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Prior studies attribute analysts' forecast superiority over time-series forecasting models to their access to a large set of rm, industry, and macroeconomic information (an information advantage), which they use to update their forecasts on a daily, weekly or monthly basis (a timing advantage). This study leverages recently developed mixed data sampling (MIDAS) regression methods to synthesize a broad spectrum of high frequency data to construct forecasts of rm-level earnings. We compare the accuracy of these forecasts to those of analysts at short horizons of one quarter or less. We find that our MIDAS forecasts are more accurate and have forecast errors that are smaller than analysts' when forecast dispersion is high and when the rm size is smaller. In addition, we find that combining our MIDAS forecasts with analysts' forecasts systematically outperforms analysts alone, which indicates that our MIDAS models provide information orthogonal to analysts. Our results provide preliminary support for the potential to automate the process of forecasting rm-level earnings, or other accounting performance measures, on a high-frequency basis.

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Automated Earnings Forecasts: Beat Analysts or Combine and Conquer?*

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April 10, 2017

Abstract

Prior studies attribute analysts' forecast superiority over time-series forecasting models to their access to a large set of firm, industry, and macroeconomic information (an *information* advantage), which they use to update their forecasts on a daily, weekly or monthly basis (a *timing* advantage). This study leverages recently developed mixed data sampling (MIDAS) regression methods to synthesize a broad spectrum of high frequency data to construct forecasts of firm-level earnings. We compare the accuracy of these forecasts to those of analysts at short horizons of one quarter or less. We find that our MIDAS forecasts are more accurate and have forecast errors that are smaller than analysts' when forecast dispersion is high and when the firm size is smaller. In addition, we find that combining our MIDAS forecasts with analysts' forecasts systematically outperforms analysts alone, which indicates that our MIDAS models provide information orthogonal to analysts. Our results provide preliminary support for the potential to automate the process of forecasting firm-level earnings, or other accounting performance measures, on a high-frequency basis.

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1 Introduction

Corporate earnings are a key input of asset pricing models and a primary indicator of companies' current and future financial health. Therefore, it is not surprising that company stakeholders (e.g., managers, investors, regulators, banks, analysts, the media) devote significant resources to producing timely and accurate forecasts of future earnings.

A large body of prior research has examined the forecast accuracy of regression-based time-series models and has generally concluded that they cannot match the forecast performance of professional analysts, especially at short forecast horizons of one quarter or less.[1] The empirical evidence for the superiority of analysts' forecasts suggests that analysts perform better because they have access to a broader spectrum of information that is frequently observed (i.e., they have both an *informational* and a *timing* advantage).

From a simple random walk to more complex ARIMA models, time-series models commonly used to forecast quarterly earnings generally rely on past earnings and/or other quarterly accounting measures (e.g., change in inventory levels or sales growth) as predictor variables. This restricts their ability to compete with analysts because of the limited frequency and scope of information employed. Because these models condition quarterly earnings forecasts on past time series of quarterly accounting data, forecasts for a given quarter can be updated only once each quarter and therefore will not change within short forecast horizons of one quarter or less. In addition, the regression-based nature of time-series models and a limited history of quarterly data significantly restricts the scope of information included in the forecasting model. In contrast, analysts have access to all available public (and potentially to private) information from a wide range of sources that are frequently updated (e.g., daily, weekly, monthly). This permits analysts to update their forecasts within short

[1] Representative studies in this area include Brown and Rozeff (1978), Collins and Hopwood (1980), Fried and Givoly (1982), Brown et al. (1987), O'Brien (1988), and Bradshaw et al. (2012). Bradshaw et al. (2012) find that earnings per share forecasts from a simple random walk model are more accurate than analyst forecasts over longer horizons, for smaller or younger firms, and when analysts forecast negative or large changes in earnings per share. For this reason, we focus on forecasts at the more challenging horizon of one quarter or less.

forecast horizons of one quarter or less.[2]

In this paper, we level the playing field by infusing a broader scope of high-frequency information into a time-series forecasting model.[3] We address three important issues: (1) does a richer time-series forecasting model *improve* performance relative to a basic autoregressive model, (2) can a richer time-series forecasting model *beat* analysts at short horizons of one fiscal quarter or less, and (3) if it cannot, then does combining the richer time-series model with analyst forecasts *conquer* analysts by themselves? Consider an analogy to the profound changes now taking place in the car industry. Some companies, like Ford and Google, are designing fully automated, driverless cars that do not rely on human intervention. Other manufacturers, notably General Motors, are betting on a less ambitious technology that complements and assists an actively engaged driver. This fundamental distinction parallels the two issues we address in the context of earnings forecasts. On one end of the spectrum is the first issue: whether or not we can fully automate earnings forecasts by making them computer-driven without input from analysts. At the other end is the second issue: whether model-based earnings forecasts provide complementary information to analysts, thereby improving the overall quality of earnings forecasts. In addition to prior quarterly earnings and five accounting-based fundamental signals considered by prior time-series forecasting models (e.g., Lev and Thiagarajan, 1993; Abarbanell and Bushee, 1997), we consider two firm-level stock return variables and six macroeconomic variables as predictors of quarterly earnings. Including these additional predictor variables is a key aspect of our study because they are observable at high frequencies, which facilitates real-time updating for our time-series forecasts.

We leverage two new econometric developments to overcome the challenges of using large amounts of high-frequency data in a regression-based time-series model. First, we use mixed

[2]Evidence exists that analysts fail to fully incorporate all available information from timely sources (e.g., stock returns). For example, Abarbanell (1991) finds that analysts do not fully incorporate information that past stock prices reflect.

[3]Throughout this paper, we describe the frequency of data in relative terms. Specifically, we use the terms "low" or "lower" to describe data that are observable on a quarterly basis (at best) and "high" or "higher" to describe data observable more frequently than quarterly (e.g., daily, weekly, monthly).

data sampling (MIDAS) regressions to build our time-series models.[4] The key feature of MIDAS models is that they permit high-frequency regressors (e.g., monthly stock returns) to enter a regression with a lower-frequency dependent variable (e.g., quarterly earnings). This critical feature permits our time-series model to include more timely information from firm-level monthly stock returns and monthly macroeconomic data, in a manner similar to analysts.

Second, we estimate a separate forecasting model for each of the thirteen predictor variables, which accommodates the large amount of information we consider. For a given firm, quarter and forecast horizon, this results in thirteen different forecasts of the same quarterly earnings number. We use a forecast combination method, based on the historical forecasting accuracy of each predictor variable, to distill a (potentially) diverse set of thirteen forecasts into one composite forecast, which we refer to as a MIDAS-combination forecast. We then evaluate the out-of-sample performance of these forecasts relative to the accuracy of an autoregressive time-series model examined in prior studies (e.g., Brown and Rozeff, 1978; Brown et al., 1987; O'Brien, 1988; Bradshaw et al., 2012) and analysts' consensus forecasts.

By using more frequent observations and a broader information set within a new class of time-series models, we find that our MIDAS-combination forecasts errors are economically and statistically smaller that those produced by a traditional autoregressive time-series model. Specifically, at the beginning of the quarter for which we forecast earnings (hereafter, the target quarter), we find that MIDAS-combination forecast errors are 30% lower than forecast errors from the benchmark autoregressive model. The performance of MIDAS-combination forecasts increases to 36% at the shorter forecast horizon at the end of the target quarter. Overall, these results underscore the importance of considering a broad scope and frequency of information in regression-based forecasting models.

Our second set of results compares the forecast errors from the MIDAS-combination model to those of analysts. We find that the MIDAS-combination model produces forecast

[4]See Andreou, Ghysels and Kourtellos (2011) and Armesto, Engemann and Owyang (2010) for recent surveys of MIDAS regression methods.

errors that are 10% smaller than analysts' forecast errors at the beginning of the target quarter. More importantly, the superiority of the MIDAS-combination forecasts is most pronounced in observations with high analyst disagreement (i.e., dispersion), in smaller firms, and in specific industries such as Manufacturing and High Tech. These gains are significant only at the longer forecast horizon at the beginning of the target quarter.

Our last set of results compares the relative performance of a unique combination of analysts *and* MIDAS-combination forecasts to predictions from analysts alone. Our findings are surprisingly sharp as we find that we are *always* better off combining MIDAS-combination forecasts with those of analysts.[5] At the beginning (end) of the target quarter, the combination of model-based and analyst forecasts reduced the forecast error by 21% (11%) relative to analysts forecasts alone. This means that the MIDAS and analyst forecasts feature complementary information.

This study contributes to a large body of research that has generally concluded that analysts' forecasts are superior to those of time-series models because of their *information* and *timing* advantages (e.g., Brown and Rozeff, 1978; Brown et al., 1987; Bradshaw et al., 2012).[6] A technique commonly employed in these studies is to level the playing field by *reducing* analysts' information and timing advantages by considering only the forecasts issued before the release of prior financial statement information. In contrast, our research design levels the playing field by *increasing* the amount and frequency of information used in time-series models to a level consistent with the information used by analysts to compare forecasting accuracy at short horizons. This is an important distinction because the higher performance of MIDAS-combination forecasts at short forecast horizons implies that they can be used to estimate earnings expectations that are updated relatively frequently in settings where analysts do not provide coverage (e.g., small public firms, most private firms, international settings). In addition, our MIDAS-combination method can be extended to forecasts of other

[5]This finding indicates that analysts, like car drivers, significantly benefit from technological intervention.

[6]In a review of capital markets research in accounting, Kothari (2001) states, "in recent years it is common practice to (implicitly) assume that analysts' forecasts are a better surrogate for market's expectations than time-series forecasts."

financial statement performance measures (e.g., sales, cost of goods sold, income taxes, cash flows, accounting accruals) that are not covered by analysts.

We also contribute to a burgeoning literature on MIDAS-based forecasting by providing the first application to forecast a firm-level financial statement performance measure (i.e., quarterly earnings).[7] In contrast, the MIDAS regression framework was first applied to forecasting market-level return volatility (Ghysels, Santa-Clara and Valkanov, 2005) and a large number of subsequent studies have focused primarily on applications involving forecasts of macroeconomic variables (e.g., Clements, Galvão and Kim, 2008; Armesto et al., 2009; Andreou, Ghysels and Kourtellos, 2013). Overall, the inherently low-frequency nature of firm-level financial statement data (i.e., quarterly or annual), the availability of other high-frequency firm- and market-level data (e.g., daily stock return, monthly GDP), and the results of our study illustrate the applicability of MIDAS regressions to capital markets research in accounting.

The remainder of the paper is organized as follows. Section 2 describes the data sources and measurements of the dependent variable (quarterly earnings) and thirteen firm-level and macroeconomic predictor variables used in our time-series models. Section 3 describes the MIDAS forecasting model, the forecast combination technique, the forecast accuracy evaluation method and three empirical tests. Section 4 presents the empirical results, and section 5 concludes.

[7] Ball and Easton (2013) use MIDAS regressions to identify two distinct elements of the accounting system by examining how the contemporaneous association between high-frequency daily returns and low-frequency annual earnings changes within the fiscal year. In contrast, our study uses MIDAS regressions to assess the accuracy of out-of-sample forecasts of firm-level earnings.

2 Data

2.1 Definition of variables

We forecast firm-level quarterly earnings per share (EPS) using low-frequency quarterly accounting data and high-frequency monthly firm-level stock market and macroeconomic data as predictor variables. Throughout, we distinguish these predictor variables by an index k. The following subsections describe all variables, and Table 1 details their category, frequency, and measurement.

2.1.1 Quarterly firm-level earnings and other accounting predictor variables

The primary variable of interest is firm-level quarterly EPS, ΔE_q, which is collected from I/B/E/S and first-differenced to account for potential non-stationarity. Specifically, we compute the difference between the I/B/E/S actual quarterly EPS values in the current quarter q and the prior fiscal quarter (i.e., $\Delta E_q = E_q - E_{q-1}$), which is described in Table 1, panel A.[8]

In addition to quarterly earnings, we consider five quarterly accounting-based predictor variables. We use quarterly changes in inventory (k=1), accounts receivable (k=2), capital expenditures (k=3), gross margin (k=4), and selling, general and administrative (SG&A) expenses (k=5), which have been examined by previous studies that forecast quarterly earnings (e.g., Lev and Thiagarajan, 1993; Abarbanell and Bushee, 1997).

2.1.2 Monthly firm-level stock market predictor variables

We also consider eight additional high-frequency predictor variables: two firm-level stock market variables and six macroeconomic variables. These monthly variables expand the scope of information contained in our forecast model and facilitate real-time updating at short forecast horizons.

[8]Prior actual EPS values are share-adjusted to account for interim stock splits, which facilitates comparability with EPS in the current quarter.

The two firm-level stock market predictor variables, excess stock returns and return volatility, are constructed from daily and monthly data available on CRSP. Excess stock return (k=6) is equal to the monthly return of the firm less the monthly same-industry portfolio return.[9] Return volatility (k=7) is computed as the average of squared daily stock return during a given month.

These two predictor variables are intended to capture investors' expectations and uncertainty about the firm's future earnings. In addition, they are more forward-looking and are updated more frequently than accounting-based fundamental signals. Therefore, these two predictors potentially incorporate timely information in our time-series regression forecasting models.

2.1.3 Monthly macroeconomic predictor variables

We include six monthly macroeconomic predictor variables: industrial production, index, oil prices, Treasury bill (T-bill) yields, the term spread and the default spread. All six variables are constructed from data retrieved from Federal Reserve Economic Data (FRED), which is maintained by the Federal Reserve Bank of St. Louis.

We include these variables because they reflect the overall state of the economy and aggregate demand conditions. They may also capture meaningful variation in firm-level earnings because of fluctuations in the business cycle. Industrial production(k=8) is a leading business cycle indicator. Rising industrial production often signals economic expansion, which can provide a signal about future earnings. Inflation (k=9) is a predictor variable that provides a complex signal about future earnings. Because firm-level earnings are reported in nominal dollars, high inflationary periods could signal stronger profits. On the other hand, the tax benefits from depreciating fixed assets based on historical costs would be reduced in an inflationary environment, which would reduce nominal profits.

Oil prices (k=10) provide a signal about future earnings through two potential channels.

[9] Industry affiliation is based on the Fama-French 10-industry classification, and monthly industry portfolio returns come from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Rising oil prices often signal economic prosperity, which would indicate increased earnings through a demand channel. From a supply perspective, oil prices and derivative products are often used as raw materials for production in many industries, which suggests that rising oil prices could signal lower future earnings by increasing the firm's expenses. T-bill rates (k=11) represent the cost of short-term borrowing. An increase in T-bill rates may signal increased interest expense, which would lower future earnings. From a business cycle perspective, higher T-bill rates may reflect a growing demand for funds during an expansionary period and, therefore, signal higher future earnings. The term spread (k=12) is the difference between the yields on a ten-year Treasury bond and a three-month T-bill and is often used a leading indicator of output growth and recessions (Wheelock and Wohar, 2009). Also, because firms are on average net borrowers of long-term funds, an increase in term spread can signal lower future earnings because of increased future interest payments.

Finally, the default spread (k=13) is the difference between yields on ten-year AAA-rated and BAA-rated corporate bonds. An increase in default spread could signal increased overall risk in the economy and a deterioration of credit quality. This would imply that firms are saddled with less favorable macroeconomic conditions and higher borrowing costs, which could stunt earnings growth.

2.2 Sample Description

Our sample contains firm-level observations between 1984 and 2014 with required data from I/B/E/S, Compustat, CRSP and FRED to compute quarterly earnings and all thirteen predictor variables. In order to ensure a sufficient number of observations to estimate the time-series regression models described in the next section, we exclude firms with fewer than forty-nine consecutive quarters of available data to compute earnings and all thirteen predictor variables. This restriction biases our sample towards larger and more successful firms.

