Assignment I - III: Macroeconometrics

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March 31, 2019

1 Data and stationarity

In the following, I provide explanation and analysis for the three times series. For the sake of compactness and due to the page number, I however only provide graphs for the full time series, that is 1948Q1 until 2018Q4 in the main document. The corresponding graphs and tables for the series 1948Q1 - 1990Q4 and 1991Q1-2018Q3 are referred to the appendix. I will by the same reasons use the word "earnings" for the deflated averga hourly earnings of production and nonsupervisory employees within U.S. manufacturing; "GNP" for the real U.S. gross national product and "unemployment rate" for the aggregate U.S. unemployment rate of individuals who are 20 years or older. All series were obtained from the FRED website on March 1st, 2019. I conduct the entire analysis with the program "R",for which the do-file is attached to this report.

1.1 Vizualize and describe the data

Deflated earnings between 1948Q1 and 2018Q4 start at a minimum value of 9.125 $ in 1948Q1 and ends at 19.472$ in 2018Q2, while the maximum value is at 19.524 $ in 2018 Q1. Within the series, a steady increase can be observed from the beginning in 1948 until around 1980, after which the level of earnings platoons for around 15 years at an average value of 17 $. **Explanation?**. Following 1995, average earnings increase up until 19$ in 2005. Between 2005 and 2018, an up- and - down movement can be observed, most probable reflecting the turbulences following the financial crisis. The mean of earnings within the entire series is 15.998 and the median 16.942

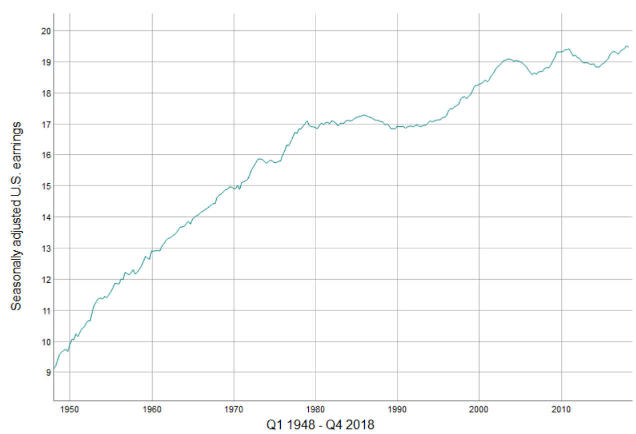

Figure 1: U.S. seasonally adjusted earnings

Deflated earnings between 1948Q1 and 1990Q4 start as well at an minimum value of 9.125$ and end at 16.928 $ while the series reaches a maximum value of 17.297 in 1986Q1, see figure28. Logically, the series show the same steady increase up until ca. 1980 as before, but now end at then platooning level of around 17 $. The series exhibits a mean of 14.432 and a median of 14.897. Deflated earnings between 1991Q1 and 2018Q2 start at a minimum of 16.87 % and end at 19.473 $, while the maximum is reached one quarter before in 2018Q1 at a value of 19.52$, see figure29. The series exhibits a nearly exponential increase in average earnings from the start up until 2003Q2 to a level of 19.1 $. Following, earnings decrease until 18.6 $ in 2006, rise up until 19.4 in 2010 fall again until around 18.8 $ in the middle of 2014 and the rise to their ending level. Interestingly, the rise and fall of earnings doesn't intersect timely with the financial crises in the U.S. within 2007- 2008. Instead, it seems that the effect negative effect of the crisis on U.S. earnings is lagged by around four years.

The time series of U.S. gross national product from 1948Q1 until 2018Q2 starts at a minimum level of 2101 billion $ and ends at 18766 billion $, which is also its maximum, see figure 2. The entire series shows and increasing acceleration of U.S. gnp with smaller decreases, which most probably reflect economic downturns or crises. The most visible of these is the drop from 15932 billion $ in 2008Q2 to 15257 billion $ in 2009Q2, a decrease of roughly 4.2 %. The series' mean is 8630 billion $ while the median is 7094, reflecting the increasing acceleration of the series.

