Project Report
Econ 460
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Background

Due to the coronavirus that is going on worldwide, all aspects of the economy are affected, especially the financial markets. One way to look at the influence of coronavirus on industries is to look at job opening rate and separation rate because as the companies try to survive through economic downturn, we would expect that the job openings would decrease and separation rate would increase. Thus, we want to learn how exactly some industries are affected and maybe after doing the prediction model, we might find out some surprising results.

This project aims to forecast job opening and separation rates for Financial Activities for the following year (more specifically, we would forecast from February 2020 to January 2021 since the data is monthly). The data description section describes the parameters we use and the description of the forecasting method section gives a general idea of the methods. The presentation of the forecasting model section is divided into two parts which separately show our procedures, decisions and reasonings of choosing certain models with regression results and plots for both job opening and job separation. Point and interval forecast section presents our final results both graphically and numerically. Finally, by Tuesday, April 7th, we will then compare our February 2020 forecast result with the true data released by BLS.

Data Description

According to BLS, job openings include jobs with work that could start within 30 days and the employers are actively recruiting from outside the companies. Separation rate measures the number of terminations of jobs both voluntarily and involuntarily including special cases like retirements, seasonal or short-term employment etc. Our historical data for job opening and separation rates for Financial Activities are both from December 2000 to January 2020, which includes 230 data points.

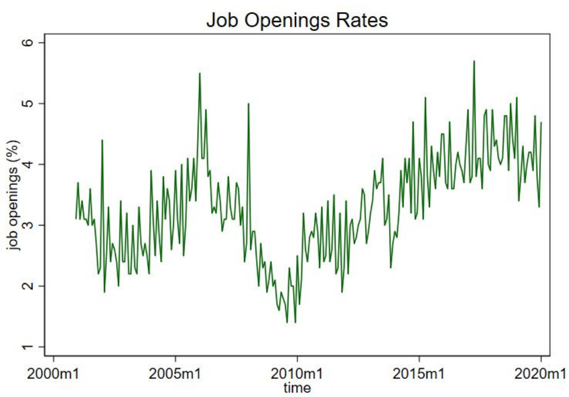
Description of Forecasting Method

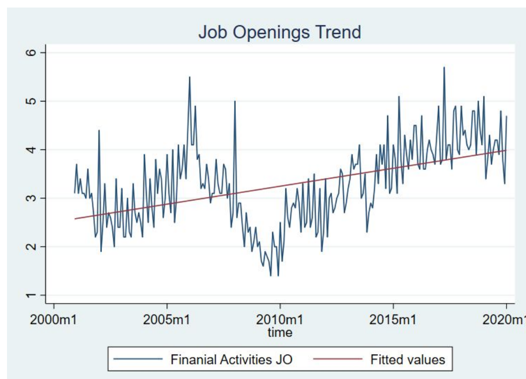
This and the next sections aim to present the process of how we finalize the forecasting model. In particular, we look at and analyze the trend, seasonal and cyclical patterns one by one to decide whether each term should be included for both job opening and separation rates. Moreover, residuals are compared throughout the process to verify our decision. In order to make the results more logical and easy to follow, we separate job opening and separation into two sections with the same analysis procedures. Furthermore, as our time series plot shows, there are changes in trends. However, we decide on the simple linear trend instead of splines as cycles with the AR(p) estimates play more important roles in forecasting. Finally, after comparing the results from the direct method with the iterated method, we decide to use direct forecast to forecast both job opening and separation rates for Financial Activities because first both methods provide similar forecasting results and second the iterated method depends on each result we forecast and this is risker. Overall, we adapt a linear trend with 12 seasonal dummies and AR(9) for job opening rates and with AR(10) for job separation rates. More details are presented in the next section.