Our final sample contains 1,057 firms. Table 2 reports the number of firms by industry

affiliation based on the Fama-French 10-industry classification. Manufacturing (MANUF) and high-technology (HITEC) industries represent the largest fractions (24.9% and 23.8%, respectively) of firms in the sample.

3 Econometric methods

This section outlines the econometric methods used to estimate and evaluate out-of-sample forecasts of firm-level quarterly earnings at horizons of zero and three months prior to the end of the fiscal quarter. Throughout, we identify a firm by the subscript f, a fiscal quarter by the subscript q, and a forecast horizon by the subscript h. Observations are identified by a unique combination of f, q, and h. Within each unique observation, we construct a number of out-of-sample forecasts from time-series regression models and analysts' consensus estimates.

Section 3.1 describes our two benchmark forecasting models based on analysts' consensus estimates and an autoregressive time-series regression. These benchmark forecasts are used to evaluate the performance of our MIDAS-combination forecasts, which are developed in section 3.2. Finally, section 3.3 describes the forecast evaluation methods we use in the three empirical tests we perform.

3.1 Benchmark forecasts

The first benchmark model is based on a consensus of analysts' forecasts. For a given firm f, quarter q, and forecast horizon h prior to the end of fiscal quarter q, we use the median of all individual analysts' quarterly EPS estimates collected from I/B/E/S and first-difference it to maintain consistency with the definition of ΔE_q (see section 2.1.1).[10] Specifically, the

[10] We use the median forecast as the analysts' consensus benchmark because it is often used in the accounting and finance literature, as well as in practice. In addition, the median consensus forecast reflects a combination of individual analysts' forecasts (i.e., a non-parametric "average") that parallels the forecast combination method we employ to aggregate individual regression-based forecasts (see section 3.2.3). However, the median forecast benchmark does not necessarily reflect the "best" combination of individual analysts' forecasts. Therefore, the results of this study, which focuses on the out-of-sample performance of an optimal combination of regression-based forecasts, should be interpreted relative to the median analysts' consensus and *not* relative to the "best" consensus. The determinants of the "best" analysts' forecast, which

analysts' consensus benchmark forecast, $\Delta\hat{E}^{Analyst}_{f,q,h}$, is equal to the median value, $\hat{E}^{Analyst}_{f,q,h}$, of all analysts' most recent EPS estimates of firm f's quarter q EPS that were issued prior to the date on which the consensus forecast is formed (h months prior to the end of fiscal quarter q) minus the split-adjusted actual quarterly EPS values reported in I/B/E/S for the prior fiscal quarter (i.e., $\Delta\hat{E}^{Analyst}_{f,q,h} = \hat{E}^{Analyst}_{f,q,h} - E_{q-1}$).[11] Throughout the paper, we focus on two forecast horizons: h=3 months prior to the end the target quarter and h=0 (i.e., the end of the target quarter). In other words, we examine forecasts made at the end of quarter $q-1$ for quarter q, and we forecast for the same target quarter but with the advantage of having all the monthly data released during the quarter.

Our second benchmark forecast is constructed from a basic autoregressive (AR) time-series regression model used in a number of prior studies (e.g., Brown et al., 1987; Bradshaw et al., 2012), as follows:

$$\Delta E_q = \alpha + \sum_{i=1+\frac{h}{3}}^{I^*} \phi_i \cdot \Delta E_{q-i} + \varepsilon_q, \qquad \text{(AR model)}$$

where ΔE_q is the difference between EPS in the current quarter, q, and EPS in the prior quarter, $q-1$; α and ϕ_i are model parameters; and I^* is the number of lags of ΔE_q included in the model and is selected using the Bayesian Information Criterion (BIC).

The lagged values of ΔE_{q-i} begin at $i=1+\frac{h}{3}$, which accounts for the fact that firms typically release quarterly accounting information one or two months after the end of the fiscal quarter. Therefore, if the AR forecast is constructed at a horizon of h=0 months prior to the end of the fiscal quarter, then the lag index begins at $i=1+\frac{0}{3}=1$, and EPS from the prior fiscal quarter, $q-1$, is included in the model because it was observable at the time of the forecast. In contrast, if the AR forecast is constructed at a horizon of h=3 months prior

is not known ex ante, are outside the scope of this paper and are left for future research.

[11] For example, consider Walmart's third fiscal quarter (Q3) ending on October 31, 2012. If the forecast horizon is h=3 months prior to the end of Q3 (i.e., July 31, 2012), then the median analysts' consensus benchmark forecast would be based on all of the most recent individual analysts' forecasts that were issued on or prior to July 31, 2012. Similarly, if the forecast horizon is h=0 months prior to the end of Q3 (i.e., October 31, 2012), then the median analysts' consensus benchmark forecast would be based on all of the most recent individual analysts' forecasts that were issued on or prior to October 31, 2012.

to the end of the fiscal quarter, then the lag index begins at $i{=}1{+}\frac{3}{3}{=}2$, and EPS from the prior fiscal quarter, $q{-}1$, is *not* included in the model because it was *not* observable at the time of the forecast.

For each unique observation (firm f, quarter q, and forecast horizon h), we estimate AR model parameters via OLS using a rolling-window sample of data from the firm's 40 most recent fiscal quarters. The AR benchmark forecast, $\Delta\hat{E}^{AR}_{f,q,h}$, is equal to the out-of-sample predicted value in quarter q from the estimated model.

3.2 MIDAS-combination forecasts

This section describes the two-step procedure we use to construct MIDAS-combination forecasts. The first step estimates regression-based forecasts based on one of two different types of time-series models that are separately estimated for each of our thirteen predictor variables. The two models, described in sections 3.2.1 and 3.2.2, are distinguished by whether the predictor variables are available at a relatively low quarterly frequency or a relatively high monthly frequency. The second step, described in section 3.2.3, uses a forecast combination technique to aggregate the individual time-series model forecasts into one composite forecast, which we term a MIDAS-combination forecast.

3.2.1 Augmented distributed lag forecast model

The first model used to construct regression-based forecasts is an augmented distributed lag (ADL) model, which augments the AR model with one *low*-frequency predictor variable as follows:

$$\Delta E_q = \alpha + \sum_{i=1+\frac{h}{3}}^{I^*} \phi_i \cdot \Delta E_{q-i} + \sum_{j=1+\frac{h}{3}}^{J^*} \beta_j \cdot X^k_{q-j} + \varepsilon_q, \qquad \text{(ADL model)}$$

where ΔE_q is the difference between EPS in the current quarter, q, and EPS in the prior quarter, $q{-}1$; X^k_q is one of five accounting-based predictor variables ($1 \leq k \leq 5$) in fiscal

quarter q;[12] α, ϕ_i and β_j are model parameters; and I^* and J^* are the number of lags of ΔE_q and X_q^k, respectively, included in the model, and both are selected using the Bayesian Information Criterion (BIC). As in the AR model described in section 3.1, the first lagged values of ΔE_{q-i} and X_q^k included in the ADL model depend on the forecast horizon h (i.e., $i = j = 1 + \frac{h}{3}$) to account for any delay in the release of quarterly accounting-based information.

We separately estimate ADL model parameters via OLS for each accounting-based predictor variable ($1 \leq k \leq 5$) and each unique observation (firm f, quarter q, and forecast horizon h) using a rolling-window sample of data from the firm's 40 most recent fiscal quarters. The resulting ADL forecast, $\Delta \hat{E}_{f,q,h}^k$, is equal to the out-of-sample predicted value in quarter q from the estimated model.

In principle, the ADL model could also be applied to the eight remaining stock market and macroeconomic predictor variables (i.e., $6 \leq k \leq 13$), which are more frequently observable. However, estimating the ADL model would require temporally aggregating (daily or) monthly values to a quarterly observation that coincides with the fiscal quarter of the firm. This method has two important drawbacks. First, temporal aggregation limits the ability of the time-series model to optimally use the real-time flow of information throughout the quarter, which is useful for providing updated real-time forecasts at short horizons within the fiscal quarter. Second, using quarterly regressors based on aggregated high-frequency data implicitly restricts the regression parameters, β_j, to be temporally constant throughout the fiscal quarter. If some months within the quarter contain more relevant forecasting information than others, then that information will be lost in the process of aggregating the high-frequency data.[13]

[12] As described in Table 1, panel B and section 2.1.1, the five accounting-based predictor variables are inventory (k=1), accounts receivable (k=2), capital expenditures (k=3), gross margin (k=4), and SG&A expense (k=5).

[13] For example, Ball and Easton (2013) hypothesize and provide evidence that properties of the accounting system result in a higher association between earnings and daily returns at the beginning of the fiscal period than at the end of the fiscal period.

3.2.2 ADL-Mixed data sampling forecast model

The second model used to construct regression-based forecasts employs a mixed data sampling (MIDAS) framework, which is designed to exploit high-frequency information embedded in the eight remaining stock market and macroeconomic predictor variables.[14] Specifically, we augment the AR model with a MIDAS specification (ADL-MIDAS) that utilizes one *high*-frequency predictor variable as follows:

$$\Delta E_q = \alpha + \sum_{i=1+\frac{h}{3}}^{I^*} \phi_i \cdot \Delta E_{q-i} + \sum_{j=\frac{h}{3}}^{J^*} \sum_{m=1}^{3} \theta_{q-j,m} \cdot x^k_{q-j,m} + \varepsilon_q, \qquad \text{(ADL-MIDAS model)}$$

where ΔE_q is the difference between EPS in the current quarter, q, and EPS in the prior quarter, $q-1$; $x^k_{q,m}$ is one of eight firm-level stock market and macroeconomic predictor variables ($6 \leq k \leq 13$) in month m within fiscal quarter q; α, ϕ_i and $\theta_{q,m}$ are model parameters; and I^* and J^* are the number of lagged quarters of ΔE_q and $x^k_{q,m}$, respectively, included in the model, and both are selected using the Bayesian Information Criterion (BIC).[15]

As in the AR model, the first lagged value of ΔE_{q-i} included in the ADL-MIDAS model depends on the forecast horizon h (i.e., $i=1+\frac{h}{3}$) in order to account for any delay in the release of quarterly accounting-based information. In contrast, the high-frequency stock market and macroeconomic predictor variables are readily observable, so information up to the forecast date is included in the model by specifying the beginning lag index as $j=\frac{h}{3}$.[16]

[14]MIDAS regressions are a class of forecasting models, developed by Ghysels, Santa-Clara and Valkanov (2006), Ghysels and Wright (2009), Andreou, Ghysels and Kourtellos (2010) and Chen and Ghysels (N.d.), that are designed to directly exploit real-time, high-frequency data. Recent studies find that MIDAS models using daily and monthly data significantly improve out-of-sample forecasts of quarterly macroeconomic variables (e.g., Schumacher and Breitung, 2008; Clements, Galvão and Kim, 2008; Armesto et al., 2009; Kuzin, Marcellino and Schumacher, 2011; Andreou, Ghysels and Kourtellos, 2013).

[15]The two monthly firm-level stock market predictor variables (see Table 1, panel C and section 2.1.2) are excess stock return (k=6) and return volatility (k=7). The six monthly macroeconomic predictor variables (see Table 1, panel D and section 2.1.3) are industrial production (k=8), inflation (k=9), oil prices (k=10), T-bill yields (k=11), the term spread (k=12), and the default spread (k=13).

[16]The six monthly macroeconomic predictor variables are measured with a lag of one month in order to account for any delay in the release of the information (see Table 1, panel D and section 2.1.3). Therefore, the lag structure in the ADL-MIDAS model does not directly account for any delay in the release of this information because it is already embedded in the variable definition. The two monthly stock market predictor variables do not need to be adjusted because they are observable in real time.

For example, if the ADL-MIDAS forecast is constructed at a horizon of h=0 months prior to the end of the fiscal quarter, then the lag index begins at $j=\frac{0}{3}=0$, and the model includes high-frequency data from all three months within the current fiscal quarter, q, as well as earlier quarters, $q-j$. If the ADL-MIDAS forecast is constructed at a horizon of h=3 months prior to the end of the fiscal quarter, then the lag index begins at $j=\frac{3}{3}=1$, and the model begins with high-frequency data from all three months within the *prior* fiscal quarter, $q-1$, as well as earlier quarters, $q-j$, but *not* from the current fiscal quarter, q.

We separately estimate ADL-MIDAS model parameters via OLS for each stock market and macroeconomic predictor variable ($6 \leq k \leq 13$) and each unique observation (firm f, quarter q, and forecast horizon h) using a rolling-window sample of data from the firm's 40 most recent fiscal quarters. The resulting ADL-MIDAS forecast, $\Delta\hat{E}^{k}_{f,q,h}$, is equal to the out-of-sample predicted value in quarter q from the estimated model.[17]

3.2.3 Forecast Combinations

For each unique observation (firm f, quarter q, and forecast horizon h) with at least 40 prior quarters of available data, we separately estimate the ADL and ADL-MIDAS models for each of the thirteen predictor variables, which results in thirteen out-of-sample forecasts, $\Delta\hat{E}^{k}_{f,q,h}$, where $1 \leq k \leq 13$. In addition, a consensus analyst benchmark forecast, $\Delta\hat{E}^{Analyst}_{f,q,h}$, and an AR model benchmark forecast, $\Delta\hat{E}^{AR}_{f,q,h}$, are computed for total of fifteen out-of-sample forecasts available for each unique observation. This section describes two forecast combination schemes that we use to aggregate these individual forecasts to produce a single composite forecast.

Forecast combination methods offer an effective way to summarize a large amount of information provided by many predictors. In a survey of the literature, Timmermann (2006) points out that estimating a separate regression for each predictor and then using forecast combination methods is more robust to model misspecification and measurement error than

[17] Technically speaking, this approach involving OLS estimation is called U-MIDAS. See Foroni, Marcellino and Schumacher (2015) for further details.

estimating a single forecasting model that includes all predictors. In addition, combination methods have better out-of-sample forecasting performance than the best-performing individual model (e.g., Makridakis and Winkler, 1983; Gupta and Wilton, 1987; Hendry and Clements, 2004).

Our first combination scheme constructs a MIDAS-composite (MC) forecast, $\Delta\hat{E}^{MC}_{f,q,h}$, for each unique observation based on a weighted-average of all thirteen ADL and ADL-MIDAS regression-based forecasts, $\Delta\hat{E}^{k}_{f,q,h}$ $(1 \leq k \leq 13)$. The MC forecast is computed as follows:

$$\Delta\hat{E}^{MC}_{f,q,h} = \sum_{k=1}^{13} \omega^{k}_{f,q,h} \cdot \Delta\hat{E}^{k}_{f,q,h}, \tag{1}$$

where $\omega^{k}_{f,q,h}$ is the weight applied to the forecast based on predictor variable k (i.e,. $\Delta\hat{E}^{k}_{f,q,h}$), which is computed for firm f at a forecast horizon of h months prior to the end of fiscal quarter q.