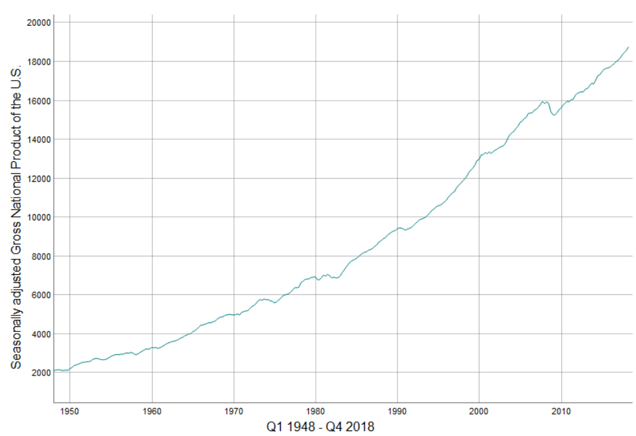

Figure 2: U.S. real gross national product

The series of U.S. real gnp between 1948Q1 and 1990Q4 starts logically as well at a minimum level of 2101 billion $ and ends at 9448 billion $, which is also its maximum, see figure 30. The overall increase of gnp within this timeframe, which is the steepest following 1983 is interrupted by several small decreases or platooning periods. Most notably is a period 1979Q3 and 1982Q4, where gnp decreases or platoons at around 6800 billion $. The series exhibits a mean of 5111 billion $ and a median of 4973 billion $. The series of U.S. real gnp between 1991Q1 and 2018Q2 starts at a minimum of 9333 billion $ and ends at its maximum of 18766 billion $. The series exhibits a very steady inrease compared to the series between 1948 and 1990, except the stark decrease following 2008 already described above, which is most probably linked to the financial crisis. The series exhibits a mean of 14132 billion $ and a median of 14624 billion $.

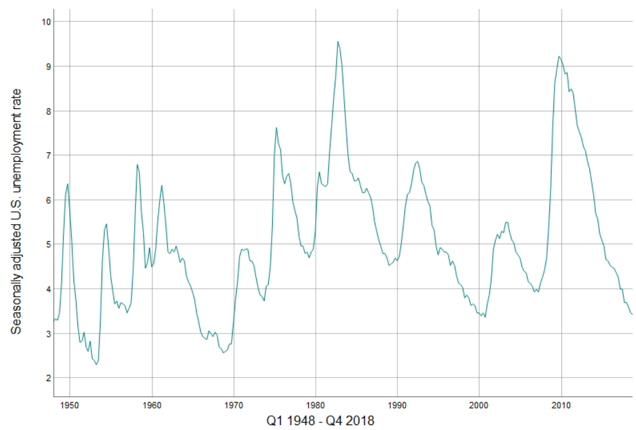

Figure 3: U.S. unemployment rate (20 years or older)

The time series of the U.S. unemplyoment rate from 1948Q1 - 2018Q3 shows as expected the most variation, see figure 3. It begins at 3.27% and ends at 3.43 %. In the time inbetween, it reaches several local maxima and minima, with the global minimum at 2.3 $ in 1951Q1 and the maximum at 9.57 % in 1982Q3. The mean of the series is 5.048 % and the median value 4.817 %.

The time series of the U.S. unemployment rate from 1948Q1 - 1990Q4, see figure 32, shows logically also much variation, with the frequency of throughs and peaks being higher in the beginning. It starts at a value at 3.27 %, ends at 5.43 %, reaches a minimum in Q1 1951Q1 and it maximum of 9.57% in 1982Q3. The mean of the series is 4.861% and the median 4.8 %. The time series of the U.S. unemployment rate from 1991Q1 - 2018Q3 shows a less turbulent but more drastic single peaks and throughs. It starts at 5.87 % ends at 3.43 %. Its minimum is at 3.37 % in 2000Q3 and its maximum at 9.23% in 2009 Q3, which most probably reflects the effects of the financial crisis 2007 - 2008. The mean of the series is 5.335 % and the median 4.9 %.

1.2 BBQ rule to identify peaks and troughs

I first computed functions for the BBQ rule using quarterly data, thus setting the parameter k to 2. However, as figure 34 shows (Appendix) some peaks and throughs in the unemployment data are not accounted for when using strict inequalities. E.g. a clearly visible through in the unemployment data around the beginning of 2006 is not shown with strict inequalities, as the unemployment rate for 2005Q3 and 2006Q1 is 3.933 % for both periods. This unlikely scenario seems due to how the values got estimated and rounded to decimal-thirds by the FRED. Thus, I chose relaxed inequalities when computing throughs and peaks for the unemployment rate. In the two figures below, peaks are depicted in green x's and throughs as red crosses. Notably, the economic interpretation between both is switched around in the two series, meaning that peaks in unemployment indicate economic downturns, whereas for earnings they indicate a positive development. From zooming in on Figure 4 and 5, it can be seen that