Presentation of Forecasting Model

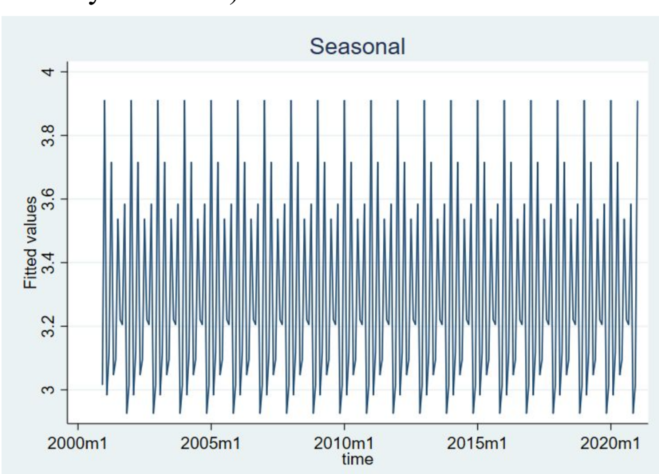
Job Opening Rates

The time series plot in the left figure below shows a general overview of job openings rates and as shown, there is an obvious trend and seasonal pattern. After generating the fitted values for the trend, the result shows a positive linear trend (figure on the right).

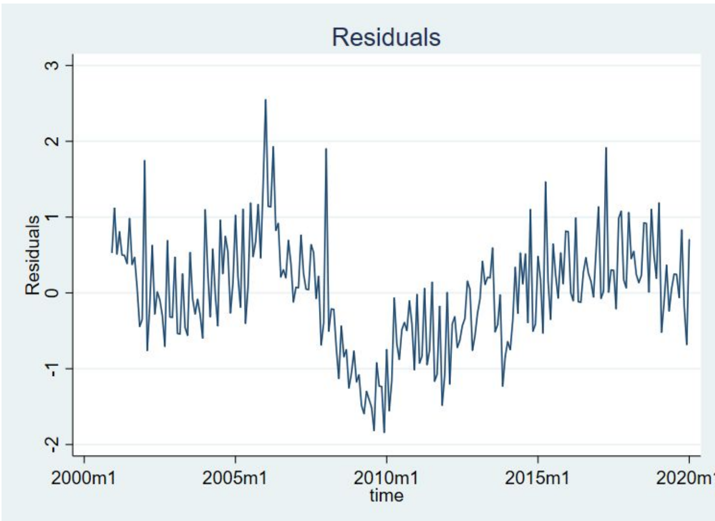




Although according to BLS, this data is deseasonalized, the following plot shows that there is still a strong seasonal pattern. Thus, it is more reasonable to include the seasonal dummies (12 monthly dummies) in our model.

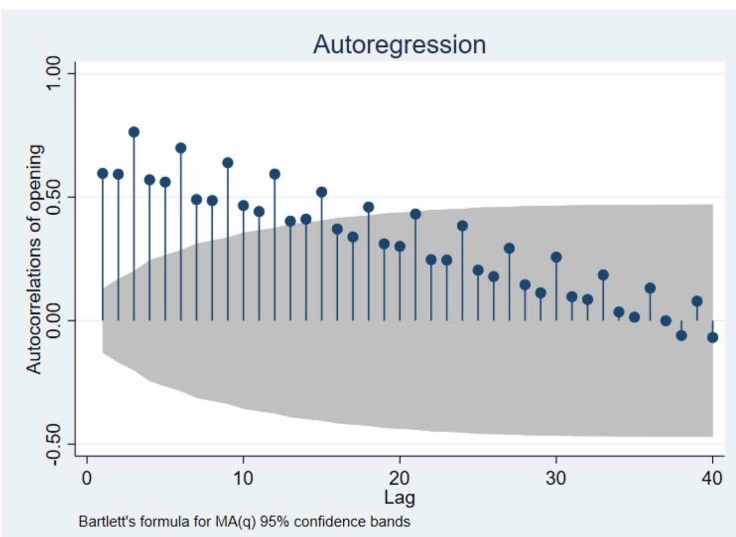


Next, we plot in-sample residuals to check whether there is a sign of cyclical trend. As the following figure indicated, the residual plot still has cyclical patterns, thus we will then include a cyclical trend.



Therefore, we have set up a general outline of the model with a linear trend, a seasonal trend, and a cyclical trend.