Our weighting scheme depends on the relative historical performance of the thirteen individual predictor variables. Specifically, we compute weights using a discounted mean squared forecast error (DMSFE) weighting scheme, which depends on the historical accuracy of forecast variable k relative to the historical accuracy of all forecasts. In addition, forecast errors from the distant past are discounted relative to more recent forecast errors (e.g., Diebold and Pauly, 1987; Stock and Watson, 2004). For each unique observation, the weight applied to an individual forecast based on predictor variable k, $\omega^{k}_{f,q,h}$, is calculated as follows:

$$\omega^{k}_{f,q,h} = \frac{(m^{k}_{f,q,h})^{-1}}{\sum_{n=1}^{13}(m^{n}_{f,q,h})^{-1}}, \tag{2}$$

where $m^{k}_{f,q,h} = \sum_{s=1}^{8} \delta^{s} \left(FE^{k}_{f,q-s,h}\right)^{2}$ is the DMSFE, with discount factor δ=0.95, and $FE^{k}_{f,q-s,h}$ is the historical forecast error from fiscal quarter $q-s$, which is equal to the difference between the actual and forecasted EPS values (i.e., $\Delta E_{f,q-s} - \Delta\hat{E}^{k}_{f,q-s,h}$). We compute weights for each of the thirteen predictor variables $(1 \leq k \leq 13)$ using forecast errors from the eight most

recent prior quarters ($1 \leq s \leq 8$).

Our second combination scheme constructs a composite forecast, $\Delta\hat{E}^{MC\text{-}An}_{f,q,h}$, for each unique observation based on the weighted average of the analysts' consensus forecast, $\Delta\hat{E}^{Analyst}_{f,q,h}$, *and* all thirteen ADL and ADL-MIDAS regression-based forecasts, $\Delta\hat{E}^{k}_{f,q,h}$ ($1 \leq k \leq 13$). the composite forecast is computed as follows:

$$\Delta\hat{E}^{MC\text{-}An}_{f,q,h} = \omega^{Analyst}_{f,q,h} \cdot \Delta\hat{E}^{Analyst}_{f,q,h} + \sum_{k=1}^{13} \omega^{k}_{f,q,h} \cdot \Delta\hat{E}^{k}_{f,q,h}, \tag{3}$$

where $\omega^{Analyst}_{f,q,h}$ is the weight applied to the analysts' consensus forecast, and $\omega^{k}_{f,q,h}$ is the weight applied to the forecast based on predictor variable k.

As in the first combination scheme, we compute the weights applied to the thirteen regression-based forecasts, $\omega^{k}_{f,q,h}$ ($1 \leq k \leq 13$), and the analysts' consensus forecast, $\omega^{Analyst}_{f,q,h}$, for each unique observation as follows:

$$\omega^{k}_{f,q,h} = \frac{(m^{k}_{f,q,h})^{-1}}{13 \times (m^{Analyst}_{f,q,h})^{-1} + \sum_{n=1}^{13}(m^{n}_{f,q,h})^{-1}}, \tag{4}$$

and:

$$\omega^{Analyst}_{f,q,h} = \frac{13 \times (m^{\text{An}}_{f,q,h})^{-1}}{13 \times (m^{Analyst}_{f,q,h})^{-1} + \sum_{n=1}^{13}(m^{n}_{f,q,h})^{-1}}, \tag{5}$$

where $m^{Analyst}_{f,q,h} = \sum_{s=1}^{8} \delta^{s} \left(FE^{Analyst}_{f,q-s,h}\right)^{2}$ is the DMSFE with discount factor δ=0.95, and $FE^{Analyst}_{f,q-s,h}$ is the historical analysts' consensus forecast error from fiscal quarter $q-s$, which is equal to the difference between the actual and forecasted EPS values (i.e., $\Delta E_{f,q-s} - \Delta\hat{E}^{Analyst}_{f,q-s,h}$). In constructing the weights for this second scheme, we multiply the analyst consensus forecast by a value of 13 (i.e., the number of regression-based forecasts) such that if all forecasts get an equal amount of weight, then one-half of the weight will be applied to the analysts' consensus forecast and the other one-half applied to the collective regression-based forecasts.

3.3 Forecast performance evaluation and three empirical tests

We use the median absolute error ratio (MABER) to evaluate the out-of-sample performance of the combination forecast of interest relative to a benchmark forecast in three empirical tests. Our choice of an absolute-deviation loss function is driven by two factors. First, Basu and Markov (2004) argue and provide evidence that analysts have a linear (or absolute-deviation) loss function. Second, the absolute-deviation loss function is more robust in the presence of outliers in the distribution. Abarbanell and Lehavy (2003) find instances of extreme negative values in the distribution of analysts' forecast errors, which they attribute to firms' recognition of unexpected accruals.

For all three empirical tests, we compute MABER values at a portfolio level, rather than a firm level, because the sample of MIDAS-combination forecasts is limited to firms with at least 49 consecutive quarterly observations of all thirteen predictor variables.[18] For a given forecast horizon, h, we form portfolios by pooling firm-quarter observations based on observable characteristics (e.g., industry, size, calendar year).

Our first test examines whether MIDAS-combination forecasts, which incorporate a broader scope of real-time data, *improve* the out-of-sample performance relative to a basic AR model, which incorporates only a limited amount of lagged low-frequency information. We call this the *improve* test. For a given forecast horizon, h, and portfolio, p, of firm-quarter observations, we evaluate the *improve* test by computing a MABER, $\lambda_{p,h}^{improve}$, that compares MIDAS-combination forecasts to AR model forecasts as follows:

$$\lambda_{p,h}^{improve} \equiv \frac{\text{median}\left(\left|\Delta E_{f,q} - \Delta \hat{E}_{f,q,h}^{MC}\right|\right)}{\text{median}\left(\left|\Delta E_{f,q} - \Delta \hat{E}_{f,q,h}^{AR}\right|\right)} \qquad \forall\,(f,q) \subset p, \tag{6}$$

where $\Delta E_{f,q} - \Delta \hat{E}_{f,q,h}^{MC}$ and $\Delta E_{f,q} - \Delta \hat{E}_{f,q,h}^{AR}$ are the MIDAS-combination and AR model forecast errors, respectively. A value of $\lambda_{p,h}^{improve}$ less than (greater than or equal to) 1.0 indicates

[18] Specifically, 40 prior quarters are required to estimate the ADL or ADL-MIDAS regression models, 8 prior quarters are needed to compute forecast combination weights, and 1 prior quarter is needed to measure MIDAS-combination forecast performance.

that MIDAS-combination forecasts *improve* (do not *improve*) out-of-sample performance relative to basic AR model forecasts.

We implement a bootstrap procedure to assess the statistical significance of $\lambda_{p,h}^{improve}$ estimates. Let $N_{p,h}$ equal the number of firm-quarter forecasts in portfolio p for forecast horizon h. We randomly draw, with replacement, a total of $N_{p,h}$ pairs $(\Delta\hat{E}_{f,q,h}^{MC},\ \Delta\hat{E}_{f,q,h}^{AR})$ from all firm-quarter observations in portfolio p with a given forecast horizon h and re-compute $\lambda_{p,h}^{improve}$ for this bootstrapped sample. We repeat this process 10,000 times to obtain a bootstrapped distribution of $\lambda_{p,h}^{improve}$. The p-value for $\lambda_{p,h}^{improve}$ is equal to the percentage of bootstrapped values that are not less than one.[19] If $\lambda_{p,h}^{improve}$ is less than one, then we conclude that MIDAS combination forecasts do *improve* out-of-sample performance relative to basic AR model forecasts at a level of statistical significance equal to the bootstrapped p-value.

Our second test examines whether MIDAS-combination forecasts *beat* analysts' consensus forecast in out-of-sample performance.[20] We call this the *beat* test. For a given forecast horizon, h, and portfolio, p, of firm-quarter observations, we evaluate the *beat* test by computing the following MABER, $\lambda_{p,h}^{beat}$, which compares MIDAS-combination forecasts to analysts' consensus forecasts:

$$\lambda_{p,h}^{beat} \equiv \frac{\text{median}\left(\left|\Delta E_{f,q} - \Delta\hat{E}_{f,q,h}^{MC}\right|\right)}{\text{median}\left(\left|\Delta E_{f,q} - \Delta\hat{E}_{f,q,h}^{Analysts}\right|\right)} \qquad \forall\,(f,q) \subset p, \tag{7}$$

where $\Delta E_{f,q} - \Delta\hat{E}_{f,q,h}^{MC}$ and $\Delta E_{f,q} - \Delta\hat{E}_{f,q,h}^{Analysts}$ are the MIDAS-combination forecast errors and analysts' consensus forecast errors, respectively. A value of $\lambda_{p,h}^{beat}$ less than (greater than or equal to) 1.0 indicates that MIDAS-combination forecasts *beat* (do not *beat*) analysts' consensus forecasts in out-of-sample performance.

[19] We use the original percentile bootstrap developed by Efron (1979). We expect some time-series as well as cross-sectional dependence, since, for example, we draw firms across time in the same industry. The unbalanced panel data dependence is rather complex, however, and therefore could not be easily handled with, say, a stationary bootstrap scheme (e.g., Politis and Romano, 1994), which applies to a pure time-series setting.

[20] Comparing the out-of-sample performance of MIDAS-combination forecasts with analysts' consensus forecasts parallels a performance comparison between a fully autonomous car and a car driven by a human being.

We implement the bootstrap procedure from the previous *improve* test to evaluate the statistical significance of $\lambda_{p,h}^{beat}$, but we construct the bootstrapped sample from $N_{p,h}$ random draws, with replacement, of pairs ($\Delta\hat{E}_{f,q,h}^{MC}$, $\Delta\hat{E}_{f,q,h}^{Analyst}$). If $\lambda_{p,h}^{beat}$ is less than one, then we conclude that MIDAS combination forecasts *beat* analysts' consensus forecasts at a level of statistical significance equal to the bootstrapped p-value.

Our third and final empirical test determines whether a combination of analysts' consensus forecasts and MIDAS-combination forecasts is able to *conquer* the out-of-sample performance of analysts' consensus forecasts alone.[21] For a given forecast horizon, h, and portfolio, p, of firm-quarter observations, we evaluate the *conquer* test by computing the MABER, $\lambda_{p,h}^{conquer}$, as follows:

$$\lambda_{p,h}^{conquer} \equiv \frac{\text{median}\left(\left|\Delta E_{f,q} - \Delta\hat{E}_{f,q,h}^{MC-An}\right|\right)}{\text{median}\left(\left|\Delta E_{f,q} - \Delta\hat{E}_{f,q,h}^{Analysts}\right|\right)} \qquad \forall\,(f,q) \subset p, \tag{8}$$

where $\Delta E_{f,q} - \Delta\hat{E}_{f,q,h}^{MC-An}$ is the combined analysts' consensus and MIDAS-combination forecast error, and $\Delta E_{f,q} - \Delta\hat{E}_{f,q,h}^{Analysts}$ is the analysts' consensus forecast error. A value of $\lambda_{p,h}^{beat}$ less than (greater than or equal to) 1.0 indicates that a combination of analysts' consensus forecasts and MIDAS-combination forecasts *conquers* (does not *conquer*) analysts' consensus forecasts in out-of-sample performance.

We implement the bootstrap procedure from the previous two tests to evaluate the statistical significance of $\lambda_{p,h}^{conquer}$, but we construct the bootstrapped sample from $N_{p,h}$ random draws, with replacement, of pairs ($\Delta\hat{E}_{f,q,h}^{MC-An}$, $\Delta\hat{E}_{f,q,h}^{Analyst}$). If $\lambda_{p,h}^{conquer}$ is less than one, then we conclude that MIDAS-combination forecasts complement analysts' forecasts by combining to *conquer* analysts' consensus forecasts alone at a level of statistical significance equal to the bootstrapped p-value.

[21] Comparing the out-of-sample performance of a combination of analysts' consensus forecasts and MIDAS-combination forecasts evaluates their ability to complement one another. This is analogous to evaluating technology-assisted cars driven by human beings.

4 Empirical results

This section summarizes our study's key empirical results. Sections 4.1, 4.2, and 4.3 present results from the *improve*, *beat*, and *conquer* tests, respectively. Section 4.4 explores whether our results are driven by informational efficiencies or reduced biases.

4.1 *Improve* test results

Columns 1 and 2 of Table 3 present $\lambda_{p,h}^{improve}$ estimates for all firm-quarter observations and by industry portfolios for forecast horizons of h=0 and h=3 months prior to end of the fiscal quarter. At the shorter forecast horizon of h=0 months (reported in column 1), the estimated $\lambda_{p,0}^{improve}$ for the full sample is 0.645, which is less than 1.0 at a 1% level of statistical significance. This indicates that MIDAS-combination forecasts reduce the median forecast error magnitude by 35.5% relative to AR model forecasts. Across industry portfolios, $\lambda_{p,0}^{improve}$ is always less than one with values ranging from 0.509 in the NODUR industry (an improvement of 49.1%), to 0.865 in the TELCM industry (an improvement of 13.5%). All values are less than 1.0 at a 1% level of statistical significance except for the TELCM industry, which has a 5% level of statistical significance.

Similar results are obtained at the longer forecast horizon of h=3 months (reported in column 2). For the full sample of firm-quarter observations, the estimated value of $\lambda_{p,3}^{improve}$ is 0.708 (29.2% improvement) and is less than 1.0 at a 1% level of statistical significance. $\lambda_{p,3}^{improve}$ is less than one in all ten industry portfolios, with values ranging from 0.504 (49.6% improvement) in the NODUR industry to 0.892 (10.8% improvement) in the ENRGY industry. All industry portfolio values are less than 1.0 at a 1% level of statistical significance, with the exception of the TELCM (5% level) and ENRGY (10% level) industries.

Columns 1 and 2 of Table 4 provide $\lambda_{p,h}^{improve}$ estimates by calendar-year portfolios for forecast horizons of h=0 (column 1) and h=3 (column 2). For both forecast horizons and across all calendar-year portfolios, $\lambda_{p,h}^{improve}$ estimates are less than 1.0 at a 1% level of statis-

tical significance with values ranging between a low of 0.597 (40.3% improvement) in 2011 (h=0) to a high of 0.812 (18.8% improvement) in 2006 (h=3).

Overall, these results of the *improve* tests provide strong and clear evidence that our MIDAS-combination forecasts provide an economically and statistically significant improvement over AR model forecasts. In addition, these results provide a strong foundation to support the subsequent *beat* and *conquer* tests, which we discuss in the next two sections.

4.2 *Beat* test results

This section presents results from the *beat* test, which directly compares the out-of-sample performance of our MIDAS-combination forecasts to analysts' consensus forecasts. The third columns of Tables 3 and 4 present $\lambda_{p,0}^{beat}$ estimates by industry portfolios and calendar-year portfolios, respectively, at the shorter forecast horizon of h=0 months prior to end of the fiscal quarter. $\lambda_{p,0}^{beat}$ estimated for the overall sample is 1.251, which indicates that our MIDAS-combination forecasts do not unconditionally beat analysts. Across industry and calendar-year portfolios, $\lambda_{p,0}^{beat}$ is always greater than 1.0 with the exception of the 0.943 estimated for the UTILS industry, which is not statistically significant.

When the forecast horizon is h=3 months, the results (reported in column 4 of Tables 3 and 4) indicate a significant improvement in MIDAS-combination forecasts relative to analyst benchmark forecasts. For example, $\lambda_{p,3}^{beat}$ estimated for all firm-quarter observations is 0.931, which is less than 1.0 at a 1% level of statistical significance. This indicates that MIDAS-combination forecasts do outperform analysts' consensus forecasts by 6.9% at an h=3 month forecast horizon. Across industries, values are less than 1.0 in all but two industries (NODUR and SHOPS). Similar results are obtained across calendar-year portfolios.