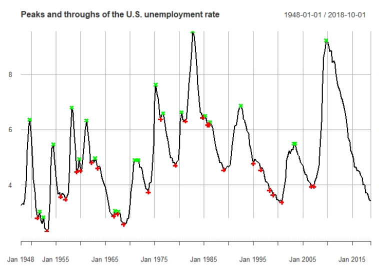

Figure 4: Earnings with strict inequality

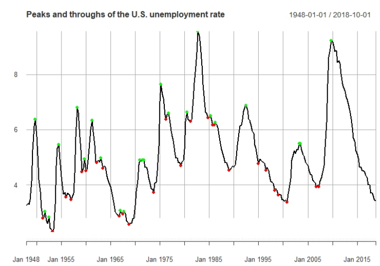

Figure 5: Unemplyoment using relaxed inequality

all visible peaks and throughs are well captured by the applied BBQ rule.

For futher inspection, the peaks and throughs are compared to the official NBER recession dates. I visualize them by adding vertical lines, whenever recessions were officially declared by NBER in hindsight. Interestingly, it can be seen from the two figures below that while the date of recessions mostly overlaps with throughs in earnings, the date of recessions pre-dates the peaks of unemployment, indicating proof for the stickyness-assumption of employment, possibly due to emplyoment protection legislation or lags in the personnel decision of firms. Furthermore, the overlap between throughs in earnings and NBER recessions only holds true for most of the periods before 2000. After 2000, the BBQ rule for earnings fails to indicate the recessions of the dotcom-bubble around 2000 and the financial crisis in 2007-2008.

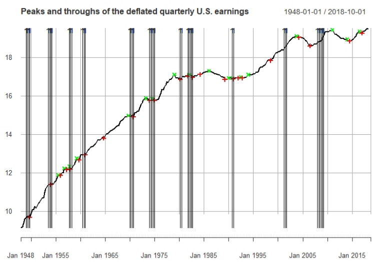

Figure 6: Comparing earnings peak/throughs with NBER recessions

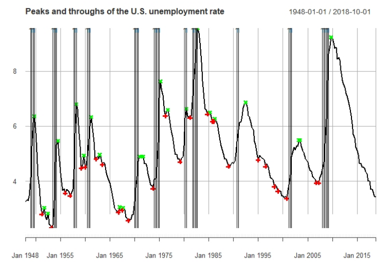

Figure 7: Comparing unemplomynet peak/throughs with NBER recessions

1.3 Compare seasonally adjusted and non-seasonally adjusted earnings

I follow the ARIMA-X11 manual which was linked in the lecture slides. First, I assume a multiplicative structure of the observed unadjusted series y_t with trend-cycle effects C_t, seasonal components S_t and its irregular component I_t:

$$y_t = S_t * C_t * I*_t \tag{1}$$

First, I extract the crude trend-cycle using the M_{2x12} algorithm and dividing the original series by the trend-cycle. Figure 8 depicts the resulting series, which still shows seasonality and a highh variation in the first ten years of the sample, especially within the first 4 quarters. This is however expected, a moving average may produce irregular behavior within the first observations. Additionally, the overall variance decreases over time, mirroring the "great moderation" period of U.S. earnings in the second half of the 20th century.

After smoothing the earnings across 24 consecutive months, I smooth the seasonal-irregular component of earnings one month at a time, using a $M_{3\times3}$ moving average, thus estimating the crude preliminary seasonal factors. Folowing the manual, I then normalize the crude average to ensure that the weights sum up to one, using a M_{2x12} moving average, the result can be seen in the appendix, figure 35. For the second step of the seasonal adjustment process, I use a Henderson H_{13} moving average to further detrend the now obtained series and extract the intermediate trend-cycle. Next, as in step one, I detrend each month to account for yearly effects, using a $M_{3\times5}$ moving average. Then, as in step one, to attain the unbiased seasonal factors, I center the weights around the 24 consecutive months to sum up to one, using the seven - term moving average $M_{2\times12}$. From step two, the final seasonally adjusted series are then obtained

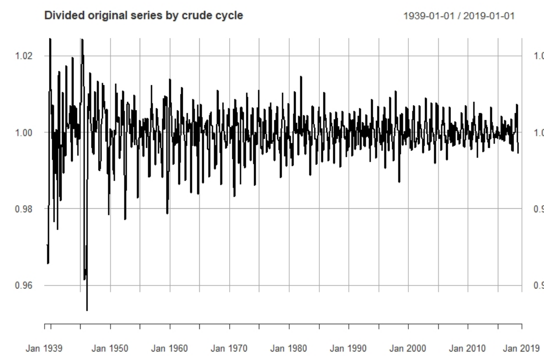

Figure 8: Step 1: Original unadjusted U.S. divided by crude-cycle

by dividing the original undadjusted series by the estimated final seasonal component. The obtained series, figure 9 shows a more regular variation across the entire period, is more centered around the mean of one and doesn't exhibit the outliers as before.

