Panel Data Nowcasting: The Case of Price-Earnings Ratios*

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Abstract

The paper uses structured machine learning regressions for nowcasting with panel data consisting of series sampled at different frequencies. Motivated by the problem of predicting corporate earnings for a large cross-section of firms with macroeconomic, financial, and news time series sampled at different frequencies, we focus on the sparse-group LASSO regularization which can take advantage of the mixed frequency time series panel data structures. Our empirical results show the superior performance of our machine learning panel data regression models over analysts' predictions, forecast combinations, firm-specific time series regression models, and standard machine learning methods.

Keywords: Corporate earnings, nowcasting, data-rich environment, high-dimensional panels, mixed frequency data, textual news data, sparse-group LASSO.

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1 Introduction

Nowcasting is intrinsically a mixed frequency data problem as the object of interest is a low-frequency data series — observed say quarterly — whereas real-time information — daily, weekly or monthly — during the quarter can be used to assess and potentially continuously update the state of the low-frequency series, or put differently, *nowcast* the series of interest. Traditional methods being used for nowcasting rely on dynamic factor models which treat the underlying low-frequency series of interest as a latent process with high-frequency data noisy observations. These models are naturally cast in a state-space form, and inference can be performed using standard techniques (in particular the Kalman filter, see Bańbura, Giannone, Modugno, and Reichlin (2013) for a recent survey).

Things get more complicated when we are operating in a data-rich environment and we have many target variables. Put differently, we are no longer interested in nowcasting a single key series such as the GDP growth where we could devote a lot of resources to that particular series. A good example is corporate earnings nowcasting for a large cross-section of corporate firms. The fundamental value of equity shares is determined by the discounted value of future payoffs. Every quarter investors get a glimpse of firms' potential payoffs with the release of corporate earnings reports. In a data-rich environment, stock analysts have many indicators regarding future earnings that are available much more frequently. Ball and Ghysels (2018) took a first stab at automating the process using MIDAS regressions. Since their original work, much progress has been made on machine learning (ML) regularized mixed frequency regression models.

In the context of earnings, we are potentially dealing with a large set of individual firms for which there are many predictors. From a practical point of view, this is clearly beyond the realm of nowcasting using state space models. In the current paper, we significantly expand the tools of nowcasting in a data-rich environment by exploiting panel data structures. Panel data regression models are well suited for the firm-level data analysis as both the time series and cross-sectional dimensions can be exploited. In such models, time-invariant firm-specific effects are typically used to capture cross-sectional heterogeneity in the data. This is combined with regularized regression machine learning methods which are becoming increasingly popular in economics and finance as a flexible way to model predictive relationships via variable selection. We focus on the panel data regressions in a high-dimensional data setting where the number of covariates could be large and potentially exceed the available sample size. This may happen when the number of firm-specific characteristics, such as textual analysis news data or firm-level stock returns, is large, and/or the number of aggregates, such as market returns, macro data, etc., is large.

Our paper relates to several existing papers in the literature. Khalaf, Kichian, Saunders, and Voia (2021) consider low-dimensional dynamic mixed frequency panel data models but do not deal with high-dimensional data situations in the context of nowcasting or forecasting. Similarly, Fosten and Greenaway-McGrevy (2019) consider nowcasting with a mixed-frequency VAR panel data model, but not in the context of a high-dimensional data-rich environment that we are interested in here. Babii, Ball, Ghysels, and Striaukas (2022) introduce the sparse-group LASSO (sg-LASSO) regularization machine learning methods for heavy-tailed dependent panel data regressions potentially sampled at different time series frequencies. They derive oracle inequalities for the pooled and fixed effects models, the debiased inference for pooled regression, and consider an application to the Granger causality testing. In this paper, we explore how to use their framework for nowcasting large panels of low-frequency time series.

We focus on nowcasting current quarter firm-specific price-earnings ratios (henceforth P/E ratios). This means we focus on evaluating model-based within-quarter predictions for very short horizons. It is widely acknowledged that P/E ratios are a good indicator of the future performance of a company and, therefore, are used by analysts and investment professionals to base their decisions on which stocks to pick for their investment portfolios. Typically investors rely on consensus forecasts of earnings made by a pool of analysts. We, therefore, choose such consensus forecasts as the benchmark for our proposed machine learning methods. Ball and Ghysels (2018) and Carabias (2018) documented that analysts tend to focus on their firm/industry when making earnings predictions while not fully taking into account the impact of macroeconomic events. Babii, Ball, Ghysels, and Striaukas (2022) tested formally in a high-dimensional data setting the hypothesis that systematic and predictable errors occur in analyst forecasts and confirmed empirically that they *leave money* on the table. The analysis in the current paper is therefore an logical extension of this prior work. In addition, we also compare our proposed new methods with the MIDAS regression forecast combination approach used by Ball and Ghysels (2018) as well as a simple random walk model.

Our high-frequency regressors include traditional macro and financial series as well as non-standard series generated by textual analysis of financial news. We consider structured pooled and fixed effects sg-LASSO panel data regressions with mixed frequency data (sg-LASSO MIDAS). By "structured" we mean that the ML procedure is set up such that it recognizes the time series and panel structure of the data. This is a departure from standard ML which is rooted in a tradition of i.i.d. covariates and therefore time series and panel data structures are not recognized. For the purpose of comparison, we include elastic net estimators in our analysis, as a representative example of standard ML.

In our empirical analysis we study nowcasting the firm-level P/E ratio for a large set of firms. Moreover, we decompose the (log of) the P/E ratio into the return for firm i and analyst prediction errors. Therefore, nowcasting the log P/E ratio could also be achieved via nowcasting its two components. The decomposition corresponds to the distinction between analyst assessments of firm i's earnings and market/investor assessments of the firm.

Our empirical results can be summarized as follows. Predictions based on analyst consensus exhibit significantly higher mean squared forecast errors (MSEs) compared to model-based predictions. These model-based predictions involve either direct log P/E ratio nowcasts or their individual components. The MSE for the random walk model and analysts' concensus are quite similar, and therefore random walk predictions are outperformed by the model-based ones as well. A substantial proportion of firms (approximately 60%) exhibit low MSE values, indicating a high level of prediction accuracy. However, there are a few firms for which the MSEs are relatively larger, suggesting lower prediction performance for these specific cases. Comparing direct log P/E ratio nowcasts versus those based on its components, we observe a substantial improvement in prediction accuracy when using the individual components. This improvement is consistently evident across individual, pooled, and fixed effects regression models. Moreover, the sparsity patterns differ significantly across the direct versus component prediction models.

Our framework allows us to go beyond providing quarterly nowcasts and generate daily updates of earnings series. Leveraging the daily influx of information throughout the quarter, we continuously re-estimate our models and produce nowcast updates as soon as new data becomes available. We report the distribution of Mean Squared Errors (MSEs) across firms for five distinct nowcast horizons: 20-day, 15-day, 10-day, and 5-day ahead, as well as the end of the quarter and show that as the horizons become shorter, both the median and upper quartile of MSEs decrease. The sg-LASSO estimator we employ in our study is well-suited for incorporating grouped fixed effects. This approach involves grouping firm-specific intercepts based on either statistical procedures or economic reasoning, as outlined in Bonhomme and Manresa (2015). In our analysis, we utilize the Fama French industry classification to form 10 distinct groups for grouping fixed effects. Our findings suggest that grouped fixed effects strike a better balance between capturing heterogeneity and pooled parameters, resulting in more accurate nowcast predictions. These results support the notion that incorporating group fixed effects enhances the overall performance of our forecasting model.

Next we address the challenge of missing earnings data, which can complicate the analysis. We examine the performance of parameter imputation methods in computing nowcasts, see, e.g, Brown, Ghysels, and Gredil (2023), even when earnings and/or earnings forecasts are missing for certain observations in the sample. The results obtained through parameter imputation outperform the analyst consensus nowcasts in terms of prediction accuracy.

The paper is organized as follows. Section 2 introduces the models and estimators. A simulation study reporting the finite sample nowcasting performance of our proposed methods appears in Section 3. The results of our empirical application analyzing price-earnings ratios for a panel of individual firms are reported in Section 4. Section 5 concludes. All technical details and detailed data descriptions appear in the Appendix and the Online Appendix.

2 High-dimensional mixed frequency panel data

In this section, we describe the methodological approach of the paper. Motivated by our application, we will refer to the cross-sectional observations as firms, the low-frequency observations as quarterly while the high-frequency observations are daily or monthly. However, the notation presented in this section is generic and can correspond to other entities and frequencies. The objective is to nowcast $\{y_{i,t} : i \in [N], t \in [T]\}$ (where for a positive integer p, we put $[p] = \{1, 2, \ldots, p\}$), in our case a panel of P/E ratios (or its decomposition into returns and analyst forecast errors) for N firms observed at T time periods. The covariates consist of K time-varying predictors measured potentially at higher frequencies

$$\left\{x_{i,t-j/n_k^H,k}: i \in [N], t \in [T], j = 0, \dots, n_k^L n_k^H - 1, k \in [K]\right\},\$$

where n_k^H is the number of high-frequency observations for the k^{th} covariate in a low-frequency time period t, and n_k^L is the number of low-frequency time periods used as lags. For instance, $n_k^L = 1$ corresponds in our application to a quarter of high-frequency lags used as covariates and $n_k^H = 3$ corresponds to monthly data with 3 month of data available per quarter. Note that we can think of mixtures of say annual, quarterly, monthly and weekly data, and therefore n_k^H represents different high frequency sampling frequencies and associated lags $n_k^L n_k^H$. In our empirical analysis we examine three types of regression model specifications: (a) regularized single equation regressions for each individual firm, (b) regularized panel regressions with pooling, and (c) regularized panel regressions with fixed effects. Hence, in (a) we do not explore the panel structure of the data, whereas in (b) and (c) we do. To discuss the model specifications, we focus here on (b) and (c), keeping in mind that the single regression case is a straightforward simplification of the panel regression models.

Consider the mixed frequency panel data regression for $y_{i,t|\tau}$, that is observation i for low-frequency nowcasting y at time t using information up to τ :

$$y_{i,t|\tau} = \alpha_i + \sum_{k=1}^{K} \psi(L^{1/n_k^H}; \beta_k) x_{i,\tau,k} + u_{i,t|\tau},$$

where α_i is the entity-specific intercept (depending on τ but we suppress this detail to simplify notation), and

$$\psi(L^{1/n_k^H};\beta_k)x_{i,\tau,k} = \frac{1}{k_{max}} \sum_{j=0}^{k_{max}-1} \beta_{j,k} L^{j/n_k^H} x_{i,\tau,k}$$
(1)

where k_{max} is the maximum lag length which may depend on the covariate k, and for each high frequency covariate $x_{i,\tau,k}$ we have the most up to date information available at time τ . This may imply that for some high frequency regressors this is stale information as they have not been updated yet, but presumably at least some of the high frequency data are fresh real-time information at the time τ the nowcast is being made. For instance, in our quarterly/monthly application we can have $\tau = (t-1) +$ 1/3 in which case we nowcast quarter t with information available at the end of the first month of that quarter. In this example, some high frequency series for the first month may be available while some may not due to say publication lags. Likewise, with $\tau = (t-1) + 2/3$ we can revise the previous nowcast with one extra month of information, which taking into account publication lags may include observations from the first month as the most recent releases. It should parenthetically be noted that for $\tau \leq t - 1$, we are dealing with a forecasting situation and therefore our analysis applies to both nowcasting and - ceteris paribus - forecasting.