Overall, these results provide modest evidence that MIDAS-combination forecasts can unconditionally beat analysts' consensus forecasts at the longer forecast horizon of h=3 months. In order to provide more clarity, we evaluate $\lambda_{p,3}^{beat}$ estimates for two additional portfolios based on the dispersion among analysts' forecasts and for portfolios based on the

size of the firm.[22]

The left panel of Figure 1 illustrates $\lambda_{p,3}^{beat}$ estimates (indicated by the blue-shaded bars) for five analyst dispersion portfolios. When analysts agree (i.e., low dispersion), analysts' forecasts clearly have an advantage over MIDAS-combination forecasts as indicated by $\lambda_{p,3}^{beat}$ estimates greater than one. However, this advantage quickly wanes as disagreement among analysts increases. For example, the $\lambda_{p,3}^{beat}$ estimates in the second- and first-highest dispersion portfolios are 0.874 (beat by 12.6%) and 0.779 (beat by 22.1%), respectively, which indicates that our MIDAS-combination forecasts *beat* analysts with a statistical significance of 1%.[23]

Figure 2 illustrates $\lambda_{p,3}^{beat}$ estimates (indicated by the blue-shaded bars) for five size portfolios. Our MIDAS-combination forecasts have an advantage over analysts in all but the largest size portfolio. For example, the $\lambda_{p,3}^{beat}$ estimate for the portfolio with the smallest firms is 0.863, which reflects a 15.7% reduction in the magnitude of the MIDAS-combination forecast errors relative to analysts' forecast errors, and is less than 1.0 at a 1% level of statistical significance.

Smaller firms tend to be characterized by a weaker information environment and covered by fewer analysts (e.g., Bushman, Piotroski and Smith, 2005). Therefore, the strong performance of our MIDAS-combination forecasts for smaller firms is important and encouraging because it provides preliminary support for future applications of MIDAS-combination forecasts for smaller firms that are not covered by analysts. Overall, the results from the *beat* test applied to dispersion and size portfolios indicate that our MIDAS-combination forecasts are well-equipped to beat analysts' consensus forecasts for small firms (potentially those not covered by analysts) and firms with a high amount of disagreement among analysts.

Finally, Figure 3 illustrates $\lambda_{p,3}^{beat}$ estimates (indicated by the blue-shaded bars) by calendar-year portfolios within the HITEC industry.[24] A majority of the $\lambda_{p,3}^{beat}$ estimates across

[22]Dispersion among analysts' forecasts is defined as the cross-sectional standard deviation of individual analyst EPS estimates for a given firm f, fiscal quarter q, and forecast horizon h. The size of the firm is defined as the market value of equity at the end of the prior fiscal quarter, $q-1$.

[23]Bootstrapped distributions used to determine p-values for all analyses in this study are reported in Tables OA.1 to OA.10 of the Online Appendix.

[24]The HITEC industry contains forecasts from 252 firms and represents one of the largest constituents of

calendar-year portfolios are either strictly less than 1.0 or slightly above one, which implies that the MIDAS-combination forecasts quite often *beat* analysts. In particular, our MIDAS-combination forecasts outperform analysts by over 25% in 2001, which coincides with the end of the "dot-com bubble." In contrast, the onset of the financial crisis in 2007 and 2008 posed a significant challenge for the regression-based forecasts.

4.3 *Conquer* test results

This section presents results from the *conquer* test, which compares the out-of-sample performance of a combination of analysts' consensus forecasts and MIDAS-combination forecasts to analysts' consensus forecasts alone. The fifth column of Tables 3 and 4 present $\lambda_{p,0}^{conquer}$ estimates by industry portfolios and calendar-year portfolios, respectively, at the shorter forecast horizon of h=0 months prior to end of the fiscal quarter. $\lambda_{p,0}^{conquer}$ for the overall sample is 0.898, which reflects an improvement of 11.2% and is less than 1.0 at a 1% level of statistical significance. In addition, $\lambda_{p,0}^{conquer}$ is consistently less than one across all industry portfolios (Table 3) and calendar-year portfolios (Table 4).

Results for the longer forecast horizon of h=3 months are reported in column 6 of Tables 3 and 4. These results are even stronger. For the overall sample, $\lambda_{p,3}^{conquer}$ is 0.792 (20.8% improvement) and is less than 1.0 at a 1% level of statistical significance. In addition, $\lambda_{p,3}^{conquer}$ is consistently less than 1.0 and statistically significant across all industry portfolios (Table 3) as well as all calendar-year portfolios (Table 4). Overall, these results provide surprisingly strong evidence that our MIDAS-combination forecasts complement analysts' consensus forecasts by providing additional information that analysts have effectively "left on the table." Thus, despite the general forecasting inferiority of MIDAS-combination forecasts documented in the *beat* test in the previous section, they do provide value by complementing analysts' consensus forecasts and improving overall performance.

We also estimate and test $\lambda_{p,3}^{conquer}$ for portfolios based on dispersion among analysts' fore-

our sample (see Table 2).

casts and firm size. The left panel of Figure 1 illustrates $\lambda_{p,3}^{conquer}$ estimates (indicated by the red-shaded bars) for five analyst dispersion portfolios, which indicate significant gains in performance for all portfolios. When analysts agree (i.e., low dispersion), combining analysts' forecasts and regression-based forecasts results in a $\lambda_{p,3}^{conquer}$ estimate of 0.903, which represents a 9.7% improvement over analysts' forecasts alone. In this case, MIDAS-combination forecasts clearly provide complementary information to analysts' consensus forecasts

The same is also true in the high dispersion portfolio where the $\lambda_{p,3}^{conquer}$ estimate is 0.753, which represents a 24.7% improvement in forecast performance from integrating MIDAS-combination forecasts with analysts' consensus forecasts. However, the converse is not true because $\lambda_{p,3}^{conquer}$ is only 3.3% smaller than $\lambda_{p,3}^{beat}$ (the blue-shaded bar) for this portfolio, which indicates that adding analysts' forecasts to MIDAS-combination forecasts does not offer much of an increase in performance relative to MIDAS-combination forecasts alone.[25] In other words, when MIDAS-combination forecasts perform poorly relative to analysts (e.g., analyst dispersion is low), they still provide complementary information to analysts and therefore yield improved combined forecasts. In contrast, when analysts perform poorly relative to MIDAS-combination forecasts (e.g., analyst dispersion is high), analysts provide very little additional information to improve forecast performance.

The left panel of Figure 1 tells us that forecast combinations always outperform analysts. Even when dispersion is low (i.e., when there is very little disagreement among analysts), combining analyst consensus forecasts with regression-based earnings forecasts yields MABER improvements of 10%, a huge improvement over using regression-based forecasts alone (the dark/blue bars discussed in the previous subsection). Hence, the information content of regression-based model forecasts is clearly complementary to analysts' forecasts, since the former are clearly inferior in this case but nevertheless useful in a combination scheme.

[25] We estimate the incremental effect of adding analysts to MIDAS-combination forecasts by computing the percentage difference between $\lambda_{p,3}^{conquer}$ and $\lambda_{p,3}^{beat}$ as follows:

$$\left[\lambda_{p,3}^{conquer}/\lambda_{p,3}^{beat}\right] - 1 = \left[\text{median}\left(\left|\Delta E_{f,q} - \Delta\hat{E}_{f,q,h}^{MC-An}\right|\right)/\text{median}\left(\left|\Delta E_{f,q} - \Delta\hat{E}_{f,q,h}^{MC}\right|\right)\right] - 1$$

based on the definitions in equations 8 and 9, respectively.

Note also that with high dispersion, there is only a modest improvement attributable to forecast combinations, and model-based earnings predictions imply a more than 20% less in terms of MABER. This is therefore a case where models are superior and analysts do not bring much additional information to improve the forecast. Note the asymmetry – when models are relatively worse, they are still useful, whereas in the opposite situation the relatively poor analyst predictions are not that helpful.

Looking at the right panel of Figure 1, we note that the median weight for the lowest dispersion portfolio is above 0.50, while the inter-quartile range spans from 0.7 to 0.4. At the other end of the dispersion ranking, we see a median significantly below 0.50 and the bulk of the distribution below 0.50 as well.

For the size-sorted portfolios reported in Figure 2, we find a similar pattern: combinations always dominate. All the improvements are again statistically significant (detailed results appear in Table OA.1 of the Online Appendix). The right panel also indicates that across the size spectrum, the weights are centered at around one half.

The right columns in both panels of Table 4 also tell us that the combination scheme is dominant across time *and* for both short and long horizons. This is again a striking and strong result in favor of combination strategies. This results holds before, during and after the recent financial crisis – quite a remarkable finding as well.

Next we turn to specific industries, reporting the High Tech industry in Figure 3 as before. The same conclusions emerge: forecast combinations improve about 15% on average. The median weights on analysts are also persistently below 0.50. Table 3 tells us that this is true across all industries for h=3, and the gains are more than 20% for many industries. Surprisingly, also for the short horizon h=0, we find that combination schemes outperform the others for a majority of industries, and the difference is statistically significant. Exceptions are ENRGY and TLCOM. The gains are smaller, yet sometimes more than 10%.

Finally, we turn our attention to Table 5, which displays the means and standard deviations of forecast combination weights pooled across the three main categories of regressors:

(1) accounting variables, (2) stock market variables and (3) macroeconomic variables discussed, respectively, in the first, second and third subsection of Section 2. The entries in the *Benchmark* column correspond to equal weights (i.e., 50% are attributed to regression-based models and 50% to analysts, and within the former group 1/13 are attributed to each of the predictors). Consider the dispersion-sorted portfolios in the top left panel. Using the benchmark equal weight standard, we see that with low dispersion there is almost a 56% weight on analysts, whereas with high dispersion it is only 44%. Recall that with high dispersion, the models did well and outperformed analysts. This is reflected in the weights, as there is a more than 10% drop from low to high. Among the predictors, the macroeconomic variables have the largest increase in weight from 20% to almost 26%. Accounting variables are next, and only a small weight is put on stock market variables. The right top panel tells us that for size-sorted portfolios there is similar pattern: for small firms more weight is put on regression models, while for large firms the reverse is true, with macroeconomic variables again taking the lead among the regressors. The lower panel of Table 5 shows some heterogeneity of the weight on analysts across the various industries, which ranges from 47% for DURBL to 59% for NODUR. Not surprisingly, macroeconomic variables are again the most important.

The aforementioned results suggest that incorporating macroeconomic news is the strongest driver of our findings. While it is beyond the scope of the paper to perform an elaborate test of that hypothesis, it seems intuitively plausible that macroeconomic data are key to the forecasting success. Indeed, as business cycle conditions are the fundamental source of earnings fluctuations, we do expect that judiciously incorporating such information in real time is important. The burgeoning literature on real-time macroeconomic forecasting shows that there are substantial gains to be made by properly incorporating the flow of macroeconomic information into forecasting business cycle conditions (e.g., Nunes, 2005; Giannone, Reichlin and Small, 2008; Andreou, Ghysels and Kourtellos, 2013; Kuzin, Marcellino and Schumacher, 2013).

The overall conclusion is "combine and conquer." There is surprisingly strong evidence in favor of combining analyst forecasts with model-based regression predictions. Both analysts' forecasts and regression-based forecasts assume approximately 50% of the combination weights. This is true across time, forecast horizons and industries.

Ball and Brown (1968) and more recently Ball, Sadka and Sadka (2009) – among others – document that between 17% and 60% of the variation in firm-level earnings is explained by contemporaneous macroeconomic conditions. Yet Carabias (2014) shows that macroeconomic news is not fully incorporated into analyst earnings expectations. Thus, analysts *leave money on the table* by not fully taking into account aggregate economy information. The methods described in this subsection achieve precisely the task of combining the information in analysts' forecasts with that provided by mixed frequency data models, with the latter providing succinct proxies for the macroeconomic environment.

4.4 Is it all about biases or about information efficiency?

While the results in the previous subsection allude to information inefficiencies, we need to explore another possible explanation for our findings. There is ample evidence that analysts' recommendations may be overly optimistic and driven by career concerns (e.g., Hong and Kubik, 2003). One may therefore wonder whether our results are simply driven by the tendency of analyst consensus forecasts to be biased. We thus repeat our analysis using instead bias-corrected analyst forecasts. While there are several possible bias correction schemes, we consider the following two approaches. Since the forecast combination schemes discussed in subsection 3.2.3 are based on the last eight quarters, we use that same information to compute either a mean or a median bias, which is then applied to augment the analyst forecast. Hence, bias corrections are firm-specific and vary through time. We report the bias-corrected results in the Online Appendix Tables OA.6 through OA.10.[26] Generally speaking, the results do not change dramatically. At horizon h=3, we note in Table OA.8

[26]The mean bias corrections are essentially similar to the median bias corrections and are available upon request.

that the TELCM industry is no longer significant at 10%. Overall, some of the ratios are smaller, while others are larger. Likewise, for h=0, we observe that the results for the NODUR, SHOPS, HLTH, and UTILS industries are all worse. Across time, similar results emerge (with notably weaker results for h=0), but the main conclusions remain. Thus, our findings are not driven by the potential bias of analysts' forecasts.

Recall that prior research concludes that regression-based forecasts cannot match the forecast performance of professional analysts at short forecast horizons of one quarter or less. Why then does our approach that make short horizon forecasts so much better? We believe the answer lies in the weighting schemes. The MIDAS regressions level the playing field by infusing a broader scope of high-frequency information into a time-series forecasting model. The fact that macroeconomic series in our mix of high-frequency series receive the highest weights – whether in terms of stand-alone regressions or in combination with analyst forecasts – implies that analysts do not take into account the general state of the economy when making earning forecasts. Perhaps it is fair to say that analysts are too myopic in their focus on a specific stock and tend not to fully consider/account for the overall economic conditions. Our results also show that this is not a business cycle phenomenon in that the advantages we identify apply uniformly across time (recall Table 4). Also, MIDAS regression-based models outperform analysts for firms in specific industries such as MANUF and HITEC. The gains are significant only at longer horizons (i.e., at the start of the target quarter for earnings forecasts).

5 Conclusions

The results of our study are promising for MIDAS forecasting models, which facilitate the use of information that is broader in scope and more frequently observed in order to level the playing field against analysts. At short forecast horizons, we find that our MIDAS forecasts are more accurate and have forecast errors that are smaller than analysts when

analysts' forecast dispersion is high and when the firm size is smaller. In addition, we find that combining our MIDAS forecasts with analysts forecasts systematically outperforms analysts alone, which indicates that our MIDAS models provide information orthogonal to analysts. These results offer evidence that the process of forecasting firm-level earnings on a high-frequency basis can be automated.

The question of whether this process can be automated using econometric models that incorporate large amounts of information evokes human-versus-machine scenarios such as a chess master playing against a computer. However, the implications of our study are more practical in nature. Our results shed light on the potential to provide high-frequency earnings expectations that are relevant for event studies and applicable to settings with reliable public data, but no analyst coverage (e.g., small public firms, most private firms, developing economies). In addition, it provides direction for future research to explore the application of MIDAS forecasting models to other financial statement performance measures, such as predicting revenue growth or constructing an expectation of accounting accruals useful in detecting earnings management.

