Economic Research Note

US: Test-driving the "data science" toolbox

- **We experiment with a variety of newer “data science” techniques in a horserace to forecast payrolls**
- **We find that state-of-the-art techniques produce only minor improvements over simple regression models**

We produce forecasts of a wide range of economic data series. Each week, the Global Data Watch (GDW) contains forecasts for dozens of different economic releases in countries around the world. We also produce “nowcasts” of GDP growth for several geographies, which use monthly data that have already been released to forecast monthly data not yet released, then use these forecasts as building blocks to forecast GDP. For many of our GDW forecasts, we maintain a collection of fairly simple ordinary least squares (OLS) regression models that we consult before judgmentally settling on a forecast. Meanwhile, our nowcasters forecast the “jagged edge” of missing monthly variables using dynamic factor models or principal components regression.

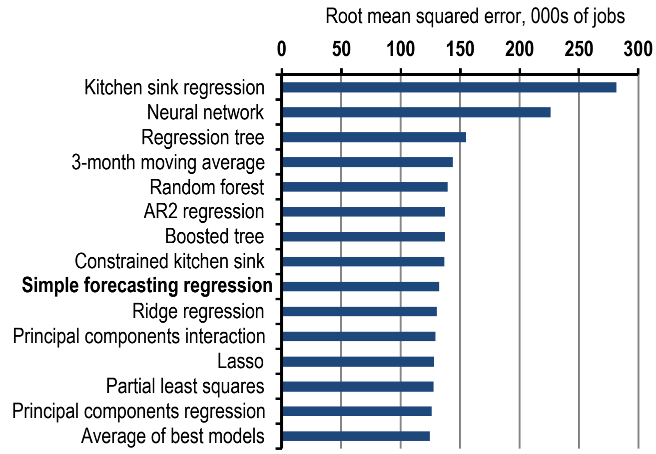
But these are not the only techniques we could use to make forecasts. Recently, the attention devoted to “data science,” “big data,” and the like has highlighted a variety of other techniques that have traditionally been outside of the standard economists’ toolbox. In this note, we experiment with a number of these techniques by running a payroll forecasting horserace that pits these techniques against simple regressions. In general, we find that the state-of-the-art techniques using many data series produce only minor improvements over very simple OLS regressions.

Got 8 cylinders and we're using them all

We set up a horserace in forecasting payrolls growth one month ahead over the period from 2007 to 2015. That is, for each month in that period, we produce a payrolls forecast using only the sample of data releases that would have been available at the time we usually produce our forecast—in the last week of the month being forecast. As predictor variables, we use a single lag of about 100 key monthly data series that have histories dating to 1998, including both hard activity data like retail sales and housing starts as well as sentiment indicators from consumers and businesses. We use the current vintage data for all series and all models as first print data are not available for all series.

Table 1 at the end of the note describes the forecasting models in the horserace. The first five are variations on simple OLS forecasting models. We highlight that the “simple forecasting regression” in the table is an OLS regression containing just three of our favorite indicators for payrolls—the lagged 3-month average of payroll growth, growth in initial claims between the reference weeks for the payroll survey, and the employment index from the Philly Fed’s Business Outlook Survey.

Figure 1: Error in forecasting monthly payrolls



Source: J.P. Morgan, Figures are out-of-sample RMSE in one-step-ahead forecast of monthly payroll growth over the period 2007-2015, using a sample beginning in 1998.

The remainder of the models in the table are based on techniques that have gained popularity among those working in “data science,” “big data,” “statistical learning,” “machine learning,” or whatever one prefers to call it. They can be grouped into a few different categories. Dimension reduction techniques like principal components and partial least squares boil down the information in many data series into a smaller number of common factors that can then be used in a forecasting regression. Penalized regression techniques, like ridge regression and the lasso, work by minimizing the deviation of the data from the predicted value of the model like OLS, but with some penalty for the magnitude of the regression coefficients. Tree-based methods like regression trees, random forests, and boosted trees work by binning the independent variables and then interacting dummies for the bins; these methods resemble what economists might call a partially “saturated” regression model, where the extent of saturation is chosen to maximize fit subject to a penalty for complexity. Finally, neural networks are a particular form of nonlinear estimator that originated in an attempt to mimic the process by which neurons process information in the brain. We recommend *An Introduction to Statistical Learning* by James, Witten, Hastie, and Tibshirani for more detail on these techniques.

