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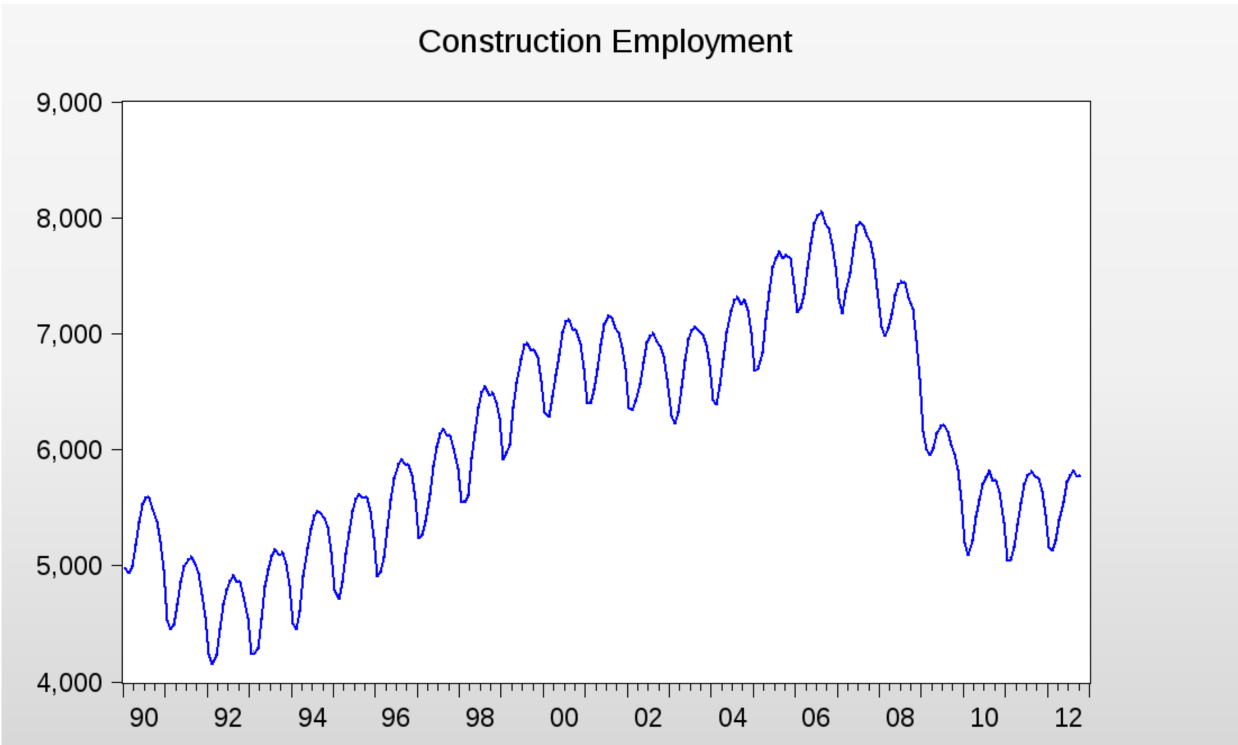
Economics 420

Final Project – Construction Employment Forecast

Introduction



The data set is the time series of monthly US construction employment from January 1990 to October 2012. Following the recession in the early 1990s, employment trended steadily upward until the recession around 2008. The construction industry is highly seasonal with peak employment generally occurring in August and the trough in February.