To proceed with the cyclical trend, it is reasonable to plot an autoregression graph to see the correlations of job openings with its monthly lags and as shown in the following figure, job opening rates have positive autocorrelation and again this autocorrelation shows a clear seasonal trend. This means that omitting seasonal trends would produce less reliable forecasting results.



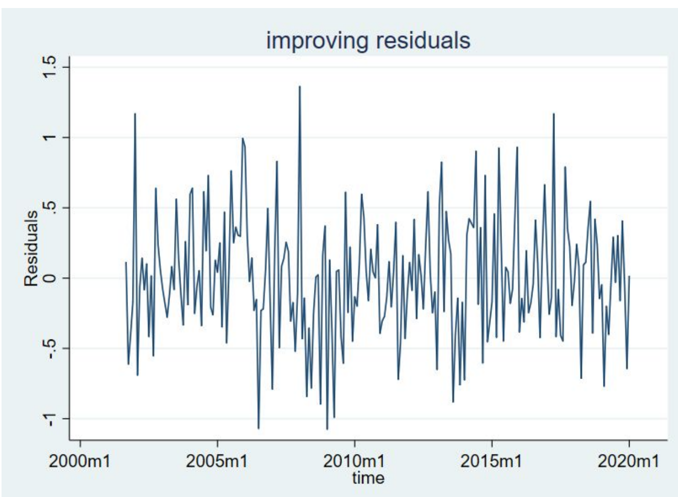
Moreover, since the MA(q) model is not usually used as a forecast model and the process is correlated with its past lags, we decided to use AR(p). To choose the best order p, we select 10 monthly lags and do an AIC analysis since compared with BIC, AIC is designed to find models with the lowest forecast risks. The lowest AIC (331.3267)shown below indicates AR(9) could generate the lowest forecast risks.

Akaike's information criterion and Bayesian information criterion

Model	N	ll(null)	ll(model)	df	AIC	BIC
ar1	220	-279.6878	-229.8658	2	463.7316	470.5189
ar2	220	-279.6878	-214.1002	3	434.2004	444.3813
ar3	220	-279.6878	-167.9937	4	343.9873	357.5618
ar4	220	-279.6878	-167.9029	5	345.8058	362.774
ar5	220	-279.6878	-167.7347	6	347.4693	367.8311
ar6	220	-279.6878	-162.0676	7	338.1353	361.8907
ar7	220	-279.6878	-159.332	8	334.664	361.813
ar8	220	-279.6878	-158.5012	9	335.0024	365.545
ar9	220	-279.6878	-155.6634	10	331.3267	365.263
ar10	220	-279.6878	-155.6599	11	333.3198	370.6497

Note: BIC uses N = number of observations. See [R] BIC note.

Before finalizing the model, we draw another residual plot to check whether adding in the linear trend, seasonal trend and cycle with AR(9) improves the residuals. As shown below, the residuals look much more like white noise and this shows that with all the added variables, the model is able to generate estimators that are closer to the truth. This is what we want.



As a consequence, we choose the Trend + Seasonal + Cycle with AR(9) Model and it is mathematically presented as:

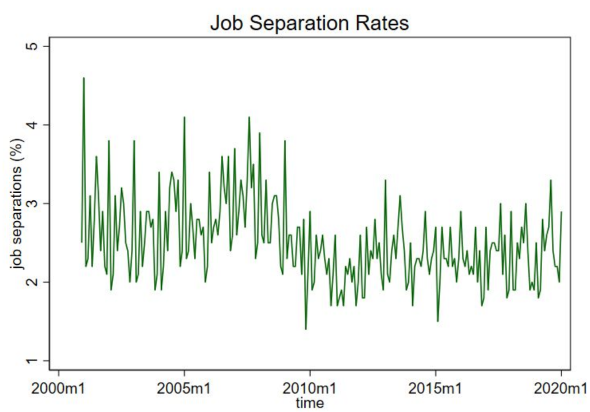
$$y_t = \theta * t + \Sigma_{i=1}^{s} \gamma_i D_{it} + \beta_1 * y_{t-1} + \cdots + \beta_9 * y_{t-9} + \varepsilon_t$$