To reduce the dimensionality of the high-frequency lag polynomial, we follow the MIDAS ML literature, see Babii, Ghysels, and Striaukas (2021, 2022), and estimate a weight function ω parameterized by a relatively small number of coefficients L

$$\psi(L^{1/n_k^H};\beta_k)x_{i,\tau,k} = \frac{1}{k_{max}} \sum_{j=0}^{k_{max}-1} \omega\left(\frac{j}{n_k^H};\beta_k\right) x_{i,\tau,k},$$

where the MIDAS weight function is $\omega(s; \beta_k) = \sum_{l=0}^{L-1} \beta_{l,k} w_l(s), (w_l)_{l\geq 0}$ is a collection of L approximating functions, called the *dictionary*, and $\beta_k \in \mathbf{R}^L$ is the unknown parameter. An example of a dictionary used in the MIDAS ML literature is the set of orthogonal Legendre polynomials. To streamline notation it will be convenient to assume, without loss of generality, a common lag length, i.e. $\bar{k}_{max} = k_{max} \forall k \in [K]$. The linear in parameters dictionaries map the MIDAS regression to a standard linear regression framework. In particular, define $\mathbf{x}_i = (X_{i,1}W, \ldots, X_{i,K}W)$, where for each $k \in [K], X_{i,k} = (x_{i,\tau-j/n_k^H,k}, j = 0, \ldots, \bar{k}_{max} - 1)_{\tau \in [T]}$ is a $T \times \bar{k}_{max}$ matrix of covariates and $\bar{k}_{max}W = (w_l(j/n_k^H; \beta_k)_{0 \leq l \leq L-1, 0 \leq j \leq \bar{k}_{max}}$ is a $\bar{k}_{max} \times L$ matrix corresponding to the dictionary. In addition, let $\mathbf{y}_i = (y_{i,t|\tau}, t, \tau \in [T])^{\top}$ and $\mathbf{u}_i = (u_{i,t|\tau}, t, \tau \in [T])^{\top}$. The regression equation after stacking time series observations for each firm $i \in [N]$ is as follows

$$\mathbf{y}_i = \iota \alpha_i + \mathbf{x}_i \beta + \mathbf{u}_i,$$

where $\iota \in \mathbf{R}^T$ is the all-ones vector and $\beta \in \mathbf{R}^{LK}$ is a vector of slope coefficients. Lastly, put $\mathbf{y} = (\mathbf{y}_1^\top, \dots, \mathbf{y}_N^\top)^\top$, $\mathbf{X} = (\mathbf{x}_1^\top, \dots, \mathbf{x}_N^\top)^\top$, and $\mathbf{u} = (\mathbf{u}_1^\top, \dots, \mathbf{u}_N^\top)^\top$. Then the regression equation after stacking all cross-sectional observations is

$$\mathbf{y} = B\alpha + \mathbf{X}\beta + \mathbf{u},$$

where $B = I_N \otimes \iota$, I_N is $N \times N$ identity matrix, and \otimes is the Kronecker product. Given that the number of potential predictors K can be large, additional regularization can improve the predictive performance in small samples. To that end, we take advantage of the sg-LASSO regularization, suggested by Babii, Ghysels, and Striaukas (2022).

The fixed effects sg-LASSO estimator $\hat{\rho} = (\hat{\alpha}^{\top}, \hat{\beta}^{\top})^{\top}$ solves

$$\min_{(a,b)\in\mathbf{R}^{N+p}} \|\mathbf{y} - Ba - \mathbf{X}b\|_{NT}^2 + 2\lambda\Omega(b),$$
(2)

where Ω is the sg-LASSO regularizing functional. It is worth stressing that the design matrix **X** does not include the intercept and that we do not penalize the fixed effects which are typically not sparse. In addition, $\|.\|_{NT}^2 = |.|^2/(NT)$ is the empirical norm and

$$\Omega(b) = \gamma |b|_1 + (1 - \gamma) ||b||_{2,1},$$

is a regularizing functional. It is a linear combination of the ℓ_1 LASSO and $\ell_{2,1}$ group LASSO norms. Note that for a group structure \mathcal{G} described as a partition of $[p] = \{1, 2, \ldots, p\}$, the group LASSO norm is computed as $||b||_{2,1} = \sum_{G \in \mathcal{G}} |b_G|_2$, while $|.|_q$ denotes the usual ℓ_q norm. The group LASSO penalty encourages sparsity between groups whereas the ℓ_1 LASSO norm promotes sparsity within groups and allows us to learn the shape of the MIDAS weights from the data. The parameter $\gamma \in [0, 1]$ determines the relative weights of the ℓ_1 (sparsity) and the $\ell_{2,1}$ (group sparsity) norms, while the amount of regularization is controlled by the regularization parameter $\lambda \geq 0$.

In Section 1, we called our approach structured ML because the group structure allows us to embed the time series structure of the data. More specifically, these structures are represented by groups covering lagged dependent variables and groups of lags for a single (high-frequency) covariate. Throughout the paper, we assume that groups have fixed size, and the group structure is known by the econometrician. Both are reasonable assumptions to make in the context of our empirical application.

For pooled regressions, we assume that all entities share the same intercept parameter $\alpha_1 = \cdots = \alpha_N = \alpha$. The pooled sg-LASSO estimator $\hat{\rho} = (\hat{\alpha}, \hat{\beta}^{\top})^{\top}$ solves

$$\min_{r=(a,b)\in\mathbf{R}^{1+p}} \|\mathbf{y} - a\iota - \mathbf{X}b\|_{NT}^2 + 2\lambda\Omega(r).$$
(3)

Pooled regressions are attractive since the effective sample size NT can be huge, yet the heterogeneity of individual time series may be lost. If the underlying series have a substantial heterogeneity over $i \in [N]$, then taking this into account might reduce the projection error and improve the predictive accuracy.

Babii, Ball, Ghysels, and Striaukas (2022) provide the theoretical analysis of predictive performance of regularized panel data regressions with the sg-LASSO regularization, including as special cases (a) standard LASSO, (b) group LASSO regularizations as well as (c) generic high-dimensional panels not involving mixed frequency data. Finally, Babii, Ball, Ghysels, and Striaukas (2022) also develop the debiased inferential methods and Granger causality tests for pooled panel data regressions.

3 Monte Carlo experiments

It is not clear that the aforementioned theory is of practical use in the context of nowcasting using modestly sized samples of data. For this reason, we investigate in this section the finite sample nowcasting performance of the machine learning methods covered so far. We consider the standard (unstructured) elastic net with UMIDAS (called Elnet-U), where UMIDAS refers to unconstrained MIDAS proposed by Foroni, Marcellino, and Schumacher (2015) in a classic non-ML context, and sg-LASSO with MIDAS. Both methods require selecting two tuning parameters λ and γ . In the case of sg-LASSO, γ is the relative weight of LASSO and group LASSO penalties while in the case of the elastic net γ interpolates between LASSO and ridge. In both cases we report results on a grid $\gamma \in \{0, 0.2, ..., 1\}$.

In addition to evaluating the performance over the grid of γ tuning parameter values, we need to select the λ tuning parameter. To do so, we consider several approaches. First, we adapt the K-fold cross-validation to the panel data setting. To that end, we resample the data by blocks respecting the time-series dimension and creating folds based on cross-sectional units instead of the pooled sample. We use the 5-fold cross-validation both in the simulation experiments and the empirical application. We also consider the following three information criteria: BIC, AIC, and corrected AIC (AICc) of Hurvich and Tsai (1989). Assuming that $y_{i,t}|x_{i,t}$ are i.i.d. draws from $N(\alpha_i + x_{i,t}^{\top}\beta, \sigma^2)$, the log-likelihood of the sample is

$$\mathcal{L}(\alpha,\beta,\sigma^2) \propto -\frac{1}{2\sigma^2} \sum_{i=1}^N \sum_{t=1}^T (y_{i,t} - \alpha_i - x_{i,t}^\top \beta)^2.$$

Then, the BIC criterion is

$$BIC = \frac{\|\mathbf{y} - \hat{\mu} - \mathbf{X}\hat{\beta}\|_{NT}^2}{\hat{\sigma}^2} + \frac{\log(NT)}{NT} \times df,$$

where df denotes the degrees of freedom, $\hat{\sigma}^2$ is a consistent estimator of σ^2 , $\hat{\mu} = \hat{\alpha}\iota$ for the pooled regression, and $\hat{\mu} = B\hat{\alpha}$ for fixed effects regression. The degrees of freedom are estimated as $\hat{df} = |\hat{\beta}|_0 + 1$ for the pooled regression and $\hat{df} = |\hat{\beta}|_0 + N$ for the fixed effects regression, where $|.|_0$ is the ℓ_0 -norm defined as a number of non-zero coefficients; see Zou, Hastie, and Tibshirani (2007) for more details. The AIC is computed as

$$AIC = \frac{\|\mathbf{y} - \hat{\mu} - \mathbf{X}\beta\|_{NT}^2}{\hat{\sigma}^2} + \frac{2}{NT} \times \hat{df},$$

and the corrected Akaike information criteria is

$$AICc = \frac{\|\mathbf{y} - \hat{\mu} - \mathbf{X}\hat{\beta}\|_{NT}^2}{\hat{\sigma}^2} + \frac{2\hat{df}}{NT - \hat{df} - 1}$$

The AICc is typically a better choice when p is large relative to the sample size. We report the results for each of the tuning parameter selection criteria for λ , along the grid choice for γ .

3.1 Simulation Design

To assess the predictive performance of pooled panel data models, we simulate the data from the following DGP with a quarterly/monthly frequency mix in mind and $\bar{k}_{max} = k_{max}$ with $n_k^H = n^H \forall k$:

$$y_{i,t|\tau} = \alpha + \sum_{k=1}^{K} \bar{k}_{max}^{-1} \sum_{j=0}^{\bar{k}_{max}-1} \omega(j/n^{H};\beta_{k}) x_{i,\tau-j/n^{H},k} + u_{i,t|\tau}$$

where $i \in [N]$, $t \in [T]$, α is the common intercept, $\bar{k}_{max}^{-1} \sum_{j=0}^{\bar{k}_{max}-1} \omega(j/n_k; \beta_k)$ the weight function for k-th high-frequency covariate and the error term is either $u_{i,t|\tau} \sim_{i.i.d.} N(0,1)$ or $u_{i,t|\tau} \sim_{i.i.d.}$ student-t(5).

We are interested in a quarterly/monthly data mix, and use four quarters of data for the high-frequency regressors which covers 12 high-frequency lags for each regressor. In terms of information sets we start with $\tau = t - 1$, which corresponds to a prediction setting and then have $\tau = t - 1 + 1/3$, i.e. nowcasting with one month's worth of information. We set the number of relevant high-frequency regressors K = 6. The high-frequency regressors are generated as K i.i.d. realizations of the univariate autoregressive (AR) process $x_h = \rho x_{h-1} + \varepsilon_h$, where $\rho = 0.6$ and either $\varepsilon_h \sim_{i.i.d.} N(0, 1)$ or $\varepsilon_h \sim_{i.i.d.}$ student-t(5), where h denotes the high-frequency sampling. We rely on a commonly used weighting scheme in the MIDAS literature, namely $\omega(s; \beta_k)$ for $k = 1, 2, \ldots, 6$ are determined by beta densities respectively equal to Beta(1, 3)for k = 1, 4, Beta(2, 3) for k = 2, 5, and Beta(2, 2) for k = 3, 6; see Ghysels, Sinko, and Valkanov (2007) or Ghysels and Qian (2019), for further details. The MIDAS regressions are estimated using Legendre polynomials of degree L = 3.

We consider DGPs featuring pooled panels and fixed effects. For the pooled panel regression DGPs we simulate the intercepts as $\alpha \sim \text{Uniform}(-4, 4)$. For the fixed effects models the individual fixed effects are simulated as $\alpha_i \sim_{\text{i.i.d}} \text{Uniform}(-4, 4)$ and are kept fixed throughout the experiment.

For $\tau = t - 1$, the Baseline scenario, in the estimation procedure we add 24 noisy covariates which are generated in the same way as the relevant covariates, use 4 low-frequency lags and the error terms $u_{i,t|\tau}$ and ε_h are Gaussian. In the student-t(5)scenario we replace the Gaussian error terms with a student-t(5) distribution while in the large dimensional scenario we add 94 noisy covariates. For each scenario, we simulate N = 25 i.i.d. time series of length T = 50; next we increase the crosssectional dimension to N = 75 and time series to T = 100.

Finally, for $\tau = t - 1 + 1/3$ the thought experiment in the simulation design is one where the first high-frequency observations during low frequency t are available. The nowcaster of course does not know which of the covariates are relevant nor does she know the parameters of the prediction rule. We will call this scheme "one-step ahead" nowcasts.