The correlogram for the series suggests both auto-regressive and moving average processes and possibly a unit-root, as well. The Augmented Dickey-Fuller test shows that we cannot reject the hypothesis that the series has a unit-root at the 95% confidence level, although we can at 90%.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.983	0.983	267.90	0.000
		2	0.947	-0.610	517.26	0.000
		3	0.902	0.135	744.47	0.000
		4	0.862	0.290	952.35	0.000
		5	0.831	0.102	1146.5	0.000
		6	0.816	0.231	1334.1	0.000
		7	0.816	0.181	1522.6	0.000
		8	0.830	0.221	1718.7	0.000
		9	0.855	0.134	1927.1	0.000
		10	0.882	0.123	2149.8	0.000
		11	0.901	-0.207	2383.2	0.000
		12	0.900	-0.387	2617.2	0.000
		13	0.873	-0.550	2837.8	0.000
		14	0.826	0.002	3036.3	0.000
		15	0.772	0.013	3210.3	0.000
		16	0.722	0.003	3363.3	0.000
		17	0.683	-0.087	3500.5	0.000
		18	0.658	-0.039	3628.5	0.000
		19	0.649	0.004	3753.5	0.000
		20	0.654	0.050	3880.9	0.000
		21	0.669	0.039	4014.7	0.000
		22	0.687	0.095	4156.4	0.000
		23	0.698	0.041	4303.2	0.000
		24	0.691	0.011	4447.5	0.000
		25	0.658	-0.174	4579.2	0.000
		26	0.609	0.057	4692.2	0.000
		27	0.553	0.071	4785.7	0.000
		28	0.501	0.014	4862.8	0.000
		29	0.460	-0.027	4928.1	0.000
		30	0.433	-0.032	4986.3	0.000
		31	0.422	0.006	5041.7	0.000
		32	0.425	0.031	5098.1	0.000
		33	0.437	-0.016	5158.0	0.000
		34	0.453	0.083	5222.7	0.000
		35	0.463	0.020	5290.5	0.000
		36	0.456	0.016	5356.5	0.000

Null Hypothesis: EMPL has a unit root
Exogenous: Constant
Lag Length: 15 (Automatic - based on SIC, maxlag=15)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.552764	0.1044
Test critical values:	1% level	-3.455585	
	5% level	-2.872542	
	10% level	-2.572707	

*MacKinnon (1996) one-sided p-values.

Leading Indicators

Using data from the United States Census Bureau, I chose and examined time series data from seven economic indicators I believed may lead construction employment. In eViews, I created an equation for each with the dependent variable ‘empl’, a constant ‘c’ and the indicator as the independent variable. In order to maximize the explanatory power of the variable, I found the lag time that maximized ‘adjusted R-Squared’. The table below shows key criteria from the estimation output for each of these indicators.

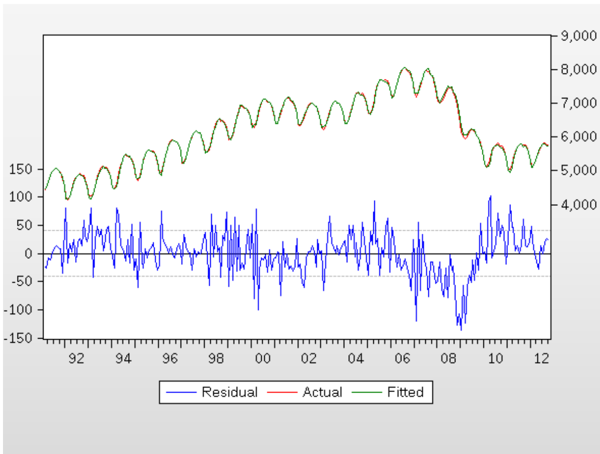
Indicator	Leading By (months)	Adjusted R-Squ	t-Stat Prob	Durbin-Waton	AIC
Total Construction Spending (TCS)	2	0.82755	1.19E-105	0.09116	14.860
Consumer Durable Goods New Orders (DUR)	7	0.51597	0.00E+00	0.76428	15.772
PPI Price Deflator (PPI)	2	0.44976	4.11E-37	0.05225	16.018
Building Permits (Unadjusted)	2	0.40183	3.43E-32	0.06767	16.102
Unemployment Rate (Unempl)	6	0.31084	1.65E-23	0.04206	16.247
Housing Starts (Starts)	1	0.31026	7.23E-24	0.03444	16.246
Construction Machinery New Orders	1	0.07931	3.63E-06	0.03439	16.492

