Aggregate Financial Misreporting and the Predictability of U.S. Recessions

Messod D. Beneish
Kelley School of Business, Indiana University

David B. Farber
Kelley School of Business, Indiana University

Matthew Glendening
Trulaske College of Business, University of Missouri

Kenneth W. Shaw
Trulaske College of Business, University of Missouri

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Abstract
We rely on the theoretical prediction that financial misreporting peaks *before* economic busts to examine whether aggregate *ex ante* measures of the likelihood of financial misreporting improve the predictability of U.S. recessions. We consider six measures of misreporting and show that the Beneish M-Score significantly improves out-of-sample recession prediction at longer forecasting horizons. Specifically, relative to leading models based on yield spreads and market returns, M-Score increases the average probability of a recession across forecast horizons of six-, seven-, and eight-quarters-ahead by 56 percent, 79 percent, and 92 percent, respectively. These findings are robust to alternative definitions of interest rate spreads, and to controlling for the federal funds rate, investor sentiment, and aggregate earnings growth. We show that the performance of M-Score likely arises because firms with high M-Scores tend to experience negative future performance. Overall, this study provides novel evidence that accounting information can be useful to forecasters and regulators interested in assessing the likelihood of U.S. recessions a few quarters ahead.

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Corresponding Author: David B. Farber, Kelley School of Business, Indiana University.
Email: dbfarber@iupui.edu

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1. Introduction

This paper examines whether a proxy for the likelihood of financial misreporting improves the predictability of U.S. recessions.[1] It differs markedly from existing research in that our principal construct is a measure of the *ex ante* likelihood of *aggregate* misreporting across U.S. firms. While economists have long studied recession prediction with measures drawn from credit markets, monetary policy, inflation, and the stock market, no study on recession prediction has, to our knowledge, considered a measure of the *ex-ante* likelihood of misreporting. We draw on prior theory and empirical work to predict a role for aggregate misreporting in forecasting recessions. Povel, Singh, and Winton (2007) provide theoretical motivation: They argue that when investors have relatively more optimistic priors, there is less monitoring of good news, leading to a build-up of distorted good news and thus to the prediction that misreporting peaks before economic busts. Further motivation is provided by empirical evidence that incentives to misreport increase when market and fundamental values diverge, and when expectations of growth and performance are heightened in periods of extended economic expansion (e.g., Beneish 1999a; Jensen 2005; Baker and Wurgler 2007; Efendi, Srivastava, and Swanson 2007).

Investigating whether aggregate misreporting predicts recessions is of interest for at least three reasons. First, predicting recessions is an important undertaking for policy makers and market participants. However, there is a dearth of empirical evidence on predicting recessions in real time, as Amiram, Bozanic, Cox, Dupont, Karpoff, and Sloan (2018) highlight in their recent review of research on misreporting.[2] Second, whereas several studies document that the *ex post* discovery of

[1] We refer to "financial misreporting" and "misreporting" interchangeably throughout the paper.

[2] We are not aware of any study that uses accounting measures to predict recessions in real time, although earnings management has been studied in relation to the business cycle. In particular, Cohen and Zarowin (2007) use relative performance evaluation to argue that upwards earnings management is more likely in periods of expansion, and Davidson (2016) documents that it is useful to distinguish misreporting related to the income statement from that related to the balance sheet, as misreporting on these financial statements depends on the business cycle.

financial misreporting has adverse capital market consequences (e.g., Feroz, Park, and Pastena 1991; Beneish 1999b; Hennes, Leone, and Miller 2008; Karpoff, Lee, and Martin 2008), we break new ground by examining the link between *ex ante* misreporting and recession prediction. Third, there is a growing body of research studying the usefulness of aggregate earnings measures to predict market returns and economic aggregates (see Ball and Sadka (2015) for a review). For example, Konchitchki and Patatoukas (2014a, 2014b) use in-sample models and find that aggregate earnings changes predict one-quarter-ahead Gross Domestic Product (GDP) growth. We add to this body of research by examining the incremental predictive power of *ex ante* measures of aggregate misreporting for recessions after controlling for changes in aggregate earnings, and by studying longer-term forecast horizons of up to eight-quarters-ahead.

Our empirical approach has three principal ingredients. First, we follow Estrella and Mishkin (1998), who develop a recession prediction model intended to alleviate problems of overfitting associated with in-sample tests. Estrella and Mishkin (1998) find that a parsimonious model based on the yield spread (*SPREAD*) and returns on the New York Stock Exchange (*NYSE*) index is the best predictor of recessions. In the spirit of their model, we analyze whether an aggregate *ex ante* measure of the likelihood of misreporting incrementally improves recession prediction after controlling for *SPREAD* and *NYSE.* In addition, while adhering to the idea of a parsimonious prediction model, we consider alternative measures of spreads used by professional forecasters (Bauer and Mertens 2018), the near-term forward spread proposed by Engstrom and Sharpe (2019), and additional control variables such as the level of the federal funds rate (Wright 2006), investor sentiment (Baker and Wurgler 2006), and, as discussed above, aggregate earnings growth.

Second, we examine six alternative measures of the likelihood of misreporting. Extant literature provides several candidate measures of misreporting, including M-Score (Beneish 1999a), F-Score (Dechow, Ge, Larson, and Sloan 2011), abnormal accruals (Allen, Larson, and Sloan 2013), the financial statement divergence (FSD) score (Amiram, Bozanic, and Rouen 2015), a comprehensive misreporting prediction model from Alawadhi, Karpoff, Koski, and Martin (2020), and the accounting and governance risk (AGR) ratings from data provider MSCI. We create aggregate versions of each of these measures to conduct our tests. Because assessing the *ex ante* probability of misreporting must be done in real time, we compute each misreporting measure using rolling four-quarter windows, with financial data drawn from the COMPUSTAT Snapshot "As First Reported" Quarterly database. It is not clear *a priori* which of these measures, if any, best predicts recessions. We therefore allow the data to inform us about which *ex ante* misreporting measure predicts recessions incrementally to previously documented determinants of recessions.

Third, our tests use data for 173 quarters from 1976:Q4 to 2019:Q4. Our dependent variable is $RECESSION_{q+k}$, an indicator for a recession quarter, as measured by the National Bureau of Economic Research (NBER). Our in-sample estimations use all available data (i.e., 173 quarters), while our out-of-sample estimations only use data available prior to the start of each recession. Our first out-of-sample recession prediction period is 1981:Q4 and our last is 2020:Q1. We estimate our models for periods ranging from one- to eight-quarters-ahead. Thus, in the case of a one- (eight-) quarter(s)-ahead prediction, our first estimation sample uses data from 1976:Q4 to 1981:Q3 (1979:Q4) and our last estimation sample uses data from 1976:Q4 to 2019:Q4 (2018:Q1). The theory we rely on does not specify the lag between observing an *ex-ante* likelihood of misreporting and the inception of a recession, so we follow prior research and examine this range of quarters.

Our findings are as follows. First, we find that three of the six measures of aggregate misreporting that we employ are linearly positively related to future recessions. Specifically, aggregate M-Score, aggregate F-Score, and aggregate Alawadhi et al. (2020) misreporting probability are positively correlated with recessions at the three- through eight-quarters-ahead horizons, one- through seven-quarters-ahead horizons, and three- though five-quarters-ahead horizons, respectively (all statistically significant at conventional levels). These correlations are consistent with a higher *ex ante* likelihood of misreporting prior to future recessions.

Second, when we consider a non-linear (i.e., probit) relation, in either univariate or multivariate settings, we find that aggregate M-Score is the only *ex-ante* misreporting measure that has incremental predictive power for recessions.[3] After controlling for *SPREAD* and *NYSE* (Estrella and Mishkin 1998), we find that aggregate M-Score is positively and significantly associated with recessions for forecasting horizons six- to eight-quarters-ahead.[4] For example, for the six-quarters-ahead out-of-sample forecasting model constructed to mimic real-time forecasting, we find that relative to models with just *SPREAD* and *NYSE*, models that include aggregate M-Score along with *SPREAD* and *NYSE* improve the out-of-sample probability of recessions by an average percentage increase of 56 percent. We document similar improvements in out-of-sample recession forecasts at the seven- and eight-quarters-ahead horizons. Moreover, we report that including M-Score in the six-quarters-ahead prediction model increases the probability of a recession in 15 of the 17 quarters (88.2%) during which the economy is in a recession in our out-of-sample test period.

[3] The (untabulated) out-of-sample results for the other misreporting measures are available from the authors upon request.

[4] This result is robust to alternative definitions of interest rate spreads (e.g., Bauer and Mertens (2018); Engstrom and Sharpe (2019), controls for the level of the federal funds rate (Wright 2006), investor sentiment (Baker and Wurgler 2006), and aggregate earnings growth (Konchitchki and Patatoukas 2014a, 2014b).

The evidence that M-Score predicts recessions six- to eight-quarters-ahead is consistent with the length of time elapsing from the beginning of the misreporting period for firms charged by the SEC and the revelation of the misreporting, either by the SEC or the news media; Beneish (1999b) reports a mean (median) of 28 months (26.5 months), while Karpoff, Koester, Lee and Martin (2017) report a median of 28.6 months for the period from the beginning of the misreporting to its revelation. In order for M-Score to capture financial misreporting, its variables, particularly those that capture financial statement distortions, need to be measured three to twelve months *after* the misreporting begins. Thus, if M-Score flags misreporting, it does so on average five to eight quarters ahead of the misreporting revelation, consistent with our recession horizon prediction results.

To provide insight as to why M-Score predicts recessions, we decompose M-Score into its distortion and incentive components and show that only the distortion component explains the recession-predictive power of aggregate M-Score. Because the distortion component is intended to capture deliberate misreporting rather than simply the effect of slower growth, these findings are consistent with Povel et al.'s (2007) prediction that financial statement fraud peaks before recessions.

As discussed above, M-Score is the only aggregate misreporting measure with predictive power for recessions. One plausible explanation for this outcome is that M-Score is more closely related to future stock returns than are the other misreporting measures. This suggests more negative future returns associated with M-Score compared to the other misreporting measures. Indeed, we find that M-Score (and its distortion component) exhibits a more pronounced negative association with 12- and 24-month future abnormal stock returns compared to the other misreporting measures. This finding is also consistent with evidence in Beneish and Vorst (2020) that, at the firm-level, M-Score has lower false positive rates.

Our study adds to existing research in two ways. First, we advance the literature on recession prediction by showing that an *ex ante* aggregate misreporting measure, namely M-Score, has incremental predictive power for recessions, even after controlling for known predictors of recessions. We thus answer Amiram et al.'s (2018, p. 774) call for more empirical research that predicts recessions in real-time. Our study also complements prior research on the relation between aggregate accounting measures and macroeconomic indicators (e.g., Konchitchki and Patatoukas (2014a) by showing that aggregate M-Score has predictive power for recessions, an economic outcome related to, but distinct from, GDP growth. Second, we contribute to the literature that examines financial misreporting. This literature focuses primarily on firm-specific measures of financial misreporting (e.g. Beneish 1999a; Dechow, Ge, Larson, and Sloan 2011; Brazel, Jones, and Zimbleman 2009; Amiram, Bozanic, and Rouen 2015). In contrast, we develop an aggregate measure of financial misreporting, which should be useful to researchers, policy makers, and others interested in understanding recession prediction.

The rest of the paper proceeds as follows. Section 2 discusses relevant research and develops the empirical prediction. We provide the research design and sample selection in section 3. We present our main results in section 4. Section 5 contains supplementary analyses, and section 6 summarizes and concludes the study.

2. Empirical Framework

The National Bureau of Economic Research (NBER) defines a recession as, "…a significant decline in economic activity spread across the economy, normally visible in production, employment, and other indicators. A recession begins when the economy reaches a peak of economic activity and ends when the economy reaches its trough. Between trough and peak, the economy is in an expansion" (NBER 2020).

Indicators of recessions typically include drops in the stock market; higher interest rates that limit the availability of funds for investing; higher inflation, which can reduce consumption demand by reducing real wages; and/or a decline in consumer confidence, which can reduce consumption demand. A deep economics literature has studied these indicators, which have recently become a focal point for accounting researchers. We next briefly discuss this literature.

2.1 Determinants of Recessions

The prediction of economic growth has been a central question to economists for at least three-quarters of a century (e.g., Tinbergen, 1939; Klein, 1950; Klein and Goldberger 1955). Over this period, economists have sought to improve prediction models by assessing a wide range of macroeconomic factors (e.g., Harvey 1988; Jorion and Mishkin 1991: Zarnowitz and Braun 1993). More to the point of our study, several studies have focused on improving prediction models for recessions by considering a number of leading indicators and factors from credit markets, monetary policy, inflation, and the stock market (Stock and Watson 1989; Watson 1991; Estrella and Hardouvelis 1991). Although prediction models for recessions have typically considered a large number of macroeconomic factors, Estrella and Mishkin (1998) argue that these complex models are prone to overfitting, particularly over longer forecasting horizons.

Estrella and Mishkin's (1998) proposed solution to this problem is to use parsimonious models with an *out-of-sample* testing approach that identifies individual financial variables associated with recessions. Estrella and Mishkin (1998) test these variables against multi-factor models (e.g., Stock and Watson 1993) over two- to eight-quarter forecasting horizons. Examining the predictive power of several candidate factors, they show that a combination of the slope of the yield curve (i.e., Spread) and the NYSE index provide the best fit over a four-quarter forecasting horizon. Estrella and Mishkin (1998) also show that while their approach is superior to more complex prediction models, it does not obviate the need for complex models. Rather, these authors argue that individual financial variables should be used in conjunction with multi-factor models to improve the overall forecast for a recession. We propose that a previously unexamined financial variable, namely the *ex ante* likelihood of misreporting, has the potential to enhance the predictive power of recession models. We next discuss research on the link between accounting measures and macroeconomic activity, followed by the development of our empirical prediction.

2.2 Aggregate Accounting Earnings and Economic Activity

Studies have investigated the relation between measures of economic activity and measures of aggregate earnings (i.e., earnings level, change in earnings, earnings growth, and accruals). Konchitchki and Patatoukas (2014a) show that aggregate accounting earnings growth incrementally explains one-quarter-ahead growth in nominal GDP. Konchitchki and Patatoukas (2014b) use a DuPont decomposition of return on assets to show that changes in operating margin (i.e., earnings before depreciation) for the largest 100 U.S.-listed firms predict one-quarter-ahead GDP growth. Kothari, Lewellen, and Warner (2006) show that aggregate earnings changes are negatively related to contemporaneous stock market returns, while Kang, Liu, and Qi (2010) predict market returns with unexpected accruals. Shivakumar (2007) shows that aggregate earnings changes are positively associated with future CPI changes, while Cready and Gurun (2010) find that aggregate earnings news is positively associated with CPI changes reflected in Treasury-Inflation-Protected Securities. Consistent with the link between aggregate earnings growth and future inflation being driven by firms changing their investments in response to earnings growth, Shivakumar and Urcan (2017) find that changes in profitability predict future investment and shifts in the Producer Price Index. Finally, Gallo, Hahn and Li (2017) show that aggregate earnings predict one-quarter-ahead federal funds rate changes. While these studies have provided important insights into the predictive role of attributes of aggregate accounting earnings, none examines aggregate misreporting or recession prediction. We attempt to fill this gap with our study.

2.3 Measures of Financial Misreporting

Considerable research in accounting examines the likelihood of financial misreporting. This research examines financial variables (Beneish 1999a; Dechow et al. 2011; Allen, Larson, and Sloan 2013; Alawadhi, Karpoff, Koski, and Martin 2019), nonfinancial variables (Brazel, Jones and Zimbleman 2009; Dechow et al. 2011), deviations from Benford's (1938) law (Amiram et al. 2015), combined variables formed from previous studies (Alawadhi et al. 2020), and variables obtained from machine-learning approaches (Cecchini, Aytug, Koehler, and Pathak 2010; Bao, Ke, Li, Yu, and Zhang 2020).

In general, financial misreporting measures are better than random assignment in identifying earnings manipulators, but they generate high false positive rates. Beneish and Vorst (2020) study a host of financial misreporting measures, and conclude that "for investors, M-Score and, in some cases, the F-Score are the only models" that provide benefits that exceed the costs from false positives. This is important for our purposes, as our goal is to consider an implementable recession prediction model.

2.4 Empirical Prediction

There are very few studies that assess the relation between misreporting and recessions. In a theory paper, Povel et al. (2007) use the anecdotal observation that accounting scandals are commonly revealed after an economic boom period ends to predict that financial misreporting peaks at the height of an economic boom. The intuition for this theoretical prediction is that there is less monitoring when the economy is doing well, such as during an economic up-cycle or boom. Povel et al. (2007) argue that investors reduce their monitoring of firms that report positive results when they perceive that many firms are doing well, and instead focus their monitoring on firms that report negative information. This shift in monitoring focus increases firms' misreporting because a firm that is not performing well has a strong incentive to engage in misreporting to avoid increased monitoring.