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Table 1: Definitions of Variables

Index, k	Description	Measurement
Panel A: Quarterly dependent variable		
–	Earnings per share (ΔE_q)	First-differenced quarterly earnings per share (EPS) from I/B/E/S, which is equal to actual EPS for fiscal quarter q, minus actual EPS for the prior fiscal quarter, $q-1$.
Panel B: Quarterly firm-level accounting predictor variables†		
1	Inventory	$\Delta\text{Inventory}_q$ ($INVTQ$) $-$ ΔSales_q ($REVTQ$)
2	Accounts receivable	$\Delta\text{Accounts Receivable}_q$ ($RECTQ$) $-$ ΔSales_q
3	Capital expenditures	$\Delta\text{Industry CAPX}_q$ $-$ $\Delta\text{Firm CAPX}_q$ ($CAPXQ$)
4	Gross margin	ΔSales_q $-$ $\Delta\text{Gross Margin}_q$ ($REVTQ - COGSQ$)
5	SG&A expenses	$\Delta\text{SG\&A}_q$ ($XSGAQ$) $-$ ΔSales_q
Panel C: Monthly firm-level stock market predictor variables		
6	Abnormal stock return	Firm-specific stock return from CRSP during month m less the same-industry portfolio return in month m, where industry classifications are based on Fama-French 10-industry definitions.
7	Return volatility	Average of squared daily firm-level stock returns from CRSP during month m.
Panel D: Monthly macroeconomic predictor variables‡		
8	Industrial production	Year-over-year growth rate of seasonally adjusted monthly industrial production index that is observed at the end of month m, which is equal to: $(INDPRO_{m-1}/INDPRO_{m-13}) - 1$.
9	Inflation	Year-over-year growth rate of seasonally adjusted monthly consumer price index that is observed at the end of month m, which is equal to: $(CPIAUCSL_{m-1}/CPIAUCSL_{m-13}) - 1$.
10	Oil prices	Year-over-year growth rate of monthly crude oil prices that is observed at the end of month m, which is equal to: $(MCOILWTICO_{m-1}/MCOILWTICO_{m-13}) - 1$.
11	T-bill yield	Monthly change in yields on 3-month treasury bills that is observed at the end of month m, which is equal to: $TB3MS_{m-1} - TB3MS_{m-2}$.
12	Term spread	Monthly change in the yield spread between 10-year treasury bonds and 3-month treasury bills that is observed at the end of month m, which is equal to: $(GS10_{m-1} - TB3_{m-1}) - (GS10_{m-2} - TB3_{m-2})$.
13	Default spread	Monthly change in the yield spread between BAA corporate bonds and AAA corporate bonds that is observed at the end of month m, which is equal to: $(BAA_{m-1} - AAA_{m-1}) - (BAA_{m-2} - AAA_{m-2})$.

† All predictor variables in panel B use firm-quarter data from Compustat. Mnemonic variable names provided in Compustat are indicated by italicized capital letters within parentheses. The Δ operator represents a one-quarter percentage change in the variable. For example, $\Delta\text{Inventory}_q = (INVTQ_q - INVTQ_{q-1}) \,/\, INVTQ_q$.

‡ All predictor variables in panel D use Federal Reserve Economic Data (FRED) provided by the Federal Reserve Bank of St. Louis. Mnemonic variable names provided in FRED are indicated by italicized capital letters. All variables are measured with a one-month lag to account for any delay in the release of the information.

Table 2: Number of Sampled Firms by Industry Affiliation

Fama-French 10-Industry Classifications			
Number	Name	Description	Number of Firms
1	NODUR	Consumer NonDurables (e.g., Food, Tobacco, Textiles, Apparel, Leather, Toys)	93
2	DURBL	Consumer Durables (e.g., Cars, TVs, Furniture, Household Appliances)	53
3	MANUF	Manufacturing (e.g., Machinery, Trucks, Planes, Chemicals, Off Furn, Paper, Com Printing)	263
4	ENRGY	Oil, Gas, and Coal Extraction and Products	42
5	HITEC	Business Equipment (e.g., Computers, Software, Electronic Equipment)	252
6	TELCM	Telephone and Television Transmission	5
7	SHOPS	Wholesale, Retail, and Some Services (e.g., Laundries, Repair Shops)	170
8	HLTH	Healthcare, Medical Equipment, and Drugs	80
9	UTILS	Utilities	5
10	OTHER	Other (e.g., Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment, Finance)	88

Table 3: Out-of-sample Forecast Performance by Industry Portfolio, p, and Forecast Horizon, h

	$\lambda_{p,h}^{improve}$		$\lambda_{p,h}^{beat}$		$\lambda_{p,h}^{conquer}$	
Industry Portfolio, p	$h=0$ (1)	$h=3$ (2)	$h=0$ (3)	$h=3$ (4)	$h=0$ (5)	$h=3$ (6)
NODUR	0.509***	0.504***	1.681	1.249	0.898***	0.844***
DURBL	0.578***	0.655***	1.242	0.911	0.923**	0.809***
MANUF	0.677***	0.756***	1.294	0.904***	0.921***	0.785***
ENRGY	0.820***	0.892*	1.221	0.912**	0.978	0.851***
HITEC	0.798***	0.811***	1.133	0.866***	0.882***	0.786***
TELCM	0.865**	0.840**	1.196	0.870	0.932	0.782*
SHOPS	0.474***	0.574***	1.380	1.024	0.896***	0.815***
HLTH	0.720***	0.650***	1.157	0.914**	0.834***	0.798***
UTILS	0.736***	0.829***	0.943	0.839	0.737***	0.774***
OTHER	0.632***	0.696***	1.277	0.917**	0.916***	0.810***
All	0.645***	0.708***	1.251	0.931***	0.898***	0.792***

This table presents three median absolute error ratio (MABER) estimates by forecast horizon, h, and industry portfolio, p, of firm-quarter observations. Columns (1) and (2) contain estimated values of $\lambda_{p,h}^{improve}$ (see equation 6 in section 3.3), which is equal to the ratio of the median MIDAS-combination forecast error to the median AR model forecast error for all firm-quarter observations within industry portfolio p with a forecast horizon of h months prior to the end of the fiscal quarter. Columns (3) and (4) contain estimated values of $\lambda_{p,h}^{beat}$ (see equation 9 in section 3.3), which is equal to the ratio of the median MIDAS-combination forecast error to the median analysts' consensus forecast error for all firm-quarter observations within industry portfolio p with a forecast horizon of h months prior to the end of the fiscal quarter. Columns (5) and (6) contain estimated values of $\lambda_{p,h}^{conquer}$ (see equation 8 in section 3.3), which is equal to the ratio of the median combined analysts' consensus and MIDAS-combination forecast errors to the median analysts' consensus forecast error for all firm-quarter observations within industry portfolio p with a forecast horizon of h months prior to the end of the fiscal quarter. Estimates in odd-numbered (even-numbered) columns are based on the shortest (longest) forecast horizon of h=0 (h=3) months prior to the end of the fiscal quarter for which earnings per share is forecasted. ***, **, and * indicate that the estimated MABER value is less than 1.0 at a 1%, 5%, and 10% level of statistical significance, respectively, based on p-values from the bootstrap procedure defined in section 3.3.

Table 4: Out-of-sample Forecast Performance by Calendar-year Portfolio, p, and Forecast Horizon, h

	$\lambda_{p,h}^{improve}$		$\lambda_{p,h}^{beat}$		$\lambda_{p,h}^{conquer}$	
Calendar-year Portfolio, p	$h=0$ (1)	$h=3$ (2)	$h=0$ (3)	$h=3$ (4)	$h=0$ (5)	$h=3$ (6)
2000	0.645***	0.597***	1.411	1.030	0.910**	0.811***
2001	0.645***	0.608***	1.375	0.729***	0.961*	0.709***
2002	0.629***	0.606***	1.375	0.914	0.925**	0.775***
2003	0.643***	0.600***	1.463	0.929*	0.960	0.767***
2004	0.694***	0.645***	1.383	1.019	0.904***	0.824***
2005	0.666***	0.698***	1.243	0.987	0.821***	0.811***
2006	0.646***	0.812***	1.194	0.982	0.880***	0.832***
2007	0.678***	0.712***	1.240	1.041	0.870***	0.872***
2008	0.677***	0.660***	1.165	0.967	0.884***	0.843***
2009	0.696***	0.712***	1.148	0.796***	0.915***	0.779***
2010	0.630***	0.729***	1.105	0.890***	0.916***	0.821***
2011	0.597***	0.743***	1.177	0.948	0.921***	0.790***
2012	0.608***	0.745***	1.192	0.970	0.879***	0.820***
2013	0.606***	0.706***	1.210	1.005	0.875***	0.796***
2014	0.600***	0.771***	1.239	0.983	0.872***	0.844***

This table presents three median absolute error ratio (MABER) estimates by forecast horizon, h, and calendar-year portfolio, p, of firm-quarter observations. Columns (1) and (2) contain estimated values of $\lambda_{p,h}^{improve}$ (see equation 6 in section 3.3), which is equal to the ratio of the median MIDAS-combination forecast error to the median AR model forecast error for all firm-quarter observations within calendar-year portfolio p with a forecast horizon of h months prior to the end of the fiscal quarter. Columns (3) and (4) contain estimated values of $\lambda_{p,h}^{beat}$ (see equation 9 in section 3.3), which is equal to the ratio of the median MIDAS-combination forecast error to the median analysts' consensus forecast error for all firm-quarter observations within calendar-year portfolio p with a forecast horizon of h months prior to the end of the fiscal quarter. Columns (5) and (6) contain estimated values of $\lambda_{p,h}^{conquer}$ (see equation 8 in section 3.3), which is equal to the ratio of the median combined analysts' consensus and MIDAS-combination forecast errors to the median analysts' consensus forecast error for all firm-quarter observations within calendar-year portfolio p with a forecast horizon of h months prior to the end of the fiscal quarter. Estimates in odd-numbered (even-numbered) columns are based on the shortest (longest) forecast horizon of h=0 (h=3) months prior to the end of the fiscal quarter for which earnings per share is forecasted. ***, **, and * indicate that the estimated MABER value is less than 1.0 at a 1%, 5%, and 10% level of statistical significance, respectively, based on p-values from the bootstrap procedure defined in section 3.3.

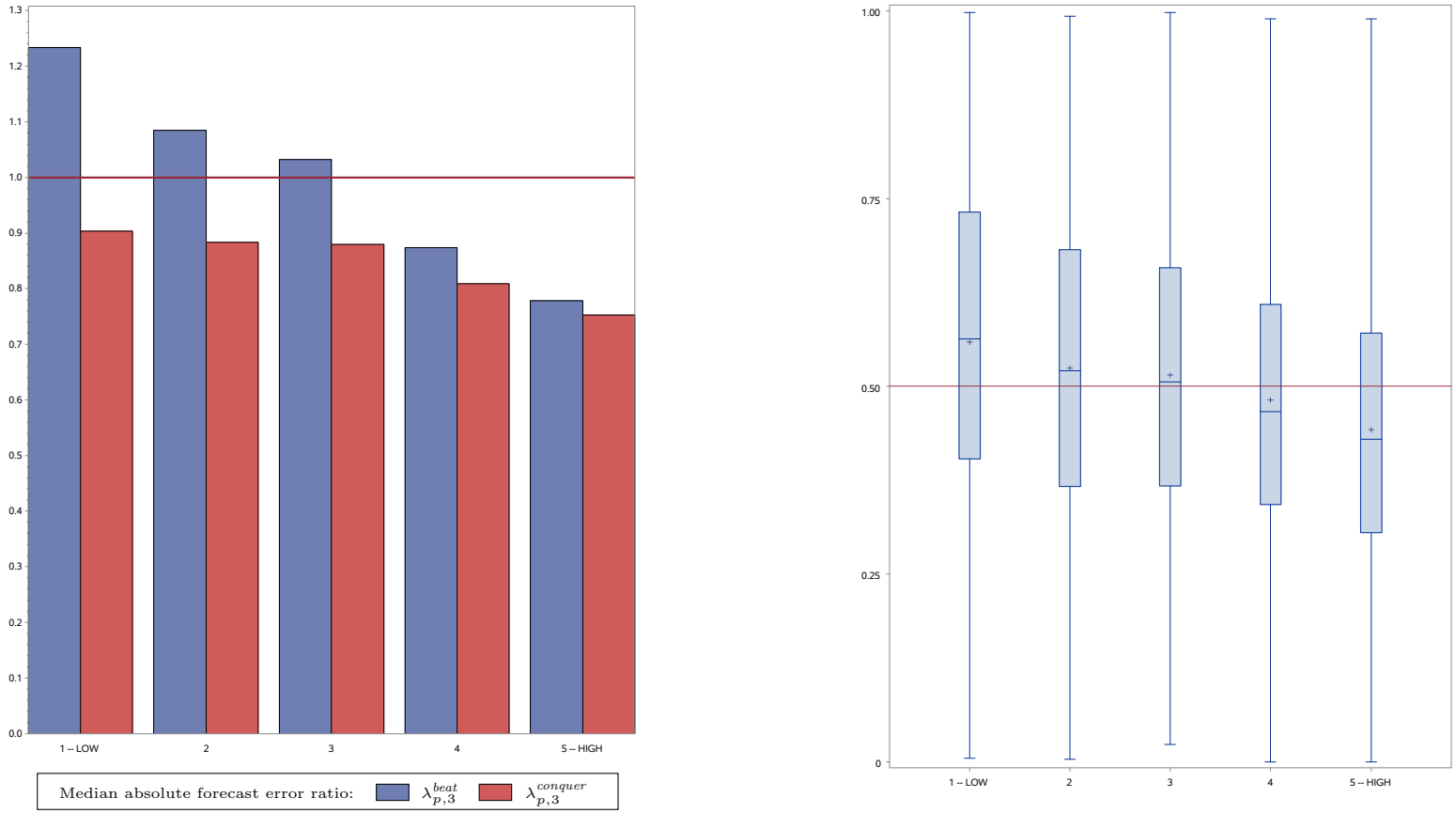
Table 5: Estimated Weights by Dispersion, Size and Industry Portfolios with a Forecast Horizon of h=3 Months

			Dispersion portfolio, p					Size portfolio, p				
		Benchmark	1 (Low)	2	3	4	5 (High)	1 (Small)	2	3	4	5 (Big)
Accounting	mean	0.192	0.170	0.184	0.188	0.200	0.214	0.208	0.192	0.191	0.189	0.177
variables	s.d.		0.086	0.081	0.077	0.074	0.074	0.080	0.079	0.078	0.080	0.079
Stock market	mean	0.077	0.068	0.073	0.074	0.080	0.087	0.081	0.076	0.076	0.077	0.071
variables	s.d.		0.036	0.034	0.032	0.033	0.035	0.035	0.034	0.033	0.036	0.034
Macroeconomic	mean	0.231	0.203	0.219	0.223	0.238	0.257	0.246	0.229	0.226	0.228	0.212
variables	s.d.		0.103	0.097	0.092	0.087	0.090	0.095	0.096	0.091	0.098	0.095
All predictor	mean	0.500	0.441	0.476	0.485	0.518	0.558	0.535	0.498	0.493	0.494	0.460
variables	s.d.		0.221	0.208	0.196	0.186	0.189	0.202	0.203	0.196	0.209	0.204
Analysts	mean	0.500	0.559	0.524	0.515	0.482	0.442	0.465	0.502	0.507	0.506	0.540
	s.d.		0.221	0.208	0.196	0.186	0.189	0.202	0.203	0.196	0.209	0.204

			Industry portfolio, p										
		Benchmark	NODUR	DURBL	MANUF	ENRGY	HITEC	TELCM	SHOPS	HLTH	UTILS	OTHER	ALL
Accounting	mean	0.192	0.156	0.203	0.198	0.197	0.208	0.194	0.177	0.184	0.187	0.188	0.191
variables	s.d		0.087	0.075	0.077	0.064	0.073	0.053	0.086	0.082	0.057	0.077	0.080
Stock market	mean	0.077	0.061	0.081	0.079	0.085	0.083	0.073	0.070	0.072	0.086	0.075	0.076
variables	s.d.		0.036	0.033	0.033	0.033	0.033	0.020	0.036	0.034	0.041	0.033	0.034
Macroeconomic	mean	0.231	0.185	0.243	0.237	0.249	0.246	0.203	0.211	0.217	0.229	0.223	0.228
variables	s.d.		0.105	0.093	0.092	0.080	0.087	0.050	0.103	0.097	0.075	0.091	0.096
All predictor	mean	0.500	0.402	0.527	0.514	0.531	0.537	0.470	0.458	0.473	0.502	0.486	0.496
variables	s.d.		0.225	0.196	0.196	0.168	0.183	0.117	0.222	0.211	0.164	0.195	0.204
Analysts	mean	0.500	0.598	0.473	0.486	0.469	0.463	0.530	0.542	0.527	0.498	0.514	0.504
	s.d.		0.225	0.196	0.196	0.168	0.183	0.117	0.222	0.211	0.164	0.195	0.204

This table presents the mean and standard deviation (s.d.) of estimated forecast combination weights for all regression-based forecasts and analysts' consensus forecasts (see equations 4 and 5 in section 3.2.3) for all portfolios of firm-quarter observations with a forecast horizon of h=3 months prior to the end of the fiscal quarter. Portfolios are formed based on one of the following three firm-quarter characteristics: (1) dispersion of analysts' forecasts, (2) firm size measured by the market value of equity at the end of the prior fiscal quarter, or (3) industry affiliation based on Fama-French 10-industry classifications.