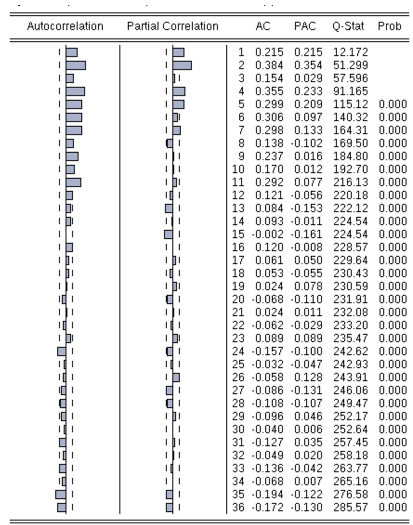
‘Total Construction Spending’ (TCS) and new orders for ‘Consumer Durable Goods’ seemed to have the most explanatory power and the lowest out-of-sample forecast errors of the group. The reason for including TCS as a leading indicator is fairly direct: spending on construction will increase in tandem with increases in labor, with labor trailing slightly as finding and contracting labor can take longer to fulfill than other purchases made. Consumer durable goods includes refrigerators, washers , dryers and other large appliances. In the retail market consumer durable goods is a trailing indicator of construction as new homes create demand for these products. The logic here is that new orders from manufacturers are made with anticipation of future construction. The PPI price measures price levels at the manufacturing level and was included out of curiosity. Building permits and housing starts are included for the same reason as they generally measure impending construction activity for which construction workers would be needed. The national unemployment rate was included simply because employment is a key criteria in securing a home mortgage and new housing is a significant portion of the construction industry. New orders for construction machinery had little explanatory power. My assumption then is most machinery is purchased independently of changes in demand for the construction industry’s products.

Model 0: ARMA

For the first model, I used none of the leading indicators above and instead used only auto-regression and moving average terms. It was important to have both an experimental control against which to measure the other model and also to have a “back-up” in case the other models were total failures. In this case, by trial-and-error I added and removed AR and MA terms until I was satisfied with the estimation output and the correlogram.

Variables	Adjusted R-Squared	Prob(f-Stat)	AIC	Durbin-Watson
ar(1), sar(12), sma(3), sma(12)	0.998328871	0	10.23723	1.567252498