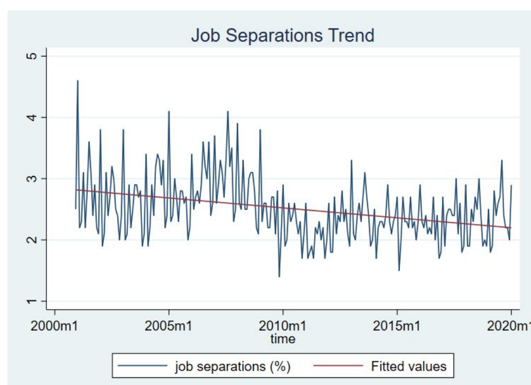
Finally, we regress y_t, the job opening rates on time, its 9 lags, and seasonal dummies. The following is our regression results, including the parameter estimates. We can see that the first three lags (lag 1 to 3) are the most important (since their P-values are less than 0.05) and the R-square is relatively high with 75%, indicating that the model is statistically significant.

```
. reg opening time L(1/9).opening b12.m

      Source |       SS           df       MS      Number of obs   =       221
-------------+----------------------------------   F(21, 199)      =     28.38
       Model |  122.785856        21  5.84694552   Prob > F        =    0.0000
    Residual |  41.0021984       199  .206041198   R-squared       =    0.7497
-------------+----------------------------------   Adj R-squared   =    0.7232
       Total |  163.788054       220  .744491156   Root MSE        =    .45392

------------------------------------------------------------------------------
     opening |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        time |   .0010103   .0005984     1.69   0.093    -.0001697    .0021902
             |
     opening |
         L1. |   .2548025   .0708294     3.60   0.000     .1151299    .3944751
         L2. |   .2412574   .0733718     3.29   0.001     .0965714    .3859434
         L3. |   .2105094    .074708     2.82   0.005     .0631884    .3578303
         L4. |   .0945196   .0762537     1.24   0.217    -.0558493    .2448885
         L5. |   .1081634   .0757495     1.43   0.155    -.0412114    .2575382
         L6. |   .0754048   .0757015     1.00   0.320    -.0738753     .224685
         L7. |  -.1358406   .0743294    -1.83   0.069     -.282415    .0107337
         L8. |  -.0112433   .0728943    -0.15   0.878    -.1549876     .132501
         L9. |   .0362294   .0706373     0.51   0.609    -.1030643     .175523
             |
           m |
          1  |    .946503   .1759835     5.38   0.000     .5994712    1.293535
          2  |   .0044861   .1860266     0.02   0.981    -.3623503    .3713226
          3  |   .0985147   .1560402     0.63   0.529    -.2091899    .4062192
          4  |   .7589767   .1835146     4.14   0.000     .3970938     1.12086
          5  |   .0584452   .1864445     0.31   0.754    -.3092152    .4261056
          6  |   .0080958   .1557576     0.05   0.959    -.2990515    .3152431
          7  |   .4748242   .1904391     2.49   0.013     .0992865    .8503619
          8  |   .3361798   .1892923     1.78   0.077    -.0370965     .709456
          9  |    .150168   .1519526     0.99   0.324    -.1494759    .4498119
         10  |    .514296    .182426     2.82   0.005     .1545599    .8740321
         11  |  -.0523706    .176368    -0.30   0.767    -.4001605    .2954194
             |
       _cons |  -.4693569   .3190055    -1.47   0.143    -1.098422    .1597081
------------------------------------------------------------------------------
```

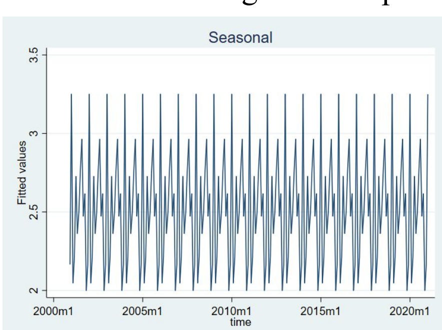
Job Separation Rates

Adapting the same procedures to job separation rates, we first observe the overall time series plot. As shown in the two figures below, job separation rates have a relatively more consistent trend and the fitted values show a decreasing linear trend.