Figure 1 plots the root-mean-squared-error (RMSE) in forecasting payrolls for each of these models, in descending order (the models forecast payrolls growth in percentage terms, but we convert the RMSEs to thousands of jobs based on the current level to make them easier to interpret). The "data science" models all involve the choice of some "tuning parameter" that varies the level of complexity allowed in the model. These include, for example, the number of principal components to include in a forecasting regression, the magnitude of the penalty parameter for ridge regression or lasso, or the number of nodes in a neural network. For all models, we compute the out-of-sample RMSEs for a range of different tuning parameters and report the lowest RMSE in this set. As we would not have known the optimal tuning parameter ahead of time, this gives some look-ahead performance boost to these models, although the differences are generally minor.

The worst model (highest RMSE) in Figure 1 is the "Kitchen sink regression" which simply includes all 100 variables in an OLS regression. Not surprisingly, this produces an overfit model whose out-of-sample predictions are mostly noise. The neural network is second worst—in a situation like this with many explanatory variables and a short history, even small neural networks involve enough parameters to produce an overfit model. Third worst is the basic regression tree, and the enhancements from random forests and boosted trees produce only slight improvements, with forecasts comparable to the 3-month moving average or the AR2 regression. In the middle of the pack are the "constrained kitchen sink" model—an OLS regression that removes any variables with the "wrong" sign— and our simple 3-variable regression. The rest of the data science techniques do slightly better, and the best overall model is the average of several of the individual models.

But we are most struck by how slight the differences are between models. When we fit several state-of-the-art data science models based on the full set of 100 variables with optimal tuning parameters, and then average their forecasts, we predict payrolls with an RMSE of 124,000. Meanwhile our humble 3-variable OLS regression has an RMSE of 132,000, an increase of just 8,000 jobs, or less than 3% of the monthly standard deviation of 290,000 jobs. The 3-variable model also has the advantage of transparency, in that it is quite easy to see what variables drive its forecast at any point and judgmentally adjust them for any relevant special factors, like seasonal adjustment issues or the recent Verizon strike. We also note that the principal components regression, which underlies our nowcasters, is the single best-performing model in the race.

We thus conclude that there is little reason to overhaul our toolbox just yet, although the fancier data science techniques may well prove useful in some future applications.

Table 1: Model Descriptions

Model	Description
Kitchen sink regression	Regression on all 100 variables
Constrained kitchen sink	Regression on all 100 variables, but variable with largest t-stat of "wrong" sign is removed until all variables have "right" sign
3-month moving average	Raw 3-month average used directly as forecast
AR2	Regression on 2 lags of dependent variable
Simple forecasting regression	Regression on 3 terms: 3-mo MA, reference week initial claims, and Philly Fed employment index
Principal component regression	Regression on first principal component of all 100 variables
Principal component interaction	Regression on first two principal components and interaction
Partial least squares	Regression on first partial least squares component
Ridge regression	Regression penalizing sum of squared values of coefficients
Lasso regression	Regression penalizing sum of absolute values of coefficients
Regression tree	Average of LHS variable in regions defined by binning RHS variables and interacting bin dummies
Random forest	Average of multiple regression trees, with binning for each tree based on random selection of RHS variables
Boosted tree	Regression trees built by repeatedly building new tree on residuals from last tree
Neural network	Nonlinear estimator loosely mimicking structure of neurons in brain
Average of best models	Average of forecasts from constrained kitchen sink, simple forecasting regression, principal components, partial least squares, ridge regression, and lasso regression.

Source: J.P. Morgan

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