Likewise, empirical research shows that firms have increased incentives to misreport during economic expansions. Jensen (2005) argues that overvalued equity creates incentives for management to take actions, including misreporting, to avoid falling short of capital market expectations. Efendi et al. (2005) provide evidence consistent with Jensen's argument in the context of in-the-money CEO stock options. Their evidence is also consistent with Povel et al.'s theory that misreporting builds up before economic busts. Using a sample of restatement announcements over January 1, 2001 through June 30, 2002, Efendi et al. (2005) show that firms with more overvalued equity in the prior year were more likely to restate earnings. This is consistent with a build-up of distorted good news over the period from 2000 to mid-2001, preceding the U.S. recession from March 2001 to November 2001. Similarly, periods of high investor sentiment, or "beliefs in future cash flows or investment risks not justified by the facts at hand" (Baker and Wurgler 2007), are also related to inflated earnings and income-increasing earnings management to avoid negative earnings surprises (Simpson 2013).

Given the above, we predict that aggregate financial misreporting will peak before a recession. Whether *ex ante* aggregate misreporting incrementally improves recession prediction models is an open empirical question tested in this paper.

3. Research Design and Sample Selection

3.1 Dependent and Independent Variables

Our tests require a measure of quarters in which the economy is in recession and a quarterly aggregate measure of the likelihood of financial misreporting. Our main dependent variable is $RECESSION_{q+k}$, which equals one for calendar quarters in a U.S. economic recession, as defined by the NBER (i.e., starting with the first quarter after a business cycle peak and continuing through the trough quarter), zero otherwise.[5]

Our key independent variable is an aggregate measure of the quarterly versions of six firm-level misreporting measures previously identified in the literature: (i) *MSCORE* equals the quarterly version of M-Score from Beneish (1999a), (ii) *FSCORE* equals the quarterly version of F-Score from Dechow, Ge, Larson, and Sloan (2011), (iii) *AKKM* equals the quarterly version of the comprehensive fraud probability from Alawadhi, Karpoff, Koski, and Martin (2020), (iv) *FSDSCORE* equals the quarterly version of the financial statement divergence score from Amiram, Bozanic, and Rouen (2015), (v) *absABNACC* equals the absolute value of the quarterly version of abnormal accruals from Allen, Larson, and Sloan (2013), and (vi) *AGR* equals the accounting and governance risk score from MSCI. We next provide some background on each of these measures.

Beneish's (1999) M-Score is one of the earliest measures of the likelihood of financial statement manipulation. To operationalize M-Score, we use the weights (coefficient estimates from a probit regression model) from Beneish (1999a) to estimate the manipulation score for each firm-quarter as:

$$\begin{aligned} MSCORE_{i,q} = \; & -4.84 + .920*DSR_{i,q} + .528*GMI_{i,q} + .404*AQI_{i,q} + .892*SGI_{i,q} \\ & + .115*DEPI_{i,q} - .172*SGAI_{i,q} + 4.679*ACCRUALS_{i,q} - .327*LEV_{i,q} \end{aligned} \tag{1}$$

[5] Panel A of Appendix A provides detailed variable definitions.

Because the dependent variable in Beneish (1999a) is a binary variable equal to one if the firm-*year* has manipulated earnings, zero otherwise, and our interest is in *quarterly* recession prediction, we first annualize any index variables contained in M-Score by summing them over the previous four quarters.[6]

$FSCORE_{i,q}$ (Dechow, Ge, Larson, and Sloan 2011) is an index based on a comprehensive database of SEC AAERs over the period 1982-2005. To form $FSCORE_{i,q}$, Dechow et al. (2011) combine accrual quality, financial performance, nonfinancial measures, off-balance sheet activities, and market-based measures for identifying misstatements. We measure $FSCORE_{i,q}$ as the firm-quarter misreporting probability based on the fitted values from Model 3 in Table 7 of Dechow et al. (2011).

$AKKM_{i,q}$ (Alawadhi, Karpoff, Koski, and Martin 2020) equals the probability of fraud from a prediction model based on multiple firm characteristics. $AKKM_{i,q}$ uses all SEC and Department of Justice enforcement actions for misreporting from 1978-2017 and applies the Receiver Operating Characteristics methodology, which assesses the model's ability to accurately identify firms that are caught by regulators for financial misconduct and to avoid false positives. We measure $AKKM_{i,q}$ as the firm-quarter misreporting probability based on the fitted values from the comprehensive misreporting prediction model in Table 6 of Alawadhi et al. (2020).

[6] Panel B of Appendix A provides further computational details. With the exception of $ACCRUALS_{i,q}$, the independent variables in the Beneish (1999a) model are index variables (i.e. ratios of the annualized current quarter amount compared to the annualized amount in the previous quarter). These index variables include: $DSR_{i,q}$ (captures distortions in receivables that can result from revenue inflation); $GMI_{i,q}$ (captures declining gross margins that can lead companies to manipulate earnings); $AQI_{i,q}$ (captures inconsistencies in noncurrent assets other than property, plant, and equipment that can result from unwarranted expenditure capitalization); $SGI_{i,q}$ (captures the incentive to manage growth perceptions which can lead companies to manipulate sales and earnings); $DPI_{i,q}$ (captures decreasing depreciation rates as a method of earnings manipulation); $SGAI_{i,q}$ (captures administrative and marketing inefficiency resulting from larger fixed SG&A expenses which can lead companies to manipulate earnings); $ACCRUALS_{i,q}$ (captures accrual-based earnings not supported by cash flows); and $LEVI_{i,q}$ (captures increasing leverage which can constrain debt and lead companies to manipulate earnings).

Amiram et al. (2015) uses Benford's (1938) Law to form the Financial Statement Divergence Score (*$FSDSCORE_{i,q}$*). Benford's Law states that the first digits of all numbers in an empirical dataset will appear with decreasing frequency (e.g., the number one will appear more frequently than the number two and so on such that the number nine is the least likely first digit). Amiram et al. (2015) show that $FSDSCORE_{i,q}$ can reliably measure material misstatements. $FSDSCORE_{i,q}$ is the quarterly version of the measure developed by Amiram et al. (2015).

Our next misreporting measure, $absABNACC_{i,q}$, is the aggregate level of absolute abnormal accruals (Allen, Larson, and Sloan 2013). We calculate each firm-quarter's abnormal accruals based on the Allen, Larson, and Sloan (2013) accrual model, estimated by calendar quarter with fixed effects included for fiscal quarter. For each calendar quarter, we aggregate firm-quarter values of absolute abnormal accruals using a value-weighted average, with weights based on market capitalization as of the beginning of the quarter.

Our final misreporting measure is the Accounting and Governance Risk ($AGR_{i,q}$) rating from data provider MSCI. This measure assesses the likelihood of misreporting based on expense recognition, revenue recognition, high-risk events, governance, and asset and liability valuation.[7] $AGR_{i,q}$ equals the firm-quarter *AGR* rating.

We next aggregate firm-quarter values of $MSCORE_{i,q}$, $FSCORE_{i,q}$, $AKKM_{i,q}$, $FSDSCORE_{i,q}$, $absABNACC_{i,q}$, and $AGR_{i,q}$ for each calendar-quarter. We delete firm-quarters with missing data for any of these measures. As we define the time horizon for the recession forecast relative to firms' fiscal quarter-end dates, we exclude firm-quarters without March, June, September, or December fiscal year-ends so that fiscal quarters align with calendar quarters. We also exclude firm-quarters not releasing the quarterly earnings announcement by the end of the

[7] Price, Sharp, and Wood (2011) show that AGR ratings are useful in predicting financial misstatements and irregularities.

first month after quarter-end to ensure real-time data availability. In addition, we exclude firm-quarters not incorporated in the U.S. and firm-quarters with market value of equity less than $75 million to ensure that each sample firm has a similar regulatory environment and filing status. We exclude firms in the financial services (SIC codes 6000-6999) or utilities industries (SIC codes 4900-4999), as these regulated firms have unique financial reporting characteristics. To mitigate the effects of outliers for each misreporting measure, we delete observations that fall in the top or bottom percentile of each firm-quarter cross-section.

For each calendar quarter, we aggregate these firm-quarter measures by computing a value-weighted average (i.e., $VWAGG\_MSCORE_q$, $VWAGG\_FSCORE_q$, $VWAGG\_AKKM_q$, $VWAGG\_FSDSCORE_q$, $VWAGG\_absABNACC_q$, and $VWAGG\_AGR_q$), where the weights are firm-quarter market capitalization at the beginning of the quarter. Value-weighting allows us to consider the relative economic importance of each firm. We then construct a moving average of the value-weighted aggregate measures from quarter *q-3* through quarter *q* (i.e., $AVG\_VWAGG\_MSCORE_q$, $AVG\_VWAGG\_FSCORE_q$, $AVG\_VWAGG\_AKKM_q$, $AVG\_VWAGG\_FSDSCORE_q$, $AVG\_VWAGG\_absABNACC_q$, and $AVG\_VWAGG\_AGR_q$) to arrive at the measures that we employ in our tests. Our misreporting measures are constructed such that higher values of each misreporting measure suggest a higher likelihood of misreporting.

3.2 Models for Predicting Recessions

We first assess whether any of the candidate measures of misreporting has univariate predictive power for recessions. To do so, we estimate the following probit model with Newey-West (1987) heteroskedasticity- and autocorrelation-consistent standard errors using four lags (Appendix A provides all variable definitions):

$$RECESSION_{q+k} = \beta_0 + \beta_1 AVG\_VWAGG\_Misreporting_q + \varepsilon_t \quad \textbf{(2)}$$

Our independent variable of interest is $AVG\_VWAGG\_Misreporting_q$, which alternatively equals $AVG\_VWAGG\_MSCORE_q$, $AVG\_VWAGG\_FSCORE_q$, $AVG\_VWAGG\_AKKM_q$, $AVG\_VWAGG\_FSDSCORE_q$, $AVG\_VWAGG\_absABNACC_q$, or $AVG\_VWAGG\_AGR_q$. As we predict that aggregate financial misreporting peaks before economic busts (i.e., recessionary periods), we predict β_1 to be significantly positive. We estimate Equation (2) using recession forecast horizons from one- to eight-quarters-ahead.

We follow the method in Estrella and Mishkin (1998) and next assess whether, individually, any of the misreporting measures has *incremental* in-sample power for predicting recessions. We estimate the following model to do so:

$$RECESSION_{q+k} = \beta_0 + \beta_1 AVG\_VWAGG\_Misreporting_q + \beta_2 SPREAD_q + \beta_3 NYSE_q + \varepsilon_t, \quad \textbf{(3)}$$

where $AVG\_VWAGG\_Misreporting_q$ is as defined above. *SPREAD* and *NYSE* are motivated by Estrella and Mishkin (1998). After testing a large number of potential predictors, Estrella and Mishkin (1998) conclude that a recession prediction model containing the yield curve spread and stock market prices "is about the best that can be constructed from financial variables for out-of-sample prediction." As such, Equation (3) controls for $SPREAD_q$ and $NYSE_q$. $SPREAD_q$ equals the 10-year constant maturity Treasury bond rate less the secondary market 3-month bond-equivalent Treasury bill rate, measured on a monthly basis and averaged over the three months during calendar quarter *q*. *NYSE* equals the growth rate of the New York Stock Exchange composite index during calendar quarter *q*.

We first estimate Equations (2) and (3) in-sample. As it is not clear which of the misreporting measures will have predictive power for recessions, we then use results from the in-sample tests to determine which of the misreporting measures to use in the out-of-sample tests. To conduct the out-of-sample tests, we follow Estrella and Mishkin (1998) and estimate a given model from the beginning of the sample period up to a particular quarter. We illustrate this method using a six-quarters-ahead horizon. We first estimate Equations (2) and (3) over the time prior to a recession. For example, for the recession beginning in 2001:Q2, we estimate Equation (3) from 1976:Q4 to 1999:Q4. We then use the resulting coefficient estimates to form a forecast for six-quarters-ahead (e.g., 2001:Q2). After adding one more quarter to the estimation period (e.g., 1976:Q4 to 2000:Q1), we re-estimate the models and form a forecast for the subsequent six-quarters-ahead (e.g., 2001:Q3). This procedure mimics what a statistical model or forecaster could have predicted with the information available at any point in the past. Data that become available after the quarter for which the prediction is made are not used to estimate or predict recessions for that prediction quarter.

3.3 Sample Selection

The sample includes 173 quarters from 1976:Q4 to 2019:Q4. We obtain the underlying firm-quarter financial statement data from the Compustat Snapshot "As First Reported" Quarterly database. While quarterly financial statement reporting is mandated in the United States after 1970, Compustat quarterly data required for calculating the financial misreporting measures is sparsely populated until the mid-1970s. This results in our sample period beginning in 1976:Q4. The sample period ends in 2019:Q4.[8] The sample for *AVG_VWAGG_FSCORE* and *AVG_VWAGG_AKKM* is reduced to 135 quarters from 1984:Q2 to 2019:Q4 due to these measures' reliance on statement of cash flow data to calculate equity and debt issuances. Due to

[8] NBER defined 2019:Q4 as a peak quarter, implying that a recession began in 2020:Q1. At the time of this writing, it is unclear when this recession will end, so we do not extend our $RECESSION_{q+k}$ definition past 2020:Q1. As a result, the sample period in the k=1, …, k=8 specification ends in 2019:Q4, …, 2018:Q1, respectively. We also note that the sample period 1976:Q4-2019:Q4 is defined in terms of quarter *q*, but we include 2020:Q1 in our definition of $RECESSION_{q+k}$.

restrictions on proprietary AGR data, the sample for *AVG_VWAGG_AGR* is reduced to 89 quarters, from 1996:Q2 to 2018:Q2.

4. Empirical Results

4.1 Descriptive Statistics

Table 1 reports descriptive statistics for the variables in Equation (2). Beneish's (1999) M-Score can be translated into an *ex ante* estimated probability of manipulation as the associated one-tailed probability of a *z*-score from a normal distribution. For example, at the firm-level, an M-Score value of -1.96 (-2.33) can be interpreted as an estimated probability of financial misreporting of 2.5 (1.0) percent. Higher (closer to zero) values of M-Score indicate a higher likelihood of manipulation. In our sample, the mean $AVG\_VWAGG\_MSCORE_q$ equals -2.862, which translates to an aggregate quarterly probability of misreporting of about 0.2 percent. The means for $AVG\_VWAGG\_FSCORE_q$ and $AVG\_VWAGG\_AKKM_q$ indicate that the aggregate quarterly probability of misreporting averages 0.3 percent and 4.6 percent, respectively. Table 1 also reports that the mean for aggregate quarterly FSD score, aggregate quarterly absolute abnormal accruals, and aggregate quarterly AGR score equals 0.037, 1.1 percent of assets, and 0.187, respectively. The means for our main control variables of *Spread* and *NYSE* are 1.593 percent and 2.1 percent, respectively.

[Insert Table 1 here]

For our dependent variable, $RECESSION_{q+k}$, Table 1 reports descriptive statistics for all eight forecast horizons. Table 1 reports that when looking six-quarters-ahead, the U.S. economy is in recession 11.3 percent of the time.

Table 2 reports Pearson (below diagonal) and Spearman (above diagonal) correlation coefficients of the variables used in our analyses. Three of the six measures of *ex-ante* aggregate misreporting that we employ are positively correlated with future recessions at various horizons. Current quarter $AVG\_VWAGG\_MSCORE_q$ is significantly positively correlated with recessions occurring three- to eight-quarters-ahead, but not with recessions one- and two-quarters-ahead; the strongest Pearson correlations range from 0.308 to 0.377 for five- to eight-quarters-ahead recessions (all p-values <0.001). Current quarter $AVG\_VWAGG\_FSCORE_q$ is significantly positively correlated with recessions occurring one- to seven-quarters-ahead, with the strongest Pearson correlations ranging from 0.241 to 0.292 for one- to four-quarters-ahead recessions (all p-values <0.01). Current quarter $AVG\_VWAGG\_AKKM_q$ is positively correlated with recessions occurring three- to five-quarters-ahead, with Pearson correlations of about 0.14 (p-values < 0.10). Current quarter AGR is significantly negatively correlated with recessions one- to eight-quarters-ahead (p-values < 0.10). In contrast to the other misreporting measures, the correlations between AGR and recessions suggest that the likelihood of recession *decreases* as the likelihood of misreporting increases. Both $AVG\_VWAGG\_MSCORE_q$ and $AVG\_VWAGG\_FSCORE_q$ are significantly negatively correlated with contemporaneous $SPREAD_q$ (-0.399 and -0.311 respectively), highlighting their potential to incrementally predict recessions. This is important, as Table 2 also reports that $SPREAD_q$ is inversely correlated with $RECESSION_{q+2}$ to $RECESSION_{q+8}$, with ρ ranging from -0.308 to -0.511 (all p-values <0.0001). On the other hand, our measures of *ex ante* misreporting are not strongly correlated with contemporaneous $NYSE_q$.