3.2 Simulation results

Tables 1 and 2 cover the average mean squared forecast errors (MSFE) for one-step ahead nowcasts for the three simulation scenarios. We report results for sg-LASSO with MIDAS weights (left block) and elastic net with UMIDAS (right block) using both pooled panel models (Table 1) and fixed effects ones (Table 2). We report results for the best choice of the γ tuning parameter.¹

Firstly, structured sg-LASSO-MIDAS consistently outperforms unstructured Elnet-U for all DGPs and in both pooled and fixed effects cases. The most significant discrepancy between the two methods is observed in situations with small N and small T, specifically when N = 25 and T = 50. As either N or T increases, this gap gradually diminishes. When comparing the results of pooled and fixed effects, it becomes evident that the difference between the two approaches — structured sg-LASSO-MIDAS versus Elnet UMIDAS — widens further in the case of fixed effects with student-t(5) data. This indicates that our structured approach yields higher quality estimates for the fixed effects and thus more accurate nowcasts.

In the case of sg-LASSO-MIDAS, the best performance is achieved for $\gamma \notin \{0, 1\}$ for both pooled panel data and fixed effects cases, while $\gamma = 0$, i.e. ridge regression, seems to be dominated by estimators that $\gamma \notin \{0, 1\}$ in both pooled and fixed effects cases. For the student-t(5) and large dimensional DGP, we observe a decrease in the performance for all methods. However, the decrease in the performance is larger for the student-t(5) DGP, revealing that heavy-tailed data have — as expected — a stronger impact on the performance of the estimators.

For the pooled panel data case, increasing N from 25 to 75 seems to have a larger positive impact on the performance than an increase in the time-series dimension from T = 50 to T = 100. The difference appears to be larger for student-t(5) and large dimensional DGPs and/or for the elastic net case. Turning to the fixed effects results, the differences seem to be even sharper, in particular for student-t(5) and large dimensional DGPs.

When comparing the results across the different model selection methods, i.e., cross-validation and the three information criteria, we find that almost always cross-

¹Results for the grid of $\gamma \in \{0.0, 0.2, \dots, 1.0\}$ are reported in the Online Appendix Tables OA.1-OA.3.

	S	g-LASS	O	Elnet-U			
N/T =	25/50	75/50	25/100	25/50	75/50	25/100	
			Panel A.	Baseline)		
CV	1.191	1.157	1.168	1.213	1.158	1.172	
BIC	1.270	1.175	1.202	1.384	1.211	1.247	
AIC	1.234	1.160	1.187	1.273	1.172	1.213	
AICc	1.237	1.161	1.188	1.279	1.172	1.217	
		F	Panel B. S	tudent-t((5)		
CV	1.280	1.245	1.248	1.299	1.243	1.256	
BIC	1.389	1.274	1.293	1.570	1.317	1.367	
AIC	1.345	1.259	1.272	1.411	1.283	1.298	
AICc	1.344	1.259	1.273	1.412	1.283	1.300	
		Pan	el C. Larg	ge-dimens	sional		
CV	1.204	1.160	1.185	1.255	1.165	1.188	
BIC	1.273	1.175	1.214	1.409	1.208	1.289	
AIC	1.259	1.166	1.191	1.350	1.198	1.232	
AICc	1.260	1.167	1.192	1.353	1.200	1.232	

Table 1: The table reports the MSFE for nowcasting accuracy for the pooled estimator for the Baseline (Panel A), student-t(5) (Panel B), and large-dimensional (Panel C) DGPs for the sg-LASSO-MIDAS (rows sg-LASSO) and elastic net UMIDAS (rows Elnet-U). We vary the cross-sectional dimension $N \in \{25, 75\}$ and time series dimension $T \in \{50, 100\}$. We report results for 5-fold cross-validation, BIC, AIC, AICc information criteria λ tuning parameter calculation methods and for the best choice of γ tuning parameter.

	S	g-LASS	O	Elnet-U			
N/T =	25/50	75/50	25/100	25/50	75/50	25/100	
			Panel A.	Baseline)		
CV	1.198	1.170	1.164	1.245	1.183	1.184	
BIC	1.304	1.202	1.213	1.537	1.259	1.313	
AIC	1.282	1.192	1.196	1.380	1.222	1.237	
AICc	1.284	1.193	1.196	1.284	1.193	1.196	
		F	Panel B. S	tudent-t((5)		
CV	1.278	1.256	1.248	1.329	1.270	1.271	
BIC	1.437	1.306	1.310	1.694	1.367	1.404	
AIC	1.389	1.292	1.294	1.478	1.316	1.342	
AICc	1.393	1.293	1.295	1.495	1.316	1.348	
		Pan	el C. Larg	ge-dimens	sional		
CV	1.214	1.170	1.172	1.282	1.197	1.193	
BIC	1.344	1.213	1.229	1.662	1.298	1.342	
AIC	1.300	1.243	1.202	1.404	1.384	1.235	
AICc	1.301	1.205	1.204	1.405	1.247	1.238	

Table 2: The table reports the MSFE for nowcasting accuracy for the fixed effects estimator for the Baseline (Panel A), student-t(5) (Panel B), and large-dimensional (Panel C) DGPs for the sg-LASSO-MIDAS (rows sg-LASSO) and elastic net UMIDAS (rows Elnet-U). We vary the cross-sectional dimension $N \in \{25, 75\}$ and time series dimension $T \in \{50, 100\}$. We report results for 5-fold cross-validation, BIC, AIC, AICc information criteria λ tuning parameter calculation methods and for the best choice of γ tuning parameter.

validation leads to smaller prediction errors in both pooled and fixed effects panel data cases. Notably, the gains appear to be larger for the large N and T values. Comparing BIC, AIC, and AICc information criteria, the results appear to be similar for AIC and AICc across DGPs and different sample sizes, while the BIC performance is slightly worse than AIC and AICc.

4 Nowcasting price-earnings ratios

Ball and Ghysels (2018), Carabias (2018) and Babii, Ball, Ghysels, and Striaukas (2022) documented that analysts make systematic and predictable errors in their P/E forecasts. We therefore consider nowcasting the P/E ratios using a set of predictors that are sampled at mixed frequencies for a large cross-section of firms.

A natural question one may ask: should we nowcast P/E ratio directly or it's components. We, therefore, decompose the (log of) the P/E ratio for firm i as follows:

$$pe_{i,t+1} \equiv \log(P_{i,t+1}/E_{i,t+1}) = \log((P_{i,t+1}/P_{i,t})/(E_{i,t+1}/P_{i,t}))$$

$$= r_{i,t+1} - \log((E_{i,t+1}/E_{i,t+1|t}^{a})/(P_{i,t}/E_{i,t+1|t}^{a}))$$

$$= r_{i,t+1} - e_{i,t+1|t}^{a} + \log(P_{i,t}/E_{i,t+1|t}^{a})$$
(4)

where $r_{i,t+1}$ is the log return from t+1 to t for firm i, $E^a_{i,t+1|t}$ the analyst's prediction at time t pertaining to t+1 earnings, and $e^a_{i,t+1|t} \equiv \log(E_{i,t+1}) - \log(E^a_{i,t+1|t})$ is the log earnings forecast error of analysts pertaining to their end of period t prediction for t+1. Finally, $\log(P_{i,t}/E^a_{i,t+1|t})$ is perfectly known at time t. The above defines an additive decomposition of the log P/E ratio into the return for firm i and the analyst prediction error. Therefore, nowcasting the log P/E ratio could also be achieved via nowcasting its two components. The decomposition corresponds to the distinction between analyst assessments of firm i's earnings and market/investor assessments of the firm.

There is a considerable literature on using machine learning to predict returns, see e.g. Rapach, Strauss, and Zhou (2010), Kim and Swanson (2014), Gu, Kelly, and Xiu (2020), D'Hondt, De Winne, Ghysels, and Raymond (2020), among others. Here we are dealing with a slightly modified setting where we are nowcasting quarterly returns with information during quarter t + 1. Nevertheless, prediction and nowcasting are closely related. The second component, $e_{i,t+1|t}^a$ has been explored by Babii, Ball, Ghysels, and Striaukas (2022), who revisit a topic raised by Ball and Ghysels (2018) and Carabias (2018), and confirmed in a rich data setting that analysts tend to focus on their firm/industry when making earnings predictions while not fully taking into account the impact of macroeconomic events. Put differently, one can forecast and nowcast analyst prediction errors.

It should also parenthetically be noted that equation (4) can be rewritten as a decomposition of returns, namely:

$$r_{i,t+1} = pe_{i,t+1} + e^a_{i,t+1|t} + \log(P_{i,t}/E^a_{i,t+1|t})$$
(5)

which can be viewed as an alternative decomposition of returns compared to Ferreira and Santa-Clara (2011). They propose forecasting separately the three components of stock market returns: (a) the dividend price ratio, (b) earnings growth, and (c) price-to-earnings ratio growth. Ferreira and Santa-Clara (2011) argue that predicting the separate components yields better return predictions compared to the usual models producing direct forecasts of the latter. They estimate the expected earnings growth using a 20-year moving average of the growth in earnings per share. The expected dividend price ratio is estimated by the current dividend price ratio. This implicitly assumes that the dividend price ratio follows a random walk. While our application is different in many regards, the arguments being considered are similar. It is worth reminding ourselves that if the nowcast $\hat{pe}_{i,t+1}$ is constructed from individual component nowcasts, then

$$MSE(\hat{p}\hat{e}_{i,t+1}) = MSE(\hat{r}_{i,t+1}) + MSE(\hat{e}^a_{i,t+1|t}) - 2\mathbb{E}\left[(r_{i,t+1} - \hat{r}_{i,t+1})(e^a_{i,t+1|t} - \hat{e}^a_{i,t+1|t})\right]$$
(6)

Hence, depending on the co-movements between returns for firm i, $r_{i,t+1}$ and analyst earning prediction errors $e^a_{i,t+1|t}$, we are better off to directly predict $pe_{i,t+1}$ or its components. If the latter are positively correlated, then we are better off direct forecasting is preferred.

Given the aforementioned decomposition, we are interested in the following LHS variables: $pe_{i,t+1}$, $r_{i,t+1}$ and $e^a_{i,t+1|t}$. First, we estimate the individual sg-LASSO MI-DAS regressions for each firm $i = 1, \ldots, N$, namely:

$$\mathbf{y}_i = \iota \alpha_i + \mathbf{x}_i \beta_i + \mathbf{u}_i,$$

where the firm-specific predictions are computed as $\hat{y}_{i,t+1} = \hat{\alpha}_i + x_{i,t+1}^{\top} \hat{\beta}_i$. As noted in Section 2, \mathbf{x}_i contains lags of the low-frequency target variable and high-frequency covariates to which we apply Legendre polynomials of degree L = 3.

Next, we estimate the following pooled and fixed effects sg-LASSO MIDAS panel data models

$$\mathbf{y} = \alpha \iota + \mathbf{X}\beta + \mathbf{u} \quad \text{Pooled} \\ \mathbf{y} = B\alpha + \mathbf{X}\beta + \mathbf{u} \quad \text{Fixed Effects}$$

and compute predictions as

$$\hat{y}_{i,t+1} = \hat{\alpha} + x_{i,t+1}^{\top} \hat{\beta} \quad \text{Pooled} \hat{y}_{i,t+1} = \hat{\alpha}_i + x_{i,t+1}^{\top} \hat{\beta} \quad \text{Fixed Effects.}$$

Once we compute the forecast for the log of P/E ratio $(pe_{i,t+1})$, log returns $(r_{i,t+1})$ and log earnings forecast error $(e^a_{i,t+1|t})$, we compute the final prediction accuracy metrics by either taking directly log P/E nowcast or the sum of its components, i.e., $\hat{S} = \hat{r}_{i,t+1} - \hat{e}^a_{i,t+1|t} + \log(P_{i,t}/E^a_{i,t+1|t})$.

