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Econ 460

Project Report

In selecting a variable, we ultimately aimed to forecast something that would be interesting, as well as relevant to what is occuring in the world today. We settled on forecasting the number of employees in the US mining and logging industry (All Employees: Mining and Logging as reported by the U.S. Bureau of Labor Statistics), which was a big point of contention in the 2016 election, especially for the candidate who ended up winning, and has a Twitter. Since the election, the number of employees in this industry have steadily increased, from 646,000 to 756,000 employees, causing the president to boast about his great successes on Twitter; however, we were curious about a slightly longer term forecast of these numbers. As for the industry as a whole, the number of employees saw huge fluctuations from when it was first recorded in the 1940s until the 1950s when it began to stabilize, which is likely due to poor data collections. The number of employees saw a boom throughout the 1970s and into the early 1980s, when it took a sharp decline in 1982 all the way until 2003. In the early 2000s, there have been a few periods of ups and down, but nothing to conclude that these jobs are coming back for good.

After noticing some of the initial behavior of the data, we aimed to try and come up with a forecast stronger than, “I’m a winner and we need coal jobs” (paraphrased). We first looked to see if there might be a trend component of this times series and concluded that there was no blatant observable trends in the data. Next we focused on the seasonality and pressed the “seasonally adjusted” option on FRED’s website. Like all employment jobs we have looked at in class, we expected to see some seasonality, and it was very apparent in the seasonally unadjusted data. We figured that the Bureau of Labor Statistics algorithms for removing the seasonal component of the model would be stronger than finding seasonally dummies ourselves and left it to them. The last component of the model was the cycle. Our first intuition was to look for a unit root, a problem that can often occur in leveled data like the one we were observing. A unit-root would mean that our series is non-stationary, breaking the assumption that we have based all of our estimation theory on. With that in mind, we ran an Augmented Dickey-Fuller (ADF) test, hoping to reject the null hypothesis of a unit root. After running the test, we found a p-value of .1475 (Figure 1), implying that we failed to reject the null hypothesis that this series has a unit root. Thus, we found that the evidence is inconclusive, but we will treat the series as though it has a unit root nonetheless. Upon finding this, we decided to difference the data, and ran another ADF test to ensure that this data did not have a unit root. We found a p-value of 0.0 (Figure 2), implying that the changes of US mining and logging employees does not have a unit root.