Figure 1: Out-of-sample Forecast Performance by Dispersion Portfolios with a Forecast Horizon of h=3 Months

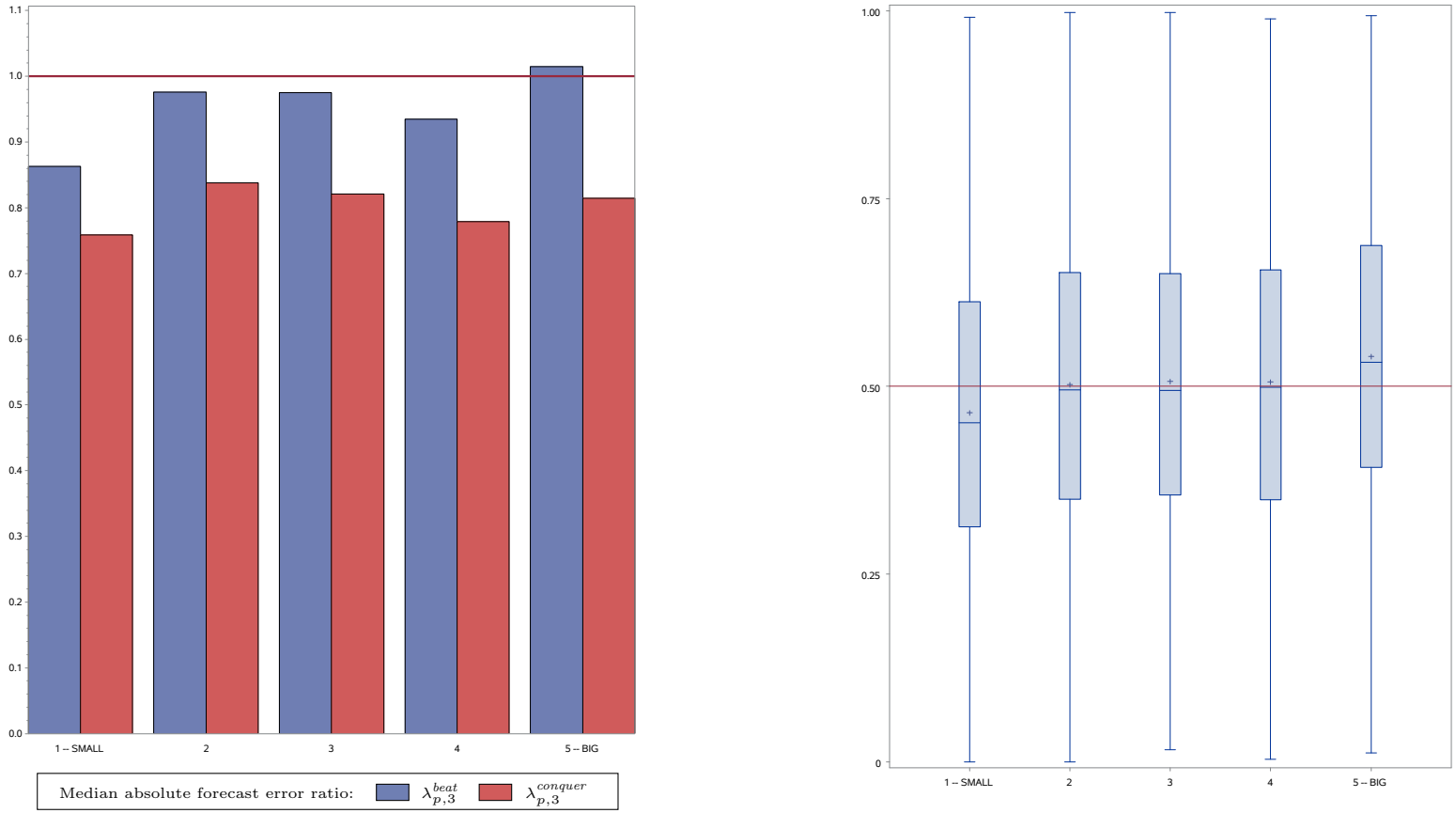


(a) Median absolute forecast error ratio

(b) Weight on analysts' consensus forecast

This figure plots the median absolute forecast error ratio (left panel) and the weight placed on analysts' consensus forecasts (right panel), at a forecast horizon of h=3 months prior to the end of the fiscal quarter, for five portfolios of firm-quarter observations based on dispersion of analysts' forecasts. The left panel reports values for two median absolute forecast error ratios: $\lambda^{beat}_{p,h=3}$ (see equation 9 in section 3.3) and $\lambda^{conquer}_{p,h=3}$ (see equation 8 in section 3.3). Formal test results are reported in Table OA.1, panels A and C of the Online Appendix. The left panel reports the weights applied to analysts' consensus forecasts, $\omega^{Analyst}_{f,q,h=3}$ (see equation 5 in section 3.3) for all firm-quarter observations within a given dispersion portfolio, p, and forecast horizon h=3. The benchmark value of 0.50 corresponds to an even weight split between MIDAS-combination forecasts and analysts' consensus forecasts.

Figure 2: Out-of-sample Forecast Performance by Size Portfolios with a Forecast Horizon of h=3 Months



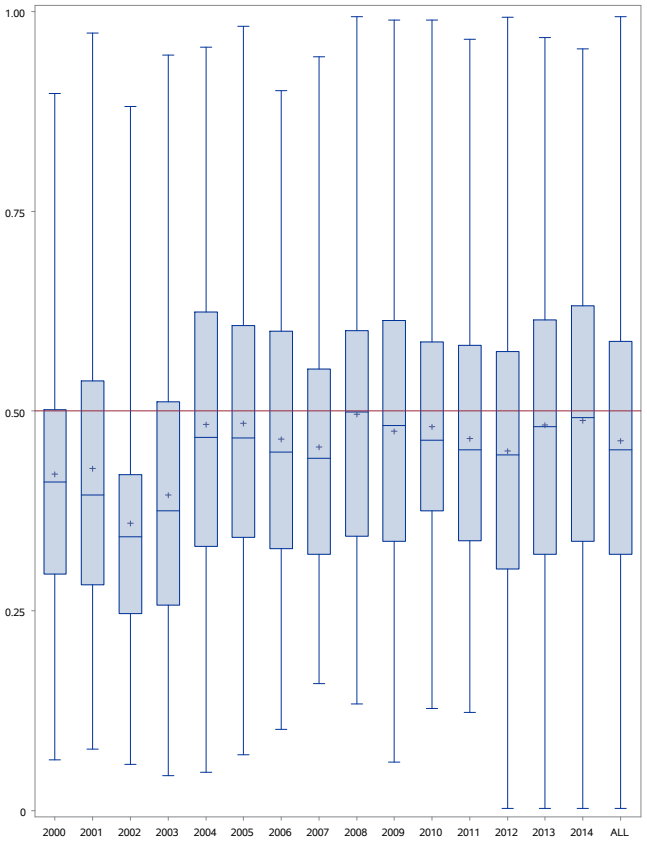
(a) Median absolute forecast error ratio

(b) Weight on analysts' consensus forecast

This figure plots the median absolute forecast error ratio (left panel) and the weight placed on analysts' consensus forecasts (right panel), at a forecast horizon of h=3 months prior to the end of the fiscal quarter, for five portfolios of firm-quarter observations based on firm size. The left panel reports values for two median absolute forecast error ratios: $\lambda^{beat}_{p,h=3}$ (see equation 9 in section 3.3) and $\lambda^{conquer}_{p,h=3}$ (see equation 8 in section 3.3). Formal test results are reported in Table OA.1, panels B and D of the Online Appendix. The left panel reports the weights applied to analysts' consensus forecasts, $\omega^{Analyst}_{f,q,h=3}$ (see equation 5 in section 3.2.3) for all firm-quarter observations within a given firm size portfolio, p, and forecast horizon h=3. The benchmark value of 0.50 corresponds to an even weight split between MIDAS-combination forecasts and analysts' consensus forecasts.

Figure 3: HITEC Out-of-sample Forecast Performance by Calendar-year Portfolios with a Forecast Horizon of h=3 Months

(a) Median absolute forecast error ratio



(b) Weight on analysts' consensus forecast

This figure plots the median absolute forecast error ratio (left panel) and the weight placed on analysts' consensus forecasts (right panel), at a forecast horizon of h=3 months prior to the end of the fiscal quarter, for calendar-year portfolios of firm-quarter observations in the HITEC industry (see industry description in Table 2). The left panel reports values for two median absolute forecast error ratios: $\lambda^{beat}_{p,h=3}$ (see equation 9 in section 3.3) and $\lambda^{conquer}_{p,h=3}$ (see equation 8 in section 3.3). The left panel reports the weights applied to analysts' consensus forecasts, $\omega^{Analyst}_{f,q,h=3}$ (see equation 5 in section 3.2.3) for all firm-quarter observations within a given given HITEC calendar-year portfolio, p, and forecast horizon h=3. The benchmark value of 0.50 corresponds to an even weight split between MIDAS-combination forecasts and analysts' consensus forecasts.

— ONLINE APPENDIX —

Automated Earnings Forecasts: Beat Analysts or Combine and Conquer?

Table OA.1: $\lambda_{p,h}^{beat}$ and $\lambda_{p,h}^{conquer}$ Bootstrap Distributions by Dispersion and Size Portfolios with a Forecast Horizon of h=3 Months

			Bootstrap Distribution								
Portfolio, p	$\lambda_{p,h}^{beat}$	(p-value)	1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel A: $\lambda_{p,h}^{beat}$ for dispersion portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
1 (Low)	1.234	(1.00)	1.154	1.176	1.184	1.204	1.229	1.252	1.278	1.294	1.320
2	1.084	(1.00)	1.014	1.039	1.046	1.063	1.086	1.104	1.124	1.133	1.155
3	1.032	(0.95)	0.978	1.000	1.007	1.017	1.034	1.048	1.062	1.075	1.101
4	0.874***	(0.00)	0.820	0.832	0.840	0.861	0.871	0.887	0.896	0.904	0.919
5 (High)	0.779***	(0.00)	0.733	0.744	0.753	0.765	0.780	0.792	0.805	0.816	0.831
Panel B: $\lambda_{p,h}^{beat}$ for size portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
1 (Small)	0.863***	(0.00)	0.812	0.819	0.832	0.846	0.863	0.879	0.894	0.901	0.920
2	0.976	(0.18)	0.920	0.938	0.947	0.961	0.973	0.993	1.011	1.022	1.038
3	0.975	(0.18)	0.919	0.933	0.945	0.959	0.977	0.996	1.006	1.013	1.023
4	0.935***	(0.00)	0.865	0.885	0.894	0.910	0.929	0.948	0.961	0.971	0.988
5 (Large)	1.015	(0.72)	0.949	0.967	0.977	0.997	1.019	1.050	1.065	1.079	1.105
			Bootstrap Distribution								
Portfolio, p	$\lambda_{p,h}^{conquer}$	(p-value)	1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel C: $\lambda_{p,h}^{conquer}$ for dispersion portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
1 (Low)	0.903***	(0.00)	0.863	0.872	0.879	0.890	0.904	0.916	0.928	0.935	0.953
2	0.883***	(0.00)	0.838	0.852	0.857	0.868	0.879	0.892	0.904	0.907	0.923
3	0.880***	(0.00)	0.847	0.855	0.860	0.869	0.878	0.888	0.901	0.907	0.920
4	0.809***	(0.00)	0.773	0.782	0.788	0.797	0.808	0.819	0.827	0.831	0.841
5 (High)	0.753***	(0.00)	0.717	0.724	0.729	0.739	0.751	0.764	0.770	0.774	0.791
Panel D: $\lambda_{p,h}^{conquer}$ for size portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
1 (Small)	0.759***	(0.00)	0.721	0.734	0.739	0.748	0.762	0.773	0.780	0.787	0.792
2	0.838***	(0.00)	0.799	0.811	0.817	0.828	0.837	0.849	0.858	0.865	0.878
3	0.821***	(0.00)	0.781	0.796	0.805	0.813	0.824	0.835	0.844	0.847	0.857
4	0.779***	(0.00)	0.744	0.751	0.759	0.768	0.778	0.790	0.801	0.807	0.816
5 (Large)	0.815***	(0.00)	0.774	0.785	0.796	0.807	0.819	0.830	0.844	0.853	0.871

Table OA.2: $\lambda_{p,h}^{beat}$ Bootstrap Distributions by Industry Portfolio, p, and Forecast Horizon, h

Industry Portfolio, p	$\lambda_{p,h}^{beat}$	(p-value)	Bootstrap Distribution 1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel A: $\lambda_{p,h}^{beat}$ for industry portfolios, p, with a forecast horizon of h=0 months prior to the end of the fiscal quarter											
NODUR	1.681	(1.00)	1.514	1.563	1.590	1.632	1.682	1.734	1.791	1.826	1.892
DURBL	1.242	(1.00)	1.069	1.118	1.145	1.185	1.232	1.279	1.325	1.350	1.400
MANUF	1.294	(1.00)	1.224	1.245	1.255	1.273	1.292	1.311	1.326	1.335	1.353
ENRGY	1.221	(1.00)	1.100	1.134	1.153	1.186	1.228	1.268	1.309	1.333	1.385
HITEC	1.133	(1.00)	1.067	1.086	1.096	1.112	1.131	1.150	1.166	1.177	1.198
TELCM	1.196	(0.88)	0.803	0.927	0.981	1.090	1.219	1.373	1.565	1.673	1.921
SHOPS	1.380	(1.00)	1.289	1.313	1.326	1.351	1.377	1.404	1.428	1.443	1.470
HLTH	1.157	(1.00)	1.052	1.081	1.097	1.127	1.161	1.197	1.229	1.250	1.287
UTILS	0.943	(0.36)	0.805	0.862	0.881	0.917	0.967	1.021	1.066	1.100	1.183
OTHER	1.277	(1.00)	1.145	1.182	1.202	1.235	1.270	1.307	1.339	1.358	1.393
All	1.251	(1.00)	1.217	1.226	1.231	1.240	1.250	1.261	1.270	1.276	1.286
Panel B: $\lambda_{p,h}^{beat}$ for industry portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
NODUR	1.249	(1.00)	1.123	1.154	1.173	1.207	1.247	1.294	1.338	1.363	1.414
DURBL	0.911	(0.12)	0.778	0.813	0.834	0.870	0.912	0.961	1.005	1.031	1.083
MANUF	0.904***	(0.00)	0.863	0.875	0.882	0.893	0.906	0.919	0.933	0.942	0.958
ENRGY	0.912**	(0.05)	0.785	0.816	0.835	0.868	0.903	0.942	0.978	1.000	1.042
HITEC	0.866***	(0.00)	0.816	0.829	0.836	0.849	0.863	0.877	0.891	0.899	0.914
TELCM	0.870	(0.25)	0.393	0.532	0.635	0.734	0.854	0.995	1.181	1.366	1.650
SHOPS	1.024	(0.77)	0.949	0.970	0.982	1.003	1.028	1.052	1.076	1.089	1.115
HLTH	0.914**	(0.03)	0.812	0.836	0.851	0.879	0.911	0.944	0.973	0.990	1.025
UTILS	0.839	(0.15)	0.648	0.701	0.727	0.792	0.864	0.944	1.030	1.079	1.182
OTHER	0.917**	(0.02)	0.837	0.860	0.874	0.895	0.918	0.943	0.966	0.981	1.014
All	0.931***	(0.00)	0.906	0.914	0.918	0.924	0.932	0.939	0.946	0.951	0.959