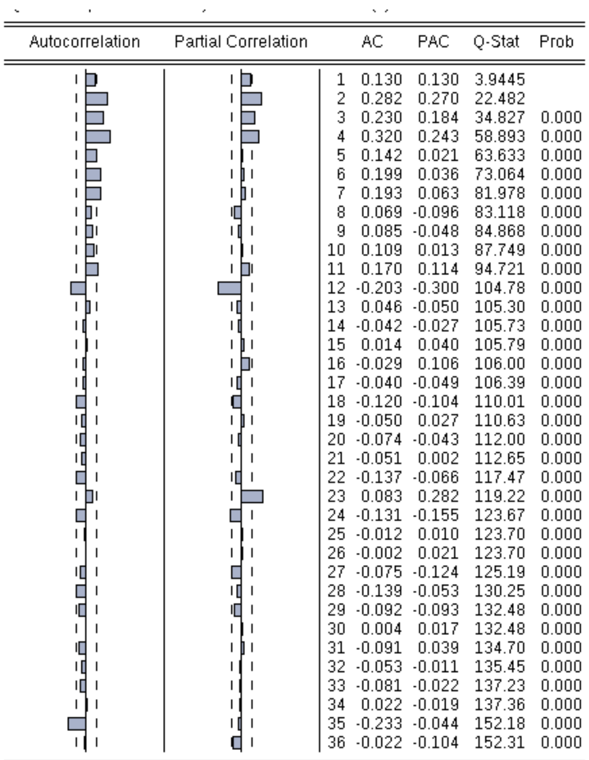
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.215	0.215	12.172	
		2	0.384	0.354	51.299	
		3	0.154	0.029	57.596	
		4	0.355	0.233	91.165	
		5	0.299	0.209	115.12	0.000
		6	0.306	0.097	140.32	0.000
		7	0.298	0.133	164.31	0.000
		8	0.138	-0.102	169.50	0.000
		9	0.237	0.016	184.80	0.000
		10	0.170	0.012	192.70	0.000
		11	0.292	0.077	216.13	0.000
		12	0.121	-0.056	220.18	0.000
		13	0.084	-0.153	222.12	0.000
		14	0.093	-0.011	224.54	0.000
		15	-0.002	-0.161	224.54	0.000
		16	0.120	-0.008	228.57	0.000
		17	0.061	0.050	229.64	0.000
		18	0.053	-0.055	230.43	0.000
		19	0.024	0.078	230.59	0.000
		20	-0.068	-0.110	231.91	0.000
		21	0.024	0.011	232.08	0.000
		22	-0.062	-0.029	233.20	0.000
		23	0.089	0.089	235.47	0.000
		24	-0.157	-0.100	242.62	0.000
		25	-0.032	-0.047	242.93	0.000
		26	-0.058	0.128	243.91	0.000
		27	-0.086	-0.131	246.06	0.000
		28	-0.108	-0.107	249.47	0.000
		29	-0.096	0.046	252.17	0.000
		30	-0.040	0.006	252.64	0.000
		31	-0.127	0.035	257.45	0.000
		32	-0.049	0.020	258.18	0.000
		33	-0.136	-0.042	263.77	0.000
		34	-0.068	0.007	265.16	0.000
		35	-0.194	-0.122	276.58	0.000
		36	-0.172	-0.130	285.57	0.000

Model 1

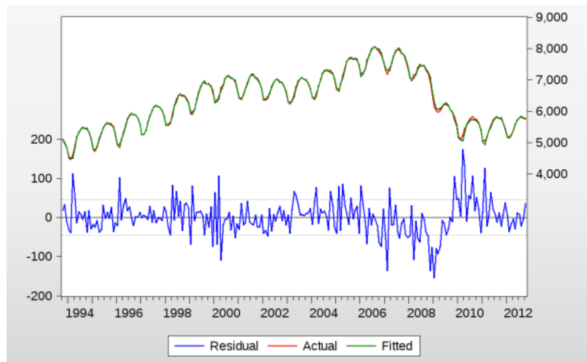
For this model, I chose the two indicators, TCS and DUR, that had the better overall estimation output (see above) and then added and removed ARMA terms until I was satisfied with overall performance of the model.

Variables	Adjusted R-Squared	Prob(f-Stat)	AIC	Durbin-Watson
TCS, DUR	0.836702474	3.30E-95	14.68978117	0.422790286
TCS, DUR, AR(1), SAR(12)	0.997266736	1.26E-286	10.48387	1.735933373
DUR,AR(1),AR(3),SAR(12)	0.997170855	5.97E-285	10.51835159	1.590463863