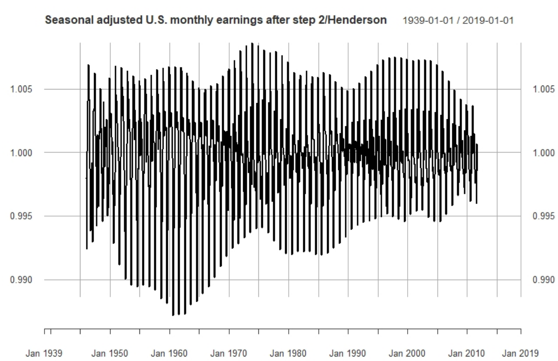

Figure 9: Step 2: Division of the original U.S. monthly earnings by the final seasonal estimates

In the third and last step, the final trend-cycle is estimated by a 13-term Henderson moving average, applied to the series of final seasonal factors obtained. Thus, it is finally possible to estimate the final irregular component by dividing the original monthly earnings by the product of seasonal and trend-cycle component. I then compare both the seasonal components, obtained by my adaption of ARIMA X-11 and the division of both unadjusted and adjusted FRED series below. On a first glance, both seasonal components of U.S. monthly

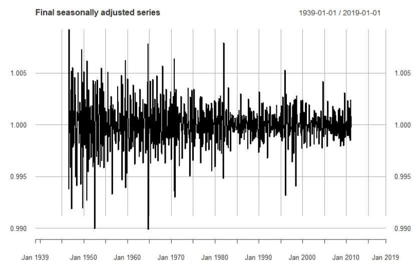

Figure 10: Final obtained seasonal element by ARIMA X-11

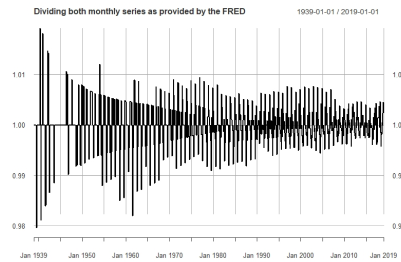

Figure 11: Division of both unadjusted and adjusted monthly U.S. earnings as obtained by the FRED

earnings look very differently. For one, my obtained series start in July 1946 and end in March 2011, thus offering a significant shorter time-span than the original series. However, that stems from me using moving averages, which thus always reduce the data by the first half of the iteration. There may be better ways of designing the algorithm, however, due to limited coding capabilites and time, I couldn't find a better option. Second, the division of the FRED series looks more discrete than the ARIMA X. However, when looking at the values of variables and scope, both series look comparable. To get a better understanding, I calculate the differences between both in percentage of the FRED seasonal component, see figure 36. From the direct differece, it can be seen that the values of the ARIMA X-11 seldomly exceed a difference of more than one percentage point, with only two months yielding a deviation of more than 1.5 percentage points. This, in my opinion, indicates a rather good fit with further areas for improvement. Also noteworthy is that I conducted an X11-ARIMA while the FRED probably used further going algorithms e.g. X13-ARIMA or combinations of them.

1.4 Testing for stationarity

In the following, I perform various Dickey-Fuller tests on the logarithmized series of adjusted U.S. quarterly earnings, U.S. GNP and the U.S. unemployment rate using different functional forms, all for the timeframe of 1948-2018.

First, I anylze quarterly earnings. From looking at the data in figure 28, it becomes clear that there exists a definitive time trend, which might be linear and/or quadratic. First, a regression of earnings on a linear and squared time trend reveals that both should be taken care of. Second, a dickey-fuller test incorporating both time - trends only show a test statistic of $-2.63 > t_{crit} = -3.42$, thus it is not possible to reject a stationary root (for both results, see table 5). Thus, I continue taking the first differences. However, as visible in table 6, also this exhibits still a linear and squared time trend. I consequently extract the trend by predicting the residuals of the regression of first differenced earnings on time. A Dickey-Fuller test on the obtained series allows to reject the existence of unit root ($t = -15.9$). Figure 12 shows the obtained series, which revolves around 0 but exhibits some higher variance in the beginning than in the second half of the 20th century.