[Insert Table 2 here]

Figure 1 reports the time series plots for the aggregate misreporting measures. Recessionary periods are shaded in the plots. Panel A of Figure 1 plots $AVG\_VWAGG\_MSCORE_q$ and shows visually that the *ex ante* likelihood of financial misreporting peaks just before or during each recession and then decreases. The figure also shows some cases when

$AVG\_VWAGG\_MSCORE_q$ peaks, but is not followed by a recession (e.g., 1995:Q4 and 2011:Q2), i.e., false positives. Note, however, that false positives are not uncommon in the literatures on recession prediction and misreporting prediction.

Panel B (Panel C) of Figure 1 plots $AVG\_VWAGG\_FSCORE_q$ ($AVG\_VWAGG\_AKKM_q$). These two measures provide some visual evidence of a peak prior to the three most recent recessions, but not before the other recessionary periods. Of note, $AVG\_VWAGG\_AKKM_q$ exhibits an upward time trend during the sample period. From Panel D of Figure 1, $AVG\_VWAGG\_FSDSCORE_q$ exhibits a downward time trend, with evidence of a slight peak prior to the recessions in the mid-1980s and early 2000s. We report the plots for $AVG\_VWAGG\_absABNACC_q$ and $AVG\_VWAGG\_AGR_q$ (for a shorter sample period) in Panel E and Panel F, respectively. Graphically, $AVG\_VWAGG\_absABNACC_q$ has a pronounced peak just before the recession in the early 2000s, while $AVG\_VWAGG\_AGR_q$ peaks late for the recessions in the early 2000s and the great recession of 2008-2009, but otherwise shows no clear pattern with respect to recessions.

[Insert Figure 1 here]

Figure 2 presents time series plots of our control variables, $SPREAD_q$ and $NYSE_q$. Panel A of Figure 2 shows that $SPREAD_q$ troughs just before each recession. This is especially the case when the trough occurs with a negative value.[9] This graphical evidence confirms the long-standing evidence that the yield curve and its inversion are strong predictors of recessions (Harvey 1988; Estrella and Mishkin 1996; 1998). That is, when high demand for a low-risk investment with a long maturity (10-year Treasury) causes its yield to decrease relative to its short maturity counterpart (3-month Treasury), a recession is looming. Panel B of Figure 2 provides some

[9] We measure Spread using quarterly averages, which obscures the fact that Spread is negative at some point prior to each recession during our sample period.

evidence that stock market returns ($NYSE_q$) are lower in the lead-up to a recession, though this pattern is difficult to ascertain visually given the volatility of $NYSE_q$.

[Insert Figure 2 here]

4.2 In-Sample Results

Following Estrella and Mishkin (1998), we first estimate in-sample recession prediction models. We do so for each aggregate misreporting measure by itself (Table 3) and then consider each aggregate misreporting measure after controlling for $SPREAD_q$ and $NYSE_q$. Table 3 reports the results from an in-sample estimation of Equation (2) for each of the aggregate misreporting measures by themselves. For each aggregate misreporting measure, we report recession forecasts one-quarter-ahead through eight-quarters-ahead. For each model, we report coefficient estimates and t-statistics (intercepts are estimated but not tabulated). We also report Estrella (1998) pseudo R^2s.

Table 3 reports that $AVG\_VWAGG\_MSCORE_q$ is the only aggregate misreporting measure with significant predictive power for future recessions. Specifically, Table 3 reports a positive and statistically significant coefficient on $AVG\_VWAGG\_MSCORE_q$ for each of the $q+4$ through $q+8$ forecast horizons, consistent with the aggregate level of the likelihood of financial misreporting having in-sample predictive value for recessions four- to eight-quarters-ahead. We report a statistically insignificant coefficient on $AVG\_VWAGG\_MSCORE_q$ for the $q+1$ through $q+3$ forecasting horizons, suggesting no in-sample predictive power for recessions one- to three-quarters-ahead. Because we find that $AVG\_VWAGG\_MSCORE_q$ is the only aggregate misreporting measure with predictive power for recessions, we restrict subsequent tabulated recession prediction analyses to this measure.

[Insert Table 3 here]

We next replicate Estrella and Mishkin's (1998) model to provide a baseline prediction model. We then add $AVG\_VWAGG\_MSCORE_q$ to this baseline model to assess whether $AVG\_VWAGG\_MSCORE_q$ has incremental predictive power for recessions or whether it is subsumed by $SPREAD_q$ and $NYSE_q$, the two variables shown by Estrella and Mishkin (1998) to have the best predictive power for recessions. We report results of these tests in Table 4.

Panel A of Table 4 reports a significantly negative coefficient on $SPREAD_q$ for forecast horizons one- to eight-quarters-ahead. The coefficient on $NYSE_q$ is significantly negative for forecast horizons one- to three-quarters-ahead, but marginally *positive* for forecast horizons six- and eight-quarters-ahead. Thus, stock market returns are lower (higher) one to three (six and eight) quarters prior to recessions. These tests reveal that both $SPREAD_q$ and $NYSE_q$ have forecasting power for recessions, but $NYSE_q$ is a less powerful predictor of recessions than $SPREAD_q$ at longer forecasting horizons. Additionally, while these results are generally consistent with those reported in Estrella and Mishkin (1998), note that the highest R^2s occur at the k=5 and k=6 forecasting horizons, while Estrella and Mishkin (1998) report stronger explanatory power at the k=4 forecasting horizon; this difference is likely due to the longer time series in our study.

[Insert Table 4 here]

The models reported in Panel B of Table 4 include $AVG\_VWAGG\_MSCORE_q$, $SPREAD_q$, and $NYSE_q$.[10] Relative to results in Table 3, controlling for $SPREAD_q$ and $NYSE_q$ causes $AVG\_VWAGG\_MSCORE_q$ to lose statistical significance at forecasting horizons of four- to five-quarters-ahead. However, $AVG\_VWAGG\_MSCORE_q$ retains significant predictive power six-

[10] As we highlighted above, we only tabulate results for $AVG\_VWAGG\_MSCORE_q$ since it is the only misreporting measure with stand-alone predictive power. When we include $SPREAD_q$ and $NYSE_q$ with each of the other misreporting measures, we again find that none of the other misreporting measures has predictive power for recessions; these untabulated results are available from the authors upon request.

quarters-ahead (coeff. est. =10.429; t-stat=2.86), seven-quarters-ahead (coeff. est. =12.071; t-stat=3.01), and eight-quarters-ahead (coeff. est. =11.417; t-stat=2.81).

Across the six- to eight-quarters-ahead forecasting horizons, the pseudo R^2 increases from Panel A (model with only $SPREAD_q$ and $NYSE_q$) to Panel B (model with $AVG\_VWAGG\_MSCORE_q$, $SPREAD_q$, and $NYSE_q$) by 7.48 percentage points, 10.17 percentage points, and 9.87 percentage points, respectively. These percentage point increases imply increases in explanatory power ranging from about 27.4 percent to about 51.9 percent.

4.2 Sensitivity Analyses for In-Sample Results

4.2.1 Controlling for Investor Sentiment

Table 5 reports the results from re-estimating the models in Table 4 after controlling for investor sentiment. This analysis is motivated by the idea that investor sentiment may peak prior to a recession and therefore be correlated with aggregate M-Score. We measure investor sentiment, $SENT_q$, as the sentiment index created by Baker and Wurgler (2006; 2007). Panel A of Table 5 reports the model with $AVG\_VWAGG\_MSCORE_q$ and $SENT_q$. Panel B reports the model with $AVG\_VWAGG\_MSCORE_q$, $SPREAD_q$, $NYSE_q$, and $SENT_q$. In both panels of Table 5, we continue to find a significantly positive coefficient on $AVG\_VWAGG\_MSCORE_q$ at the six- to eight-quarters-ahead forecast horizons, suggesting that investor sentiment does not alter our inferences for the predictive power of aggregate misreporting for recessions.

[Insert Table 5 here]

4.2.2 Controlling for Aggregate Earnings Growth

Our next supplementary analysis re-estimates the models in Table 4 after controlling for $VWAGG\_\Delta EARN_q$, the main variable of interest in Konchitchki and Patatoukas (2014a), and

$NGDP1_q$.[11] $VWAGG\_\Delta EARN_q$ equals aggregate earnings growth for quarter q. $NGDP1_q$ is the first estimate of nominal GDP growth for quarter q (released approximately one month after the end of calendar quarter q) obtained from the Real-Time Data Set for Macroeconomists provided by the Federal Reserve Bank of Philadelphia. We report results in Table 6, where we show that the coefficient on $VWAGG\_\Delta EARN_q$ is negative and highly significant in the one- and three-quarter-ahead forecasts, and negative and marginally significant in the two-quarter-ahead forecast, suggesting that the probability of recession decreases with aggregate earnings. In contrast, we show a positive and significant coefficient on $VWAGG\_\Delta EARN_q$ in the eight-quarter-ahead forecast, suggesting that the probability of recession increases with aggregate earnings. Overall, the results suggest a mixed story for aggregate earnings to predict recessions. Importantly, however, we continue to show a positive and significant coefficient on $AVG\_VWAGG\_MSCORE_q$ for the six- through eight-quarters-ahead forecasts.[12]

[Insert Table 6 here]

4.2.3 Controlling for Alternative Interest Rate Measures

Estrella and Mishkin (1998) use the difference between 3-month U.S. Treasury-bill rates and 10-year U.S. Treasury-bond rates (also referred to as "Spread") to measure the slope of the yield curve. While we adopt the same measure in our main tests, we also consider alternative measures of interest rates that have been examined in prior work, such as including the level of the

[11] Konchitchki and Patatoukas (2014a) examine future growth in *nominal* GDP, while Konchitchki and Patatoukas (2014b) examine future growth in *real* GDP. In this sensitivity analysis, we follow Konchitchki and Patatoukas (2014a) and control for estimated current quarter nominal GDP. However, our results are not sensitive to controlling for estimated current quarter real GDP (untabulated).

[12] We also re-estimate the models in Table 4 after controlling for $VWAGG\_\Delta ATO_q$, $VWAGG\_\Delta OM_q$, $VWAGG\_\Delta DEP_q$, and $CRSP_q$, which are the main variables used in Konchitchki and Patatoukas (2014b). $VWAGG\_\Delta ATO_q$ equals the aggregate change in asset turnover for quarter q. $VWAGG\_\Delta OM_q$ equals the aggregate change in operating margin for quarter q. $VWAGG\_\Delta DEP_q$ equals the aggregate change in depreciation-to-sales ratio for quarter q. $CRSP$ equals the monthly CRSP index return summed over the 12-month period ending with calendar quarter $q+1$. We alternatively re-estimate this model with either NYSE or CRSP due to collinearity issues between these variables. Results from any of the alternative specifications of this test do not alter inferences for $AVG\_VWAGG\_MSCORE_q$ (untabulated).

federal funds rate, following Wright (2006); redefining $SPREAD_q$ as the difference between the 2-year and the 10-year U.S. Treasury-bond rates, as is commonly used by professional forecasters (e.g., Bauer and Mertens, 2018); and redefining $SPREAD_q$ as the "near-term forward spread" of Engstrom and Sharpe (2019), measured as the difference between the six-quarters-ahead forward rate on U.S. Treasuries and the current three-month Treasury bill rate. In untabulated analyses, we continue to find a positive and significant coefficient ($p<0.01$) on $AVG\_VWAGG\_MSCORE_q$ when predicting recessions six-, seven-, and eight-quarters-ahead.

4.3 Out-of-Sample Results

We now turn to the out-of-sample analyses, which are intended to assess the incremental power of aggregate M-Score to predict recessions. For these analyses, we follow Estrella and Mishkin (1996; 1998) and estimate recession prediction models using data that precede recessions. Following Estrella and Mishkin (1996; 1998), we use recursive estimations of Equations (2) and (3) to obtain out-of-sample recession probabilities and pseudo R^2s. We focus our analysis of out-of-sample performance using the models predicting recession six-, seven-, and eight-quarters-ahead, as these are the forecast horizons in Panel B of Table 4 for which aggregate M-Score has significant in-sample predictive value for future recessions.

Table 7 reports the out-of-sample probabilities (based on recursive estimations of Equation (3)) of recessions six-quarters-ahead (Panel A), seven-quarters-ahead (Panel B), and eight-quarters-ahead (Panel C). The out-of-sample probability labeled "AVG_VWAGG_MSCORE" denotes the forecasts from the model using only $AVG\_VWAGG\_MSCORE_q$ as an explanatory variable. The out-of-sample probability labeled "SPREAD and NYSE" denotes the forecasts from the model using only $SPREAD_q$ and $NYSE_q$ as the explanatory variables. The out-of-sample probability labeled "AVG_VWAGG_MSCORE, SPREAD, and NYSE" denotes the forecasts from the model using $AVG\_VWAGG\_MSCORE_q$, $SPREAD_q$, and $NYSE_q$ as the explanatory variables.[13] While the recursive regressions provide recession probabilities for non-recession periods, Table 7 reports recession probabilities only for recession periods.[14] Note that discrete recession periods in Table 7 are separated by a dotted line. Table 7 also reports the average pseudo R^2 for each model for all sample quarters and for recession quarters.

The results reported in Panel A of Table 7 are consistent with $AVG\_VWAGG\_MSCORE_q$ having incremental out-of-sample predictive ability for recessions six-quarters-ahead. We base this conclusion on the fact that the forecasted probability for recessionary periods is, on average, higher using the model with $AVG\_VWAGG\_MSCORE_q$, $SPREAD_q$, and $NYSE_q$ compared to the model using just $SPREAD_q$ and $NYSE_q$. This improvement occurs for 15 out of the 17 quarters (88.2%) in which the economy is in a recession over our out-of-sample period (1981:Q4 to 2020:Q1). For example, for the recession beginning in 2008:Q1, the six-quarters-ahead recession probability based on the model with just $SPREAD_q$ and $NYSE_q$ is 28.6 percent, while the six-quarter–ahead recession probability based on the model that adds $AVG\_VWAGG\_MSCORE_q$ to $SPREAD_q$, and $NYSE_q$ is 46.9 percent.[15] These results imply that M-Score incrementally increases the six-quarters-ahead recession probability by 63.99 percent for 2008:Q1. In broader economic terms, the six-quarters-ahead recession forecast probability averages 33.8 percent using the model with $SPREAD_q$ and $NYSE_q$. When using the model with $AVG\_VWAGG\_MSCORE_q$, $SPREAD_q$,

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[13] Following Estrella and Mishkin (1996; 1998), our out-of-sample analyses in Table 7 evaluate the quality of recession forecasts, whereas our in-sample analyses in Tables 3 and 4 evaluate regression parameter estimates. In untabulated analyses, we find similar estimation results using the distribution of the calendar quarter coefficients obtained from the recursive estimation of the three models we use to make out-of-sample forecasts for the k+6, k+7, and k+8 forecast horizons.
[14] The first data point we are able to obtain parameter estimates to form forecasts of quarter k+6 (Panel A), k+7 (Panel B), and k+8 (Panel C) across all three models is the 15th quarter (i.e., q=1980:Q2), 10th quarter (i.e., q=1979:Q1), and 13th quarter (i.e., q=1979:Q4) in our sample, respectively. Since the forecasts are for the contemporaneous quarter and use data from n quarters earlier, the left side of the time series is trimmed by n observations.
[15] Both probabilities are economically significant relative to a naïve forecast of recession probability of 11.3 percent (based on descriptive statistics in Table 1).

and $NYSE_q$, the six-quarters-ahead recession forecast probability increases to an average of 45.9 percent. Across the 17 recession quarters, there is an overall average increase of 55.55 percent (p=0.006) in the probability of a recession six-quarters-ahead when using the model with $AVG\_VWAGG\_MSCORE_q$, $SPREAD_q$, and $NYSE_q$ compared to the model with $SPREAD_q$ and $NYSE_q$; we find similar results at the k=7 (Panel B) and k=8 (Panel C) forecast horizons, with average percentage increases of 78.56 percent (p<0.001) and 91.71 percent (p=0.001), respectively.[16]

[Insert Table 7 here]

Whereas Table 7 tabulates the recession probabilities only for the recession quarters, Figure 3 plots the time series of the out-of-sample probabilities for recessions across the entire sample period (i.e., both non-recession quarters and recession quarters). For brevity, we focus on the six-quarters-ahead forecasting horizon. Specifically, Figure 3 plots the quarterly time series of recession probabilities using the model with $AVG\_VWAGG\_MSCORE_q$ (Panel A), the model with $SPREAD_q$ and $NYSE_q$ (Panel B), and the model with $AVG\_VWAGG\_MSCORE_q$, $SPREAD_q$, and $NYSE_q$ (Panel C).

