \)

where \( P_q (T_q) \) is an estimated peak (trough) in quarter \( q \).
Delay (discrepancy) represents the number of quarters between the NBER official date and the NBER announcement (the date identified by the dating algorithm). Type II error represents the percentage error from classifying a non-turning point as a turning point.
Table 6
Conservatism and Growth Recognition Components of Aggregate Book-to-Market

Panel A: Book-to-Market Decomposition and the aggregate components

\[ btm_{q,t} = \eta_{i,t} + \eta_{q,t} + \sum_{r=1}^{6} K_r \Delta m_{q,t-r} + \zeta_{q,t}, \]
where \( cbtm_q = \eta_i \), and \( rbtm_q = \sum_{r=1}^{6} K_r \Delta m_{q,t-r} \)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>1%</th>
<th>5%</th>
<th>25%</th>
<th>Median</th>
<th>75%</th>
<th>95%</th>
<th>99%</th>
</tr>
</thead>
<tbody>
<tr>
<td>( cbtm_q )</td>
<td>0.000</td>
<td>0.020</td>
<td>-0.061</td>
<td>-0.037</td>
<td>-0.008</td>
<td>0.002</td>
<td>0.012</td>
<td>0.026</td>
<td>0.045</td>
</tr>
<tr>
<td>( rbtm_q )</td>
<td>0.000</td>
<td>0.064</td>
<td>-0.193</td>
<td>-0.098</td>
<td>-0.029</td>
<td>-0.002</td>
<td>0.027</td>
<td>0.110</td>
<td>0.185</td>
</tr>
</tbody>
</table>

Panel B: Aggregate Book-to-Market Components and Future GDP Growth

\[ gdp_{t+1} = \alpha + \beta_{c} cbtm_q + \beta_{r} rbtm_q + \gamma_{g} gdp_q + \delta SPF_{q} (gdp_{q+1}) + \epsilon_{t+1} \]

<table>
<thead>
<tr>
<th>Variables</th>
<th>Int.</th>
<th>( n = 1 )</th>
<th>( n = 2 )</th>
<th>( n = 3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( cbtm_q )</td>
<td>0.00349</td>
<td>(0.84)</td>
<td>Shapley</td>
<td>0.172</td>
</tr>
<tr>
<td>( rbtm_q )</td>
<td>-0.147***</td>
<td>(-4.33)</td>
<td>-0.287</td>
<td>(2.92)</td>
</tr>
<tr>
<td>( gdp_q )</td>
<td>0.120</td>
<td>(1.32)</td>
<td>0.111</td>
<td>(-0.19)</td>
</tr>
<tr>
<td>SPF_{q} (gdp_{q+1})</td>
<td>0.745***</td>
<td>(5.24)</td>
<td>0.365</td>
<td>(3.62)</td>
</tr>
<tr>
<td>Adj.R^2</td>
<td>37%</td>
<td>28%</td>
<td>5%</td>
<td></td>
</tr>
</tbody>
</table>

The table reports results of the conservatism and recognition components of aggregate book-to-market. Panel A reports results of the mean coefficients of the B/M decomposition at the firm level and descriptive statistics of the aggregate components of B/M. Panel B reports time-series regression results of the forecasting ability of the aggregate components for future GDP.
growth. Financial data is from Wharton Research Data Services (WRDS) and GDP data is from Real-Time Data Research Center, Federal Reserve Bank of Philadelphia. For every firm-quarter, the book-to-market ratio, is measured as the book value of equity (seqq) divided by market value. \( \Delta m_{i,q-1} \) is growth in market value for firm \( i \) at quarter \( q - 1 \). The terms \( \eta_i \) and \( \eta_q \) are the firm fixed effects and quarter fixed effects, respectively. Aggregate book-to-market, is value-weighted cross-sectional averages, with weights based on market capitalization as of the beginning of the quarter. Aggregate book-to-market innovations, \( btm_q \), are the residuals of the AR (1) process. \( cbtm_q \) and \( rbtm_q \) are the aggregate conservatism component and the aggregate recognition components of book-to-market. The aggregate components are innovations estimated as residuals of the AR (1) process. The estimation of these two components is described in details in the appendix. GDP growth variables, \( gdp_{q+n} \) and \( gdp_q \), are the quarter-over-quarter annual real GDP growth rates, where the former is the third release of GDP growth in quarter \( q + n \) and latter is the first release of GDP growth in quarter \( q \). SPF \( gdp_q \) is the mean consensus GDP growth forecast from the Survey of Professional Forecasters (SPF). Reported t-statistics are based on Newey and West-HAC standard errors with a lag length of four. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively, using two-tailed tests. Shapley values are additive decompositions of the total adjusted \( R^2 \) of the model and show the contribution of each independent variable to the total adjusted \( R^2 \) (See Shapley 1953). “Standardized” are standardized regression coefficients presented in italic. “Standardized” are standardized regression coefficients presented in italic.
### Table 7