Table OA.3: $\lambda_{p,h}^{conquer}$ Bootstrap Distributions by Industry Portfolio, p, and Forecast Horizon, h

Industry Portfolio, p	$\lambda_{p,h}^{conquer}$	(p-value)	Bootstrap Distribution 1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel A: $\lambda_{p,h}^{conquer}$ for industry portfolios, p, with a forecast horizon of h=0 months prior to the end of the fiscal quarter											
NODUR	0.898***	(0.00)	0.835	0.855	0.864	0.883	0.902	0.924	0.945	0.958	0.985
DURBL	0.923**	(0.02)	0.840	0.861	0.873	0.895	0.920	0.947	0.971	0.984	1.007
MANUF	0.921***	(0.00)	0.882	0.892	0.898	0.908	0.920	0.933	0.944	0.951	0.962
ENRGY	0.978	(0.29)	0.910	0.929	0.939	0.959	0.982	1.004	1.024	1.038	1.063
HITEC	0.882***	(0.00)	0.845	0.855	0.860	0.869	0.880	0.891	0.900	0.905	0.916
TELCM	0.932	(0.31)	0.658	0.749	0.798	0.881	0.950	1.021	1.088	1.171	1.321
SHOPS	0.896***	(0.00)	0.855	0.867	0.874	0.884	0.897	0.909	0.921	0.929	0.942
HLTH	0.834***	(0.00)	0.774	0.792	0.802	0.819	0.837	0.858	0.876	0.887	0.908
UTILS	0.737***	(0.00)	0.643	0.672	0.689	0.717	0.749	0.778	0.817	0.838	0.890
OTHER	0.916***	(0.00)	0.849	0.868	0.878	0.894	0.913	0.932	0.949	0.958	0.978
All	0.898***	(0.00)	0.878	0.884	0.887	0.892	0.897	0.903	0.908	0.911	0.917
Panel B: $\lambda_{p,h}^{conquer}$ for industry portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
NODUR	0.844***	(0.00)	0.777	0.794	0.804	0.821	0.839	0.859	0.875	0.886	0.909
DURBL	0.809***	(0.00)	0.724	0.748	0.761	0.783	0.809	0.834	0.859	0.874	0.901
MANUF	0.785***	(0.00)	0.747	0.757	0.763	0.773	0.783	0.792	0.801	0.806	0.817
ENRGY	0.851***	(0.00)	0.764	0.787	0.801	0.827	0.857	0.888	0.915	0.932	0.965
HITEC	0.786***	(0.00)	0.751	0.761	0.766	0.775	0.785	0.796	0.807	0.814	0.826
TELCM	0.782*	(0.07)	0.357	0.487	0.544	0.644	0.747	0.851	0.929	1.042	1.219
SHOPS	0.815***	(0.00)	0.769	0.782	0.789	0.802	0.817	0.831	0.844	0.853	0.870
HLTH	0.798***	(0.00)	0.723	0.743	0.753	0.773	0.796	0.818	0.839	0.851	0.871
UTILS	0.774***	(0.00)	0.637	0.673	0.694	0.736	0.781	0.831	0.879	0.912	0.976
OTHER	0.810***	(0.00)	0.745	0.764	0.773	0.790	0.809	0.829	0.847	0.858	0.881
All	0.792***	(0.00)	0.774	0.779	0.782	0.787	0.793	0.799	0.804	0.807	0.814

Table OA.4: $\lambda_{p,h}^{beat}$ Bootstrap Distributions by Calendar-year Portfolio, p, and Forecast Horizon, h

Calendar-year Portfolio, p	$\lambda_{p,h}^{beat}$	(p-value)	Bootstrap Distribution 1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel A: $\lambda_{p,h}^{beat}$ for calendar-year portfolios, p, with a forecast horizon of h=0 months prior to the end of the fiscal quarter											
2000	1.411	(1.00)	1.225	1.280	1.307	1.357	1.411	1.470	1.524	1.563	1.641
2001	1.375	(1.00)	1.189	1.244	1.273	1.324	1.378	1.428	1.478	1.509	1.561
2002	1.375	(1.00)	1.244	1.283	1.304	1.338	1.381	1.434	1.487	1.521	1.598
2003	1.463	(1.00)	1.274	1.328	1.360	1.404	1.458	1.513	1.564	1.596	1.651
2004	1.383	(1.00)	1.231	1.275	1.296	1.338	1.389	1.442	1.493	1.519	1.575
2005	1.243	(1.00)	1.124	1.160	1.179	1.209	1.246	1.288	1.331	1.357	1.405
2006	1.194	(1.00)	1.090	1.123	1.139	1.164	1.194	1.230	1.265	1.287	1.329
2007	1.240	(1.00)	1.112	1.150	1.169	1.202	1.242	1.281	1.317	1.342	1.389
2008	1.165	(1.00)	1.056	1.085	1.101	1.130	1.165	1.200	1.232	1.253	1.292
2009	1.148	(1.00)	1.021	1.055	1.073	1.106	1.144	1.183	1.220	1.242	1.280
2010	1.105	(0.99)	1.001	1.033	1.049	1.075	1.106	1.136	1.166	1.184	1.219
2011	1.177	(1.00)	1.069	1.102	1.118	1.147	1.177	1.208	1.235	1.253	1.286
2012	1.192	(1.00)	1.071	1.107	1.127	1.161	1.196	1.233	1.265	1.283	1.323
2013	1.210	(1.00)	1.112	1.141	1.157	1.182	1.210	1.239	1.268	1.285	1.320
2014	1.239	(1.00)	1.147	1.174	1.189	1.215	1.242	1.271	1.301	1.320	1.356
Panel B: $\lambda_{p,h}^{beat}$ for calendar-year portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
2000	1.030	(0.67)	0.862	0.905	0.934	0.981	1.031	1.083	1.132	1.159	1.213
2001	0.729***	(0.00)	0.611	0.642	0.661	0.694	0.726	0.755	0.786	0.811	0.865
2002	0.914	(0.15)	0.747	0.792	0.818	0.865	0.913	0.970	1.019	1.049	1.100
2003	0.929*	(0.10)	0.814	0.848	0.865	0.895	0.929	0.964	0.998	1.020	1.060
2004	1.019	(0.68)	0.891	0.929	0.948	0.989	1.033	1.079	1.128	1.149	1.201
2005	0.987	(0.34)	0.853	0.892	0.909	0.941	0.978	1.014	1.047	1.068	1.108
2006	0.982	(0.39)	0.879	0.909	0.926	0.953	0.985	1.021	1.052	1.070	1.106
2007	1.041	(0.76)	0.899	0.942	0.964	1.001	1.041	1.083	1.121	1.145	1.184
2008	0.967	(0.24)	0.869	0.897	0.913	0.940	0.967	0.998	1.028	1.045	1.074
2009	0.796***	(0.00)	0.721	0.741	0.752	0.774	0.797	0.824	0.848	0.863	0.892
2010	0.890***	(0.00)	0.790	0.815	0.833	0.856	0.883	0.910	0.934	0.948	0.972
2011	0.948	(0.12)	0.851	0.882	0.897	0.921	0.949	0.978	1.004	1.019	1.047
2012	0.970	(0.17)	0.884	0.907	0.920	0.941	0.966	0.991	1.012	1.024	1.052
2013	1.005	(0.47)	0.899	0.927	0.943	0.968	0.996	1.026	1.052	1.067	1.096
2014	0.983	(0.35)	0.896	0.922	0.935	0.959	0.985	1.011	1.037	1.055	1.088

Table OA.5: $\lambda_{p,h}^{conquer}$ Bootstrap Distributions by Calendar-year Portfolio, p, and Forecast Horizon, h

Calendar-year Portfolio, p	$\lambda_{p,h}^{conquer}$	(p-value)	Bootstrap Distribution 1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel A: $\lambda_{p,h}^{conquer}$ for calendar-year portfolios, p, with a forecast horizon of h=0 months prior to the end of the fiscal quarter											
2000	0.910**	(0.02)	0.788	0.826	0.844	0.874	0.903	0.934	0.962	0.978	1.012
2001	0.961*	(0.09)	0.859	0.888	0.901	0.923	0.950	0.977	0.999	1.010	1.037
2002	0.925**	(0.03)	0.818	0.844	0.858	0.888	0.921	0.949	0.973	0.992	1.028
2003	0.960	(0.10)	0.859	0.884	0.895	0.920	0.949	0.978	1.000	1.017	1.053
2004	0.904***	(0.00)	0.839	0.858	0.868	0.886	0.905	0.925	0.944	0.956	0.978
2005	0.821***	(0.00)	0.765	0.783	0.793	0.808	0.828	0.850	0.870	0.882	0.907
2006	0.880***	(0.00)	0.814	0.831	0.841	0.857	0.876	0.895	0.912	0.923	0.944
2007	0.870***	(0.00)	0.795	0.815	0.826	0.848	0.868	0.891	0.910	0.923	0.948
2008	0.884***	(0.00)	0.801	0.823	0.835	0.853	0.874	0.895	0.915	0.926	0.947
2009	0.915***	(0.00)	0.843	0.863	0.873	0.891	0.912	0.932	0.951	0.962	0.983
2010	0.916***	(0.00)	0.842	0.860	0.871	0.888	0.910	0.930	0.948	0.958	0.976
2011	0.921***	(0.00)	0.849	0.869	0.881	0.898	0.919	0.939	0.958	0.967	0.987
2012	0.879***	(0.00)	0.825	0.842	0.851	0.867	0.886	0.905	0.924	0.934	0.954
2013	0.875***	(0.00)	0.813	0.831	0.840	0.854	0.873	0.891	0.908	0.917	0.934
2014	0.872***	(0.00)	0.824	0.841	0.848	0.860	0.873	0.886	0.898	0.907	0.925
Panel B: $\lambda_{p,h}^{conquer}$ for calendar-year portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
2000	0.811***	(0.00)	0.686	0.718	0.738	0.769	0.804	0.838	0.869	0.886	0.925
2001	0.709***	(0.00)	0.641	0.660	0.672	0.689	0.710	0.733	0.761	0.780	0.812
2002	0.775***	(0.00)	0.667	0.701	0.716	0.748	0.784	0.821	0.857	0.878	0.914
2003	0.767***	(0.00)	0.669	0.699	0.715	0.742	0.769	0.799	0.826	0.843	0.880
2004	0.824***	(0.00)	0.740	0.768	0.783	0.811	0.837	0.867	0.896	0.919	0.947
2005	0.811***	(0.00)	0.737	0.759	0.770	0.791	0.813	0.836	0.858	0.871	0.896
2006	0.832***	(0.00)	0.759	0.782	0.795	0.815	0.839	0.863	0.886	0.899	0.924
2007	0.872***	(0.00)	0.767	0.798	0.814	0.838	0.865	0.890	0.914	0.926	0.948
2008	0.843***	(0.00)	0.768	0.792	0.803	0.822	0.841	0.862	0.881	0.892	0.915
2009	0.779***	(0.00)	0.707	0.727	0.738	0.756	0.775	0.797	0.815	0.826	0.847
2010	0.821***	(0.00)	0.743	0.764	0.774	0.790	0.810	0.829	0.846	0.856	0.874
2011	0.790***	(0.00)	0.718	0.737	0.748	0.768	0.789	0.810	0.828	0.840	0.860
2012	0.820***	(0.00)	0.757	0.774	0.784	0.800	0.818	0.836	0.854	0.866	0.888
2013	0.796***	(0.00)	0.727	0.746	0.755	0.771	0.788	0.805	0.820	0.830	0.847
2014	0.844***	(0.00)	0.785	0.801	0.810	0.826	0.844	0.861	0.877	0.887	0.908

Table OA.6: Bias-corrected $\lambda_{p,h}^{beat}$ and $\lambda_{p,h}^{conquer}$ Bootstrap Distributions by Dispersion and Size Portfolios with h=3 Months

			Bootstrap Distribution								
Portfolio, p	$\lambda_{p,h}^{beat}$	(p-value)	1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel A: Bias-corrected $\lambda_{p,h}^{beat}$ for dispersion portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
1 (Low)	1.083	(0.99)	0.998	1.020	1.033	1.053	1.077	1.101	1.122	1.134	1.156
2	0.929***	(0.01)	0.876	0.892	0.901	0.914	0.929	0.946	0.963	0.977	0.999
3	0.862***	(0.00)	0.814	0.829	0.837	0.849	0.863	0.878	0.893	0.902	0.919
4	0.763***	(0.00)	0.715	0.729	0.736	0.749	0.763	0.776	0.788	0.794	0.808
5 (High)	0.741***	(0.00)	0.699	0.711	0.718	0.730	0.743	0.756	0.768	0.776	0.790
Panel B: Bias-corrected $\lambda_{p,h}^{beat}$ for size portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
1 (Small)	0.776***	(0.00)	0.716	0.731	0.740	0.755	0.772	0.790	0.805	0.814	0.832
2	0.851***	(0.00)	0.800	0.817	0.825	0.839	0.853	0.868	0.882	0.890	0.905
3	0.837***	(0.00)	0.787	0.802	0.810	0.823	0.839	0.854	0.868	0.876	0.893
4	0.872***	(0.00)	0.806	0.824	0.835	0.852	0.871	0.891	0.908	0.919	0.940
5 (Large)	0.978	(0.24)	0.909	0.931	0.943	0.960	0.980	0.999	1.017	1.028	1.048
			Bootstrap Distribution								
Portfolio, p	$\lambda_{p,h}^{conquer}$	(p-value)	1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel C: Bias-corrected $\lambda_{p,h}^{conquer}$ for dispersion portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
1 (Low)	0.840***	(0.00)	0.794	0.805	0.812	0.823	0.837	0.849	0.861	0.867	0.878
2	0.805***	(0.00)	0.766	0.776	0.781	0.791	0.802	0.813	0.822	0.828	0.840
3	0.806***	(0.00)	0.774	0.784	0.789	0.798	0.808	0.818	0.827	0.833	0.845
4	0.740***	(0.00)	0.707	0.718	0.723	0.732	0.742	0.752	0.762	0.768	0.778
5 (High)	0.722***	(0.00)	0.691	0.700	0.705	0.714	0.725	0.736	0.747	0.754	0.766
Panel D: Bias-corrected $\lambda_{p,h}^{conquer}$ for size portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
1 (Small)	0.745***	(0.00)	0.702	0.713	0.719	0.729	0.741	0.754	0.765	0.771	0.784
2	0.781***	(0.00)	0.753	0.763	0.768	0.776	0.785	0.795	0.804	0.809	0.820
3	0.763***	(0.00)	0.728	0.738	0.744	0.753	0.764	0.774	0.784	0.790	0.801
4	0.769***	(0.00)	0.734	0.747	0.752	0.762	0.773	0.785	0.796	0.802	0.815
5 (Large)	0.805***	(0.00)	0.761	0.776	0.783	0.793	0.805	0.817	0.828	0.834	0.846