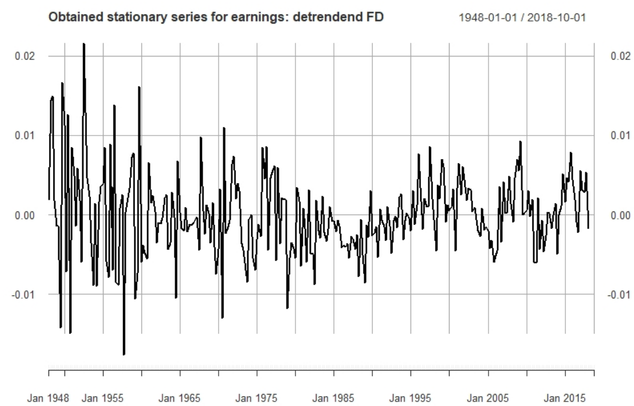

Figure 12: Obtained stationary series for earnings

Unemployment exhibits both visibly and from running a short regression a time trend (see table 7). Here, simply taking first differences already leads to being able to statistically reject a unit root. GNP behaves similarily in that it is both dependent on a linear and quadratic time trend, see table 8. Similar to earnings, I thus take first differences and then extract the still existing time trend by predicting the residuals of a regression on a linear time trend. The resulting detrended first differences are stationary in the sense that the t-value of the lag is -11.764 and thus smaller than the critical value. Below are the resulting two series of unemployment and gnp. Whereas the stationary series

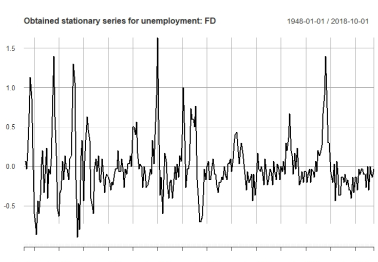

Figure 13: Obtained stationary series for unemployment

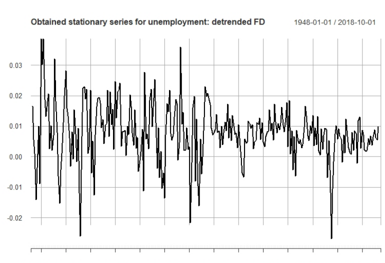

Figure 14: Obtained stationary series for GNP

shows some evidence of the great moderation period until the financial crises, the stationary series of unemployment still shows several spikes, which are of higher positive than negative magnitude, reflecting several economic crises.

2 Assignment 2: VAR models

2.1 VAR(1) models for all three time periods

In all the subsequent analysis, I use the three obtained stationary series I obtained from Assignment 1. First, I look at the entire time period. I use the stationary logarithmized series obtained from Assignment one. First, I run three manual regression on each earnings, GNP and unemployment on all first other lags. For the full time period the the results are in table 1, for the period 1948 - 1990 in figure 2 and for the period 1991 - 2018 in figure 3.

Table 1: Reduced form coefficients from VAR(1), 1948 - 2018

lag(df1$dif1_earning, 1)	lag(df1$dif1_gnp, 1)	lag(df1$dif1_unemp, 1)
0.136	0.078	0.001
-0.102	0.245	0.005
11.039	-14.395	0.444

Table 2: Reduced form coefficients from VAR(1), 1948-1990

lag(df1_e$dif1_earning, 1)	lag(df1_e$dif1_gnp, 1)	lag(df1_e$dif1_unemp, 1)
0.040	0.056	−0.001
−0.232	0.232	−0.007
9.806	−15.214	0.402

Table 3: Reduced form coefficients from VAR(1), 1991-2018

lag(df1_t$dif1_earning, 1)	lag(df1_t$dif1_gnp, 1)	lag(df1_t$dif1_unemp, 1)
0.265	0.018	0.004
0.265	0.189	-0.005
11.925	-14.067	0.502

Some coefficients across time periods are qualitatively equal or very similar, e.g. all one-period lagged effects on the growth rates of unemployment, which are also all significant. Looking at the three extended regression tables in the appendix (tables 9, 10 and 11), these three coefficient also remain significant over time. However, the coefficients of the impact of the growth rate of gnp on earnings, earnings on gnp and gnp on unemployment change considerably across periods, both in value and significance.