Panels A to C of Figure 3 offer visual evidence that the predicted recession probability spikes during actual recession periods, suggesting that all three prediction models can predict recessions six-quarters-ahead. More importantly, the spikes in recession probability in Panel C tend to be higher and more concentrated during actual recession periods than the spikes in recession probability in Panel B, suggesting that adding $AVG\_VWAGG\_MSCORE_q$ to the model with $SPREAD_q$, and $NYSE_q$ (i.e., Panel C) improves recession prediction at the six-quarters-ahead

[16] In untabulated results, we find no incremental change in recession probability due to M-Score for the four-quarters-ahead forecasting horizon and an increase of 48.53 percent in recession probability due to M-Score for the five-quarters-ahead forecasting horizon.

forecasting horizon. Collectively, the results reported in Table 7 and Figure 3 suggest that an *ex ante* measure of the aggregate likelihood of financial misreporting based on M-Score improves out-of-sample recession probabilities when forecasting recessions six- to eight-quarters-ahead.

[Insert Figure 3 here]

5. Supplementary Analyses

This section reports supplementary analyses of the predictive power of the distortion and incentive components of aggregate M-Score, as well as of future stock returns associated with each misreporting measure.

5.1 Distortion and Incentive Components of M-Score

M-Score captures both actual financial statement misreporting ("distortion") and the incentives (e.g., capital market; financing) to engage in misreporting. Povel et al. (2007) suggest that actual financial statement misreporting peaks before recession, implying that the distortion component of M-Score should explain its predictive power for predicting recessions. We decompose $AVG\_VWAGG\_MSCORE_q$ into $AVG\_VWAGG\_DISTORT_q$ and $AVG\_VWAGG\_INCENT_q$.[17] We measure $AVG\_VWAGG\_DISTORT_q$ as the moving average of $VWAGG\_DISTORT_q$ for the four calendar quarters from $q\text{-}3$ to q. $VWAGG\_DISTORT_q$ equals the aggregate distortion component of M-Score (Beneish 1999a) for calendar-quarter q ($DISTORT_q$). The firm-quarter variable, $DISTORT_{i,q}$, equals the following component of Equation (1):

$$DISTORT_{i,q} = -4.84 + .920*DSR_{i,q} + .404*AQI_{i,q} + .115*DEPI_{i,q} + 4.679*ACCRUALS_{i,q}, \quad \textbf{(4)}$$

[17] The eight variables in M-Score can be categorized into components that capture incentives and distortions. Because the typical manipulator is a growth firm with deteriorating conditions, these firms have incentives to manipulate earnings due to lower profit margins, lower sales growth, increasing costs, and increasing leverage. Earnings distortions stem from aggressive/manipulative accounting practices that result in receivables growing much faster than sales, deteriorating asset quality, large income-inflating accruals, and decreasing depreciation expense.

where the incentive component variables (i.e., $GMI_{i,q}$, $SGI_{i,q}$, $SGAI_{i,q}$, and $LEV_{i,q}$) are reset to zero.

We measure $AVG\_VWAGG\_INCENT_q$ as the moving average of $VWAGG\_INCENT_q$ for the four calendar quarters from q-3 to q. $VWAGG\_INCENT_q$ equals the aggregate incentive component of M-Score (Beneish 1999a) for calendar-quarter q ($INCENT_q$). The firm-quarter variable, $INCENT_{i,q}$, equals the following component of Equation (1):

$$INCENT_{i,q} = -4.84 + .528*GMI_{i,q} + .892*SGI_{i,q} - .172*SGAI_{i,q} - .327*LEV_{i,q}, \qquad \textbf{(5)}$$

where the distortion component variables (i.e., $DSR_{i,q}$, $AQI_{i,q}$, $DEPI_{i,q}$, and $ACCRUALS_{i,q}$) are reset to zero.

Table 8 reports the in-sample regression results forecasting recessions six-quarters-ahead.[18] Each panel in Table 8 reports two models, where the first (second) uses $AVG\_VWAGG\_DISTORT_q$ ($AVG\_VWAGG\_INCENT_q$) as the recession predictor. In Panel A, when $SPREAD_q$, and $NYSE_q$ are excluded, we document a positive and significant coefficient on both $AVG\_VWAGG\_DISTORT_q$ and $AVG\_VWAGG\_INCENT_q$. However, after $SPREAD_q$, and $NYSE_q$ are included as controls in Panel B, only $AVG\_VWAGG\_DISTORT_q$ has a significantly positive coefficient.[19]

[Insert Table 8 here]

Table 9 reports out-of-sample results for $AVG\_VWAGG\_DISTORT_q$ and $AVG\_VWAGG\_INCENT_q$ in Panel A and Panel B, respectively. The results reported in Panel A

[18] For brevity, our in-sample and out-of-sample analyses of the distortion and incentive components of M-Score use the model predicting recession six-quarters-ahead, as the in-sample model for this forecast horizon has the highest pseudo R^2 in Panel B of Table 4. In untabulated tests, we conduct the in-sample and out-of-sample analyses of the distortion and incentive components of M-Score using the seven- and eight-quarters-ahead models, leaving inferences unchanged.

[19] In untabulated analyses, we find that $SPREAD_q$ exhibits a negative and significant correlation with $AVG\_VWAGG\_DISTORT_q$ (ρ=-0.315; p<0.0001) and $AVG\_VWAGG\_INCENT_q$ (ρ=-0.478; p<0.0001). We also find that neither $AVG\_VWAGG\_DISTORT_q$ nor $AVG\_VWAGG\_INCENT_q$ are significantly correlated with $NYSE_q$. The greater negative correlation between $SPREAD_q$ and $AVG\_VWAGG\_INCENT_q$ (compared to the negative correlation between $SPREAD_q$ and $AVG\_VWAGG\_DISTORT_q$) is consistent with the positive and significant coefficient $AVG\_VWAGG\_INCENT_q$ being subsumed once $SPREAD_q$, and $NYSE_q$ are included as controls.

(Panel B) are consistent with the *ex ante* aggregate level of financial misreporting distortions (financial misreporting incentives) having considerable (slight) incremental out-of-sample predictive value for recessions six-quarters-ahead. To illustrate, the six-quarters-ahead recession forecast averages 33.8 percent using the model with $SPREAD_q$ and $NYSE_q$. After adding $AVG\_VWAGG\_DISTORT_q$ ($AVG\_VWAGG\_INCENT_q$) as a predictor in Panel A (Panel B), the six-quarters-ahead recession forecast probability increases to an average of 46.3 percent (35.6) during recessions. Across the 17 recession quarters, the mean percent increase in the six-quarters-ahead recession forecast probability after adding $AVG\_VWAGG\_DISTORT_q$ ($AVG\_VWAGG\_INCENT_q$) as a predictor in Panel A (Panel B) equals 53.62 percent (p=0.010) (26.76 percent (p=0.233)). Collectively, the in-sample results reported in Table 8 and the out-of-sample results reported in Table 9 suggest that actual financial statement distortion, and not the incentives to distort, drives the predictive power of $AVG\_VWAGG\_MSCORE_q$ with respect to recessions. This result aligns with the theory in Povel et al. (2007).

[Insert Table 9 here]

5.4 The Association between Firm-quarter Misreporting Measures and Future Stock Returns

Our final supplementary analysis explores whether the lack of predictive power for aggregate misreporting measures other than M-Score with respect to future recessions can be partially explained by the association (or lack thereof) between our misreporting measures (measured at the firm-quarter level) and future stock returns. Prior research finds that declines in stock market indices serve as precursors to economic recessions (Estrella and Mishkin 1996; 1998). In addition, firms with elevated levels of misreporting have been shown to exhibit lower future returns, though the extant empirical evidence documenting a significant negative association between firm misreporting and future returns has, except for M-Score, been limited (Beneish 1997;

Beneish, Lee, Nichols 2013). As a result, we posit that one plausible reason the other aggregate misreporting measures do not predict future recessions is that these other measures exhibit a less pronounced negative association (or lack a negative association) with future stock returns.

For this analysis, we estimate cross-sectional regressions of future abnormal stock returns on each current firm-quarter misreporting measure (*Misreporting Measure*) and a set of control variables using a sample of firm-quarters with available data. *Misreporting Measure* equals the quarterly decile ranking of the firm-quarter value for $MSCORE_{i,q}$, $FSCORE_{i,q}$, $AKKM_{i,q}$, $FSDSCORE_{i,q}$, $absABNACC_{i,q}$, $AGR_{i,q}$, $DISTORT_{i,q}$, or $INCENT_{i,q}$. For each of these measures, we use the same firm-quarter values used to construct the aggregate misreporting measures from Table 3.[20] Table 10 reports the results from this analysis. The dependent variable in Panel A (Panel B) is the future 12-month (24-month) abnormal buy-and-hold return, where the return accumulation period begins 1 month after quarter *q* and ends 12 months after quarter *q* (24 months after quarter *q*). In each panel of Table 10, we report results of six seemingly unrelated estimations to test the equality of the *Misreporting Measure* coefficients across models.

Specifically, we conduct the following six comparisons: $MSCORE_{i,q}$ (Model (1a)) and $FSCORE_{i,q}$ (Model (1b)), $MSCORE_{i,q}$ (Model (2a)) and $AKKM_{i,q}$ (Model (2b)), $MSCORE_{i,q}$ (Model (3a)) and $FSDSCORE_{i,q}$ (Model (3b)), $MSCORE_{i,q}$ (Model (4a)) and $absABNACC_{i,q}$ (Model (4b)), $MSCORE_{i,q}$ (Model (5a)) and $AGR_{i,q}$ (Model (5b)), and $DISTORT_{i,q}$ (Model (6a)) and $INCENT_{i,q}$ (Model (6b)). For each comparison, we report the p-value from testing the equality of the coefficients on *Misreporting Measure*. To facilitate the test of coefficient equality, we require both regressions in each comparison to be estimated using the same sample of firm-quarters.

[20] The results from our future returns analyses are inferentially similar if we define *Misreporting Measure* as the q-3 to q average of the quarterly decile ranking of the firm-quarter value for $MSCORE_{i,q}$, $FSCORE_{i,q}$, $AKKM_{i,q}$, $FSDSCORE_{i,q}$, $absABNACC_{i,q}$, $AGR_{i,q}$, $DISTORT_{i,q}$, or $INCENT_{i,q}$.

Following prior research (e.g., Sloan 1996), we include the following controls: $SIZE_{i,q}$ is the natural log of market value of equity measured at the end of quarter q. $BTM_{i,q}$ is the natural log of book-to-market ratio measured at the end of quarter q. $EP_{i,q}$ is earnings-per-share scaled by stock price measured at the end of quarter q. $BETA_{i,q}$ is CAPM beta for quarter q. We decile-rank all independent variables by calendar quarter. We also control for industry (2-digit SIC level) fixed effects and calendar-quarter fixed effects.

For the first five comparisons in Panel A (Panel B) of Table 10, we find that $MSCORE_{i,q}$ exhibits a significantly negative association with future 12-month (24-month) abnormal stock returns. We also find that $FSCORE_{i,q}$ and $AKKM_{i,q}$ are significantly negatively associated with future 12-month (24-month) abnormal stock returns in Panel A (Panel B). In addition, we find that $AGR_{i,q}$ exhibits a negative and significant association with future 24-month abnormal stock returns in Panel B, but the coefficient on $AGR_{i,q}$ is insignificant for 12-month abnormal stock returns in Panel A. The other measures, $FSDSCORE_{i,q}$ and $absABNACC_{i,q}$ are not associated with lower future abnormal stock returns.

Importantly, both panels in Table 10 report that for the first five comparisons, the negative and significant coefficient on $MSCORE_{i,q}$ is significantly more negative than the coefficients on the other misreporting measures, as indicated by X^2 tests. In the sixth comparison in Panel A (Panel B) of Table 10, we find that the $DISTORT_{i,q}$ component of M-Score exhibits a significantly negative association with future 12-month (24-month) abnormal stock returns, but the coefficient on $INCENT_{i,q}$ is insignificant in both panels. Further, the negative and significant coefficient on $DISTORT_{i,q}$ is significantly different from the coefficient on $INCENT_{i,q}$.

[Insert Table 10 here]

Overall, the results reported in Table 10 show that $MSCORE_{i,q}$ consistently predicts negative future returns, and that the negative association between $MSCORE_{i,q}$ and future returns is more pronounced, both economically and statistically, than the association between the other misreporting measures and future returns. The $DISTORT_{i,q}$ component is the primary driver of the significantly negative association between $MSCORE_{i,q}$ and future returns. These results help explain why aggregate M-Score (and its aggregate distortion component), but not other misreporting measures, improves recession prediction.

6. Summary and Conclusions

Motivated in part by theoretical and empirical research suggesting that the likelihood of misreporting peaks before recessions, as well as by Amiram et al.'s (2018, p. 774) call for more empirical research that predicts recessions in real-time, this study examines whether an *ex ante* measure of aggregate misreporting is useful in predicting recessions. Our tests employ a host of misreporting measures from extant research, including M-Score (Beneish 1999a), F-Score (Dechow, Ge, Larson, and Sloan 2011), abnormal accruals (Allen, Larson, and Sloan 2013), FSD score (Amiram, Bozanic, and Rouen 2015), a comprehensive misreporting prediction model from Alawadhi, Karpoff, Koski, and Martin (AKKM) (2020), and the AGR ratings from MSCI.

We augment Estrella and Mishkin's (1998) model of recession prediction, which includes yield spread and the change in the NYSE index as independent variables, with each of the misreporting measures. Both in-sample and out-of-sample results show that from among the misreporting measures we employ, only M-Score has predictive power for recessions. Importantly, we further show that M-Score provides significant incremental predictive power for recessions, even after controlling for yield spreads and the NYSE index.

In additional tests, we group components of M-Score by actual financial statement distortion and incentives to distort financial statements. Results using these components indicate that only actual distortion explains the significant predictive power of M-Score. In robustness tests, we show that controlling for investor sentiment (Baker and Wurgler 2007) and aggregate earnings (Konchitchki and Patatoukas 2014a; 2014b) does not alter our main inferences. We also show that future returns for M-Score are significantly more negative compared to the other misreporting measures that we employ, providing some support for why M-Score is the only misreporting measure with predictive power for recessions.

Our study extends understanding of the usefulness of accounting information to the prediction of economic recessions, a fundamentally important economic phenomenon. We thus add to a growing stream of research that examines consequences of aggregate accounting information, as well as to macroeconomics research on recession prediction. Results from our study should be useful to forecasters and others interested in understanding factors that enhance recession prediction.

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Appendix A Variable Definitions		
Panel A: Variables Used in Analyses		
AVG_VWAGG_MSCORE	=	moving average of VWAGG_MSCORE for the four calendar quarters from q-3 to q. VWAGG_MSCORE equals the aggregate M-Score (Beneish 1999a) for calendar quarter q. Each firm-quarter's M-Score is calculated based on the fitted values from Beneish (1999a). For income statement inputs, we annualize the inputs by summing over the previous four quarters. For each calendar quarter, we aggregate firm-quarter values of M-Score using a value-weighted average, with weights based on the market capitalization as of the beginning of the quarter.
AVG_VWAGG_FSCORE	=	moving average of VWAGG_FSCORE for the four calendar quarters from q-3 to q. VWAGG_FSCORE equals the aggregate F-score (Dechow, Ge, Larson, and Sloan 2011) for calendar quarter q. Each firm-quarter's F-score is calculated based on the fitted values from Model 3 in Table 7 of Dechow, Ge, Larson, and Sloan (2011). For income statement inputs, we annualize the inputs by summing over the previous four quarters. For inputs available only on an annual basis, we use the most recent annually reported input. For each calendar quarter, we aggregate firm-quarter values of F-score using a value-weighted average, with weights based on the market capitalization as of the beginning of the quarter.
AVG_VWAGG_AKKM	=	moving average of VWAGG_AKKM for the four calendar quarters from q-3 to q. VWAGG_AKKM equals the aggregate comprehensive fraud probability (Alawadhi, Karpoff, Koski, and Martin 2019) for calendar quarter q. Each firm-quarter's fraud probability is calculated based on the fitted values from the comprehensive fraud prediction model in Table 6 of Alawadhi, Karpoff, Koski, and Martin (2019). For income statement inputs, we annualize the inputs by summing over the previous four quarters. For inputs available only on an annual basis, we use the most recent annually reported input. For each calendar quarter, we aggregate firm-quarter values of fraud probability using a value-weighted average, with weights based on the market capitalization as of the beginning of the quarter.