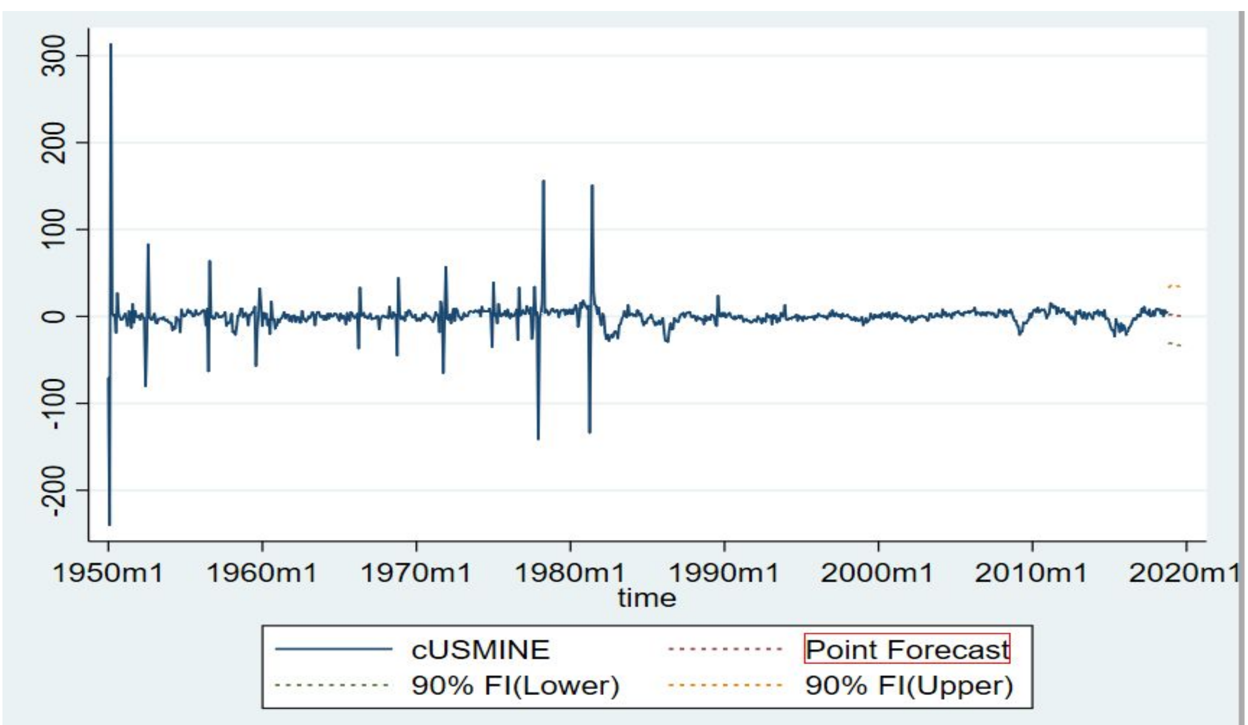
Next we aimed to find an explanatory variable to help describe some of the variation in our US Mining and Logging employees which we aimed to forecast. From class we know that including correlated variables in our model will help to explain the variation in the dependant variables. We also know that these variables have an effect on the dependent variable distributed over time, those we aimed to use an Autoregressive Distributed Lag (ADL) model. We also wanted to make sure the variable we included predictively causes changes in the number of mining and logging industry employees. We set off to find our explanatory variable. We considered many possible time series that might predictively cause some of the changes in mining and logging jobs, but narrowed it down to four. The four variables we settled on were, “Personal Consumption Expenditure on Energy Goods and Services”, “Industrial Production: Energy Materials: Energy, Total”, “Industrial Production: Energy Materials: Converted Fuel”, and “Producer Price Index by Commodity for Final Demand: Government Purchased Energy”. The intuition on picking these variables was that energy production and prices would have a strong relationship with the number of employees in the mining and coal industry. We then set to conduct Granger non-causality tests on each of the variables, hoping we could reject the null hypothesis of non-causality for at least one of them. Then we created a model with 12 autoregressive and 12 distributive lags, and did an F-test on the distributive lags for each variable. On the first go around the results were incredible. Every single variable we tested was significant and we were all but spoilt for choice. However, soon afterwards we realized we had fallen into the same pitfall that the faithful forecasters who found massive similarities between Egyptian mortality rate and Honduran money supply had fallen into. After realizing that we were not selecting the changes of the variables when we ran causality tests, we ran the tests again with the changes in each of the variables and still had interesting findings. The test with the lowest p-value (0.0, Figure 3) was the one on "Personal Consumption Expenditure on Energy Goods and Services", thus we chose to use the changes in that variable. Just to be cautious, we did Dickey-Fuller tests on all of our explanatory variables to make sure that their changes did not have a unit root, and actually found that changes in ""Producer Price Index by Commodity for Final Demand: Government Purchased Energy" could not reject the null.

When deciding on a model, we first created forecasting equations with combinations of 0,1,3,6 and 12 autoregressive and distributed lags, creating 25 total forecasts. In class, we went over a handful of model selection techniques. Perhaps the poorest method of model selection is one that analyzes the results of sequential F-testing. This method simply asks if there is strong statistical evidence against the restricted model. While f-testing was a good initial indicator of the predictive causality of our explanatory variables, selection based on testing does not attempt to evaluate which model will lead to the best forecast. To get a general idea of our most powerful forecasts, we compared the AIC and BIC of each of the models (Figure 4). BIC assumes that one of the models is the true model and seeks to find which model has the highest posterior probability of the model being the true model, given the observed data. BIC also puts a higher penalty on the number of parameters than AIC, which looks at the models that will minimize the mean squared forecast error. Initially, we were going to pick the model with the lowest AIC, however we later learned that we could lower the out-of-sample root mean squared error by combining a few of our forecasts. Because we had a bunch of forecasts with similar AIC, there was no clear best forecast, thus we took a combined approach.