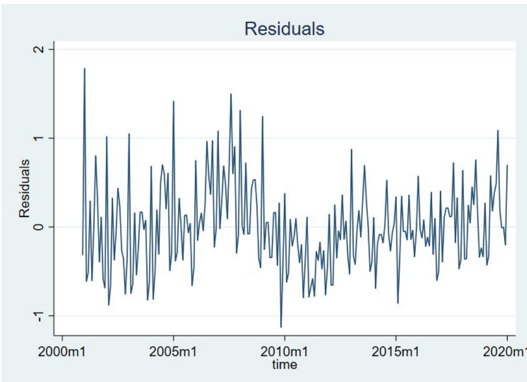




Similarly with job opening rates, this data is deseasonalized, but as the following plot shows, there is still a strong seasonal pattern. Thus, we will include seasonal dummies in our model.

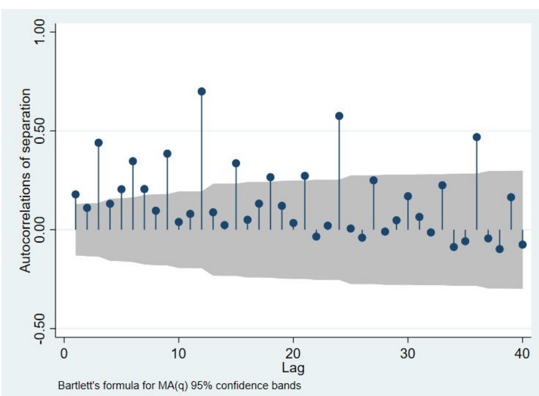


Next, we plot in-sample residuals to check whether there is a sign of cyclical trend. As the following figure indicated, the residual plot still has cyclical patterns, but comparing with the residuals of job openings, the residuals show a relatively better in-sample trend estimate. Since the result is not a white noise, we will then include a cyclical trend to pursue a better forecast model.



Thus, job separation rates have a general outline of the model with a linear trend, seasonal, and a cyclical trend.

To proceed with the cyclical trend, the autoregression plot shows in the following figure that job separation rates have positive autocorrelation and a clear seasonal pattern repeated every 11 lags.



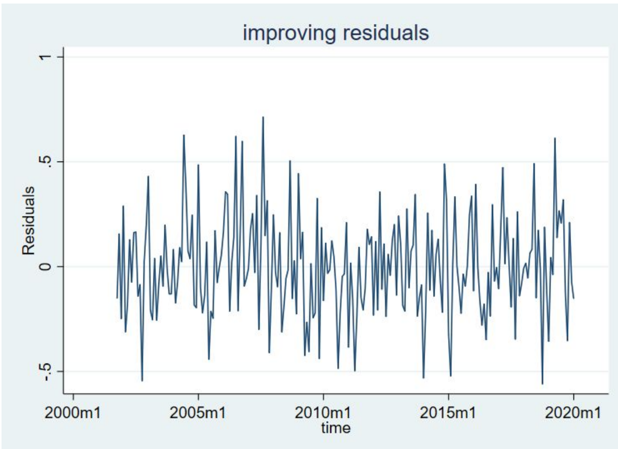
With the same reasoning for job opening rates, we decided to use AR(p) for analyzing cycles. To choose the best order p, we look at 10 lags and the lowest AIC (230.5308) shows that we should choose AR(10) for analyzing the cyclical trend.

Akaike's information criterion and Bayesian information criterion

Model	N	ll(null)	ll(model)	df	AIC	BIC
ar1	220	-160.6569	-156.1196	2	316.2391	323.0264
ar2	220	-160.6569	-155.0569	3	316.1139	326.2947
ar3	220	-160.6569	-132.0366	4	272.0731	285.6476
ar4	220	-160.6569	-132.0345	5	274.0691	291.0372
ar5	220	-160.6569	-128.2462	6	268.4924	288.8542
ar6	220	-160.6569	-126.6397	7	267.2795	291.0349
ar7	220	-160.6569	-125.3827	8	266.7653	293.9143
ar8	220	-160.6569	-124.301	9	266.602	297.1447
ar9	220	-160.6569	-114.3149	10	248.6298	282.5661
ar10	220	-160.6569	-104.2654	11	230.5308	267.8607

Note: BIC uses N = number of observations. See [R] BIC note.