We benchmark firm-specific and panel data regression-based nowcasts against two simple alternatives. First, we compute forecasts for the RW model as

$$\hat{y}_{i,t+1|t} = y_{i,t}.$$

Second, we consider predictions of P/E implied by analysts' earnings nowcasts using the information up to time t + 1, i.e.

$$\hat{y}_{i,t+1|t} = \bar{y}_{i,t+1|t}^{a}$$

where the predicted/nowcasted log of P/E ratio is based on consensus earnings forecasts pertaining to the end of the t + 1 quarter using the stock price at the end of quarter t. To measure the forecasting performance, we compute the mean squared forecast errors (MSE) for each method. Let $\bar{\mathbf{y}}_i = (y_{i,T_{is}+1}, \ldots, y_{i,T_{os}})^{\mathsf{T}}$ represent the out-of-sample realized P/E ratio values, where T_{is} and T_{os} denote the last in-sample observation for the first prediction and the last out-of-sample observation respectively, and let $\hat{\mathbf{y}}_i = (\hat{y}_{i,t_{is}+1}, \ldots, \hat{y}_{i,t_{os}})$ collect the out-of-sample forecasts. Then, the mean squared forecast errors are computed as

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{T - T_{is} + 1} (\bar{\mathbf{y}}_i - \hat{\mathbf{y}}_i)^\top (\bar{\mathbf{y}}_i - \hat{\mathbf{y}}_i).$$

We look at 210 US firms and use 24 predictors, including traditional macro and financial series as well as non-traditional series from textual analysis of financial news. We apply (a) single regression individual firm high-dimensional regressions, (b) pooled and (c) individual fixed effects sg-LASSO MIDAS panel data models and report results for several choices of the tuning parameters. We compare these three type of models with several benchmarks, which include a random walk (RW) model and analysts' consensus forecasts. The remainder of the section is structured as follows. We start with a short review of the data followed by a summary of the empirical results.

4.1 Data description

The full sample consists of observations between the 1st of January, 2000 and the 30th of June, 2017. Due to the lagged dependent variables in the models, our effective sample starts in the third fiscal quarter of 2000. We use the first 25 observations for the initial sample, and use the remaining 42 observations for evaluating the out-of-sample forecasts, which we obtain by using an expanding window forecasting scheme. We collect data from CRSP and I/B/E/S to compute the quarterly P/E ratios and firm-specific financial covariates; RavenPack is used to compute daily firm-level textual-analysis-based data; real-time monthly macroeconomic series are from the FRED-MD dataset, see McCracken and Ng (2016) for more details; FRED is used to compute daily financial markets data and, lastly, monthly news attention series extracted from the *Wall Street Journal* articles are retrieved from Bybee, Kelly, Manela, and Xiu (2021).² Online Appendix Section OA.2 provides a detailed description of the data sources.³

Our target variable is the P/E ratio for each firm. To compute it, we use CRSP stock price data and I/B/E/S earnings data. Earnings data are subject to release delays of 1 to 2 months depending on the firm and quarter. Therefore, to reflect the real-time information flow, we compute the target variable using stock prices that are available in real-time. We also take into account that different firms have different fiscal quarters, which also affects the real-time information flow.

For example, suppose for a particular firm the fiscal quarters are at the end of the third month in a quarter, i.e. end of March, June, September, and December. The consensus forecast of the P/E ratio is computed using the same end-of-quarter price data which is divided by the earnings consensus forecast value. The consensus is computed by taking all individual prediction values up to the end of the quarter and aggregating those values by taking either the mean or the median. To compute the target variable, we adjust for publication lags and use prices of the publication date instead of the end of fiscal quarter prices. More precisely, suppose we predict the P/E ratio for the first quarter. As noted earlier, earnings are typically published with 1 to 2 months delay; say for a particular firm the data is published on the 25thof April. In this case, we record the stock price for the firm on 25th of April, and divide it by the earnings announced on that date.

²The dataset is publicly available at http://www.structureofnews.com/.

 $^{^{3}}$ In particular, firm-level variables, including P/E ratios, are described in Online Appendix Table OA.4, and the other predictor variables in Online Appendix Table OA.5. The list of all firms we consider in our analysis appears in Online Appendix Table OA.6.

4.2 Models and main results

To simplify the exposition, we denote y as one of the three target variables we consider. The main findings from our analysis are presented in Table 3. Column $\hat{p}e_{i,t+1}$ reports results for directly nowcasting the log P/E ratio, column \hat{S} reports the results of nowcasting and summing up the components, column $r_{i,t+1}$ reports results for the log return component and column $\hat{e}^a_{i,t+1|t}$ reports results for the log earnings forecast error of analysts component. Row RW reports results for the random walk, while row *Consensus* for the median consensus nowcast. Panels *Individual*, *Pooled* and *Fixed effects* report results for different panel data models relative to the consensus MSE (columns $\hat{p}e_{i,t+1}$ and \hat{S}) and for the components (columns $r_{i,t+1}$ and $\hat{e}^a_{i,t+1|t}$) we report ratios relative to the RW MSE since there are obviously no concensus series notably for the analyst forecast errors.

Nowcasting Performance

In light of the simulation evidence, we report the empirical results using crossvalidation in Table 3 and provide the full set of results in Online Appendix Table OA.7. The entries in the top panel of Table 3 reveal that predictions based on analyst consensus exhibit significantly higher mean squared forecast errors (MSEs) compared to model-based predictions since all the ratios with respect to the concensus are less than one (see first two columns). These model-based predictions involve either direct log P/E ratio nowcasts (first column) or their individual components (second column). Since the MSE for RW and concensus are quite similar, this also implies that RW predictions are outperformed by the model-based ones. The substantial improvement in the accuracy of model-based predictions compared to analyst-based predictions underscores the value of employing machine learning techniques for nowcasting log P/E ratios. Across various machine learning methods, including single-firm and panel data regressions, we consistently observe enhanced performance. When comparing the first and second columns, which correspond to direct log P/E ratio nowcasts versus those based on its components, we observe a substantial enhancement in prediction accuracy when using the individual components. This improvement is consistently evident across individual, pooled, and fixed effects regression models. To shed light on these findings, we computed the pooled correlation between returns and earnings for the entire sample, i.e. $\operatorname{Corr}(r_{i,t+1}, e^a_{i,t+1|t})$ = -0.206. The correlation indicates a (weak) negative relationship between returns and earnings. Consequently, the prediction errors of each component tend to offset each other, resulting in more accurate aggregated nowcasts (recall equation (6)). The last two columns of Table 3 present the prediction results for these components.

	$\hat{p}e_{i,t+1}$	\hat{S}	$\hat{r}_{i,t+1}$	$\hat{e}^a_{i,t+1 t}$	
			All firms		
RW	1.355		0.054	0.194	
Consensus	1.305				
			Individual		
	0.905	0.890	1.088	0.848	
DM p-val RW	0.117	0.115	0.181	0.090	
DM p-val Cons.	0.156	0.131			
			Pooled		
	0.894	0.790	0.964	0.799	
DM p-val RW	0.060	0.023	0.128	0.021	
DM p-val Cons.	0.075	0.053			
			Fixed effects	8	
	0.814	0.793	0.971	0.803	
DM p-val RW	0.051	0.033	0.164	0.032	
DM p-val Cons.	0.078	0.063			
	With si	ngle CC	I outlier remo	ved (see Figure 2	2)
		0		(U	
RW	1.333		0.053	0.173	
Consensus	1.275				
			Individual		
	0.978	0.790	1.001	0.812	
DM p-val RW	0.585	0.027	0.912	0.081	
DM p-val Cons.	0.606	0.034			
			Pooled		
	0.777	0.768	0.943	0.788	
DM p-val RW	0.025	0.004	0.103	0.018	
DM p-val Cons.	0.029	0.006			
_			Fixed effects	3	
	0.782	0.767	0.954	0.783	
DM p-val RW	0.028	0.004	0.119	0.021	
DM p-val Cons.	0.030	0.006			

Table 3: Column $\hat{p}e_{i,t+1}$ reports results for directly nowcasting the log P/E ratio, \hat{S} for nowcasting and summing up the components, $r_{i,t+1}$ for the log return and $\hat{e}^a_{i,t+1|t}$ for the log earnings forecast error of analysts. *RW* is for the random walk, while *Consensus* is the median consensus nowcast. Panels *Individual, Pooled* and *Fixed effects* report results for models relative to the consensus MSE $(\hat{p}e_{i,t+1} \text{ and } \hat{S})$ and for the components $(r_{i,t+1} \text{ and } \hat{e}^a_{i,t+1|t})$ relative to the RW MSE. DM is the Diebold and Mariano (1995) test statistic p-values using one-sided critical values. We observe that analyst earnings prediction errors appear to be more predictable than those of log returns. We also report Diebold and Mariano (1995) test statistic p-values comparing each model against the RW and consensus benchmarks, pooling all the nowcasting errors across firms. Using one-sided test critical values we observe that our models outperform both the RW and consensus benchmarks, particularly when we use the component approach. While we cannot compare the $\hat{p}e_{i,t+1}$ component with the consensus, judging by the RW benchmark it is clear that the second component is the most important in terms of nowcasting gains. When we use individual MIDAS regressions the evidence is less compelling, underscoring the importance of using panel data models.⁴

Sparsity Patterns

Figure 1 illustrates the sparsity patterns of selected covariates for the most effective methods in predicting either log P/E ratios (Panel a) or their components (Panels b and c). It is worth noting that the sparsity patterns differ significantly across the three panels. For instance, firm volatility is often chosen as a relevant covariate across all targets, albeit not consistently throughout the entire out-of-sample period. In the case of log P/E ratios, news series related to earnings are frequently selected, along with firm and market volatility series. Conversely, for log returns, a denser pattern of covariate selection is observed, distinct from the other two cases. Interestingly, none of the news-based firm series are chosen for this target. Regarding log analyst earnings forecast errors, macroeconomic series such as the unemployment rate, short-term rates, and TED rate are frequently selected. Moreover, unlike log P/E ratios and returns, news-based firm series occasionally appear in the selected covariates for this target. The fact that macroeconomic series are drivers for now-casting the $e_{i,t+1|t}^a$ component is a confirmation of the findings reported in Ball and Ghysels (2018), Carabias (2018) and Babii, Ball, Ghysels, and Striaukas (2022).

Figure 2 depicts the histogram of mean squared errors (MSEs) across firms. Notably, a substantial proportion of firms (approximately 60%) exhibit low MSE values, indicating a high level of prediction accuracy. However, there are a few firms for which the MSEs are relatively larger, suggesting lower prediction performance for these specific cases. The largest MSE is for Crown castle international corporation (CCI) which appears as a strong outlier.

⁴We also experimented with the forecast combination of MIDAS regressions used by Ball and Ghysels (2018) and found them to be inferior to the individual MIDAS ML regressions as well as the panel data models. We therefore refrain from reporting the details here.



Figure 1: Sparsity patterns.

Removing the single outlier firm has a dramatic impact on the nowcasting performance evaluation as shown in the lower panel of Table 3. We now have very strong evidence that the panel regression models dominate analyst predictions. Again the component nowcasts are the best, but even the individual regression models do significantly better when the component specification is used.

Daily Updates of Nowcasts

Our framework allows us to go beyond providing quarterly nowcasts and generate daily updates of earnings series. Leveraging the daily influx of information throughout the quarter, we continuously re-estimate our models and produce nowcast updates as soon as new data becomes available. In Figure 3, we present the distribution of Mean Squared Errors (MSEs) across firms for five distinct nowcast horizons: 20-day, 15-day, 10-day, and 5-day ahead, as well as the end of the quarter. We report the best model based on Table 3. Notably, as the horizons become shorter, both the median and upper quartile of MSEs decrease. Therefore, updating nowcasts with daily information appears to significantly enhance the prediction performance of log earnings ratios. The largest errors persist for the same firm, CCI.

> Grouped Fixed Effects based on Fama-French Industry Classification



Figure 2: Histogram of mean squared errors.

The sg-LASSO estimator we employ in our study is well-suited for incorporating grouped fixed effects. This approach involves grouping firm-specific intercepts based on either statistical procedures or economic reasoning, as outlined in Bonhomme and Manresa (2015). In our analysis, we utilize the Fama French industry classification to form 10 distinct groups for grouping fixed effects. Rather than assuming a common fixed effect for all firms within a group, we apply a group penalty to the fixed effects of firms belonging to the same industry. This allows us to capture industry-specific heterogeneity while avoiding overfitting.