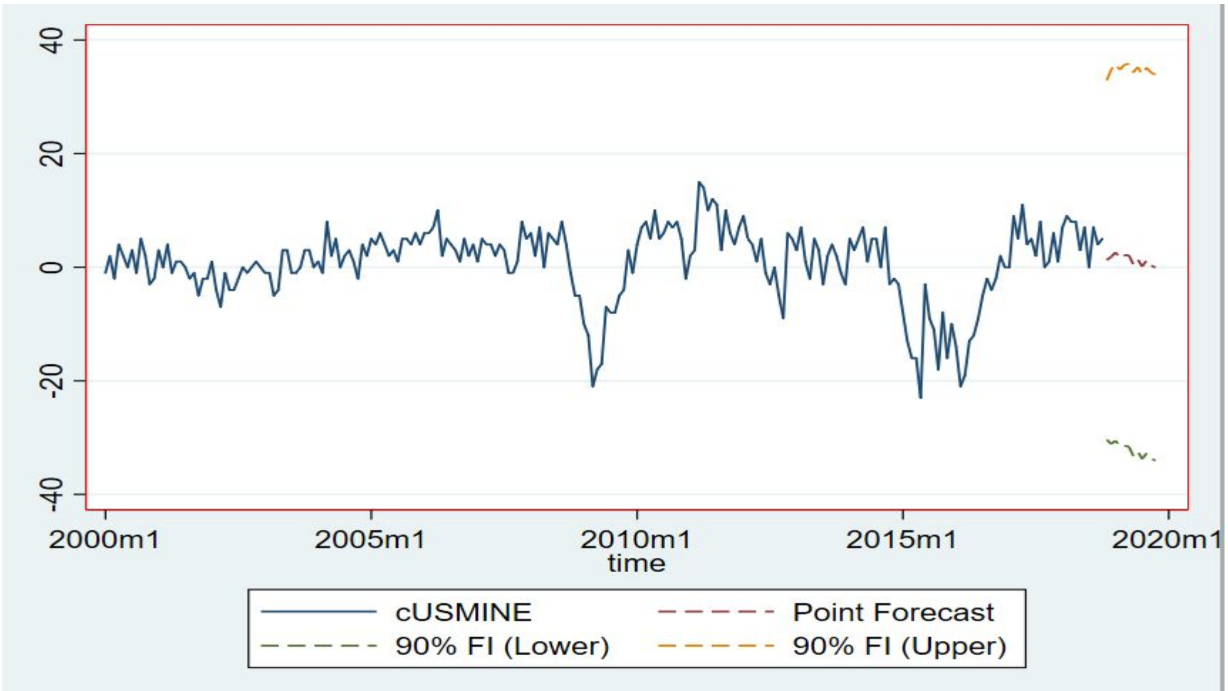
In taking a combined approach, we attempted to find the optimal weights for each of our 25 forecasts using the Granger-Ramanathan method. We started by creating a break at 2005m2, using 1960m2-2005m2 to create the model and using the dates after 2005m2 to construct pseudo-out-of-sample forecasts for each of our 25 models. This will allow us to see the forecast variances for each model, in which we will minimize. We then constrained the sum of each of our 25 forecasts to 1, and ran a regression without an intercept (Figure 5). After omitting collinear models and removing the most model with the most negative coefficient, we re-constrained the models and reran the regression until we reduced it to all models with positive weights. The three models left at the end of this procedure were model112 (1 autoregressive lag and 12 distributive lags), model120, and model126 (Figure 6), with weights of .574, .38, and .044, respectively. Something important to note is that the model with the lowest AIC did not have the highest weight of the forecasts in our combination model. But here we are simply trying to pick the model that minimizes the MSFE, and the research suggests that combination generally generate lower MSFE. With this in mind, we made point forecasts and found forecast errors for each of our three models. Then, we weighted our forecasts based on the weights we derived from the Granger-Ramanathan method. Below is the final forecast combination we created:

changes(US M&L employees)^ = .574*model112 + .38*model120 + .044*model126 + et^

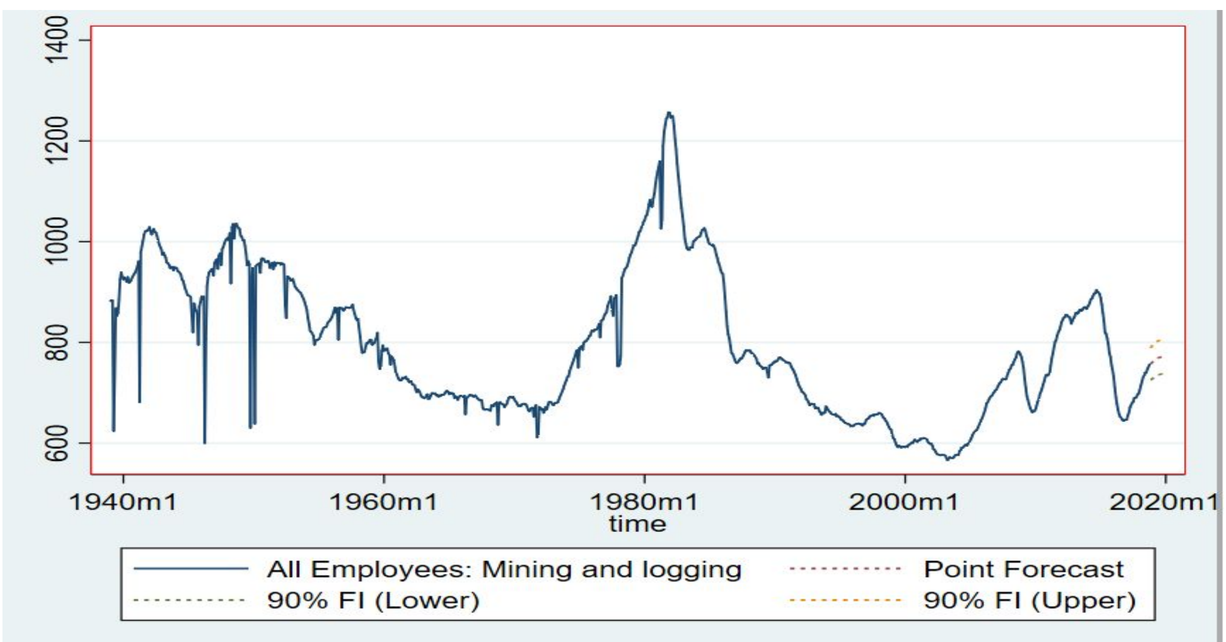
Finally, we constructed our point and interval forecasts for the changes in All Employees: Mining and Logging and arrived constructed the attached graph.