AVG_VWAGG_FSDSCORE	=	moving average of VWAGG_FSDSCORE for the four calendar quarters from q-3 to q. VWAGG_FSDSCORE equals the aggregate quarterly FSD Score, where the FSD Score is the quarterly version of the measure developed by Amiram, Bozanic, and Rouen (2015). For each calendar quarter, we aggregate firm-quarter values of fraud probability using a value-weighted average, with weights based on the market capitalization as of the beginning of the quarter.
AVG_VWAGG_absABNACC	=	moving average of VWAGG_absABNACC for the four calendar quarters from q-3 to q. VWAGG_absABNACC equals the aggregate level of absolute abnormal accruals (Allen, Larson, and Sloan 2013) for calendar quarter q. Each firm-quarter's abnormal accruals is calculated based on the Allen, Larson, and Sloan (2013) accrual model, estimated by quarter with fixed effects included for fiscal quarter. For each calendar quarter, we aggregate firm-quarter values of absolute abnormal accruals using a value-weighted average, with weights based on the market capitalization as of the beginning of the quarter.
AVG_VWAGG_AGR	=	moving average of VWAGG_AGR for the four calendar quarters from q-3 to q. VWAGG_AGR equals aggregate Accounting and Governance Risk (AGR) ratings (MSCI) for quarter q. For each calendar quarter, we aggregate firm-quarter values of AGR using a value-weighted average, with weights based on the market capitalization as of the beginning of the quarter.
RECESSION	=	1 for calendar quarters in a U.S. economic recession as defined by the NBER (i.e., starting with the first quarter after a business cycle peak and continuing through the trough quarter), zero otherwise.
SPREAD	=	10-year constant maturity Treasury rate less the secondary market 3-month bond-equivalent Treasury rate, measured on a monthly basis and averaged over the three months during the calendar quarter q.
NYSE	=	growth rate of the New York Stock Exchange composite index during the calendar quarter q.
SENT	=	sentiment index in Baker and Wurgler (2006); updated version of Eq. (2) in that paper; based on first principal component of five (standardized) sentiment proxies.

AVG_VWAGG_DISTORT	=	moving average of VWAGG_DISTORT for the four calendar quarters from q-3 to q. VWAGG_DISTORT equals the aggregate distortion component of M-Score (Beneish 1999a) for calendar quarter q. Each firm-quarter's distortion component of M-Score equals: -4.84 + .920*DSR + .404*AQI + .115*DEPI + 4.679*ACCRUALS, which is calculated based on the fitted values from Beneish (1999a) where the incentive component variables (i.e., GMI, SGI, SGAI, and LEV) are reset to zero.
AVG_VWAGG_INCENT	=	moving average of VWAGG_INCENT for the four calendar quarters from q-3 to q. VWAGG_INCENT equals the aggregate incentive component of M-Score (Beneish 1999a) for calendar quarter q. Each firm-quarter's incentive component of M-Score equals: -4.84 + .528*GMI + .892*SGI - .172*SGAI - .327*LEV, which is calculated based on the fitted values from Beneish (1999a) where the distortion component variables (i.e., DSR, AQI, DEPI, and ACCRUALS) are reset to zero.

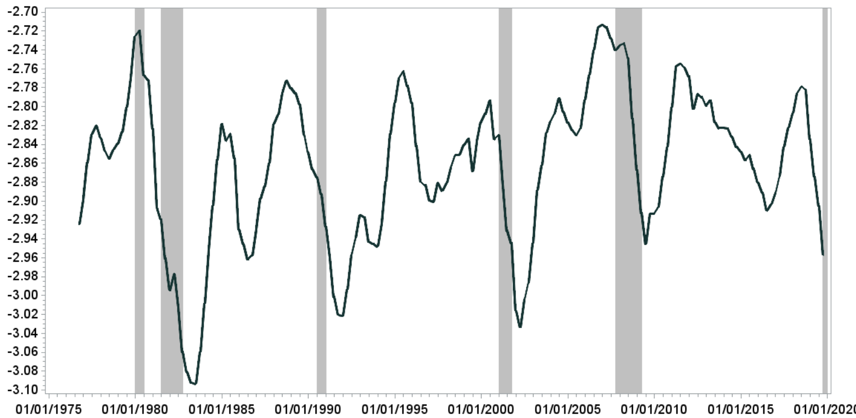
Panel B: Firm-quarter MSCORE Measure

MSCORE	=	estimated probability that the firm has engaged in earnings manipulation during the quarter following Beneish (1999a). For each firm-quarter, we calculate MSCORE as: -4.84 + .920*DSR + .528*GMI + .404*AQI + .892*SGI + .115*DEPI - .172*SGAI + 4.679*ACCRUALS - .327*LEV, where:
DSR	=	$(RECTQ_q$ / $SALEQ\_ANNUALIZED_t)$ / $(RECTQ_{q-1}$ / $SALEQ\_ANNUALIZED_{q-1})$
GMI	=	$((SALEQ\_ANNUALIZED_{q-1}$ - $COGSQ\_ANNUALIZED_{q-1})$ / $SALESQ\_ANNUALIZED_{q-1})$ / $((SALEQ\_ANNUALIZED_q$ - $COGSQ\_ANNUALIZED_q)$ / $SALESQ\_ANNUALIZED_q)$
AQI	=	$(1 - ((ACTQ_q + PPENTQ_q) / ATQ_q)) / (1 - ((ACTQ_{q-1} + PPENTQ_{q-1}) / ATQ_{q-1}))$
SGI	=	$SALEQ\_ANNUALIZED_q$ / $SALEQ\_ANNUALIZED_{q-1}$
DEPI	=	$(DPQ\_ANNUALIZED_{q-1}$ / $(DPQ\_ANNUALIZED_{q-1} + PPENTQ_{q-1}))$ / $(DPQ\_ANNUALIZED_q$ / $(DPQ\_ANNUALIZED_q + PPENTQ_q))$
SGAI	=	$(XSGAQ\_ANNUALIZED_q$ / $SALESQ\_ANNUALIZED_q)$ / $(XSGAQ\_ANNUALIZED_{q-1}$ / $SALESQ\_ANNUALIZED_{q-1})$
ACCRUALS	=	$ACCRUALSQ\_ANNUALZED_q/ATQ_q$
LEV	=	$((DLTTQ_q + LCTQ_q) / ATQ_q) / ((DLTTQ_{q-1} + LCTQ_{q-1}) / ATQ_{q-1})$

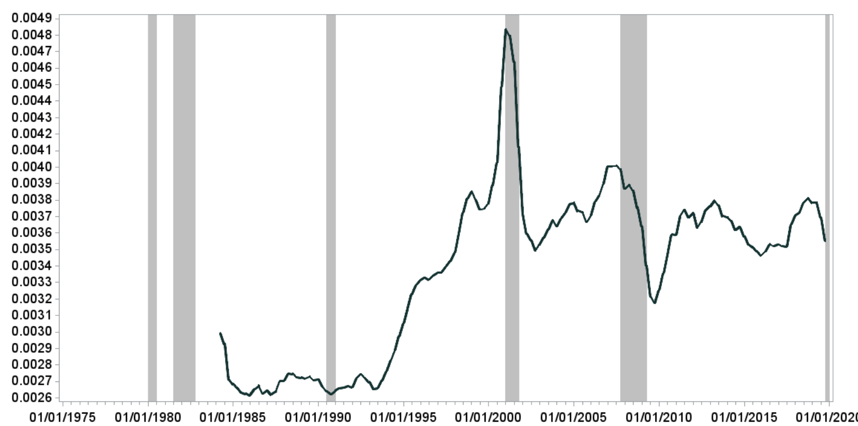
- ANNUALIZED versions of SALEQ, COGSQ, DPQ, and XSGAQ in period q are computed by summing the quarterly values over q-3 to q.
- ACRRUALSQ = $(\Delta ACTQ_q - \Delta CHEQ_q) - (\Delta LCTQ_q - \Delta DLCQ_q - \Delta TXPQ_q) - DPQ_q$.
- ANNUALIZED version ACCRUALSQ in period q is computed by summing the quarterly values over q-3 to q.
- Firm-quarters with missing XSGAQ have XSGAQ set equal to zero.
- When cash flow statement data is available, the amount of AMCY attributable to the current quarter is subtracted from DPQ when calculating DEPI.
- We exclude from our sample firms in the financial services industry (SIC codes 6000-6999) or utilities industry (SIC codes 4900-4999) when computing MSCORE because these regulated firms have unique financial reporting characteristics.
- DSR, GMI, AQI, SGI, DEPI, SGAI, ACCRUALS, and LEV are winsorized at the 1st and 99th percentiles by calendar quarter.

Figure 1
Time Series of Aggregate Misreporting Measures

Panel A: Time Series of AVG_VWAGG_MSCORE



Panel B: Time Series of AVG_VWAGG_FSCORE



Panel C: Time Series of AVG_VWAGG_AKKM

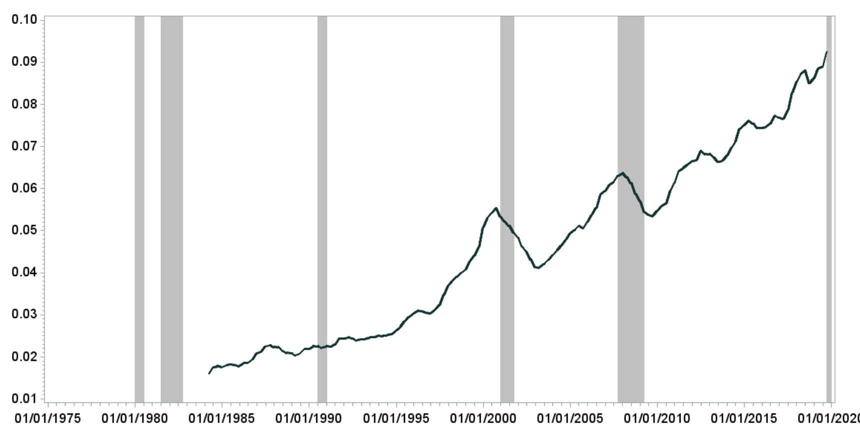
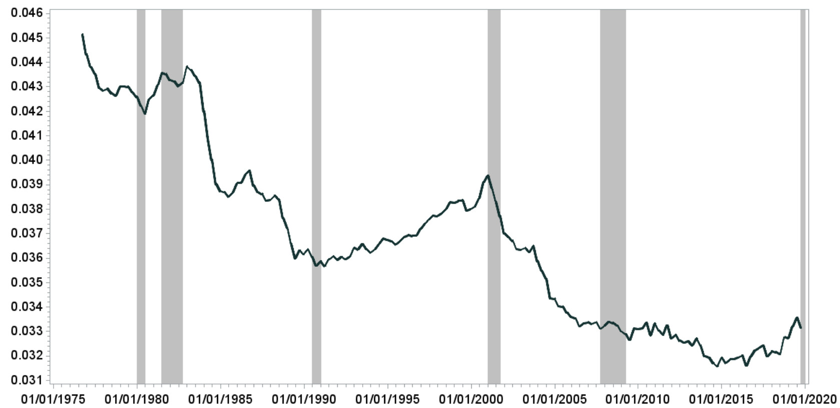
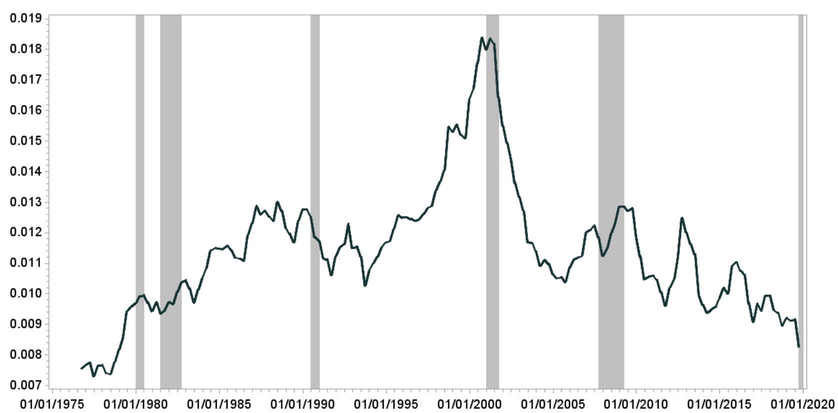


Figure 1 (continued)

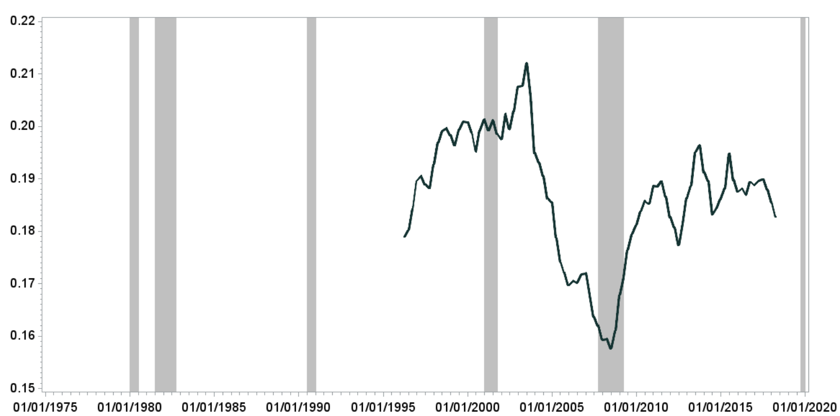
Panel D: Time Series of AVG_VWAGG_FSDSCORE



Panel E: Time Series of AVG_VWAGG_absABNACC



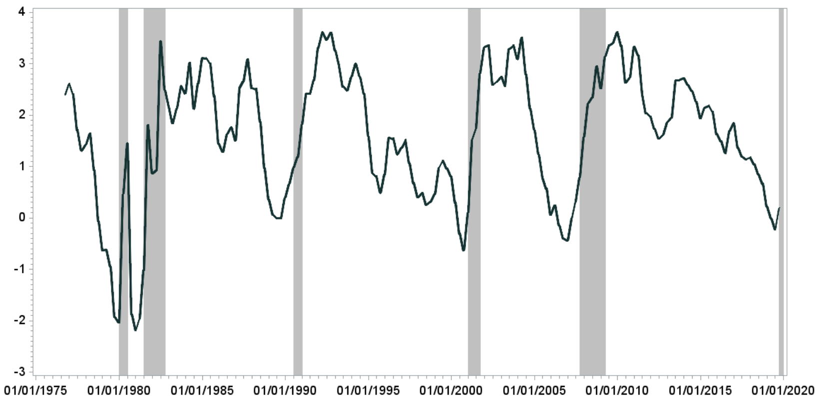
Panel F: Time Series of AVG_VWAGG_AGR



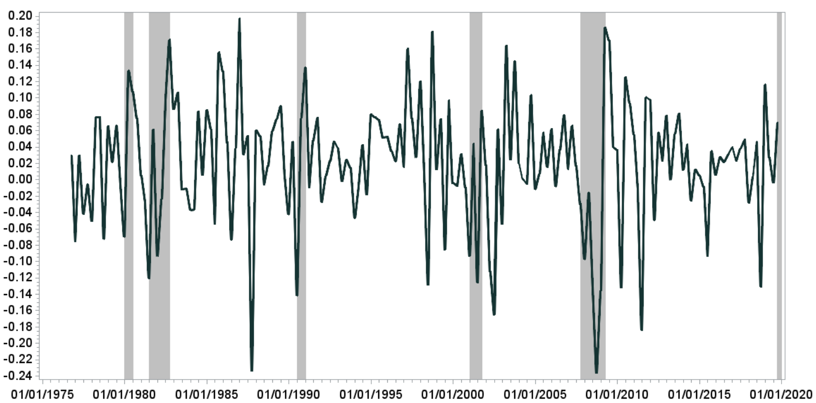
This figure plots the quarterly time series of each aggregate misreporting measure across the entire sample period.