We present the findings in Table 4, which highlight several key observations. Similar to previous analyses, our results suggest that predicting individual components of the log price-earnings ratio leads to more accurate aggregate nowcasts compared to a direct nowcast approach. Furthermore, we observe that the use of group fixed effects improves the accuracy of our nowcasts when forecasting individual components. This can be seen in column 2 of both Tables 3 and 4. Comparatively, when considering the best tuning parameter choice, grouped fixed effects outperform other panel models, including the pooled panel model. Therefore, our findings suggest that grouped fixed effects strike a better balance between capturing heterogeneity and pooled parameters, resulting in more accurate nowcast predictions. These re-



Figure 3: Distribution of MSEs of the best performing model in Table 3. Models are re-estimated for each horizon. The best model based on Table 3 is reported.

sults support the notion that incorporating group fixed effects enhances the overall performance of our forecasting model.

In Figure 4, we present the distribution of (MSEs) across firms for five industries, based on the best model specification from Table 4. The industries we focus on are the ones with the highest number of firms in our sample. The results reveal variations in performance among different industries. Specifically, the firms categorized as *Consumer Durables* exhibit the lowest accuracy in terms of the median MSE, although the quartiles are comparatively lower compared to the other industries. On the other hand, the nowcasts for firms in the *Consumer Nondurables* and *Others* categories demonstrate the highest accuracy at the median. However, it is important to note that the largest errors occur within the firms classified as *Others*.

Nowcasting with Missing Data — Parameter Imputation Method

Next we address the challenge of missing earnings data, which can complicate the analysis. We examine the performance of parameter imputation methods in computing nowcasts, see, e.g, Brown, Ghysels, and Gredil (2023), even when earnings and/or earnings forecasts are missing for certain observations in the sample. We

		^
	$\hat{p}e_{i,t+1}$	\hat{S}
	Group fi	xed effects
CV	0.862	0.789
BIC	0.834	0.789
AIC	0.842	0.791
AICc	0.842	0.790

Table 4: Nowcasting results. Column $\hat{p}e_{i,t+1}$ reports results for directly nowcasting the log P/E ratio and the column \hat{S} reports the results of nowcasting and summing up the components. Results are reported relative to the *Consensus* nowcasts that appear in Table 3.

identify a subset of 117 firms for which at least one earnings observation is available in our out-of-sample period, and for which we have matched daily news data. To handle missing data, we match these firms with missing observations to firms in our main sample using the Fama French industry classification. We then utilize the parameter estimates obtained from the best group fixed effects model, as shown in Table 4, to compute the nowcasts of log earnings ratios, either directly or based on its components. The results of this analysis appear in Table 5.

Firstly, the results obtained through parameter imputation support the conclusion that nowcasting the components of the log earnings ratio yields higher quality predictions. This indicates that incorporating the individual components of the ratio improves the accuracy of the nowcasts. Secondly, the panel models with the parameter imputation method outperform the analyst consensus nowcasts in terms of prediction accuracy. This suggests that employing machine learning panel data models along with parameter imputation could be a straightforward yet effective approach in situations where earnings data is not available. Overall, these findings highlight the potential benefits of leveraging machine learning techniques and imputation methods for improving nowcasting accuracy, particularly in cases where earnings data may be missing.

5 Conclusions

This paper uses a new class of high-dimensional panel data nowcasting models with dictionaries and sg-LASSO regularization which is an attractive choice for the predictive panel data regressions, where the low- and/or the high-frequency lags define a clear group structure. Our empirical results showcase the advantages of using reg-



Figure 4: Distribution of MSEs for five industries based on Fama French classification. The reported results are based on the best model specification from Table 4.

ularized panel data regressions for nowcasting corporate earnings either directly or using a decomposition which separates stock market return predictions and analyst assessments of a firm's performance. While nowcasting earnings is a leading example of applying panel data MIDAS machine learning regressions, one can think of many other applications of interest in finance. Beyond earnings, analysts are also interested in sales, dividends, etc. Our analysis can also be useful for other areas of interest, such as regional and international panel data settings.

	$\hat{p}e_{i,t+1}$	\hat{S}
Consensus	1.605	
CV	0.883	0.753
BIC	0.877	0.756
AIC	0.883	0.754
AICc	0.883	0.753

Table 5: Nowcasting results — parameter imputation method. Column $\hat{p}e_{i,t+1}$ reports results for directly nowcasting the log P/E ratio and the column \hat{S} reports the results of nowcasting and summing up the components. Row *Consensus* for the median consensus nowcast. Panels *Individual*, *Pooled* and *Fixed effects* report results for different panel data models relative to the consensus MSE.

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ONLINE APPENDIX

OA.1 Additional simulation results

	Pooled panel data							Fixed effects					
	N/T	$\gamma = 0$	0.2	0.4	0.6	0.8	1	$\gamma = 0$	0.2	0.4	0.6	0.8	1
							Cross-v	validation					
sg-LASSO	$25/50 \\ 75/50 \\ 25/100$	$1.194 \\ 1.160 \\ 1.175$	$1.191 \\ 1.162 \\ 1.174$	$1.192 \\ 1.159 \\ 1.175$	$1.200 \\ 1.157 \\ 1.172$	$1.212 \\ 1.165 \\ 1.168$	$1.207 \\ 1.161 \\ 1.183$	$1.202 \\ 1.171 \\ 1.166$	$1.200 \\ 1.171 \\ 1.165$	$1.198 \\ 1.170 \\ 1.165$	$1.199 \\ 1.171 \\ 1.164$	$1.205 \\ 1.173 \\ 1.166$	$1.210 \\ 1.174 \\ 1.171$
elnet-U	$25/50 \\ 75/50 \\ 25/100$	$1.334 \\ 1.209 \\ 1.242$	$1.216 \\ 1.160 \\ 1.172$	$1.213 \\ 1.158 \\ 1.172$	$1.213 \\ 1.158 \\ 1.172$	$1.214 \\ 1.158 \\ 1.172$	$1.214 \\ 1.158 \\ 1.173$	$1.370 \\ 1.236 \\ 1.255$	$1.248 \\ 1.186 \\ 1.184$	$1.245 \\ 1.184 \\ 1.184$	$1.245 \\ 1.183 \\ 1.184$	$1.246 \\ 1.183 \\ 1.184$	$1.245 \\ 1.183 \\ 1.185$
							E	BIC					
sg-LASSO	$25/50 \\ 75/50 \\ 25/100$	$1.272 \\ 1.177 \\ 1.207$	$1.270 \\ 1.175 \\ 1.202$	$1.273 \\ 1.177 \\ 1.203$	$1.289 \\ 1.180 \\ 1.205$	$1.315 \\ 1.180 \\ 1.223$	$1.357 \\ 1.199 \\ 1.260$	$1.310 \\ 1.202 \\ 1.213$	$1.304 \\ 1.202 \\ 1.213$	$1.317 \\ 1.208 \\ 1.220$	$1.346 \\ 1.209 \\ 1.219$	$1.410 \\ 1.222 \\ 1.247$	$1.471 \\ 1.282 \\ 1.307$
elnet-U	$25/50 \\ 75/50 \\ 25/100$	$1.524 \\ 1.236 \\ 1.298$	$1.411 \\ 1.226 \\ 1.255$	$1.388 \\ 1.216 \\ 1.247$	$1.385 \\ 1.213 \\ 1.248$	$1.384 \\ 1.211 \\ 1.248$	$1.385 \\ 1.211 \\ 1.249$	$1.537 \\ 1.259 \\ 1.313$	$1.575 \\ 1.274 \\ 1.318$	$1.595 \\ 1.276 \\ 1.318$	$1.611 \\ 1.278 \\ 1.318$	$1.626 \\ 1.279 \\ 1.320$	$1.639 \\ 1.280 \\ 1.320$
							A	AIC					
sg-LASSO	$25/50 \\ 75/50 \\ 25/100$	$1.252 \\ 1.167 \\ 1.193$	$1.247 \\ 1.165 \\ 1.190$	$1.242 \\ 1.163 \\ 1.191$	$1.234 \\ 1.160 \\ 1.196$	$1.245 \\ 1.166 \\ 1.187$	$1.265 \\ 1.166 \\ 1.200$	$1.288 \\ 1.199 \\ 1.200$	$1.282 \\ 1.196 \\ 1.196$	$1.283 \\ 1.197 \\ 1.196$	$1.287 \\ 1.198 \\ 1.202$	$1.284 \\ 1.192 \\ 1.209$	$1.303 \\ 1.205 \\ 1.208$
elnet-U	$25/50 \\ 75/50 \\ 25/100$	$1.524 \\ 1.236 \\ 1.298$	1.282 1.179 1.213	$1.274 \\ 1.174 \\ 1.215$	$1.273 \\ 1.173 \\ 1.216$	$1.273 \\ 1.172 \\ 1.215$	1.274 1.172 1.215	1.537 1.259 1.313	$\begin{array}{c} 1.388 \\ 1.222 \\ 1.255 \end{array}$	1.381 1.223 1.243	$1.380 \\ 1.222 \\ 1.240$	$1.378 \\ 1.222 \\ 1.238$	$\begin{array}{c} 1.378 \\ 1.222 \\ 1.237 \end{array}$
	ar (ra		1 9 1 9				A	<u>ICc</u>	1		1 000		4
sg-LASSO	$\frac{25}{50}$ $\frac{75}{50}$ $\frac{25}{100}$	$1.255 \\ 1.168 \\ 1.193$	$1.248 \\ 1.165 \\ 1.190$	$1.244 \\ 1.164 \\ 1.191$	$1.237 \\ 1.161 \\ 1.196$	$1.246 \\ 1.166 \\ 1.188$	$1.270 \\ 1.167 \\ 1.201$	$1.291 \\ 1.200 \\ 1.200$	$1.284 \\ 1.197 \\ 1.196$	$1.285 \\ 1.197 \\ 1.196$	$1.290 \\ 1.199 \\ 1.202$	$1.291 \\ 1.193 \\ 1.210$	1.307 1.205 1.210
elnet-U	$25/50 \\ 75/50 \\ 25/100$	$1.524 \\ 1.236 \\ 1.298$	$1.286 \\ 1.179 \\ 1.217$	$1.279 \\ 1.174 \\ 1.219$	$1.280 \\ 1.173 \\ 1.218$	$1.208 \\ 1.172 \\ 1.218$	$1.281 \\ 1.172 \\ 1.218$	$1.537 \\ 1.259 \\ 1.313$	$1.410 \\ 1.227 \\ 1.257$	$1.396 \\ 1.226 \\ 1.244$	$1.390 \\ 1.226 \\ 1.240$	$1.388 \\ 1.225 \\ 1.238$	$1.387 \\ 1.225 \\ 1.237$

Table OA.1: The table reports the MSFE for nowcasting accuracy for pooled and fixed effects estimators for the baseline DGP for the sg-LASSO-MIDAS (rows sg-LASSO) and elastic net UMIDAS (rows elnet-U). We vary the cross-sectional dimension $N \in \{25, 75\}$ and time series dimension $T \in \{50, 100\}$. We report results for 5-fold cross-validation, BIC, AIC, AICc information criteria λ tuning parameter calculation methods and for a grid of $\gamma \in \{0, 0.2, \ldots, 1\}$ tuning parameter.