Again, we draw another residual plot to check after adding in the linear trend, seasonal trend and cycle with AR(10), there is any improvement on the residuals. As shown below, the residuals are much better improved.



As a consequence, we choose the Trend + Seasonal + Cycle with AR(10) Model:

As we regress y_t (job separation rates) on time, its 10 lags, and seasonal dummies, the following regression results show that lag 1, lag 3, lag 6 and lag 9 are the most important out of all 10 lags and the R-squared value of 0.7693 shows the statistical significance of our model estimate.

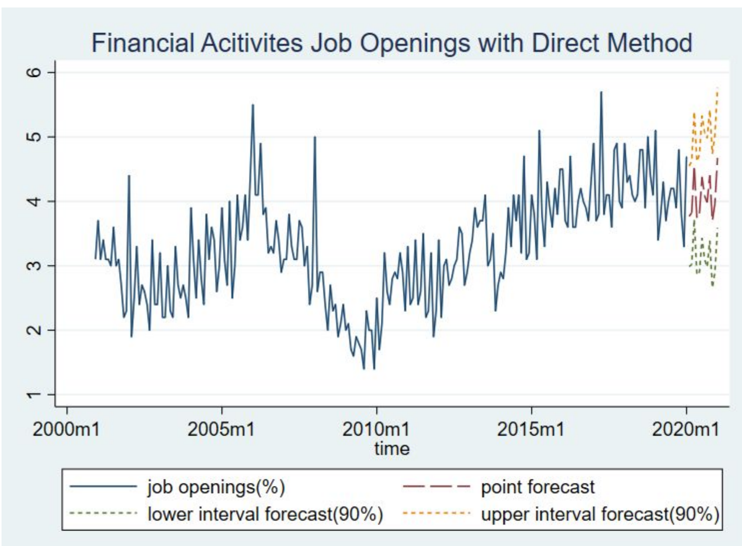
				F(22, 197)	=	29.86
Model	42.6916809	22	1.94053095	Prob > F	=	0.0000
Residual	12.80191	197	.064984315	R-squared	=	0.7693
				Adj R-squared	=	0.7435
Total	55.4935909	219	.253395392	Root MSE	=	.25492

separation	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
time	-.0005325	.000353	-1.51	0.133	-.0012287	.0001637
m						
1	.9333703	.1158561	8.06	0.000	.7048929	1.161848
2	-.2396244	.1476698	-1.62	0.106	-.5308409	.0515922
3	.113044	.1374401	0.82	0.412	-.1579987	.3840867
4	.4704345	.144381	3.26	0.001	.1857037	.7551652
5	.2851591	.1388239	2.05	0.041	.0113874	.5589309
6	.4078035	.1486845	2.74	0.007	.1145858	.7010211
7	.3016585	.1464332	2.06	0.041	.0128806	.5904364
8	.8536463	.1362639	6.26	0.000	.5849231	1.122369
9	.1937046	.1320306	1.47	0.144	-.0666701	.4540793
10	.0571019	.1406733	0.41	0.685	-.220317	.3345208
11	-.2429003	.140815	-1.72	0.086	-.5205986	.0347979
separation						
L1.	.2480593	.0707304	3.51	0.001	.1085734	.3875452
L2.	.1342096	.0722889	1.86	0.065	-.0083498	.276769
L3.	.2330144	.0722911	3.22	0.001	.0904506	.3755781
L4.	.0441002	.0745299	0.59	0.555	-.1028787	.1910791
L5.	.0576	.0722583	0.80	0.426	-.084899	.200099
L6.	.1730217	.0725358	2.39	0.018	.0299755	.316068
L7.	-.0272326	.0734725	-0.37	0.711	-.1721262	.1176609
L8.	-.0898623	.0716197	-1.25	0.211	-.2311019	.0513773
L9.	.1232468	.0694908	1.77	0.078	-.0137946	.2602881
L10.	-.0994489	.0683316	-1.46	0.147	-.2342044	.0353065
_cons	.5672758	.3762842	1.51	0.133	-.1747864	1.309338