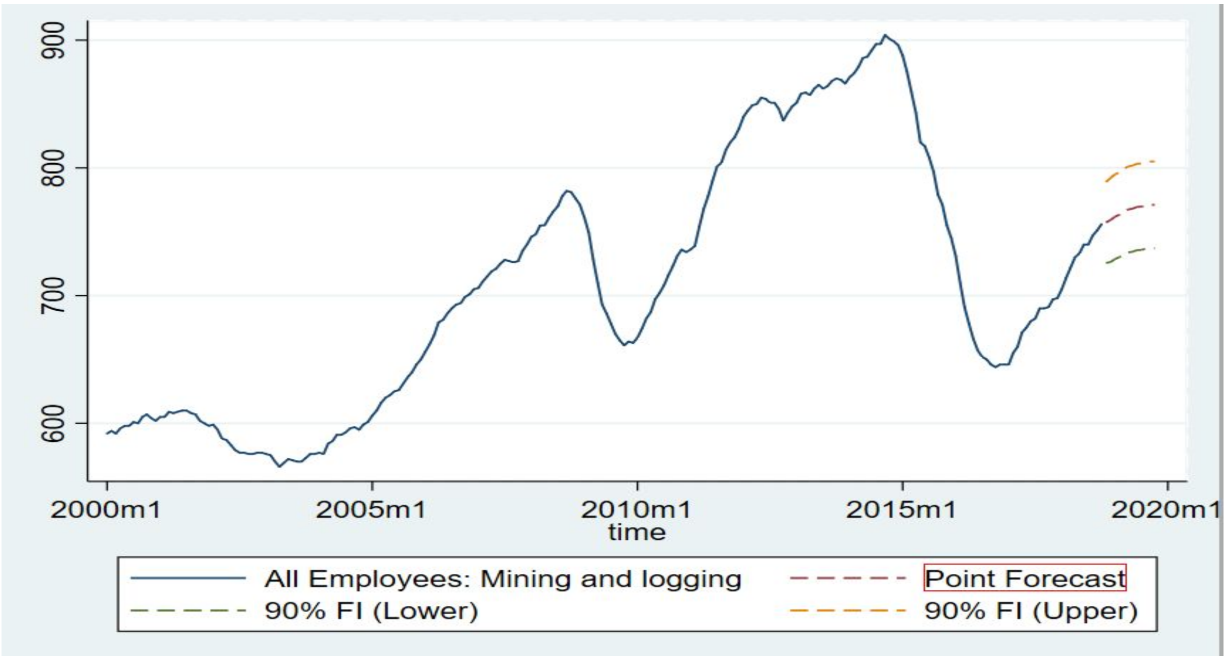
Here we cut off at 2000m1 to get a better look at our forecasts



Lastly we converted our changes forecast back into levels as we have done many times in class. The result of said conversion are shown in the following two graphs.



And again we cut off the graph at 2000m1 to get a better look at our forecasts



In the end, we forecasted that US Mining and Logging employment will be **757,265** people with the 90% confidence intervals of **[725,655, 788,874]**. There a couple things to note about our forecast. Firstly, we saw some fairly large standard errors which are responsible for the somewhat wide confidence intervals one can observe above. This can be attributed to the large spikes in the data, seen towards the earlier dates of our sample (Figure 7).

However, what is most interesting about our forecast is that it predicts a decline in the pace of coal jobs in the upcoming horizons. Even stronger, it appears the we will be forecasting a decline in the number of US mining and logging jobs in just a few horizons after the 12 we forecasted. We found this result pretty interesting, and maybe even comforting. We believe that the general intuition is that we should be trying to move away from coal mining and other industries fueled fossil fuels to more renewable sources of energy. The data does show a clear insurgence in the amount of mining and logging jobs, surely brought on by a certain political leader in the last couple of years. However, our forecasts suggest that scientific consensus will prevail and we will revert back to the dated notion that coal jobs might not be the in the best interest for future Americans.

Figures

FIGURE 1.

Augmented Dickey-Fuller test for unit root Number of obs = 945

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		---------- Interpolated Dickey-Fuller ---------		
Z(t)	-2.380	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.1475

FIGURE 2.

Augmented Dickey-Fuller test for unit root Number of obs = 944

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		---------- Interpolated Dickey-Fuller ---------		
Z(t)	-8.206	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

Figure 3.

(1) L.cPCEENERGY = 0
(2) L2.cPCEENERGY = 0
(3) L3.cPCEENERGY = 0
(4) L4.cPCEENERGY = 0
(5) L5.cPCEENERGY = 0
(6) L6.cPCEENERGY = 0
(7) L7.cPCEENERGY = 0
(8) L8.cPCEENERGY = 0
(9) L9.cPCEENERGY = 0
(10) L10.cPCEENERGY = 0
(11) L11.cPCEENERGY = 0
(12) L12.cPCEENERGY = 0

F(12, 680) = 6.26
Prob > F = 0.0000

FIGURE 4.