	Pooled panel data							Fixed	effects				
	N/T	$\gamma = 0$	0.2	0.4	0.6	0.8	1	$\gamma = 0$	0.2	0.4	0.6	0.8	1
							Cross-v	alidation					
sg-LASSO	$25/50 \\ 75/50 \\ 25/100$	$1.289 \\ 1.247 \\ 1.250$	$1.288 \\ 1.245 \\ 1.248$	$1.288 \\ 1.247 \\ 1.248$	$1.282 \\ 1.253 \\ 1.254$	$1.280 \\ 1.246 \\ 1.264$	$1.302 \\ 1.255 \\ 1.257$	$1.282 \\ 1.256 \\ 1.249$	$1.279 \\ 1.256 \\ 1.248$	$1.278 \\ 1.256 \\ 1.248$	$1.280 \\ 1.256 \\ 1.249$	$1.282 \\ 1.257 \\ 1.252$	$1.291 \\ 1.261 \\ 1.255$
elnet-U	$25/50 \\ 75/50 \\ 25/100$	$1.452 \\ 1.304 \\ 1.342$	$1.302 \\ 1.244 \\ 1.258$	$1.299 \\ 1.243 \\ 1.257$	$1.300 \\ 1.243 \\ 1.256$	$1.300 \\ 1.243 \\ 1.256$	$1.301 \\ 1.243 \\ 1.256$	$1.487 \\ 1.333 \\ 1.359$	$1.334 \\ 1.271 \\ 1.273$	$1.331 \\ 1.270 \\ 1.271$	$1.331 \\ 1.270 \\ 1.271$	$1.330 \\ 1.270 \\ 1.271$	$1.329 \\ 1.270 \\ 1.271$
							E	BIC					
sg-LASSO	$25/50 \\ 75/50 \\ 25/100$	$1.395 \\ 1.275 \\ 1.296$	$1.389 \\ 1.274 \\ 1.293$	$1.395 \\ 1.278 \\ 1.297$	$1.401 \\ 1.278 \\ 1.306$	$1.444 \\ 1.281 \\ 1.308$	$1.517 \\ 1.310 \\ 1.364$	$1.437 \\ 1.306 \\ 1.311$	$1.437 \\ 1.309 \\ 1.310$	$1.450 \\ 1.319 \\ 1.319$	$1.468 \\ 1.321 \\ 1.325$	$1.553 \\ 1.317 \\ 1.342$	$1.657 \\ 1.370 \\ 1.431$
elnet-U	$25/50 \\ 75/50 \\ 25/100$	$1.652 \\ 1.337 \\ 1.389$	$1.582 \\ 1.318 \\ 1.387$	$1.570 \\ 1.317 \\ 1.373$	$1.570 \\ 1.318 \\ 1.369$	$1.572 \\ 1.319 \\ 1.368$	$1.575 \\ 1.319 \\ 1.367$	$1.694 \\ 1.367 \\ 1.404$	$1.754 \\ 1.401 \\ 1.430$	$1.781 \\ 1.393 \\ 1.427$	$1.803 \\ 1.393 \\ 1.432$	$1.813 \\ 1.394 \\ 1.434$	$1.820 \\ 1.396 \\ 1.436$
							A	AIC					
sg-LASSO	$25/50 \\ 75/50 \\ 25/100$	$1.354 \\ 1.261 \\ 1.282$	$1.345 \\ 1.259 \\ 1.280$	$1.342 \\ 1.259 \\ 1.279$	$1.351 \\ 1.264 \\ 1.272$	$1.370 \\ 1.271 \\ 1.279$	$1.372 \\ 1.266 \\ 1.290$	$1.397 \\ 1.292 \\ 1.305$	1.396 1.293 1.301	1.393 1.294 1.302	1.389 1.292 1.300	$1.407 \\ 1.301 \\ 1.294$	$1.450 \\ 1.309 \\ 1.320$
elnet-U	$25/50 \\ 75/50 \\ 25/100$	$1.652 \\ 1.337 \\ 1.389$	$1.435 \\ 1.293 \\ 1.304$	$1.419 \\ 1.287 \\ 1.298$	$1.414 \\ 1.285 \\ 1.298$	$1.412 \\ 1.284 \\ 1.298$	$1.411 \\ 1.283 \\ 1.298$	$1.694 \\ 1.367 \\ 1.404$	$1.489 \\ 1.327 \\ 1.342$	$1.480 \\ 1.319 \\ 1.342$	$1.479 \\ 1.317 \\ 1.342$	$1.478 \\ 1.316 \\ 1.343$	$1.478 \\ 1.316 \\ 1.343$
							A	ICc					
sg-LASSO	$25/50 \\ 75/50 \\ 25/100$	$1.357 \\ 1.261 \\ 1.282$	$1.348 \\ 1.259 \\ 1.280$	$1.344 \\ 1.259 \\ 1.279$	$1.352 \\ 1.264 \\ 1.273$	$1.372 \\ 1.271 \\ 1.279$	$1.377 \\ 1.266 \\ 1.292$	$1.402 \\ 1.293 \\ 1.306$	$1.402 \\ 1.295 \\ 1.302$	$1.398 \\ 1.295 \\ 1.303$	1.393 1.293 1.301	$1.409 \\ 1.301 \\ 1.295$	$1.459 \\ 1.312 \\ 1.321$
elnet-U	$25/50 \\ 75/50 \\ 25/100$	$1.652 \\ 1.337 \\ 1.389$	$1.436 \\ 1.294 \\ 1.305$	$1.420 \\ 1.287 \\ 1.300$	$1.415 \\ 1.285 \\ 1.300$	$1.414 \\ 1.284 \\ 1.300$	$1.412 \\ 1.283 \\ 1.300$	$1.694 \\ 1.367 \\ 1.404$	$1.503 \\ 1.328 \\ 1.348$	$1.495 \\ 1.320 \\ 1.348$	$1.496 \\ 1.318 \\ 1.348$	$1.496 \\ 1.317 \\ 1.348$	$1.495 \\ 1.316 \\ 1.348$

Table OA.2: The table reports the MSFE for nowcasting accuracy for pooled and fixed effects estimators for the student-t(5) DGP for the sg-LASSO-MIDAS (rows sg-LASSO) and elastic net UMIDAS (rows elnet-U). We vary the cross-sectional dimension $N \in \{25, 75\}$ and time series dimension $T \in \{50, 100\}$. We report results for 5-fold cross-validation, BIC, AIC, AICc information criteria λ tuning parameter calculation methods and for a grid of $\gamma \in \{0, 0.2, \ldots, 1\}$ tuning parameter.

	Pooled panel data							<u>Fixed effects</u>					
	N/T	$\gamma = 0$	0.2	0.4	0.6	0.8	1	$\gamma = 0$	0.2	0.4	0.6	0.8	1
							Cross-v	validation					
sg-LASSO	$25/50 \\ 75/50 \\ 25/100$	$1.208 \\ 1.168 \\ 1.188$	$1.207 \\ 1.168 \\ 1.185$	$1.204 \\ 1.168 \\ 1.187$	$1.207 \\ 1.160 \\ 1.194$	$1.226 \\ 1.161 \\ 1.186$	$1.249 \\ 1.178 \\ 1.199$	$1.217 \\ 1.171 \\ 1.173$	$1.214 \\ 1.170 \\ 1.172$	$1.215 \\ 1.170 \\ 1.172$	$1.218 \\ 1.173 \\ 1.174$	$1.225 \\ 1.180 \\ 1.176$	1.242 1.187 1.181
elnet-U	$25/50 \\ 75/50 \\ 25/100$	$1.291 \\ 1.259 \\ 1.258$	$1.263 \\ 1.170 \\ 1.196$	$1.257 \\ 1.167 \\ 1.190$	$1.255 \\ 1.166 \\ 1.189$	$1.255 \\ 1.165 \\ 1.189$	$1.255 \\ 1.165 \\ 1.188$	$1.292 \\ 1.273 \\ 1.999$	$1.290 \\ 1.204 \\ 1.199$	$1.285 \\ 1.199 \\ 1.196$	$1.283 \\ 1.198 \\ 1.194$	$1.283 \\ 1.197 \\ 1.194$	$1.282 \\ 1.197 \\ 1.193$
							Ī	BIC					
sg-LASSO	$25/50 \\ 75/50 \\ 25/100$	$1.273 \\ 1.176 \\ 1.226$	$1.274 \\ 1.175 \\ 1.218$	$1.278 \\ 1.177 \\ 1.217$	$1.295 \\ 1.184 \\ 1.214$	$1.336 \\ 1.200 \\ 1.227$	$1.408 \\ 1.234 \\ 1.273$	$1.358 \\ 1.215 \\ 1.232$	$1.344 \\ 1.213 \\ 1.229$	$1.353 \\ 1.218 \\ 1.236$	$1.374 \\ 1.218 \\ 1.240$	$1.443 \\ 1.237 \\ 1.267$	$1.505 \\ 1.305 \\ 1.332$
elnet-U	$25/50 \\ 75/50 \\ 25/100$	$1.524 \\ 1.359 \\ 1.304$	$1.428 \\ 1.229 \\ 1.297$	$1.409 \\ 1.215 \\ 1.209$	$1.412 \\ 1.211 \\ 1.209$	$1.413 \\ 1.209 \\ 1.289$	$1.417 \\ 1.208 \\ 1.290$	$1.689 \\ 1.306 \\ 1.414$	$1.675 \\ 1.298 \\ 1.372$	$1.662 \\ 1.299 \\ 1.349$	$1.670 \\ 1.301 \\ 1.343$	$1.682 \\ 1.302 \\ 1.342$	$1.689 \\ 1.303 \\ 1.342$
							A	AIC					
sg-LASSO	$25/50 \\ 75/50 \\ 25/100$	$1.263 \\ 1.175 \\ 1.195$	$1.259 \\ 1.172 \\ 1.191$	$1.264 \\ 1.174 \\ 1.191$	$1.272 \\ 1.176 \\ 1.200$	$1.264 \\ 1.166 \\ 1.217$	$1.285 \\ 1.185 \\ 1.216$	$1.307 \\ 1.250 \\ 1.210$	$1.300 \\ 1.246 \\ 1.205$	$1.300 \\ 1.245 \\ 1.202$	$1.315 \\ 1.243 \\ 1.203$	$1.343 \\ 1.250 \\ 1.222$	$1.380 \\ 1.261 \\ 1.251$
elnet-U	$25/50 \\ 75/50 \\ 25/100$	$1.527 \\ 1.359 \\ 1.301$	$1.381 \\ 1.201 \\ 1.252$	$1.361 \\ 1.200 \\ 1.239$	$1.354 \\ 1.199 \\ 1.235$	$1.351 \\ 1.199 \\ 1.233$	$1.350 \\ 1.198 \\ 1.232$	$1.559 \\ 1.401 \\ 1.314$	$1.458 \\ 1.400 \\ 1.255$	$1.421 \\ 1.385 \\ 1.241$	$1.411 \\ 1.384 \\ 1.238$	$1.406 \\ 1.384 \\ 1.236$	$1.404 \\ 1.392 \\ 1.235$
							A	ICc					
sg-LASSO	$25/50 \\ 75/50 \\ 25/100$	$1.264 \\ 1.175 \\ 1.195$	$1.260 \\ 1.172 \\ 1.192$	$1.264 \\ 1.174 \\ 1.192$	$1.274 \\ 1.176 \\ 1.200$	$1.267 \\ 1.167 \\ 1.218$	$1.286 \\ 1.185 \\ 1.218$	$1.312 \\ 1.209 \\ 1.211$	$1.301 \\ 1.205 \\ 1.206$	$1.302 \\ 1.205 \\ 1.204$	$1.316 \\ 1.212 \\ 1.203$	$1.347 \\ 1.224 \\ 1.222$	$1.390 \\ 1.228 \\ 1.263$
elnet-U	$25/50 \\ 75/50 \\ 25/100$	$1.524 \\ 1.359 \\ 1.302$	$1.390 \\ 1.203 \\ 1.252$	$1.364 \\ 1.202 \\ 1.239$	$1.358 \\ 1.201 \\ 1.235$	$1.354 \\ 1.200 \\ 1.233$	$1.353 \\ 1.200 \\ 1.232$	$1.559 \\ 1.306 \\ 1.314$	$1.460 \\ 1.271 \\ 1.256$	$1.422 \\ 1.255 \\ 1.242$	$1.413 \\ 1.250 \\ 1.239$	$1.408 \\ 1.248 \\ 1.238$	$1.405 \\ 1.247 \\ 1.238$

Table OA.3: The table reports the MSFE for nowcasting accuracy for pooled and fixed effects estimators for the large-dimensional DGP for the sg-LASSO-MIDAS (rows sg-LASSO) and elastic net UMIDAS (rows elnet-U). We vary the cross-sectional dimension $N \in \{25, 75\}$ and time series dimension $T \in \{50, 100\}$. We report results for 5-fold cross-validation, BIC, AIC, AICc information criteria λ tuning parameter calculation methods and for a grid of $\gamma \in \{0, 0.2, ..., 1\}$ tuning parameter.

OA.2 Data description

OA.2.1 Firm-level data

The full list of firm-level data is provided in Table OA.4. We also add two daily firm-specific stock market predictor variables: stock returns and a realized variance measure, which is defined as the rolling sample variance over the previous 60 days (i.e. 60-day historical volatility).