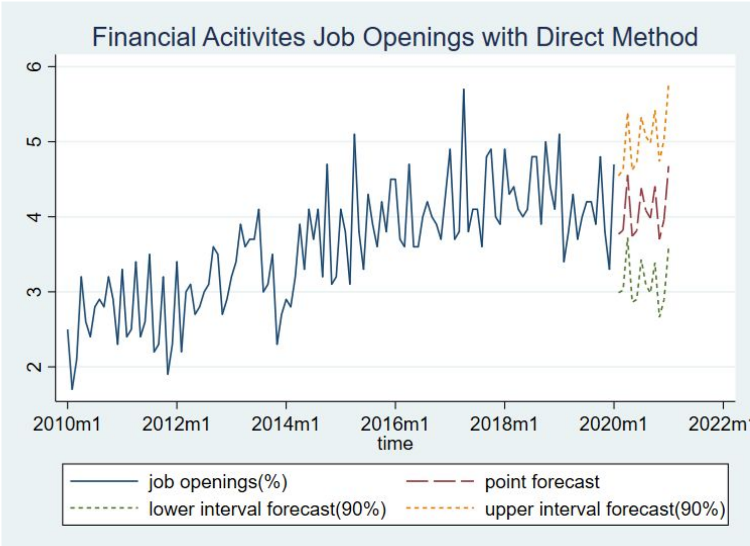
Point Forecast and Interval Forecast

Job Opening Rates

After thoroughly going through our process on selecting models, the plot below gives the final result of our forecast. The point forecast is consistent with the trend of previous periods (12 months ahead of the forecasting period) and the upper interval forecast (90%) indicates an increasing trend while the lower interval forecast (90%) indicates a decreasing trend. While the range of upper and lower forecast intervals is slightly big, we believe that the truth would be lower than what we have predicted in the lower forecast intervals for the following year because with the COVID-19, the financial market is experiencing a downturn and most businesses have faced the crisis. It is reasonable to think that less job openings would be offered on the market and job openings would decrease with time as the condition is becoming more serious along with the government-forced lockdowns in the major cities.



To be more clear, we only include the plot beginning in 2010m1:



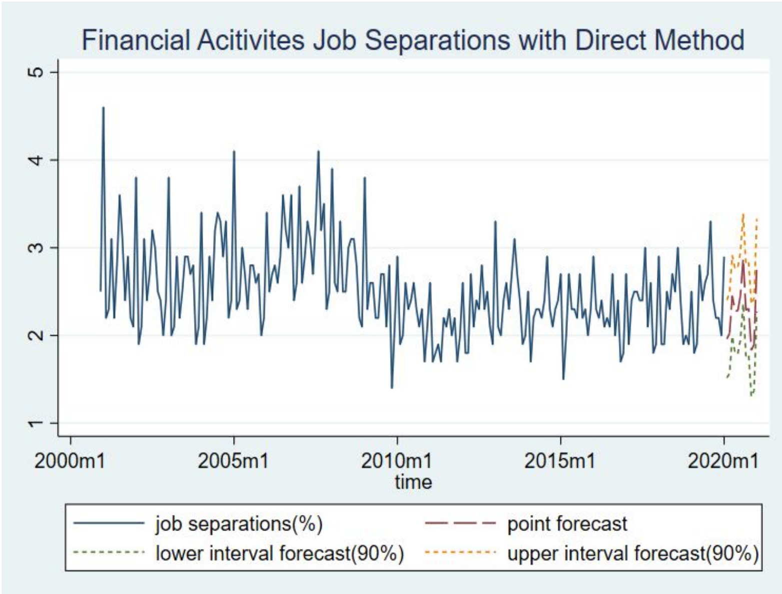
The list shown below gives a numerical summary of the point and interval forecast. The lower and upper interval forecasts are close and the differences between each month is small.

```
. list time point lower upper if time>=tm(2020m2)
```

	time	point	lower	upper
231.	2020m2	3.767972	2.988396	4.547547
232.	2020m3	3.822261	3.02035	4.624172
233.	2020m4	4.556118	3.722154	5.390081
234.	2020m5	3.74002	2.859895	4.620144
235.	2020m6	3.812964	2.898472	4.727456
236.	2020m7	4.379835	3.430357	5.329313
237.	2020m8	4.084233	3.098217	5.070248
238.	2020m9	3.981671	2.982346	4.980995
239.	2020m10	4.405355	3.389627	5.421083
240.	2020m11	3.69846	2.659898	4.737022
241.	2020m12	3.964253	2.896935	5.031571
242.	2021m1	4.675307	3.588608	5.762007