Figure 2
Time Series of Estrella and Mishkin (1998) Variables

Panel A: Time Series of the Interest Rate Spread



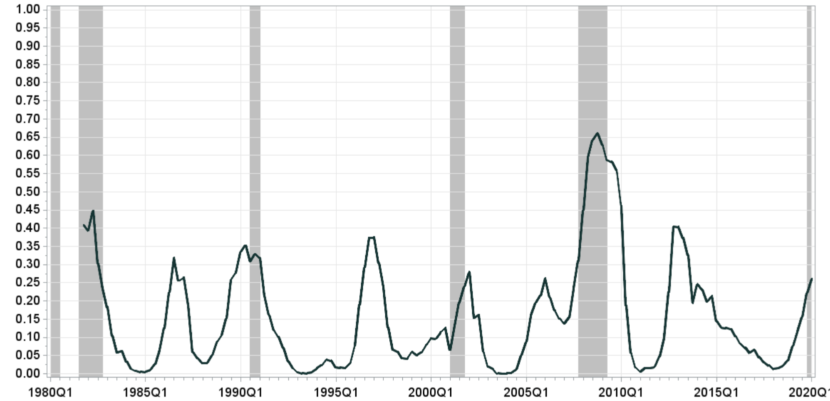
Panel B: Time Series of the NYSE Quarterly Growth Rate



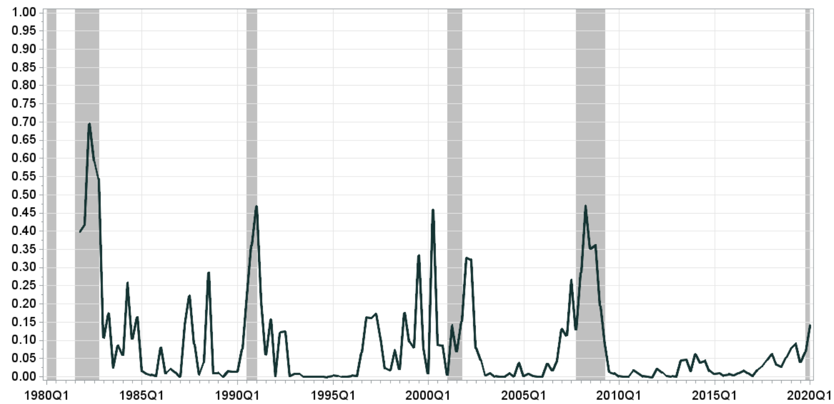
This figure plots the quarterly time series of the Estrella and Mishkin (1998) variables of interest rate spread and NYSE index (i.e., our control variables) across the entire sample period.

Figure 3
Out-of-Sample Probability of Recession Forecasting Six-Quarters-Ahead

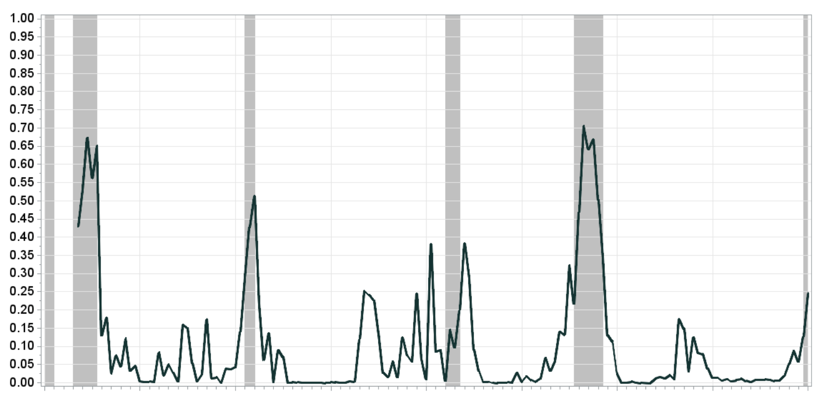
Panel A: Time Series of the Recession Probability using AVG_VWAGG_MSCORE



Panel B: Time Series of the Recession Probability using SPREAD and NYSE



Panel C: Time Series of the Recession Probability using AVG_VWAGG_MSCORE, SPREAD, and NYSE



This figure plots recession probabilities derived from out-of-sample forecasts six-quarters-ahead for AVG_VWAGG_MSCORE (Panel A), SPREAD and NYSE (Panel B), and AVG_VWAGG_MSCORE, SPREAD, and NYSE (Panel C). The grey bands represent recession periods.

Table 1
Descriptive Statistics

Variable	N	Mean	Median	Std. Dev.	Q1	Q3
$AVG\_VWAGG\_MSCORE_q$	173	-2.862	-2.849	0.081	-2.912	-2.807
$AVG\_VWAGG\_FSCORE_q$	143	0.003	0.004	0.001	0.003	0.004
$AVG\_VWAGG\_AKKM_q$	143	0.046	0.046	0.021	0.024	0.064
$AVG\_VWAGG\_FSDSCORE_q$	173	0.037	0.036	0.004	0.033	0.039
$AVG\_VWAGG\_ABSABNACC_q$	173	0.011	0.011	0.002	0.010	0.012
$AVG\_VWAGG\_AGR_q$	89	0.187	0.188	0.012	0.181	0.196
$RECESSION_{q+1}$	173	0.110	0.000	0.314	0.000	0.000
$RECESSION_{q+2}$	172	0.110	0.000	0.314	0.000	0.000
$RECESSION_{q+3}$	171	0.111	0.000	0.315	0.000	0.000
$RECESSION_{q+4}$	170	0.112	0.000	0.316	0.000	0.000
$RECESSION_{q+5}$	169	0.112	0.000	0.317	0.000	0.000
$RECESSION_{q+6}$	168	0.113	0.000	0.318	0.000	0.000
$RECESSION_{q+7}$	167	0.114	0.000	0.318	0.000	0.000
$RECESSION_{q+8}$	166	0.114	0.000	0.319	0.000	0.000
$SPREAD_q$	173	1.593	1.705	1.278	0.804	2.587
$NYSE_q$	173	0.021	0.028	0.076	-0.009	0.068

This table reports descriptive statistics for key variables. The sample includes 173 quarters from 1976:Q4 to 2019:Q4. The underlying firm-quarter financial statement data is obtained from the Compustat Snapshot "As First Reported" Quarterly database. The sample excludes firms not incorporated in the U.S., firms without March, June, September, or December fiscal year-ends, firms not releasing the quarterly earnings announcement by the end of the first month after the quarter ends, and firms not listed on the NYSE, Amex, or NASDAQ. To mitigate the effects of outliers, before calculating aggregated measures we delete firm-quarter observations that fall in the top and bottom one percentile of each quarterly cross-section of MSCORE, FSCORE, AKKM, FSDSCORE, absABNACC, AGR, and beginning market capitalization. While quarterly reporting is mandated after 1970, Compustat quarterly data required for measuring M-Score is sparsely populated until the mid-1970s. This results in our sample period beginning in 1976:Q4. The sample period ends in 2019:Q4. The sample for AVG_VWAGG_FSCORE and AVG_VWAGG_AKKM is reduced to 135 quarters from 1984:Q2 to 2019:Q4. The sample for AVG_VWAGG_AGR is reduced to 89 quarters from 1996:Q2 to 2018:Q2. The NBER defined 2019:Q4 as a peak quarter, thus a recession began in 2020:Q1. At the time of this writing it is unclear when this recession will end, so we do not extend our RECESSION definition past 2020:Q1. As a result, the sample period in the k=1, …, k=8 specification ends in 2019:Q4, …, 2018:Q1, respectively.

Table 2
Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) $AVG\_VWAGG\_MSCORE_{q}$	1.000	0.506	0.312	0.268	-0.040	-0.444	-0.004	0.078	0.160	0.231	0.317	0.362	0.386	0.380	-0.394	0.009
		<.0001	*0.000*	*0.000*	*0.603*	*<.0001*	*0.954*	*0.310*	*0.037*	*0.002*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*0.910*
	173	143	143	173	173	89	173	172	171	170	169	168	167	166	173	173
(2) $AVG\_VWAGG\_FSCORE_{q}$	0.397	1.000	0.713	0.354	0.000	0.006	0.228	0.279	0.319	0.321	0.319	0.303	0.278	0.260	-0.331	-0.166
	<.0001		*<.0001*	*<.0001*	*0.997*	*0.954*	*0.006*	*0.001*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*	*0.002*	*<.0001*	*0.048*
	143	143	143	143	143	89	143	142	141	140	139	138	137	136	143	143
(3) $AVG\_VWAGG\_AKKM_{q}$	0.316	0.725	1.000	0.817	-0.443	-0.338	0.122	0.143	0.149	0.145	0.131	0.111	0.092	0.074	-0.160	-0.142
	0.000	*<.0001*		*<.0001*	*<.0001*	*0.001*	*0.148*	*0.090*	*0.079*	*0.088*	*0.125*	*0.195*	*0.285*	*0.392*	*0.057*	*0.092*
	143	143	143	143	143	89	143	142	141	140	139	138	137	136	143	143
(4) $AVG\_VWAGG\_FSDSCORE_{q}$	0.321	0.401	0.828	1.000	-0.028	-0.444	-0.107	-0.131	-0.119	-0.095	-0.073	-0.055	-0.069	-0.086	0.160	-0.030
	<.0001	*<.0001*	*<.0001*		*0.717*	*<.0001*	*0.161*	*0.088*	*0.121*	*0.216*	*0.346*	*0.480*	*0.374*	*0.271*	*0.036*	*0.695*
	173	143	143	173	173	89	173	172	171	170	169	168	167	166	173	173
(5) $AVG\_VWAGG\_ABSABNACC_{q}$	-0.026	0.262	-0.308	0.071	1.000	0.381	0.015	0.009	-0.003	-0.018	-0.036	-0.041	-0.058	-0.065	0.084	0.044
	0.731	*0.002*	*0.000*	*0.352*		*0.000*	*0.843*	*0.909*	*0.969*	*0.811*	*0.638*	*0.599*	*0.457*	*0.406*	*0.271*	*0.565*
	173	143	143	173	173	89	173	172	171	170	169	168	167	166	173	173
(6) $AVG\_VWAGG\_AGR_{q}$	-0.522	0.075	-0.262	-0.517	0.403	1.000	-0.206	-0.218	-0.226	-0.222	-0.202	-0.168	-0.172	-0.176	0.106	0.033
	<.0001	*0.484*	*0.013*	*<.0001*	<.0001		*0.053*	*0.041*	*0.033*	*0.037*	*0.058*	*0.115*	*0.108*	*0.101*	*0.322*	*0.756*
	89	89	89	89	89	89	89	89	89	89	89	89	89	88	89	89
(7) $RECESSION_{q+1}$	0.016	0.272	0.122	-0.117	0.085	-0.351	1.000	0.667	0.364	0.181	0.059	-0.002	-0.003	-0.004	-0.114	-0.230
	0.839	*0.001*	*0.146*	*0.127*	*0.264*	*0.001*		*<.0001*	*<.0001*	*0.018*	*0.444*	*0.978*	*0.970*	*0.963*	*0.134*	*0.002*
	173	143	143	173	173	89	173	172	171	170	169	168	167	166	173	173
(8) $RECESSION_{q+2}$	0.098	0.292	0.136	-0.128	0.089	-0.370	0.667	1.000	0.667	0.363	0.181	0.059	-0.003	-0.004	-0.267	-0.315
	0.200	*0.000*	*0.107*	*0.095*	*0.245*	*0.000*	*<.0001*		*<.0001*	*<.0001*	*0.019*	*0.451*	*0.970*	*0.963*	*0.000*	*<.0001*
	172	142	142	172	172	89	172	172	171	170	169	168	167	166	172	172
(9) $RECESSION_{q+3}$	0.171	0.277	0.147	-0.120	0.076	-0.361	0.364	0.667	1.000	0.667	0.363	0.180	0.058	-0.004	-0.365	-0.203
	0.025	*0.001*	*0.083*	*0.118*	*0.325*	*0.001*	*<.0001*	*<.0001*		*<.0001*	*<.0001*	*0.020*	*0.457*	*0.963*	*<.0001*	*0.008*
	171	141	141	171	171	89	171	171	171	170	169	168	167	166	171	171
(10) $RECESSION_{q+4}$	0.240	0.241	0.147	-0.105	0.051	-0.324	0.181	0.363	0.667	1.000	0.666	0.362	0.180	0.057	-0.422	-0.104
	0.002	*0.004*	*0.083*	*0.175*	*0.506*	*0.002*	*0.018*	*<.0001*	*<.0001*		*<.0001*	*<.0001*	*0.020*	*0.464*	*<.0001*	*0.179*
	170	140	140	170	170	89	170	170	170	170	169	168	167	166	170	170
(11) $RECESSION_{q+5}$	0.308	0.211	0.140	-0.089	0.012	-0.281	0.059	0.181	0.363	0.666	1.000	0.666	0.362	0.179	-0.455	-0.057
	<.0001	*0.013*	*0.100*	*0.250*	*0.881*	*0.008*	*0.444*	*0.019*	*<.0001*	*<.0001*		*<.0001*	*<.0001*	*0.021*	*<.0001*	*0.460*
	169	139	139	169	169	89	169	169	169	169	169	168	167	166	169	169
(12) $RECESSION_{q+6}$	0.353	0.197	0.127	-0.075	-0.015	-0.229	-0.002	0.059	0.180	0.362	0.666	1.000	0.666	0.361	-0.454	0.093
	<.0001	*0.021*	*0.137*	*0.334*	*0.843*	*0.031*	*0.978*	*0.451*	*0.020*	*<.0001*	*<.0001*		*<.0001*	*<.0001*	*<.0001*	*0.231*
	168	138	138	168	168	89	168	168	168	168	168	168	167	166	168	168
(13) $RECESSION_{q+7}$	0.377	0.179	0.110	-0.081	-0.040	-0.204	-0.003	-0.003	0.058	0.180	0.362	0.666	1.000	0.666	-0.430	0.058
	<.0001	*0.037*	*0.201*	*0.296*	*0.607*	*0.055*	*0.970*	*0.970*	*0.457*	*0.020*	*<.0001*	*<.0001*		*<.0001*	*<.0001*	*0.457*
	167	137	137	167	167	89	167	167	167	167	167	167	167	166	167	167
(14) $RECESSION_{q+8}$	0.372	0.166	0.092	-0.092	-0.053	-0.193	-0.004	-0.004	-0.004	0.057	0.179	0.361	0.666	1.000	-0.391	0.116
	<.0001	*0.053*	*0.288*	*0.237*	*0.499*	*0.072*	*0.963*	*0.963*	*0.963*	*0.464*	*0.021*	*<.0001*	*<.0001*		*<.0001*	*0.137*
	166	136	136	166	166	88	166	166	166	166	166	166	166	166	166	166
(15) $SPREAD_{q}$	-0.399	-0.311	-0.186	0.215	0.030	0.151	-0.111	-0.308	-0.418	-0.489	-0.511	-0.486	-0.454	-0.412	1.000	-0.016
	<.0001	*0.000*	*0.026*	*0.005*	*0.691*	*0.158*	*0.145*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*	*<.0001*		*0.832*
	173	143	143	173	173	89	173	172	171	170	169	168	167	166	173	173
(16) $NYSE_{q}$	-0.023	-0.147	-0.119	-0.027	-0.034	0.119	-0.299	-0.322	-0.181	-0.066	-0.056	0.089	0.050	0.092	-0.007	1.000
	0.764	*0.079*	*0.158*	*0.724*	*0.661*	*0.268*	*<.0001*	*<.0001*	*0.018*	*0.394*	*0.470*	*0.253*	*0.522*	*0.237*	*0.929*	
	173	143	143	173	173	89	173	172	171	170	169	168	167	166	173	173

This table reports Pearson (Spearman) correlation coefficients below (above) the diagonal. P-values are italicized. Sample sizes are reported under p-values.