OA.2.1.1 Firm sample selection

We select a sample of firms based on data availability. First, we remove all firms from I/B/E/S which have missing values in earnings time series. Next, we retain firms that we are able to match with CRSP dataset. Finally, we keep firms that we can match with the RavenPack dataset.

OA.2.1.2 Firm-specific text data

We create a link table of RavenPack ID and PERMNO identifiers which enables us to merge I/B/E/S and CRSP data with firm-specific textual analysis generated data from RavenPack. The latter is a rich dataset that contains intra-daily news information about firms. There are several editions of the dataset; in our analysis, we use the Dow Jones (DJ) and Press Release (PR) editions. The former contains relevant information from Dow Jones Newswires, regional editions of the Wall Street Journal, Barron's and MarketWatch. The PR edition contains news data, obtained from various press releases and regulatory disclosures, on a daily basis from a variety of newswires and press release distribution networks, including exclusive content from PRNewswire, Canadian News Wire, Regulatory News Service, and others. The DJ edition sample starts at 1^{st} of January, 2000, and PR edition data starts at 17^{th} of January, 2004.

We construct our news-based firm-level covariates by filtering only highly relevant news stories. More precisely, for each firm and each day, we filter out news that has the *Relevance Score* (REL) larger or equal to 75, as is suggested by the RavenPack News Analytics guide and used by practitioners, see for example Kolanovic and Krishnamachari (2017). REL is a score between 0 and 100 which indicates how strongly a news story is linked with a particular firm. A score of zero means that the entity is vaguely mentioned in the news story, while 100 means the opposite. A score of 75 is regarded as a significantly relevant news story. After applying the REL filter, we apply a novelty of the news filter by using the *Event Novelty Score* (ENS); we

keep data entries that have a score of 100. Like REL, ENS is a score between 0 and 100. It indicates the novelty of a news story within a 24-hour time window. A score of 100 means that a news story was not already covered by earlier announced news, while subsequently published news story score on a related event is discounted, and therefore its scores are less than 100. Therefore, with this filter, we consider only novel news stories. We focus on *five sentiment indices* that are available in both DJ and PR editions. They are:

Event Sentiment Score (ESS), for a given firm, represents the strength of the news measured using surveys of financial expert ratings for firm-specific events. The score value ranges between 0 and 100 - values above (below) 50 classify the news as being positive (negative), 50 being neutral.

Aggregate Event Sentiment (AES) represents the ratio of positive events reported on a firm compared to the total count of events measured over a rolling 91-day window in a particular news edition (DJ or PR). An event with ESS > 50 is counted as a positive entry while ESS < 50 as negative. Neutral news (ESS = 50) and news that does not receive an ESS score does not enter into the AES computation. As ESS, the score values are between 0 and 100.

Aggregate Event Volume (AEV) represents the count of events for a firm over the last 91 days within a certain edition. As in AES case, news that receives a non-neutral ESS score is counted and therefore accumulates positive and negative news.

Composite Sentiment Score (CSS) represents the news sentiment of a given news story by combining various sentiment analysis techniques. The direction of the score is determined by looking at emotionally charged words and phrases and by matching stories typically rated by experts as having short-term positive or negative share price impact. The strength of the scores is determined by intra-day price reactions modeled empirically using tick data from approximately 100 large-cap stocks. As for ESS and AES, the score takes values between 0 and 100, 50 being the neutral.

News Impact Projections (NIP) represents the degree of impact a news flash has on the market over the following two-hour period. The algorithm produces scores to accurately predict a relative volatility - defined as scaled volatility by the average of volatilities of large-cap firms used in the test set - of each stock price measured

within two hours following the news. Tick data is used to train the algorithm and produce scores, which take values between 0 and 100, 50 representing zero impact news.

For each firm and each day with firm-specific news, we compute the average value of the specific sentiment score. In this way, we aggregate across editions and groups, where the later is defined as a collection of related news. We then map the indices that take values between 0 and 100 onto [-1, 1]. Specifically, let $x_i \in \{\text{ESS}, \text{AES}, \text{CSS}, \text{NIP}\}$ be the average score value for a particular day and firm. We map $x_i \mapsto \bar{x}_i \in [-1, 1]$ by computing $\bar{x}_i = (x_i - 50)/50$.

	id	Frequency	Source	T-code					
-	Pane	el A.							
-	Price/Earnings ratio	quarterly	CRSP & I/B/E/S	1					
-	Price/Earnings ratio consensus forecasts	quarterly	CRSP & I/B/E/S	1					
	Panel B.								
1	Stock returns	daily	CRSP	1					
2	Realized variance measure	daily	CRSP/computations	1					
	Pane	el C.							
1	Event Sentiment Score (ESS)	daily	RavenPack	1					
2	Aggregate Event Sentiment (AES)	daily	RavenPack	1					
3	Aggregate Event Volume (AEV)	daily	RavenPack	1					
4	Composite Sentiment Score (CSS)	daily	RavenPack	1					
5	News Impact Projections (NIP)	daily	RavenPack	1					

Table OA.4: Firm-level data description table – The *id* column gives mnemonics according to data source, which is given in the second column *Source*. The column *frequency* states the sampling frequency of the variable. The column *T-code* denotes the data transformation applied to a time-series, which are: (1) not transformed, (2) Δx_t , (3) $\Delta^2 x_t$, (4) $\log(x_t)$, (5) $\Delta \log(x_t)$, (6) $\Delta^2 \log(x_t)$. Panel A. describes earnings data, panel B. describes quarterly firm-level accouting data, panel C. daily firm-level stock market data and panel D. daily firm-level sentiment data series.

	id	Frequency	Source	T-code
		Panel A.		
1	Industrial Production Index	monthly	FRED-MD	5
2	CPI Inflation	monthly	FRED-MD	6
		Panel B.		
1	Crude Oil Prices	daily	FRED	6
2	S&P 500	daily	CRSP	5
3	VIX Volatility Index	daily	FRED	1
4	Moodys Aaa - 10-Year Treasury	daily	FRED	1
5	Moodys Baa - 10-Year Treasury	daily	FRED	1
6	Moodys Baa - Aaa Corporate Bond	daily	FRED	1
7	10-Year Treasury - 3-Month Treasury	daily	FRED	1
8	3-Month Treasury - Effective Federal funds rate	daily	FRED	1
9	TED rate	daily	FRED	1
		Panel C.		
1	Earnings	monthly	Bybee, Kelly, Manela, and Xiu (2021)	1
2	Earnings forecasts	monthly	Bybee, Kelly, Manela, and Xiu (2021)	1
3	Earnings losses	monthly	Bybee, Kelly, Manela, and Xiu (2021)	1
4	Recession	monthly	Bybee, Kelly, Manela, and Xiu (2021)	1
5	Revenue growth	monthly	Bybee, Kelly, Manela, and Xiu (2021)	1
6	Revised estimate	monthly	Bybee, Kelly, Manela, and Xiu (2021)	1

Table OA.5: Other predictor variables description table – The *id* column gives mnemonics according to data source, which is given in the second column *Source*. The column *frequency* states the sampling frequency of the variable. The column *T-code* denotes the data transformation applied to a time-series, which are: (1) not transformed, (2) Δx_t , (3) $\Delta^2 x_t$, (4) $\log(x_t)$, (5) $\Delta \log(x_t)$, (6) $\Delta^2 \log(x_t)$. Panel A. describes real-time monthly macro series, panel B. describes daily financial markets data and panel C. monthly news attention series.

	Ticker	Firm name	PERMNO	RavenPack ID
1	MMM	3M	22592	03B8CF
2	ABT	Abbott labs	20482	520632
3	AUD	Automatic data processing	44644	66ECFD
4	ADTN	Adtran	80791	9E98F2
5	AEIS	Advanced energy industries	82547	1D943E
6	AMG	Affiliated managers group	85593	30E01D
7	AKST	A K steel holding	80303	41588B
8	ATI	Allegheny technologies	43123	D1173F
9	AB	AllianceBernstein holding l.p.	75278	CB138D
10	ALL	Allstate corp.	79323	E1C16B
11	AMZN	Amazon.com	84788	0157B1
12	AMD	Advanced micro devices	61241	69345C
13	DOX	Amdocs ltd.	86144	45D153
14	AMKR	Amkor technology	86047	5C8D61
15	APH	Amphenol corp.	84769	BB07E4
16	AAPL	Apple	14593	D8442A
17	ADM	Archer daniels midland	10516	2B7A40
18	ARNC	Arconic	24643	EC821B
19	ATTA	AT&T	66093	251988
20	AVY	Avery dennison corp.	44601	662682
21	BHI	Baker hughes	75034	940C3D
22	BAC	Bank of america corp.	59408	990AD0
23	BAX	Baxter international inc.	27887	1FAF22
24	BBT	BB&T corp.	71563	1A3E1B
25	BDX	Becton dickinson & co.	39642	873DB9
26	BBBY	Bed bath & beyond inc.	77659	9B71A7
27	BHE	Benchmark electronics inc.	76224	6CF43C
28	BA	Boeing co.	19561	55438C
29	BK	Bank of new york mellon corp.	49656	EF5BED
30	BWA	BorgWarner inc.	79545	1791E7
31	BP	BP plc	29890	2D469F
32	EAT	Brinker international inc.	23297	732449
33	BMY	Bristol-Myers squibb co.	19393	94637C
34	BRKS	Brooks automation inc.	81241	FC01C0
35	CA	CA technologies inc.	25778	76DE40
36	COG	Cabot oil & gas corp.	76082	388E00
37	CDN	Cadence design systems inc.	11403	CC6FF5
38	COF	Capital one financial corp.	81055	055018
39	CRR	Carbo ceramics inc.	83366	8B66CE
40	CSL	Carlisle cos.	27334	9548BB
41	CCL	Carnival corporation & plc	75154	067779
42	CERN	Cerner corp.	10909	9743E5
43	CHRW	C.H. robinson worldwide inc.	85459	C659EB
44	SCHW	Charles schwab corp.	75186	D33D8C
45	CHKP	Check point software technologies ltd.	83639	531 EF1
46	CHV	Chevron corp.	14541	D54E62
47	CI	CIGNA corp.	64186	86A1B9
48	CTAS	Cintas corp.	23660	BFAEB4
49	CLX	Clorox co.	46578	719477
50	KO	Coca-Cola co.	11308	EEA6B3
51	CGNX	Cognex corp.	75654	709AED
52	COLM	Columbia sportswear co.	85863	5D0337
53	CMA	Comerica inc.	25081	8CF6DD
54	CRK	Comstock resources inc.	11644	4D72C8
55	CAG	ConAgra foods inc.	56274	FA40E2
56	STZ	Constellation brands inc.	69796	1D1B07
57	CVG	Convergys corp.	86305	914819