In this model, TCS, DUR, AR(1) and SAR(12) had the best estimation output with the correlogram and residual graph shown below.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.130	0.130	3.9445	
		2	0.282	0.270	22.482	
		3	0.230	0.184	34.827	0.000
		4	0.320	0.243	58.893	0.000
		5	0.142	0.021	63.633	0.000
		6	0.199	0.036	73.064	0.000
		7	0.193	0.063	81.978	0.000
		8	0.069	-0.096	83.118	0.000
		9	0.085	-0.048	84.868	0.000
		10	0.109	0.013	87.749	0.000
		11	0.170	0.114	94.721	0.000
		12	-0.203	-0.300	104.78	0.000
		13	0.046	-0.050	105.30	0.000
		14	-0.042	-0.027	105.73	0.000
		15	0.014	0.040	105.79	0.000
		16	-0.029	0.106	106.00	0.000
		17	-0.040	-0.049	106.39	0.000
		18	-0.120	-0.104	110.01	0.000
		19	-0.050	0.027	110.63	0.000
		20	-0.074	-0.043	112.00	0.000
		21	-0.051	0.002	112.65	0.000
		22	-0.137	-0.066	117.47	0.000
		23	0.083	0.282	119.22	0.000
		24	-0.131	-0.155	123.67	0.000
		25	-0.012	0.010	123.70	0.000
		26	-0.002	0.021	123.70	0.000
		27	-0.075	-0.124	125.19	0.000
		28	-0.139	-0.053	130.25	0.000
		29	-0.092	-0.093	132.48	0.000
		30	0.004	0.017	132.48	0.000
		31	-0.091	0.039	134.70	0.000
		32	-0.053	-0.011	135.45	0.000
		33	-0.081	-0.022	137.23	0.000
		34	0.022	-0.019	137.36	0.000
		35	-0.233	-0.044	152.18	0.000
		36	-0.022	-0.104	152.31	0.000



Model 2: The Kitchen Sink

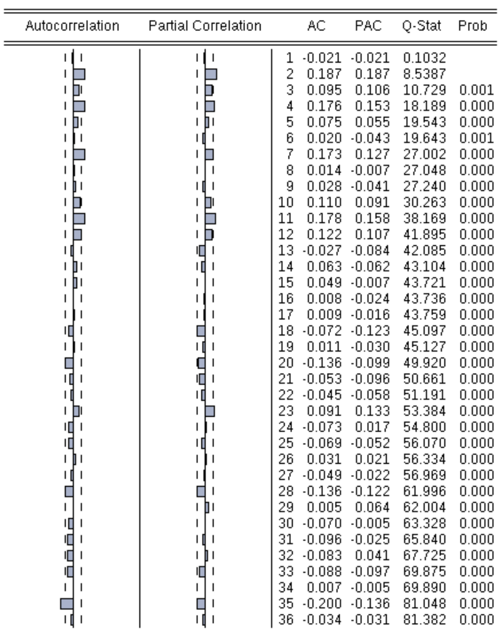
As an anti-thesis to Model 0, I chose to create a model that included all of the leading indicators listed above then added and removed terms iteratively based on the estimation output and correlogram. Not surprisingly, this was the poorest of the four models I explored.

Variables	Adjusted R-Squared	Prob(f-Stat)	AIC	Durbin-Watson
tcs, ppi, unempl, starts	0.960912182	1.25E-184	13.38788963	0.365168522
tcs,ppi,unempl,starts, ar1, ar24, ma12	0.992657199	2.19E-249	11.61757	1.195041

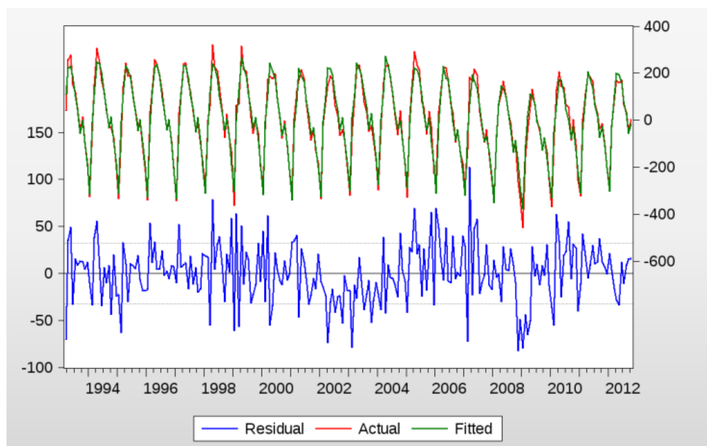
Model 3: The Difference Model

The unit-root test result shows that we cannot reject the null hypothesis – that EMPL has a unit root – at the 5% confidence level. Considering this, I chose to difference EMPL and then implement a model along the lines of Model 1. Ultimately, this proved to be the best performing of the four models in the hold-out sample forecast.