Table 3
Predicting Future Recessions with Aggregate Misreporting

$P(RECESSION_{q+k}=1) = \beta_0 + \beta_1 X_q + \varepsilon_{q+k}$

X_q Variables	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8
AVG_VWAGG_MSCORE								
Coefficient	0.300	2.058	3.898	6.235*	9.475**	12.373***	14.367***	13.787***
(*t*-stat)	(0.10)	(0.64)	(1.11)	(1.75)	(2.52)	(3.44)	(3.32)	(3.07)
Pseudo R^2	0.0002	0.0097	0.0312	0.0672	0.1234	0.1743	0.2083	0.1998
N quarters	173	172	171	170	169	168	167	166
AVG_VWAGG_FSCORE								
Coefficient	945.026	1,042.457	1,007.354	889.416	782.860	729.608	659.775	611.697
(*t*-stat)	(1.29)	(1.33)	(1.40)	(1.40)	(1.35)	(1.32)	(1.29)	(1.28)
Pseudo R^2	0.0688	0.0817	0.0758	0.0595	0.0463	0.0406	0.0336	0.0291
N quarters	143	142	141	140	139	138	137	136
AVG_VWAGG_AKKM								
Coefficient	10.732	12.137	13.185	13.363	12.811	11.637	10.164	8.637
(*t*-stat)	(1.29)	(1.38)	(1.42)	(1.41)	(1.35)	(1.24)	(1.10)	(0.95)
Pseudo R^2	0.0156	0.0193	0.0224	0.0225	0.0204	0.0167	0.0125	0.0088
N quarters	143	142	141	140	139	138	137	136
AVG_VWAGG_FSDSCORE								
Coefficient	49.770	55.075	52.825	47.429	40.810	34.394	36.511	40.019
(*t*-stat)	(0.81)	(0.90)	(0.86)	(0.78)	(0.69)	(0.59)	(0.63)	(0.68)
Pseudo R^2	0.0132	0.0161	0.0149	0.0120	0.0088	0.0062	0.0070	0.0084
N quarters	173	172	171	170	169	168	167	166
AVG_VWAGG_ABSABNACC								
Coefficient	57.215	59.781	51.251	35.305	8.238	-11.501	-30.871	-41.551
(*t*-stat)	(0.62)	(0.65)	(0.55)	(0.37)	(0.08)	(-0.12)	(-0.32)	(-0.44)
Pseudo R^2	0.0063	0.0068	0.0050	0.0023	0.0001	0.0002	0.0016	0.0028
N quarters	173	172	171	170	169	168	167	166
AVG_VWAGG_AGR								
Coefficient	-40.671	-43.227	-43.495	-40.216	-35.126	-28.508	-25.679	-24.815
(*t*-stat)	(-1.05)	(-1.10)	(-1.19)	(-1.23)	(-1.13)	(-0.93)	(-0.93)	(-0.95)
Pseudo R^2	0.0988	0.1102	0.1083	0.0904	0.0691	0.0461	0.0381	0.0351
N quarters	89	89	89	89	89	89	89	88

This table predicts future U.S. recessions using measures of aggregate misreporting in the current quarter *q*. The table reports coefficient estimates and t-statistics from estimating probit models in sample. Estrella (1998) pseudo R^2s are also reported. Intercepts are not tabulated. The models have a dependent variable set equal to $RECESSION_{q+k}$ and predict whether the U.S. will be in recession during a specific quarter q+k. Statistical significance at the 0.01, 0.05, and 0.10 level is denoted by ***, **, and *, respectively, based on two-tailed tests. T-statistics are computed using Newey-West heteroskedasticity- and autocorrelation-consistent standard errors using four lags.

Table 4

Predicting Future Recessions with Estrella and Mishkin (1998) Variables and Aggregate M-Score

Panel A: SPREAD and NYSE as Predictors

$$P(RECESSION_{q+k}=1) = \beta_0 + \beta_1 SPREAD_q + \beta_2 NYSE_q + \varepsilon_{q+k}$$

	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8
SPREAD								
Coefficient	-0.164*	-0.473***	-0.598***	-0.699***	-0.772***	-0.797***	-0.675***	-0.598***
(*t*-stat)	(-1.93)	(-5.19)	(-5.04)	(-4.30)	(-3.53)	(-4.13)	(-4.73)	(-4.37)
NYSE								
Coefficient	-6.082***	-8.602***	-5.494***	-1.964	-1.414	4.989*	2.581	3.876*
(*t*-stat)	(-2.91)	(-5.18)	(-3.79)	(-0.99)	(-0.57)	(1.86)	(1.05)	(1.78)
Pseudo R^2	0.0946	0.2154	0.2170	0.2464	0.2763	0.2734	0.2206	0.1903
N quarters	173	172	171	170	169	168	167	166

Panel B: AVG_VWAGG_MSCORE, SPREAD, and NYSE as Predictors

$$P(RECESSION_{q+k}=1) = \beta_0 + \beta_1 AVG\_VWAGG\_MSCORE_q + \beta_2 SPREAD_q + \beta_3 NYSE_q + \varepsilon_{q+k}$$

	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8
AVG_VWAGG_MSCORE								
Coefficient	-0.937	-0.205	1.165	2.916	7.802	10.429***	12.071***	11.417***
(*t*-stat)	(-0.26)	(-0.04)	(0.23)	(0.55)	(1.60)	(2.86)	(3.01)	(2.81)
SPREAD								
Coefficient	-0.186	-0.477***	-0.576***	-0.646***	-0.687**	-0.661***	-0.542***	-0.441***
(*t*-stat)	(-1.64)	(-3.34)	(-3.55)	(-3.47)	(-2.51)	(-2.77)	(-3.84)	(-4.34)
NYSE								
Coefficient	-6.128***	-8.605***	-5.516***	-2.040	-2.159	4.719	1.422	3.604
(*t*-stat)	(-2.91)	(-4.83)	(-3.30)	(-0.88)	(-0.71)	(1.48)	(0.59)	(1.39)
Pseudo R^2	0.0964	0.2155	0.2189	0.2562	0.3236	0.3482	0.3223	0.2890
N quarters	173	172	171	170	169	168	167	166

This table predicts future U.S. recessions using *SPREAD* and *NYSE* (Panel A) and *AVG_VWAGG_MSCORE*, *SPREAD*, and *NYSE* (Panel B). The table reports coefficient estimates and t-statistics from estimating probit models in sample. Estrella (1998) pseudo R^2s are also reported. Intercepts are not tabulated. The models have a dependent variable set equal to $RECESSION_{q+k}$ and predict whether the U.S. will be in recession during a specific quarter q+k. Statistical significance at the 0.01, 0.05, and 0.10 level is denoted by ***, **, and *, respectively, based on two-tailed tests. T-statistics are computed using Newey-West heteroskedasticity- and autocorrelation-consistent standard errors using four lags.

Table 5
Predicting Future Recessions with Estrella and Mishkin (1998) Variables, Baker and Wurgler (2006) Investor Sentiment, and Aggregate M-Score

Panel A: AVG_VWAGG_MSCORE and SENT as Predictors

$$P(RECESSION_{q+k}=1) = \beta_0 + \beta_1 AVG\_VWAGG\_MSCORE_q + \beta_2 SENT_q + \varepsilon_{q+k}$$

	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8
AVG_VWAGG_MSCORE								
Coefficient	3.130	5.348	7.186*	8.320**	10.364***	12.515***	14.649***	15.174***
(*t*-stat)	(1.06)	(1.57)	(1.87)	(2.29)	(2.90)	(3.49)	(3.29)	(2.87)
SENT								
Coefficient	0.588**	0.683***	0.709***	0.523**	0.310	0.101	-0.254	-0.609**
(*t*-stat)	(2.56)	(3.34)	(3.17)	(2.16)	(1.20)	(0.37)	(-0.85)	(-2.09)
Pseudo R^2	0.0640	0.0891	0.1108	0.1084	0.1366	0.1755	0.2142	0.2279
N quarters	169	169	169	169	169	168	167	166

Panel B: AVG_VWAGG_MSCORE, SPREAD, NYSE and SENT as Predictors

$$P(RECESSION_{q+k}=1) = \beta_0 + \beta_1 AVG\_VWAGG\_MSCORE_q + \beta_2 SPREAD_q + \beta_3 NYSE_q + \beta_4 SENT_q + \varepsilon_{q+k}$$

	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8
AVG_VWAGG_MSCORE								
Coefficient	2.401	3.669	4.849	5.310	8.524*	10.622***	12.226***	12.265**
(*t*-stat)	(0.64)	(0.77)	(0.90)	(1.00)	(1.95)	(2.85)	(2.92)	(2.53)
SPREAD								
Coefficient	-0.117	-0.439***	-0.560***	-0.646***	-0.686***	-0.662***	-0.556***	-0.481***
(*t*-stat)	(-0.96)	(-2.94)	(-3.63)	(-3.77)	(-2.71)	(-2.82)	(-3.08)	(-3.90)
NYSE								
Coefficient	-6.595***	-9.033***	-5.493***	-2.439	-1.803	4.801	1.143	3.321
(*t*-stat)	(-2.64)	(-3.98)	(-2.90)	(-1.06)	(-0.60)	(1.36)	(0.48)	(1.15)
SENT								
Coefficient	0.588***	0.718***	0.724***	0.519**	0.265	0.093	-0.324	-0.667***
(*t*-stat)	(2.84)	(3.88)	(3.39)	(2.00)	(0.99)	(0.27)	(-1.14)	(-2.66)
Pseudo R^2	0.1597	0.2792	0.2775	0.2893	0.3315	0.3490	0.3318	0.3232
N quarters	169	169	169	169	169	168	167	166

This table predicts future U.S. recessions using *AVG_VWAGG_MSCORE* and *SENT* (Panel A) or *AVG_VWAGG_MSCORE*, *SPREAD*, *NYSE*, and *SENT* (Panel B). The table reports coefficient estimates and t-statistics from estimating probit models in sample. Estrella (1998) pseudo R^2 are also reported. Intercepts are not tabulated. The models have a dependent variable set equal to $RECESSION_{q+k}$ and predict whether the U.S. will be in recession during a specific quarter q+k. Statistical significance at the 0.01, 0.05, and 0.10 level is denoted by ***, **, and *, respectively, based on two-tailed tests. T-statistics are computed using Newey-West heteroskedasticity- and autocorrelation-consistent standard errors using four lags.

Table 6
Predicting Future Recessions with an Augmented Model: Aggregate M-Score, SPREAD, NYSE, and two variables (Aggregate Earnings Growth and Nominal GDP Growth) studied by Konchitchki and Patatoukas (2014a)

$P(RECESSION_{q+k}=1) = \beta_0 + \beta_1 AVG\_VWAGG\_MSCORE_q + \beta_2 SPREAD_q + \beta_3 NYSE_q + \beta_4 VWAGG\_\Delta EARN_q + \beta_5 NGDP1_q + \varepsilon_{q+k}$

	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8
AVG_VWAGG_MSCORE								
Coefficient	-2.114	-0.754	0.778	2.449	7.627	10.865***	16.739***	17.138***
(*t*-stat)	(-0.58)	(-0.16)	(0.15)	(0.48)	(1.59)	(2.76)	(2.85)	(2.58)
SPREAD								
Coefficient	-0.277*	-0.631***	-0.716***	-0.755***	-0.681**	-0.593**	-0.417*	-0.391**
(*t*-stat)	(-1.68)	(-3.49)	(-3.26)	(-3.84)	(-2.33)	(-2.17)	(-1.83)	(-2.12)
NYSE								
Coefficient	-5.064***	-6.707***	-4.023***	-0.339	-1.128	5.334*	0.935	3.066
(*t*-stat)	(-2.85)	(-3.92)	(-2.59)	(-0.17)	(-0.36)	(1.68)	(0.32)	(0.93)
VWAGG_ΔEARN								
Coefficient	-30.270**	-26.310*	-10.933	-16.319***	-13.745	-10.444	13.795	27.086***
(*t*-stat)	(-2.51)	(-1.91)	(-1.55)	(-3.05)	(-1.52)	(-0.82)	(1.11)	(2.84)
NGDP1								
Coefficient	-14.125**	-11.026**	-8.373	-4.976	1.579	5.793	15.517***	13.389*
(*t*-stat)	(-2.36)	(-2.16)	(-1.62)	(-1.40)	(0.27)	(0.97)	(3.29)	(1.93)
Pseudo R^2	0.2515	0.3212	0.2566	0.2903	0.3391	0.3637	0.3876	0.3664
N quarters	172	171	170	169	168	167	166	165

This table predicts future U.S. recessions using *AVG_VWAGG_MSCORE, SPREAD*, *NYSE*, and Konchitchki and Patatoukas (2014a) variables (i.e., aggregate earnings growth (*VWAGG_ΔEARN*) and current quarter nominal GDP growth (*NGDP1*)). The table reports coefficient estimates and t-statistics from estimating probit models in sample. Estrella (1998) pseudo R^2s are also reported. Intercepts are not tabulated. The models have a dependent variable set equal to $RECESSION_{q+k}$ and predict whether the U.S. will be in recession during a specific quarter q+k. Statistical significance at the 0.01, 0.05, and 0.10 level is denoted by ***, **, and *, respectively, based on two-tailed tests. T-statistics are computed using Newey-West heteroskedasticity- and autocorrelation-consistent standard errors using four lags.

Table 7
Aggregate M-Score and the Out-of-Sample Probability of Recession

Panel A: Forecasting Recession Six-Quarters-Ahead

	Recession Probability			
Calendar Quarter	AVG_VWAGG _MSCORE (A)	SPREAD and NYSE (B)	AVG_VWAGG_MSCORE, SPREAD, and NYSE (C)	% Change in Recession Probability (C) vs. (B)
1981Q4	0.409	0.398	0.429	7.79%
1982Q1	0.394	0.417	0.532	27.58%
1982Q2	0.448	0.695	0.673	-3.17%
1982Q3	0.302	0.594	0.563	-5.22%
1982Q4	0.235	0.543	0.651	19.89%
1990Q4	0.329	0.362	0.428	18.23%
1991Q1	0.318	0.468	0.513	9.62%
2001Q2	0.132	0.141	0.145	2.84%
2001Q3	0.197	0.070	0.098	40.00%
2001Q4	0.239	0.153	0.199	30.07%
2008Q1	0.450	0.286	0.469	63.99%
2008Q2	0.595	0.470	0.705	50.00%
2008Q3	0.642	0.352	0.641	82.10%
2008Q4	0.661	0.362	0.669	84.81%
2009Q1	0.631	0.195	0.503	157.95%
2009Q2	0.587	0.090	0.345	283.33%
2020Q1	0.260	0.141	0.246	74.47%
Average	0.402	0.338	0.459	55.55% (p=0.006)

	Average Pseudo R^2			
	AVG_VWAGG _MSCORE (A)	SPREAD and NYSE (B)	AVG_VWAGG_MSCORE, SPREAD, and NYSE (C)	% Change in Average Pseudo R^2 (C) vs. (B)
All Quarters	0.1706	0.3038	0.3425	12.50%
Recession Quarters	0.1537	0.2674	0.3019	13.11%

Table 7 (continued)

Panel B: Forecasting Recession Seven-Quarters-Ahead

Calendar Quarter	AVG_VWAGG _MSCORE (A)	SPREAD and NYSE (B)	AVG_VWAGG_MSCORE, SPREAD, and NYSE (C)	% Change in Recession Probability (C) vs. (B)
	Recession Probability			
1981Q4	0.528	0.612	0.545	-10.95%
1982Q1	0.725	0.323	0.703	117.65%
1982Q2	0.588	0.360	0.694	92.78%
1982Q3	0.623	0.718	0.661	-7.94%
1982Q4	0.348	0.692	0.502	-27.46%
1990Q4	0.480	0.263	0.489	85.93%
1991Q1	0.480	0.384	0.571	48.70%
2001Q2	0.050	0.057	0.059	3.51%
2001Q3	0.134	0.142	0.122	-14.08%
2001Q4	0.223	0.126	0.212	68.25%
2008Q1	0.424	0.178	0.436	144.94%
2008Q2	0.613	0.281	0.644	129.18%
2008Q3	0.771	0.392	0.797	103.32%
2008Q4	0.805	0.358	0.836	133.52%
2009Q1	0.811	0.328	0.798	143.29%
2009Q2	0.770	0.229	0.744	224.89%
2020Q1	0.244	0.099	0.198	100.00%
Average	0.507	0.326	0.530	78.56% ($p<0.001$)

	Average Pseudo R^2			
	AVG_VWAGG _MSCORE (A)	SPREAD and NYSE (B)	AVG_VWAGG_MSCORE, SPREAD, and NYSE (C)	% Change in Average Pseudo R^2 (C) vs. (B)
All Quarters	0.2715	0.2218	0.3411	53.60%
Recession Quarters	0.2489	0.1904	0.3023	58.95%

Table 7 (continued)

Panel C: Forecasting Recession Eight-Quarters-Ahead

Calendar Quarter	Recession Probability: AVG_VWAGG _MSCORE (A)	SPREAD and NYSE (B)	AVG_VWAGG_MSCORE, SPREAD, and NYSE (C)	% Change in Recession Probability (C) vs. (B)
1981Q4	0.512	0.249	0.359	44.18%
1982Q1	0.861	0.427	0.821	92.27%
1982Q2	0.921	0.716	1.000	39.66%
1982Q3	0.773	0.588	1.000	70.07%
1982Q4	0.791	0.890	0.984	10.56%
1990Q4	0.671	0.119	0.564	373.95%
1991Q1	0.639	0.306	0.762	149.02%
2001Q2	0.105	0.139	0.130	-6.47%
2001Q3	0.049	0.058	0.046	-20.69%
2001Q4	0.144	0.183	0.169	-7.65%
2008Q1	0.301	0.254	0.371	46.06%
2008Q2	0.489	0.166	0.447	169.28%
2008Q3	0.691	0.285	0.700	145.61%
2008Q4	0.839	0.417	0.866	107.67%
2009Q1	0.864	0.340	0.855	151.47%
2009Q2	0.865	0.351	0.862	145.58%
2020Q1	0.162	0.068	0.101	48.53%
Average	0.569	0.327	0.590	91.71% (p=0.001)