58	COST	Costco wholesale corp.	87055	B8EF97
59	CCI	Crown castle international corp.	86339	275300
60	DHR	Danaher corp.	49680	E124EB
61	DRI	Darden restaurants inc.	81655	9BBFA5
62	DVA	DaVita inc.	82307	EFD406
63	DO	Diamond offshore drilling inc.	82298	331BD2
64	D	Dominion resources inc.	64936	977A1E
65	DOV	Dover corp.	25953	636639
66	DOW	Dow chemical co.	20626	523A06
67	DHI	D.R. horton inc.	77661	06EF42
68	EMN	Eastman chemical co.	80080	D4070C
69	EBAY	eBay inc.	86356	972356
70	EOG	EOG resources inc.	75825	A43906
71	EL	Estee lauder cos. inc.	82642	14ED2B
72	ETH	Ethan allen interiors inc.	79037	65CF8E
73	ETFC	E*TRADE financial corp.	83862	28DEFA
74	XOM	Exxon mobil corp.	11850	E70531
75	FII	Federated investors inc.	86102	73C9E2
76	FDX	FedEx corp.	60628	6844D2
77	FITB	Fifth third bancorp	34746	8377DB
78	FISV	Fiserv inc.	10696	190B91
79	FLEX	Flex ltd.	80329	B4E00D
80	F	Ford motor co.	25785	A6213D
81	FWRD	Forward air corp.	79841	10943B
82	BEN	Franklin resources inc.	37584	5B6C11
83	GE	General electric co.	12060	1921DD
84	GIS	General mills inc.	17144	9CA619
85	GNTX	Gentex corp.	38659	CC339B
86	HAL	Halliburton Co.	23819	2B49F4
87	HLIT	Harmonic inc.	81621	DD9E41
88	HIG	Hartford financial services group inc.	82775	766047
89	HAS	Hasbro inc.	52978	AA98ED
90	HLX	Helix energy solutions group inc.	85168	6DD6BA
91	HP	Helmerich & payne inc.	32707	1DE526
92	HSY	Hershey co.	16600	9F03CF
93	HES	Hess corp.	28484	D0909F
94	HON	Honeywell international inc.	10145	FF6644
95	JBHT	J.B. Hunt transport services Inc.	42877	72DF04
96	HBAN	Huntington bancshares inc.	42906	C9E107
97	IBM	IBM corp.	12490	8D4486
98	IEX	IDEX corp.	75591	E8B21D
99	IR	Ingersoll-Rand plc	12431	5A6336
100	IDTI	Integrated device technology inc.	44506	8A957F
101	INTC	Intel corp.	59328	17EDA5
102	IP	International paper co.	21573	8E0E32
103	IIN	ITT corp.	12570	726 EEA
104	JAKK	Jakks pacific inc.	83520	5363A2
105	JNJ	Johnson & johnson	22111	A6828A
106	JPM	JPMorgan chase & co.	47896	619882
107	K	Kellogg co.	26825	9AF3DC
108	KMB	Kimberly-Clark corp.	17750	3DE4D1
109	KNGT	Knight transportation inc.	80987	ED9576
110	LSTR	Landstar system inc.	78981	FD4E8D
111	LSCC	Lattice semiconductor corp.	75854	8303CD
112	LLY	Eli lilly & co.	50876	F30508
113	LFUS	Littelfuse inc.	77918	D06755
114	LNC	Lincoln national corp.	49015	5C7601
115	LMT	Lockheed martin corp.	21178	96F126

116	MTB	M&T bank corp.	35554	D1AE3B
117	MANH	Manhattan associates inc.	85992	031025
118	MAN	ManpowerGroup inc.	75285	C0200F
119	MAR	Marriott international inc.	85913	385DD4
120	MMC	Marsh & mcLennan cos.	45751	9B5968
121	MCD	McDonald's corp.	43449	954E30
122	MCK	McKesson corp.	81061	4A5C8D
123	MDU	MDU resources group inc.	23835	135B09
124	MRK	Merck & co. inc.	22752	1EBF8D
125	MTOR	Meritor inc	85349	00326E
126	MTG	MGIC investment corp.	76804	E28F22
127	MGM	MGM resorts international	11891	8E8E6E
128	MCHP	Microchip technology inc.	78987	CDFCC9
129	MU	Micron technology inc.	53613	49BBBC
130	MSFT	Microsoft corp.	10107	228D42
131	MOT	Motorola solutions inc.	22779	E49AA3
132	MSM	MSC industrial direct co.	82777	74E288
133	MUR	Murphy oil corp.	28345	949625
134	NBR	Nabors industries ltd.	29102	E4E3B7
135	NOI	National oilwell varco inc.	84032	5D02B7
136	NYT	New york times co.	47466	875F41
137	NFX	Newfield exploration co.	79915	9C1A1F
138	NEM	Newmont mining corp.	21207	911AB8
139	NKE	NIKE inc.	57665	D64C6D
140	NBL	Noble energy inc.	61815	704DAE
141	NOK	Nokia corp.	87128	C12ED9
142	NOC	Northrop grumman corp.	24766	FC1B7B
143	NTRS	Northern trust corp.	58246	3CCC90
144	NUE	NuCor corp.	34817	986AF6
145	ODEP	Office depot inc.	75573	B66928
146	ONB	Old national bancorp	12068	D8760C
147	OMC	Omnicom group inc.	30681	C8257F
148	OTEX	Open text corp.	82833	34E891
149	ORCL	Oracle corp.	10104	D6489C
150	ORBK	Orbotech ltd.	78527	290820
151	PCAR	Paccar inc.	60506	ACF77B
152	PRXL	Parexel international corp.	82607	EF8072
153	PH	Parker hannifin corp.	41355	6B5379
154	PTEN	Patterson-uti energy inc.	79857	57356F
155	PBCT	People's united financial inc.	12073	449A26
156	PEP	PepsiCo inc.	13856	013528
157	PFE	Pfizer inc.	21936	267718
158	PIR	Pier 1 imports inc.	51692	170A6F
159	PXD	Pioneer natural resources co.	75241	2920D5
160	PNCF	PNC financial services group inc.	60442	61B81B
161	POT	Potash corporation of saskatchewan inc.	75844	FFBF74
162	PPG	PPG industries inc.	22509	39FB23
163	PX	Praxair inc.	77768	285175
164	PG	Procter & gamble co.	18163	2E61CC
165	PTC	PTC inc.	75912	D437C3
166	PHM	PulteGroup inc.	54148	7D5FD6
167	QCOM	Qualcomm inc.	77178	CFF15D
168	DGX	Quest diagnostics inc.	84373	5F9CE3
169	RL	Ralph lauren corp.	85072	D69D42
170	RTN	Raytheon co.	24942	1981BF
171	RF	Regions financial corp.	35044	73C521
172	RCII	Rent-a-center inc.	81222	C4FBDC
173	RMD	ResMed inc.	81736	434F38

174	RHI	Robert half international inc.	52230	A4D173
175	RDC	Rowan cos. inc.	45495	3FFA00
176	RCL	Royal caribbean cruises ltd.	79145	751A74
177	RPM	RPM international inc.	65307	F5D059
178	RRD	RR R.R. donnelley & sons co.	38682	0BE0AE
179	SLB	Schlumberger ltd. n.v.	14277	164D72
180	SCTT	Scotts miracle-gro co.	77300	F3FCC3
181	SM	SM st. mary land & exploration co.	78170	6A3C35
182	SONC	Sonic corp.	76568	80D368
183	SO	Southern co.	18411	147C38
184	LUV	Southwest airlines co.	58683	E866D2
185	SWK	Stanley black & decker inc.	43350	CE1002
186	STT	State street corp.	72726	5BC2F4
187	TGNA	TEGNA inc.	47941	D6EAA3
188	TXN	Texas instruments inc.	15579	39BFF6
189	TMK	Torchmark corp.	62308	E90C84
190	TRV	The travelers companies inc.	59459	E206B0
191	TBI	TrueBlue inc.	83671	9D5D35
192	TUP	Tupperware brands corp.	83462	2B0AF4
193	TYC	Tyco international plc	45356	99333F
194	TSN	Tyson foods inc.	77730	AD1ACF
195	X	United states Steel corp.	76644	4E2D94
196	UNH	UnitedHealth group inc.	92655	205AD5
197	VIAV	Viavi solutions inc.	79879	E592F0
198	GWW	W.W. grainger inc.	52695	6EB9DA
199	WDR	Waddell & reed financial inc.	85931	2F24A5
200	WBA	Walgreens boots alliance inc.	19502	FACF19
201	DIS	Walt disney co.	26403	A18D3C
202	WAT	Waters corp.	82651	1F9D90
203	WBS	Webster financial corp.	10932	B5766D
204	WFC	Wells fargo & co.	38703	E8846E
205	WERN	Werner enterprises inc.	10397	D78BF1
206	WABC	Westamerica bancorp	82107	622037
207	WDC	Western digital corp.	66384	CE96E7
208	WHR	Whirlpool corp.	25419	BDD12C
209	WFM	Whole foods market inc.	77281	319E7D
210	XLNX	Xilinx inc.	76201	373E85

Table OA.6: Final list of firms – The table contains the information about the full list of firms: tickers, firm names, CRSP PERMNO code and RavenPack ID. Tickers and firm names are taken as of June, 2017. PERMNO and RavenPack ID columns are used to match firms and firm news data.

OA.3 Additional Empirical Results

$\hat{p}e_{i,t+1}$	S	$\hat{r}_{i,t+1}$	$\hat{e}^a_{i,t+1 t}$	
1.355		0.054	0.194	
1.305				
Individual				
0.915	0.883	0.930	0.819	
0.119	0.113			
0.901	0.893	1.065	0.875	
0.118	0.115			
0.926	0.902	1.073	0.896	
0.123	0.115			
	Pooled			
0.894	0.790	0.926	0.794	
0.060	0.026			
0.893	0.794	0.930	0.798	
0.058	0.027			
0.893	0.795	0.930	0.799	
0.058	0.028			
Fixed effects				
0.818	0.794	0.932	0.801	
0.053	0.032			
0.814	0.797	0.947	0.804	
0.051	0.034			
0.814	0.798	0.947	0.804	
0.051	0.035			
	$\hat{p}e_{i,t+1}$ 1.355 1.305 0.915 0.119 0.901 0.118 0.926 0.123 0.894 0.060 0.893 0.058 0.893 0.058 0.893 0.058 0.814 0.051 0.814 0.051	$\begin{array}{cccc} \hat{p}e_{i,t+1} & \bar{S} \\ 1.355 \\ 1.305 \\ & India \\ 0.915 & 0.883 \\ 0.119 & 0.113 \\ 0.901 & 0.893 \\ 0.118 & 0.115 \\ 0.926 & 0.902 \\ 0.123 & 0.115 \\ & Po \\ 0.894 & 0.790 \\ 0.060 & 0.026 \\ 0.893 & 0.794 \\ 0.058 & 0.027 \\ 0.893 & 0.795 \\ 0.058 & 0.028 \\ & Fixed \\ 0.818 & 0.794 \\ 0.053 & 0.032 \\ 0.814 & 0.797 \\ 0.051 & 0.034 \\ 0.814 & 0.798 \\ 0.051 & 0.035 \\ \end{array}$	$\begin{array}{c ccccc} \hat{p}e_{i,t+1} & S & \hat{r}_{i,t+1} \\ \hline \\ 1.355 & 0.054 \\ 1.305 & & & \\ \hline \\ 1.305 & & & \\ 0.915 & 0.883 & 0.930 \\ 0.119 & 0.113 & & \\ 0.901 & 0.893 & 1.065 \\ 0.118 & 0.115 & & \\ \hline \\ 0.926 & 0.902 & 1.073 \\ 0.123 & 0.115 & & \\ \hline \\ 0.926 & 0.902 & 1.073 \\ 0.123 & 0.115 & & \\ \hline \\ 0.926 & 0.902 & 1.073 \\ 0.0123 & 0.115 & & \\ \hline \\ 0.926 & 0.902 & 1.073 \\ 0.0123 & 0.115 & & \\ \hline \\ 0.926 & 0.902 & 1.073 \\ 0.0123 & 0.115 & & \\ \hline \\ 0.926 & 0.902 & 1.073 \\ 0.026 & 0.902 & 1.073 \\ 0.058 & 0.026 & & \\ \hline \\ 0.893 & 0.794 & 0.930 \\ 0.058 & 0.027 & & \\ 0.930 & 0.058 & 0.027 \\ \hline \\ 0.893 & 0.795 & 0.930 \\ 0.058 & 0.028 & & \\ \hline \\ Fixed \ effects \\ 0.814 & 0.797 & 0.947 \\ 0.051 & 0.034 & \\ 0.814 & 0.798 & 0.947 \\ 0.051 & 0.035 \end{array}$	

Table OA.7: Column $\hat{p}e_{i,t+1}$ reports results for directly nowcasting the log P/E ratio, column \hat{S} reports the results of nowcasting and summing up the components, column $r_{i,t+1}$ reports results for the log return and column $\hat{e}^a_{i,t+1|t}$ reports results for the log earnings forecast error of analysts. Row *RW* reports results for the random walk, while row *Consensus* for the median consensus nowcast. Panels *Individual, Pooled* and *Fixed effects* report results for different panel data models relative to the consensus MSE (columns $\hat{p}e_{i,t+1}$ and \hat{S}) and for the components (columns $r_{i,t+1}$ and $\hat{e}^a_{i,t+1|t}$) relative to the RW MSE. DM is the Diebold and Mariano (1995) test statistic p-values using one-sided critical values.