2.2 Testing for Granger causality

From the anova F-tests, see tables 12, 13 and 14 it can be seen that the inclusion of the two respective other variables leads to a significant better perfomance of the model for predicting the growth rates of GNP and unemployment. For the growth rate of real wages, the null hypothesis that the inclusion of the two other series increases performance can't be rejected.
Concerning the individual coefficients, one can see from the t-values in tables 9, 10 and 11 that earning-growth appear to not be granger caused by the other two series, corroborating the anova test (respective t-values 1.521 for gnp and 1.2 for unemploymnet). GNP-growth is granger caused by unemployment (t-value of -2.657) and the growth rate of unemployment is granger caused by both GNP (t-value of -5.99) and earnings (t-value of 3.635).

2.3 Estimate a VAR(p) model for p = 1; 2; 3; 4 and use various information criteria to determine which lag order is most appropriate

Disclaimer: I estimate the reduced VAR model with 4 lags, using the generic R-function var(), as I've shown in my code that manual regression and the command yield to comparable outcomes.

Figure 15: Aikake Information criteria for all three time-periods

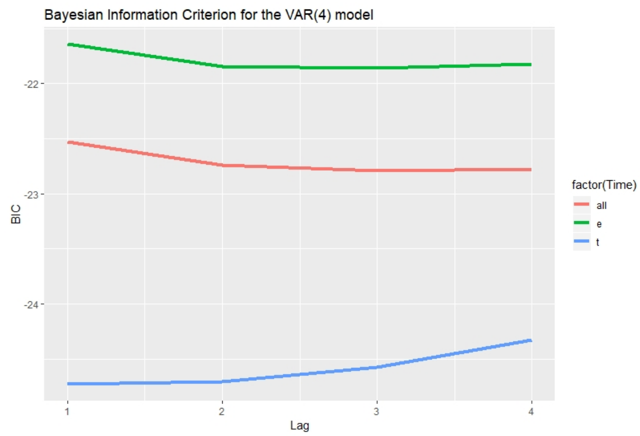

Figure 16: Bayesian Information criteria for all three time periods

From both figures and the values itself, one would choose a number of lags of 4 for both the full time-period and the period from 1948-1990 when looking at the AIC. For the period from 1991- 2018 AIC indicates a number of 3 lacks to yield the best fit. However, the Bayesian Information criteria suggest quite different results. For the full period 1, for the period 1948 - 1990 four lags and for the period 1991 - 2018 only one lag. From where these quite drastic differences originate is at this point not obvious to me. Still, it points to some problematic differences across information criteria. If the method can be trusted it indicates at least a number of lags between 3-4 for both subperiods.

2.4 Discuss an identification scheme for the structural shocks

For the following I choose to continue with a number of $p = 1$ lags, as otherwise the amount of coefficient matrices makes it considerably more difficult to compute the identification scheme and impulse response functions. I follow GJ and use long-run restrictions. In particular, I use the following three restrictions :

1. Aggregate demand has no long-run impact on the log of real output
2. Aggregate demand has no long-run impact on the log of real wages
3. Labor-supply shock has no long-run impact on the log of real wages.

Speaking about the series I deal with that means that an increase in real wage growth doesn't have a long-term level effect on growth of GNP, and that the same holds true for both the effect of GNP and earnings on unemployment. Through these three restrictions, I am thus able to compute the underlying B matrix.

2.5 Plot the appropriate impulse response functions and discuss your findings

Below are the impulse response functions that I obtained by following the methodology of the lecture slides and applying them to the three time series.