	Average Pseudo R^2: AVG_VWAGG _MSCORE (A)	SPREAD and NYSE (B)	AVG_VWAGG_MSCORE, SPREAD, and NYSE (C)	% Change in Average Pseudo R^2 (C) vs. (B)
All Quarters	0.3289	0.2064	0.4032	95.63%
Recession Quarters	0.3000	0.2058	0.3974	92.72%

The recession probabilities in this table are derived from out-of-sample forecasts. Panel A, Panel B, and Panel C examine out-of-sample forecasts of a recession six-quarters-ahead, seven-quarters-ahead, and eight-quarters-ahead, respectively. The out-of-sample results are obtained in the following way (using a k=6 forecast as an example): First, a given model is estimated from the beginning of the sample up to a particular quarter (e.g., 1976:Q4 to 1999:Q4). Then these estimates are used to form a forecast for six quarters ahead (e.g., 2001:Q2). After adding one more quarter to the estimation period (e.g., 1976:Q4 to 2000:Q1), the model is re-estimated and a forecast is formed for six quarters ahead (e.g., 2001:Q3). This procedure mimics what a statistical model would have predicted with the information available at any point in the past. Data that become available subsequent to prediction are not used to estimate or predict recessions. The first data point we are able to obtain parameter estimates to form forecasts of quarter k+6 (Panel A), k+7 (Panel B), and k+8 (Panel C) across all three models is the 15th quarter (i.e., q=1980:Q2), 10th quarter (i.e., q=1979:Q1), and 13th quarter (i.e., q=1979:Q4) in our sample. Since the forecasts are for the contemporaneous quarter and use data from n quarters earlier, the left side of the time series is trimmed by n observations. We report recession probabilities only for recession periods, where different recession periods are separated by a dotted line. The table reports the Estrella (1998) pseudo R^2, averaged over (i) all sample quarters and (ii) recession quarters. % Change is the percentage change in recession probability or average pseudo R^2 from the second column of results to the third column of results. The table also reports the p-value from a t-test of whether the average % Change in recession probability is different from zero.

Table 8
Predicting Future Recessions with Estrella and Mishkin (1998) Variables and Components of Aggregate M-Score

Panel A: Components of AVG_VWAGG_MSCORE as Predictors

	k=6	k=6
AVG_VWAGG_DISTORT		
Coefficient	9.590**	
(*t* -stat)	(2.53)	
AVG_VWAGG_INCENT		
Coefficient		27.736***
(*t* -stat)		(2.70)
Pseudo R^2	0.1164	0.0949
N quarters	168	168

Panel B: Components of AVG_VWAGG_MSCORE, SPREAD, and NYSE as Predictors

	k=6	k=6
AVG_VWAGG_DISTORT		
Coefficient	9.246**	
(*t* -stat)	(2.47)	
AVG_VWAGG_INCENT		
Coefficient		8.421
(*t* -stat)		(0.65)
SPREAD		
Coefficient	-0.735***	-0.730***
(*t* -stat)	(-3.25)	(-2.95)
NYSE		
Coefficient	4.554	5.234*
(*t* -stat)	(1.45)	(1.84)
Pseudo R^2	0.3354	0.2789
N quarters	168	168

This table predicts U.S. recessions six-quarters-ahead using *AVG_VWAGG_MSCORE* components (Panel A) or *AVG_VWAGG_MSCORE* components, *SPREAD*, and *NYSE* (Panel B). The table reports coefficient estimates and t-statistics from estimating probit models in sample. Estrella (1998) pseudo R^2s are also reported. Intercepts are not tabulated. Statistical significance at the 0.01, 0.05, and 0.10 level is denoted by ***, **, and *, respectively, based on two-tailed tests. T-statistics are computed using Newey-West heteroskedasticity- and autocorrelation-consistent standard errors using four lags.

Table 9
Components of Aggregate M-Score and the Out-of-Sample Probability of Recession Six-Quarters-Ahead

Panel A: Distortion Component of Aggregate M-Score

Calendar Quarter	Recession Probability: AVG_VWAGG _MSCORE (A)	SPREAD and NYSE (B)	AVG_VWAGG_DISTORT, SPREAD, and NYSE (C)	% Change in Recession Probability (C) vs. (B)
1981Q4	0.390	0.398	0.444	11.56%
1982Q1	0.341	0.417	0.497	19.18%
1982Q2	0.389	0.695	0.672	-3.31%
1982Q3	0.257	0.594	0.590	-0.67%
1982Q4	0.328	0.543	0.754	38.86%
1990Q4	0.336	0.362	0.451	24.59%
1991Q1	0.338	0.468	0.543	16.03%
2001Q2	0.108	0.141	0.131	-7.09%
2001Q3	0.139	0.070	0.077	10.00%
2001Q4	0.140	0.153	0.152	-0.65%
2008Q1	0.394	0.286	0.449	56.99%
2008Q2	0.530	0.470	0.689	46.60%
2008Q3	0.585	0.352	0.638	81.25%
2008Q4	0.607	0.362	0.659	82.04%
2009Q1	0.593	0.195	0.506	159.49%
2009Q2	0.565	0.090	0.355	294.44%
2020Q1	0.248	0.141	0.257	82.27%
Average	0.370	0.338	0.463	53.62% (p=0.010)

	Average Pseudo R^2: AVG_VWAGG _MSCORE (A)	SPREAD and NYSE (B)	AVG_VWAGG_DISTORT, SPREAD, and NYSE (C)	% Change in Recession Probability (C) vs. (B)
All Quarters	0.1173	0.3038	0.3339	9.87%
Recession Quarters	0.1059	0.2674	0.2937	10.11%

Table 9 (continued)				
Panel B: Incentive Component of Aggregate M-Score				
	Recession Probability			
Calendar Quarter	AVG_VWAGG _INCENT (A)	SPREAD and NYSE (B)	AVG_VWAGG_INCENT, SPREAD, and NYSE (C)	% Change in Recession Probability (C) vs. (B)
1981Q4	0.420	0.398	0.383	-3.77%
1982Q1	0.514	0.417	0.608	45.80%
1982Q2	0.573	0.695	0.687	-1.15%
1982Q3	0.562	0.594	0.592	-0.34%
1982Q4	0.553	0.543	0.554	2.03%
1990Q4	0.054	0.362	0.232	-35.91%
1991Q1	0.083	0.468	0.372	-20.51%
2001Q2	0.292	0.141	0.255	80.85%
2001Q3	0.487	0.070	0.228	225.71%
2001Q4	0.776	0.153	0.573	274.51%
2008Q1	0.079	0.286	0.212	-25.87%
2008Q2	0.083	0.470	0.389	-17.23%
2008Q3	0.091	0.352	0.274	-22.16%
2008Q4	0.106	0.362	0.320	-11.60%
2009Q1	0.111	0.195	0.167	-14.36%
2009Q2	0.116	0.090	0.078	-13.33%
2020Q1	0.089	0.141	0.130	-7.80%
Average	0.293	0.338	0.356	26.76% (p=0.233)
	Average Pseudo R^2			
	AVG_VWAGG _INCENT (A)	SPREAD and NYSE (B)	AVG_VWAGG_INCENT, SPREAD, and NYSE (C)	% Change in Recession Probability (C) vs. (B)
All Quarters	0.1751	0.3038	0.3259	7.24%
Recession Quarters	0.1585	0.2674	0.2924	9.36%

The recession probabilities in this table are derived from out-of-sample forecasts six-quarters-ahead. The out-of-sample results are obtained using the same method described in Table 7. We report recession probabilities only for recession periods, where different recession periods are separated by a dotted line. The table reports the Estrella (1998) pseudo R^2 averaged over (i) all sample quarters and (ii) recession quarters. % Change is the percentage change in recession probability or average pseudo R^2 from the second column of results to the third column of results. The table also reports the p-value from a t-test of whether the average % Change in recession probability is different from zero.

Table 10

Cross-sectional Regression Tests of the Explanatory Power of Misreporting Measures with Respect to Future Stock Returns

Panel A: Cross-sectional Regressions of Future 12-month Stock Returns on Misreporting Measures

Misreporting Measure:	*MSCORE*	*FSCORE*	*MSCORE*	*AKKM*	*MSCORE*	*FSDSCORE*
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Intercept	-0.127	-0.182**	-0.050	-0.112	-0.145***	-0.234***
	(-1.49)	(-2.01)	(-0.52)	(-1.15)	(-3.34)	(-4.54)
Misreporting Measure	-0.011***	-0.006***	-0.011***	-0.004**	-0.011***	0.001*
	(-9.78)	(-4.50)	(-9.75)	(-2.04)	(-10.15)	(1.71)
SIZE	-0.013***	-0.012***	-0.014***	-0.009***	-0.014***	-0.013***
	(-9.61)	(-8.52)	(-9.64)	(-3.93)	(-11.22)	(-10.52)
BTM	0.003**	0.005***	0.003**	0.005***	0.003**	0.005***
	(2.53)	(3.36)	(2.21)	(3.27)	(2.55)	(3.76)
EP	0.012***	0.011***	0.012***	0.010***	0.013***	0.011***
	(10.49)	(9.89)	(10.24)	(9.08)	(11.83)	(10.88)
BETA	0.001	0.001	0.001	0.001	0.001	0.001
	(0.79)	(0.71)	(0.66)	(0.75)	(0.85)	(0.87)
SIC 2-Digit Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
N	50,990	50,990	48,964	48,964	58,294	58,294
Adjusted R^2	0.0645	0.0614	0.0650	0.0610	0.0654	0.0615
P-value from a $\chi2$ test of the difference in Misreporting Measure coefficients:	<0.001		<0.001		<0.001	
Misreporting Measure:	*MSCORE*	*absABNACC*	*MSCORE*	*AGR*	*DISTORT*	*INCENT*
	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
Intercept	0.071	0.017	-0.227***	-0.307***	-0.148***	-0.228***
	(1.13)	(0.28)	(-5.40)	(-6.87)	(-3.30)	(-4.54)
Misreporting Measure	-0.011***	-0.001	-0.010***	-0.002	-0.011***	0.000
	(-9.85)	(-1.06)	(-6.58)	(-1.59)	(-10.46)	(0.25)
SIZE	-0.014***	-0.014***	-0.013***	-0.012***	-0.014***	-0.014***
	(-10.96)	(-10.44)	(-7.32)	(-6.75)	(-11.22)	(-10.64)
BTM	0.003**	0.004***	0.006***	0.007***	0.003***	0.005***
	(2.15)	(3.15)	(3.66)	(4.22)	(2.65)	(3.74)
EP	0.012***	0.011***	0.010***	0.008***	0.013***	0.011***
	(11.26)	(10.32)	(6.36)	(5.52)	(11.82)	(10.76)
BETA	0.001	0.001	0.001	0.001	0.001	0.001
	(0.78)	(0.82)	(0.66)	(0.68)	(0.86)	(0.87)
SIC 2-Digit Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
N	55,078	55,078	30,042	30,042	58,294	58,294
Adjusted R^2	0.0651	0.0612	0.0678	0.0648	0.0655	0.0614
P-value from a $\chi2$ test of the difference in Misreporting Measure coefficients:	<0.001		<0.001		<0.001	

Table 10 (continued)
Cross-sectional Regression Tests of the Explanatory Power of Misreporting Measures with Respect to Future Stock Returns

Panel B: Cross-sectional Regressions of Future 24-month Stock Returns on Misreporting Measures

Misreporting Measure:	*MSCORE*	*FSCORE*	*MSCORE*	*AKKM*	*MSCORE*	*FSDSCORE*
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Intercept	-0.397**	-0.483**	-0.067	-0.165	-0.420***	-0.549***
	(-2.06)	(-2.36)	(-0.31)	(-0.74)	(-5.09)	(-6.07)
Misreporting Measure	-0.017***	-0.008***	-0.018***	-0.007*	-0.017***	0.001
	(-8.49)	(-3.56)	(-8.61)	(-1.80)	(-8.83)	(0.80)
SIZE	-0.021***	-0.018***	-0.020***	-0.013***	-0.023***	-0.022***
	(-7.21)	(-6.43)	(-6.97)	(-2.80)	(-8.88)	(-8.41)
BTM	0.007***	0.009***	0.007***	0.009***	0.007***	0.010***
	(2.68)	(3.33)	(2.61)	(3.46)	(2.92)	(3.78)
EP	0.014***	0.013***	0.014***	0.011***	0.015***	0.013***
	(7.15)	(6.53)	(6.86)	(5.68)	(8.08)	(7.13)
BETA	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(-0.78)	(-0.84)	(-0.86)	(-0.78)	(-0.99)	(-0.97)
SIC 2-Digit Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
N	50,990	50,990	48,964	48,964	58,294	58,294
Adjusted R^2	0.0682	0.0651	0.0678	0.0638	0.0693	0.0657
P-value from a $\chi 2$ test of the difference in Misreporting Measure coefficients:	<0.001		0.009		<0.001	

Misreporting Measure:	*MSCORE*	*absABNACC*	*MSCORE*	*AGR*	*DISTORT*	*INCENT*
	(4a)	(4b)	(5a)	(5b)	(6a)	(6b)
Intercept	0.175	0.098	-0.454**	-0.557***	-0.427***	-0.539***
	(1.19)	(0.68)	(-2.56)	(-3.24)	(-5.26)	(-5.95)
Misreporting Measure	-0.017***	-0.002	-0.015***	-0.007***	-0.016***	-0.001
	(-8.77)	(-1.56)	(-5.98)	(-2.97)	(-8.78)	(-0.76)
SIZE	-0.022***	-0.021***	-0.022***	-0.020***	-0.023***	-0.022***
	(-8.42)	(-8.09)	(-6.00)	(-5.35)	(-8.88)	(-8.47)
BTM	0.007***	0.009***	0.011***	0.013***	0.008***	0.009***
	(2.77)	(3.48)	(3.21)	(3.77)	(3.01)	(3.64)
EP	0.015***	0.013***	0.012***	0.009***	0.015***	0.013***
	(7.58)	(6.66)	(4.81)	(3.78)	(8.02)	(7.15)
BETA	-0.002	-0.002	-0.003	-0.003	-0.002	-0.002
	(-1.08)	(-1.03)	(-1.02)	(-0.96)	(-0.98)	(-0.96)
SIC 2-Digit Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Quarter Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes
N	55,078	55,078	30,042	30,042	58,294	58,294
Adjusted R^2	0.0683	0.0645	0.0783	0.0760	0.0693	0.0657
P-value from a $\chi 2$ test of the difference in Misreporting Measure coefficients:	<0.001		0.020		<0.001	

The dependent variable in Panel A (Panel B) is defined as the future 12-month (24-month) abnormal buy-and-hold return, i.e., the buy-and-hold return for the firm minus the buy-and-hold return for the CRSP value-weighted market portfolio, where the return accumulation begins 1 month after quarter q and ends 12 months after quarter q (24 months after quarter q). Misreporting Measure equals the quarter q firm-quarter value for MSCORE, FSCORE, AKKM, FSDSCORE, absABNACC, AGR, DISTORT component of MSCORE, or INCENT component of MSCORE. SIZE is the natural log of market value of equity measured at the end of quarter q. BTM is the natural log of book-to-market ratio measured at the end of quarter q. EP is earnings-per-share scaled by stock price measured at the end of quarter q. BETA is CAPM beta for quarter q. All independent variables are decile ranked by calendar quarter. The decile ranking variable, Misreporting Measure, uses the same firm-quarter values used to construct the aggregate measures we examine in Table 3. A seemingly unrelated estimation (SUEST) is used to test the equality of the Misreporting Measure coefficients between models, where Model 1 compares MSCORE and FSCORE, Model 2 compares MSCORE and AKKM, Model 3 compares MSCORE and FSDSCORE, Model 4 compares MSCORE and absABNACC, Model 5 compares MSCORE and AGR, and Model 6 compares DISTORT component of MSCORE and INCENT component of MSCORE. t-statistics based on two-tailed tests are reported in parentheses. Statistical significance at the 0.01, 0.05, and 0.10 level is denoted by ***, **, and *, respectively. Standard errors are clustered by firm.