Table OA.7: Bias-corrected $\lambda_{p,h}^{beat}$ Bootstrap Distributions by Industry Portfolio, p, and Forecast Horizon, h

Industry Portfolio, p	$\lambda_{p,h}^{beat}$	(p-value)	Bootstrap Distribution 1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel A: Bias-corrected $\lambda_{p,h}^{beat}$ for industry portfolios, p, with a forecast horizon of h=0 months prior to the end of the fiscal quarter											
NODUR	1.767	(1.00)	1.593	1.646	1.674	1.719	1.771	1.827	1.884	1.914	1.978
DURBL	1.172	(0.99)	1.008	1.051	1.076	1.115	1.161	1.209	1.250	1.275	1.320
MANUF	1.316	(1.00)	1.247	1.266	1.277	1.295	1.315	1.335	1.353	1.364	1.385
ENRGY	1.138	(0.99)	1.002	1.043	1.065	1.103	1.149	1.195	1.240	1.272	1.327
HITEC	1.174	(1.00)	1.111	1.128	1.138	1.154	1.174	1.194	1.212	1.223	1.246
TELCM	1.076	(0.71)	0.718	0.818	0.874	0.979	1.120	1.304	1.509	1.640	2.012
SHOPS	1.477	(1.00)	1.368	1.399	1.415	1.441	1.473	1.502	1.528	1.547	1.582
HLTH	1.505	(1.00)	1.371	1.414	1.436	1.474	1.515	1.554	1.592	1.613	1.659
UTILS	1.152	(0.94)	0.914	0.990	1.026	1.092	1.166	1.251	1.332	1.390	1.495
OTHER	1.200	(1.00)	1.089	1.122	1.141	1.169	1.203	1.239	1.278	1.299	1.344
All	1.309	(1.00)	1.270	1.282	1.288	1.298	1.308	1.319	1.329	1.335	1.346
Panel B: Bias-corrected $\lambda_{p,h}^{beat}$ for industry portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
NODUR	0.841***	(0.00)	0.792	0.804	0.812	0.825	0.839	0.853	0.865	0.873	0.888
DURBL	0.773***	(0.00)	0.667	0.694	0.711	0.735	0.764	0.792	0.822	0.838	0.866
MANUF	0.731***	(0.00)	0.684	0.698	0.705	0.717	0.730	0.743	0.754	0.761	0.774
ENRGY	0.677	(0.25)	0.436	0.502	0.561	0.642	0.805	0.993	1.166	1.344	1.614
HITEC	0.985	(0.36)	0.915	0.936	0.948	0.967	0.987	1.011	1.032	1.044	1.067
TELCM	0.922**	(0.04)	0.823	0.852	0.868	0.894	0.922	0.952	0.979	0.997	1.025
SHOPS	0.942	(0.36)	0.666	0.737	0.783	0.852	0.943	1.045	1.146	1.207	1.332
HLTH	0.825***	(0.00)	0.749	0.774	0.787	0.806	0.826	0.848	0.871	0.885	0.911
UTILS	0.853***	(0.00)	0.829	0.836	0.840	0.847	0.854	0.862	0.870	0.874	0.881
OTHER	0.000^0	(0.00)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
All	0.000^0	(0.00)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table OA.8: Bias-corrected $\lambda_{p,h}^{conquer}$ Bootstrap Distributions by Industry Portfolio, p, and Forecast Horizon, h

Industry Portfolio, p	$\lambda_{p,h}^{conquer}$	(p-value)	Bootstrap Distribution 1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel A: Bias-corrected $\lambda_{p,h}^{conquer}$ for industry portfolios, p, with a forecast horizon of h=0 months prior to the end of the fiscal quarter											
NODUR	1.001	(0.54)	0.924	0.946	0.959	0.980	1.004	1.027	1.048	1.061	1.088
DURBL	0.910***	(0.01)	0.814	0.839	0.852	0.875	0.901	0.929	0.954	0.967	0.997
MANUF	0.968**	(0.02)	0.932	0.943	0.949	0.958	0.969	0.979	0.988	0.994	1.006
ENRGY	0.961	(0.21)	0.878	0.900	0.915	0.940	0.966	0.995	1.021	1.038	1.068
HITEC	0.917***	(0.00)	0.880	0.891	0.897	0.907	0.918	0.930	0.940	0.946	0.959
TELCM	0.973	(0.51)	0.710	0.794	0.836	0.919	1.002	1.103	1.224	1.309	1.502
SHOPS	0.969*	(0.07)	0.914	0.930	0.938	0.953	0.968	0.983	0.996	1.004	1.019
HLTH	1.024	(0.72)	0.941	0.963	0.976	0.997	1.021	1.047	1.069	1.081	1.106
UTILS	0.875*	(0.06)	0.722	0.768	0.790	0.835	0.875	0.927	0.970	1.004	1.067
OTHER	0.871***	(0.00)	0.821	0.838	0.846	0.862	0.878	0.897	0.916	0.928	0.949
All	0.954***	(0.00)	0.933	0.939	0.942	0.948	0.954	0.960	0.965	0.968	0.975
Panel B: Bias-corrected $\lambda_{p,h}^{conquer}$ for industry portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
NODUR	0.897***	(0.00)	0.832	0.855	0.865	0.882	0.904	0.926	0.944	0.957	0.978
DURBL	0.708***	(0.00)	0.654	0.670	0.680	0.696	0.716	0.739	0.759	0.770	0.795
MANUF	0.781***	(0.00)	0.739	0.750	0.756	0.765	0.776	0.787	0.797	0.803	0.815
ENRGY	0.765***	(0.00)	0.690	0.710	0.720	0.742	0.765	0.786	0.806	0.819	0.845
HITEC	0.720***	(0.00)	0.685	0.695	0.700	0.709	0.719	0.729	0.738	0.743	0.754
TELCM	0.806	(0.29)	0.536	0.630	0.686	0.767	0.865	1.023	1.147	1.308	1.595
SHOPS	0.829***	(0.00)	0.783	0.798	0.804	0.816	0.830	0.845	0.860	0.869	0.885
HLTH	0.843***	(0.00)	0.770	0.791	0.802	0.820	0.841	0.863	0.881	0.892	0.915
UTILS	0.753***	(0.01)	0.594	0.652	0.669	0.716	0.763	0.822	0.882	0.912	0.977
OTHER	0.779***	(0.00)	0.716	0.733	0.743	0.760	0.778	0.796	0.814	0.826	0.845
All	0.780***	(0.00)	0.763	0.768	0.771	0.776	0.781	0.787	0.792	0.795	0.801

Table OA.9: Bias-corrected $\lambda_{p,h}^{beat}$ Bootstrap Distributions by Calendar-year Portfolio, p, and Forecast Horizon, h

Calendar-year Portfolio, p	$\lambda_{p,h}^{beat}$	(p-value)	Bootstrap Distribution 1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel A: Bias-corrected $\lambda_{p,h}^{beat}$ for calendar-year portfolios, p, with a forecast horizon of h=0 months prior to the end of the fiscal quarter											
2000	1.421	(1.00)	1.227	1.275	1.304	1.353	1.416	1.481	1.556	1.603	1.687
2001	1.248	(1.00)	1.089	1.135	1.161	1.203	1.254	1.319	1.382	1.418	1.479
2002	1.231	(1.00)	1.076	1.121	1.144	1.188	1.241	1.296	1.345	1.376	1.438
2003	1.375	(1.00)	1.200	1.247	1.276	1.322	1.374	1.430	1.482	1.515	1.578
2004	1.613	(1.00)	1.380	1.444	1.482	1.546	1.612	1.682	1.749	1.787	1.852
2005	1.367	(1.00)	1.212	1.257	1.277	1.319	1.367	1.417	1.462	1.487	1.538
2006	1.347	(1.00)	1.217	1.261	1.282	1.317	1.355	1.398	1.443	1.472	1.525
2007	1.348	(1.00)	1.175	1.218	1.243	1.286	1.338	1.390	1.437	1.465	1.524
2008	1.295	(1.00)	1.162	1.198	1.220	1.254	1.294	1.334	1.371	1.393	1.433
2009	1.216	(1.00)	1.091	1.127	1.148	1.184	1.227	1.270	1.313	1.341	1.385
2010	1.211	(1.00)	1.092	1.123	1.140	1.173	1.212	1.256	1.295	1.322	1.368
2011	1.121	(1.00)	1.038	1.065	1.078	1.101	1.128	1.157	1.185	1.202	1.239
2012	1.277	(1.00)	1.146	1.184	1.207	1.243	1.284	1.325	1.363	1.386	1.433
2013	1.370	(1.00)	1.239	1.284	1.303	1.335	1.370	1.401	1.431	1.451	1.492
2014	1.327	(1.00)	1.217	1.251	1.270	1.302	1.333	1.366	1.397	1.418	1.459
Panel B: Bias-corrected $\lambda_{p,h}^{beat}$ for calendar-year portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
2000	0.797***	(0.00)	0.699	0.727	0.745	0.776	0.816	0.859	0.898	0.927	0.975
2001	0.705***	(0.00)	0.588	0.620	0.638	0.669	0.700	0.734	0.768	0.787	0.822
2002	0.799***	(0.00)	0.662	0.701	0.721	0.758	0.794	0.835	0.869	0.893	0.940
2003	0.855***	(0.00)	0.736	0.771	0.792	0.821	0.853	0.885	0.914	0.931	0.965
2004	0.980	(0.33)	0.834	0.877	0.896	0.934	0.973	1.017	1.053	1.071	1.114
2005	0.974	(0.27)	0.817	0.858	0.880	0.917	0.961	1.004	1.039	1.063	1.114
2006	1.001	(0.42)	0.877	0.906	0.924	0.955	0.990	1.023	1.055	1.075	1.111
2007	0.861***	(0.00)	0.750	0.782	0.799	0.827	0.860	0.893	0.924	0.943	0.982
2008	0.931*	(0.08)	0.837	0.866	0.880	0.902	0.935	0.967	0.994	1.013	1.048
2009	0.814***	(0.00)	0.723	0.747	0.761	0.785	0.813	0.841	0.867	0.885	0.915
2010	0.785***	(0.00)	0.697	0.722	0.735	0.758	0.784	0.811	0.835	0.851	0.875
2011	0.756***	(0.00)	0.668	0.692	0.705	0.727	0.751	0.776	0.799	0.812	0.837
2012	0.845***	(0.00)	0.762	0.785	0.798	0.817	0.840	0.863	0.885	0.897	0.924
2013	0.905**	(0.01)	0.809	0.837	0.851	0.876	0.905	0.933	0.959	0.974	1.001
2014	0.921**	(0.04)	0.833	0.857	0.871	0.894	0.921	0.947	0.974	0.992	1.022

Table OA.10: Bias-corrected $\lambda_{p,h}^{conquer}$ Bootstrap Distributions by Calendar-year Portfolio, p, and Forecast Horizon, h

Calendar-year Portfolio, p	$\lambda_{p,h}^{conquer}$	(p-value)	Bootstrap Distribution 1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel A: Bias-corrected $\lambda_{p,h}^{conquer}$ for calendar-year portfolios, p, with a forecast horizon of h=0 months prior to the end of the fiscal quarter											
2000	0.984	(0.48)	0.895	0.922	0.937	0.964	0.997	1.033	1.070	1.093	1.135
2001	0.945	(0.15)	0.859	0.882	0.895	0.917	0.946	0.980	1.012	1.030	1.064
2002	0.872***	(0.00)	0.781	0.808	0.823	0.846	0.873	0.903	0.929	0.944	0.974
2003	0.909**	(0.02)	0.825	0.852	0.863	0.886	0.914	0.942	0.966	0.980	1.011
2004	1.037	(0.81)	0.933	0.965	0.982	1.010	1.040	1.070	1.096	1.115	1.155
2005	0.930**	(0.03)	0.833	0.858	0.871	0.894	0.919	0.947	0.974	0.989	1.013
2006	0.981	(0.35)	0.894	0.921	0.935	0.957	0.985	1.012	1.037	1.051	1.082
2007	0.948	(0.11)	0.857	0.880	0.896	0.921	0.948	0.975	1.003	1.020	1.050
2008	0.956	(0.11)	0.877	0.901	0.912	0.932	0.956	0.979	1.001	1.015	1.044
2009	0.984	(0.42)	0.918	0.939	0.949	0.969	0.993	1.016	1.039	1.052	1.077
2010	0.970	(0.16)	0.889	0.911	0.923	0.941	0.964	0.989	1.012	1.027	1.053
2011	0.906***	(0.00)	0.836	0.856	0.867	0.884	0.902	0.921	0.939	0.950	0.970
2012	0.939**	(0.05)	0.880	0.898	0.909	0.927	0.947	0.968	0.987	0.999	1.024
2013	0.965	(0.11)	0.900	0.920	0.930	0.947	0.963	0.982	1.002	1.015	1.037
2014	0.973	(0.15)	0.908	0.927	0.937	0.954	0.972	0.990	1.006	1.017	1.034
Panel B: Bias-corrected $\lambda_{p,h}^{conquer}$ for calendar-year portfolios, p, with a forecast horizon of h=3 months prior to the end of the fiscal quarter											
2000	0.720***	(0.00)	0.636	0.663	0.676	0.705	0.735	0.766	0.794	0.813	0.847
2001	0.726***	(0.00)	0.654	0.675	0.687	0.706	0.732	0.759	0.783	0.797	0.825
2002	0.745***	(0.00)	0.660	0.687	0.700	0.722	0.747	0.775	0.802	0.821	0.858
2003	0.809***	(0.00)	0.698	0.729	0.743	0.770	0.799	0.826	0.848	0.863	0.885
2004	0.829***	(0.00)	0.731	0.753	0.769	0.793	0.818	0.845	0.867	0.882	0.912
2005	0.846***	(0.00)	0.742	0.769	0.785	0.811	0.842	0.874	0.903	0.920	0.950
2006	0.889***	(0.00)	0.793	0.819	0.832	0.855	0.881	0.909	0.935	0.949	0.981
2007	0.792***	(0.00)	0.722	0.741	0.753	0.770	0.791	0.812	0.831	0.843	0.867
2008	0.828***	(0.00)	0.769	0.786	0.795	0.811	0.828	0.846	0.864	0.874	0.896
2009	0.831***	(0.00)	0.748	0.770	0.782	0.800	0.822	0.845	0.864	0.876	0.901
2010	0.766***	(0.00)	0.709	0.727	0.736	0.752	0.770	0.788	0.806	0.816	0.837
2011	0.687***	(0.00)	0.626	0.642	0.652	0.666	0.683	0.702	0.717	0.726	0.745
2012	0.749***	(0.00)	0.687	0.704	0.713	0.729	0.748	0.765	0.780	0.791	0.810
2013	0.787***	(0.00)	0.727	0.744	0.753	0.771	0.791	0.810	0.827	0.839	0.858
2014	0.825***	(0.00)	0.763	0.781	0.790	0.807	0.824	0.844	0.861	0.872	0.893