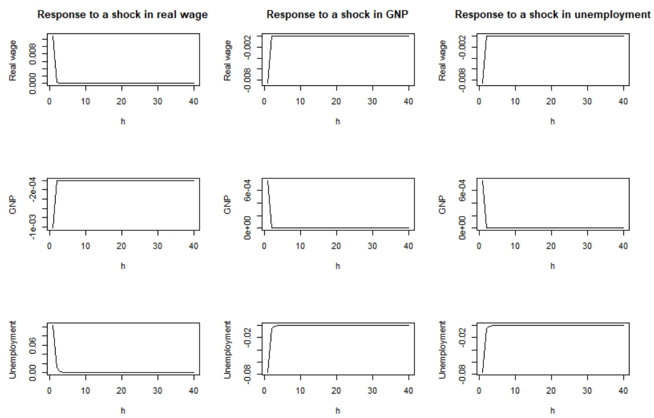

Figure 17: Impulse response functions for time 1948-2018

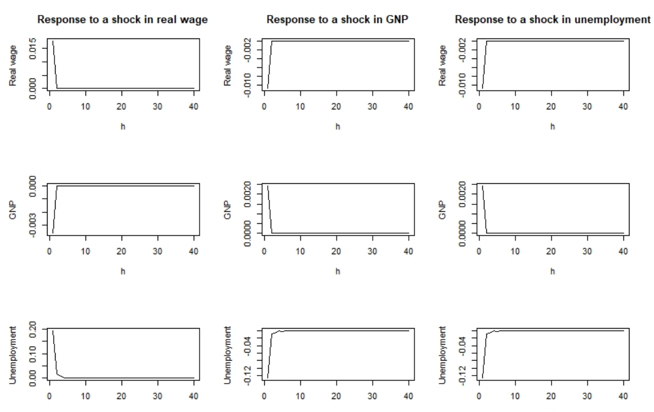

Figure 18: Impulse response functions for time 1948-2018

Overall; the three response functions are strikingly similar, which is surprising, given the partly diverging results found in earlier exercises for the three series. However, some doubt remains if the function were specified correctly, as more than half of them show qualitatively and quantitatively stark differences to the IRF's found in GJ.

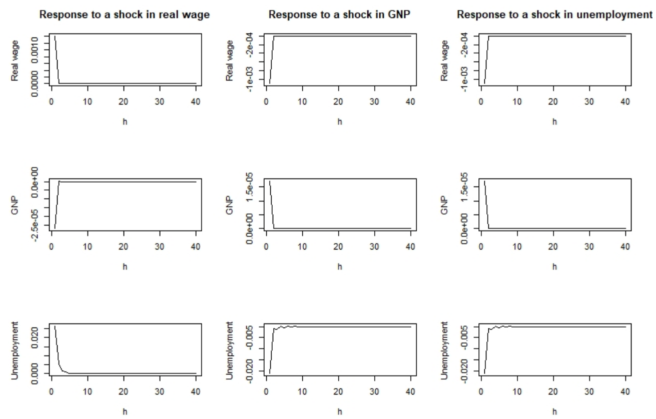

Figure 19: Impulse response functions for time 1948-2018

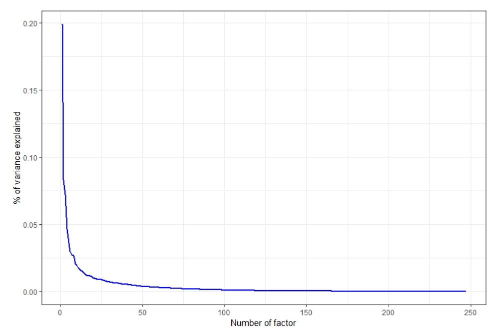

Figure 20: Calculated share of explained variance for each factor/eigenvalue

3 Big Data

3.1 Use principal component analysis to extract factors from the data

I follow the lecture slides by creating a correlation matrix and then calculating the vectors of loadings and factors through an eigenvalue-decomposition. To then calculate how much variance is explained by each factor, I calculate the ratio of the individual eigenvalues in respect to the sum of all. E.g. the largest eigenvalue (which is 48.97) explains 19.9 percentage of the variation in of the entire data matrix. The entire distribution is shown below in figure 20. From the data, it can be said that only the first factor explains more than 10% , while the next 19 factors explain more than 1% of the total variance.

3.2 Analyze the factor loadings for the first three factors

By taking the absolute values of the individual loadings and computing the averages of these, I can plot the mean-loading distribution of the factors across the classification of variables. The first factor loads the most heavily on the four groups of output & income, employment, consumption and real inventories. Thus, it can be classified as a mostly slow-moving factor.

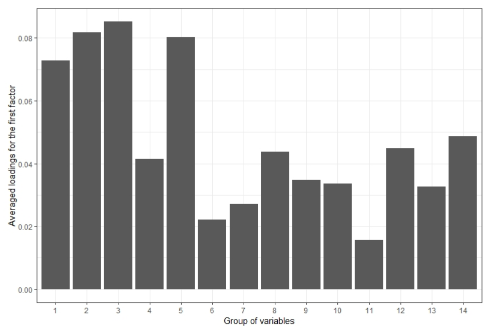

Figure 21: Calculated share of explained variance each variable group: first factor