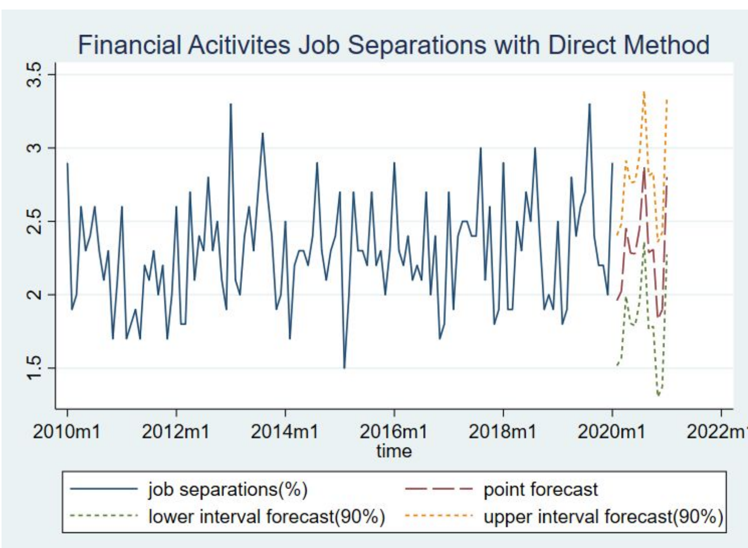
Job Separation Rates

On the contrary to job openings, job separations have a decreasing trend for both the upper and lower forecast interval while the point forecast stays at constant. However, with the COVID-19, we believe that the truth would be higher than the predicted upper interval forecast since there are involuntarily leave of positions during quarantines and lockdowns and more importantly we have already seen the increasing number of unemployment.



To be more clear, we only include the plot beginning in 2010m1:

In the figure below, it is more clear to see that point and interval forecasts of job separation rates almost stay the same and the range of upper and lower forecast intervals is small and The list below gives specific numerical results of the point and interval forecasts. The list in the second figure below gives a numerical presentation.



	time	point	lower	upper
231.	2020m2	1.960529	1.516892	2.404166
232.	2020m3	2.025403	1.568067	2.482739
233.	2020m4	2.452746	1.992119	2.913373
234.	2020m5	2.284244	1.804806	2.763682
235.	2020m6	2.279036	1.788485	2.769587
236.	2020m7	2.454086	1.954823	2.95335
237.	2020m8	2.875263	2.360911	3.389614
238.	2020m9	2.287399	1.764476	2.810322
239.	2020m10	2.308717	1.785624	2.831809
240.	2020m11	1.830856	1.303155	2.358557
241.	2020m12	1.899274	1.372662	2.425886
242.	2021m1	2.801872	2.274552	3.329193

Conclusion

Overall, based on the data, the job openings show an increasing trend and the point forecast also shows an increase in the future while the job separations show the opposite. This was expected before the pandemic because the economy was booming and the unemployment rates had been decreasing. However, while the interval forecast gives more room for the real situations, we tend to believe that the truth would hit below or close to the lower interval forecast. For job separations, it is the opposite situation that it has a decreasing overall trend and both the interval forecasts have narrower range. Even though an increase in job separation does not necessarily mean an increase in involuntary leave, the reality has proved an increase in unemployment rates and as the death rates and infection rates higher, job separation rates would keep growing. Thus, for job separation rates, we have the reason to believe the truth would be closer to the upper interval forecast and this may be able to present the conditions of job markets.

References

U.S. Bureau of Labor Statistics: https://data.bls.gov/cgi-bin/surveymost?jt