Variables	Adjusted R-Squared	Prob(f-Stat)	AIC	Durbin-Watson
tcs, dur, unempl, starts, ar(12), ma(12)	0.961119667	1.08E-159	9.819111439	2.019705157



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.021	-0.021	0.1032	
		2	0.187	0.187	8.5387	
		3	0.095	0.106	10.729	0.001
		4	0.176	0.153	18.189	0.000
		5	0.075	0.055	19.543	0.000
		6	0.020	-0.043	19.643	0.001
		7	0.173	0.127	27.002	0.000
		8	0.014	-0.007	27.048	0.000
		9	0.028	-0.041	27.240	0.000
		10	0.110	0.091	30.263	0.000
		11	0.178	0.158	38.169	0.000
		12	0.122	0.107	41.895	0.000
		13	-0.027	-0.084	42.085	0.000
		14	0.063	-0.062	43.104	0.000
		15	0.049	-0.007	43.721	0.000
		16	0.008	-0.024	43.736	0.000
		17	0.009	-0.016	43.759	0.000
		18	-0.072	-0.123	45.097	0.000
		19	0.011	-0.030	45.127	0.000
		20	-0.136	-0.099	49.920	0.000
		21	-0.053	-0.096	50.661	0.000
		22	-0.045	-0.058	51.191	0.000
		23	0.091	0.133	53.384	0.000
		24	-0.073	0.017	54.800	0.000
		25	-0.069	-0.052	56.070	0.000
		26	0.031	0.021	56.334	0.000
		27	-0.049	-0.022	56.969	0.000
		28	-0.136	-0.122	61.996	0.000
		29	0.005	0.064	62.004	0.000
		30	-0.070	-0.005	63.328	0.000
		31	-0.096	-0.025	65.840	0.000
		32	-0.083	0.041	67.725	0.000
		33	-0.088	-0.097	69.875	0.000
		34	0.007	-0.005	69.890	0.000
		35	-0.200	-0.136	81.048	0.000
		36	-0.034	-0.031	81.382	0.000



Comparison of the Models

	Actual	Model 0: ARMA			Model 1: TCS,DUR			Model 2: Kitchen Sink			Model 3: Difference		
		Forecast	Error	SE	Forecast	Error	SE	Forecast	Error	SE	Forecast	Error	SE
Jan-12	5158	5111	**47**	41	5152	6	46	5115	43	84	5137	21	34
Feb-12	5133	5113	20	40	5170	-37	46	5137	4	81	5130	3	33
Mar-12	5220	5220	0	40	5237	-17	45	5095	125	82	5237	17	33
Apr-12	5389	5405	16	41	5393	-4	46	5349	40	81	5417	28	33
May-12	5548	5576	28	40	5578	-30	46	5683	**135**	83	5582	**34**	33
Jun-12	5716	5703	13	40	5705	11	45	5752	36	82	5705	11	33
Jul-12	5782	5783	1	40	5775	7	45	5860	78	81	5793	11	33
Aug-12	5813	5793	20	40	5835	-22	46	5805	8	81	5805	8	33
Sep-12	5770	5745	25	40	5774	-4	46	5907	**137**	81	5755	15	33
Oct-12	5770	5746	24	40	5736	34	46	5858	**88**	82	5754	16	33
12-Nov		5662.9536		40.487022	5704.8498		46.17689	5797.0614		80.789629	5670.8995		32.980794

The contrast in performance of each model is clearest in the above table, with Model 3 best performing. Although the model forecast for September and October was lower than actual, I will not include an add-factor in my final forecast but instead will simply submit what the model produced. My forecast is 5671 and with 2 Standard Errors, the forecast interval is 5605 to 5737.