**Horse Race with Aggregate Earnings Growth Innovations**

**Panel A: Predicting Real GDP Growth**

\[ gdp_{tn} = \alpha + \lambda btm_{tn} + \omega \Delta ern_{tn} + \epsilon_{tn} \]

<table>
<thead>
<tr>
<th>Variables</th>
<th>( n = 1 )</th>
<th>( n = 2 )</th>
<th>( n = 3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Int.</td>
<td>0.025***</td>
<td>0.025***</td>
<td>0.025***</td>
</tr>
<tr>
<td></td>
<td>(8.28)</td>
<td>(8.61)</td>
<td>(8.02)</td>
</tr>
<tr>
<td>btm(_t)</td>
<td>(-0.139***)</td>
<td>(-0.192***)</td>
<td>(-0.137***)</td>
</tr>
<tr>
<td></td>
<td>((-3.07))</td>
<td>((-2.91))</td>
<td>((-2.87))</td>
</tr>
<tr>
<td>( \Delta ern(_t) )</td>
<td>0.282***</td>
<td>0.142</td>
<td>0.164*</td>
</tr>
<tr>
<td></td>
<td>(2.77)</td>
<td>(1.41)</td>
<td>(1.71)</td>
</tr>
<tr>
<td>Adj.R(^2)</td>
<td>12%</td>
<td>16%</td>
<td>9%</td>
</tr>
</tbody>
</table>

**Panel B: Predicting Real Investments Growth**

\[ inv_{tn} = \alpha + \lambda btm_{tn} + \omega \Delta ern_{tn} + \epsilon_{tn} \]

<table>
<thead>
<tr>
<th>Variables</th>
<th>( n = 1 )</th>
<th>( n = 2 )</th>
<th>( n = 3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Int.</td>
<td>0.0488***</td>
<td>0.0477***</td>
<td>0.0479***</td>
</tr>
<tr>
<td></td>
<td>(4.81)</td>
<td>(4.93)</td>
<td>(4.89)</td>
</tr>
<tr>
<td>btm(_t)</td>
<td>(-0.153)</td>
<td>(-0.353***)</td>
<td>(-0.362***)</td>
</tr>
<tr>
<td></td>
<td>((-1.24))</td>
<td>((-3.06))</td>
<td>((-2.67))</td>
</tr>
<tr>
<td>( \Delta ern(_t) )</td>
<td>1.774***</td>
<td>1.496***</td>
<td>1.247***</td>
</tr>
<tr>
<td></td>
<td>(2.68)</td>
<td>(3.85)</td>
<td>(3.52)</td>
</tr>
<tr>
<td>Adj.R(^2)</td>
<td>10%</td>
<td>13%</td>
<td>11%</td>
</tr>
</tbody>
</table>

This table reports results from time series regressions of future real GDP growth and real aggregate investments on current quarter Book-to-market innovations and earnings growth innovations. Panel A reports the real GDP growth results. Panel B reports the real aggregate investments results. Financial data is from Wharton Research Data Services (WRDS) and GDP and aggregate investment data is from Real-Time Data Research Center, Federal Reserve Bank of Philadelphia. For every firm-quarter, the book-to-market ratio, is measured as the book value of equity (seqq) divided by market value. Aggregate book-to-market, is value-weighted cross-sectional averages, with weights based on market capitalization as of the beginning of the quarter. Aggregate book-to-market innovations, \( btm\(_t\) \), are the residuals of the AR (1) process. Aggregate earnings growth is measured as the value weighted average of year-over-year change in scaled quarterly earnings before extraordinary items. Accounting earnings are scaled by sales. Aggregate earnings growth innovations, \( \Delta ern\(_t\) \), are the residuals of an AR (1)
process. GDP growth, \( gdp_{q+n} \), is the official (third) release measured as the quarter-over-quarter annual real GDP growth rate. Aggregate (nonresidential) investment is the official (third) release of measured as the quarter-over-quarter annual real investment growth rate. Reported t-statistics are based on Newey and West -HAC standard errors with a lag length of four. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively, using two-tailed tests. Shapley values are additive decompositions of the total adjusted \( R^2 \) of the model and show the contribution of each independent variable to the total adjusted \( R^2 \) (See Shapley 1953). “Standardized” are standardized regression coefficients presented in italic. “Standardized” are standardized regression coefficients presented in italic.
Table 8
Alternative GDP Growth Forecast Error Specifications

\[ gdp_{q+n} - SPF_q(gdp_{q+n}) = \alpha + \lambda btm_q + \kappa gdp_q + \theta \left[ SPF_q(gdp_{q+n}) \right] + \varepsilon_{q+n} \]