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
model00	705	-2860.269	-2860.269	1	5722.538	5727.096
model10	705	-2860.269	-2853.71	2	5711.42	5720.536
model30	705	-2860.269	-2849.331	4	5706.663	5724.896
model60	705	-2860.269	-2840.066	7	5694.133	5726.04
model120	705	-2860.269	-2831.432	13	5688.863	5748.12
model01	705	-2860.269	-2859.454	2	5722.908	5732.024
model11	705	-2860.269	-2853.063	3	5712.127	5725.801
model31	705	-2860.269	-2848.643	5	5707.287	5730.078
model61	705	-2860.269	-2839.37	8	5694.74	5731.206
model121	705	-2860.269	-2830.783	14	5689.566	5753.381
model06	705	-2860.269	-2848.369	7	5710.737	5742.645
model16	705	-2860.269	-2844.177	8	5704.353	5740.819
model36	705	-2860.269	-2839.741	10	5699.483	5745.065
model66	705	-2860.269	-2830.425	13	5686.851	5746.107
model126	705	-2860.269	-2821.295	19	5680.59	5767.196
model012	705	-2860.269	-2839.039	13	5704.079	5763.335
model112	705	-2860.269	-2836.596	14	5701.192	5765.007
model312	705	-2860.269	-2831.766	16	5695.533	5768.464
model612	705	-2860.269	-2823.404	19	5684.807	5771.413
model1212	705	-2860.269	-2815.859	25	5681.719	5795.674

Note: N=Obs used in calculating BIC; see [R] BIC note.

- **modelpq -> p AR lags, q regressor lags**
- **YELLOW are the four lowest AIC's**
- **BLUE are the three remaining forecasts after using the Granger Ramanathan Combination method**

FIGURE 5.

. constraint 4 y06 + y012 + y13 + y16 + y112 + y30 + y33 + y36 + y312 + y63 + y612 + y120 + y121 + y123 + y126 +y1212 = 1

. cnsreg cUSMINE y06 y012 y13 y16 y112 y30 y33 y36 y312 y63 y612 y120 y121 y123 y126 y1212, constraints(4) noconstant

Constrained linear regression Number of obs = 164
Root MSE = 4.0755

(1) y06 + y012 + y13 + y16 + y112 + y30 + y33 + y36 + y312 + y63 + y612 + y120 + y121 + y123 + y126 + y1212 = 1

cUSMINE	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
y06	-8.289163	1.773662	-4.67	0.000	-11.79394	-4.784383
y012	4.09313	1.769161	2.31	0.022	.5972454	7.589015
y13	3.060428	3.952436	0.77	0.440	-4.749639	10.87049
y16	6.464397	4.032737	1.60	0.111	-1.504345	14.43314
y112	-2.109154	2.207328	-0.96	0.341	-6.470865	2.252556
y30	1.135205	2.196954	0.52	0.606	-3.206006	5.476416
y33	7.830581	8.325251	0.94	0.348	-8.620225	24.28139
y36	-12.33186	8.138492	-1.52	0.132	-28.41363	3.749906
y312	1.181474	1.594881	0.74	0.460	-1.970032	4.33298
y63	1.205311	1.82592	0.66	0.510	-2.402732	4.813354
y612	-2.257973	1.527535	-1.48	0.141	-5.276403	.7604571
y120	-.757706	2.433245	-0.31	0.756	-5.56583	4.050418
y121	-.3440236	.2536781	-1.36	0.177	-.8452948	.1572477
y123	-12.53281	5.403744	-2.32	0.022	-23.21068	-1.854936
y126	15.62325	5.244241	2.98	0.003	5.260563	25.98594
y1212	-.9710919	.8864134	-1.10	0.275	-2.722656	.7804725

- **modelpq -> p AR lags, q regressor lags**

FIGURE 6.

Constrained linear regression Number of obs = 164
Root MSE = 4.8600

(1) y112 + y120 + y126 = 1

cUSMINE	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
y112	.5738973	.0708411	8.10	0.000	.4340063	.7137882
y120	.3824363	.0550893	6.94	0.000	.2736505	.4912221
y126	.0436664	.0852128	0.51	0.609	-.1246047	.2119374

- **modelpq -> p AR lags, q regressor lags**

FIGURE 7