<table>
<thead>
<tr>
<th>Variables</th>
<th>( n = 1 )</th>
<th>( n = 2 )</th>
<th>( n = 3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>\text{Int.}</td>
<td>(-0.003)</td>
<td>(-0.004)</td>
<td>(-0.002)</td>
</tr>
<tr>
<td>( btm_q )</td>
<td>(-0.154***) ([-0.78])</td>
<td>(-0.180***) ([-1.10])</td>
<td>(-0.149**) ([-0.91])</td>
</tr>
<tr>
<td>( gdp_q )</td>
<td>(0.112) ([10%])</td>
<td>(-0.114) ([-1.08])</td>
<td>(-0.007) ([-0.10])</td>
</tr>
<tr>
<td>( SPF_q - (gdp_q) )</td>
<td>(0.311**) ([2.47])</td>
<td>(0.192**) ([2.52])</td>
<td>(0.278***) ([3.32])</td>
</tr>
</tbody>
</table>

\( \text{Adj.R}^2 \)

<table>
<thead>
<tr>
<th>( n = 1 )</th>
<th>( n = 2 )</th>
<th>( n = 3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>14%</td>
<td>17%</td>
<td>16%</td>
</tr>
<tr>
<td>16%</td>
<td>18%</td>
<td>7%</td>
</tr>
<tr>
<td>13%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The table reports results from time-series regressions of future real GDP growth forecast errors on current-quarter aggregate book-to-market ratio innovations. Financial data is from Wharton Research Data Services (WRDS) and GDP data is from Real-Time Data Research Center, Federal Reserve Bank of Philadelphia. For every firm-quarter, the book-to-market ratio, is measured as the book value of equity (seqq) divided by market value. Aggregate book-to-market, is value-weighted cross-sectional averages, with weights based on market capitalization as of the beginning of the quarter. Aggregate book-to-market innovations, \( btm_q \), are the residuals of the AR (1) process. GDP growth variables, \( gdp_q \), are the quarter-over-quarter annual real GDP growth rates, where the former is the official (third) release of GDP growth in quarter \( q+n \) and latter is the first release of GDP growth in quarter \( q \). \( SPF_q(gdp_q) \) is the mean consensus GDP growth forecast from the Survey of Professional Forecasters (SPF). Reported t-statistics are based on Newey and West-HAC standard errors with a lag length of four. ***, **, * denote significance at the 1, 5, and 10 percent levels, respectively, using two-tailed tests. Shapley values are additive decompositions of the total adjusted \( R^2 \) of the model and show the contribution of each independent variable to the total adjusted \( R^2 \) (See Shapley 1953).
This figure plots raw aggregate book-to-market and aggregate book-to-market innovations, Q3:1971-Q4:2015. Aggregate book-to-market, is value-weighted cross-sectional averages, with weights based on market capitalization as of the beginning of the quarter. Aggregate book-to-market innovations are the residuals of the AR (1) process.
Figure 2
Full Sample Probability of US Recessions One-Quarter-Ahead as Predicted by Aggregate Book-to-Market Innovations

This figure plots the predicted probability of US recessions, one-quarter-ahead from a probit time series regression of a recession binary on lagged aggregate book-to-market innovations, Q3:1971-Q4:2015. Shaded areas denote the standard NBER recession quarters. Aggregate book-to-market, is value-weighted cross-sectional averages, with weights based on market capitalization as of the beginning of the quarter. Aggregate book-to-market innovations are the residuals of the AR (1) process.
Figure 3
Aggregate Book-to-Market Innovations around Business Cycle Peaks and Troughs

Graph 1: Real GDP over Time
- Peak
- Recession
- Trough

Graph 2: Innovations in Aggregate Book-to-Market
- NBER Troughs
- Event Quarter
- Q1: 1975
- Q4: 1982
- Q1: 1991
- Q4: 2001
- Q2: 2009
This figure plots the behavior of aggregate book to market innovations around the NBER business cycle turning points (troughs and peaks), Q3:1971-Q4:2015. Event quarter is the quarter that has been officially dated as a turning point by the NBER. Aggregate book-to-market, is value-weighted cross-sectional averages, with weights based on market capitalization as of the beginning of the quarter. Aggregate book-to-market innovations are the residuals of the AR (1) process.
This figure plots real-time standardized probabilities of recession for the contemporaneous quarter based on lagged aggregate book-to-market innovations consistent with the book-to-market dating algorithm. Q3:1971-Q4:2015 where Q3: 1971-Q2:1978 is the required estimation period, and Q3: 1978-Q5:2015 is the test period. Shaded areas denote the standard NBER recession quarters. Aggregate book-to-market is value-weighted cross-sectional averages, with weights based on market capitalization as of the beginning of the quarter. Aggregate book-to-market innovations are the residuals of the AR (1) process. Type II error represents the percentage error from classifying a non-turning point as a turning point.