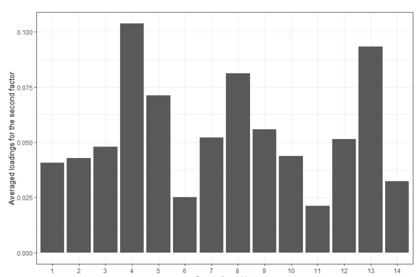

Figure 22: Calculated share of explained variance each variable group: second factor

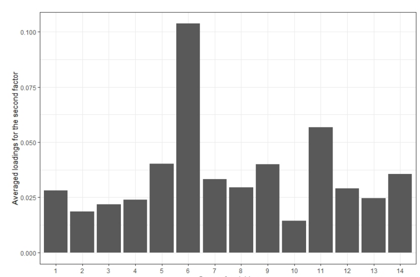

Figure 23: Calculated share of explained variance each variable group: third factor

The second factor loads most heavily on the group of housing, followed by average hourly earnings and interest rates. This makes this factor hard to classify, as also the difference between the average factor loadings are not high. Lastly, the third factor loads significantly the most on stock prices (more than 10% of total loading), which allows to classify this factor as mostly fast-moving.

3.3 Estimate an AR(4) + factor model

I decided to extract slow-moving factors from fast-moving factors, following Bernanke et al. (2005). Thus, I extracted slow-moving factors first by a classification of groups and then by regressing them with the dependent variable on all factors. I then calculated the model and compared the number of included factors (lagged) up to twelve with both BIC and AIC criteria.

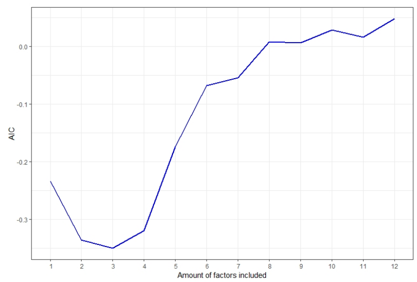

Figure 24: Aikake Information Criteria for the number of factors: AR(4) + factors

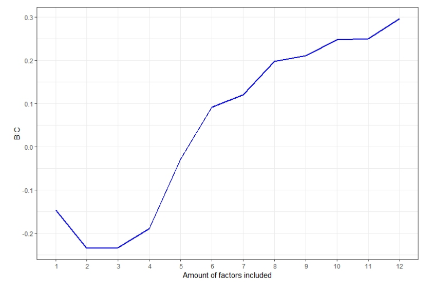

Figure 25: Bayesian Information Criteria for the number of factors: AR(4) + factors

From both information critera, I conclude that a number of two to three factors yields the best fit. Looking at the explained variance of each factor, this is somewhat understandable: whereas the second and the third factor explain around eight and seven percent of total variance, this value drops to around 4 for the fourth factor. Still, the number of included factors from two to three is fewer than the five factors usually employed, e.g. by Bernanke at al. (2005).

3.4 Forecasting exercise

Following the assignment, I calculate an $AR(4) + 8factor$ model and use the timeframe from 1959Q4 - 2003Q3 to calibrate the coefficients. Then I use an expanding window to forecast quarterly GDPC up until 2018Q3. Both forecast, including factors and only the AR(4) model forecast are depicted below.

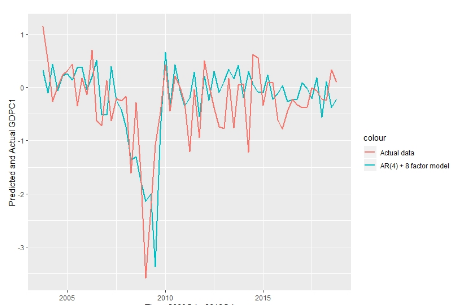

Figure 26: Comparing the forecast including factors to the actual data

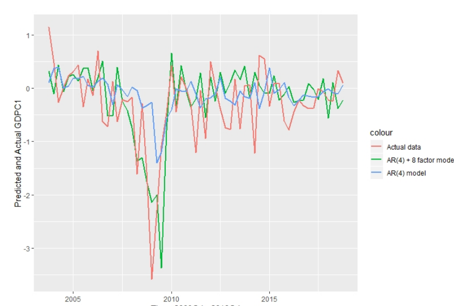

Figure 27: Comparing both forecast with or without factors to the actual data

From only looking at the graphs, the forecasts using eight factors seem to fit the actual data better than the AR(4) model. E.g. the stark decrease in GDPC following the financial crisis in 2008 is better forecasted by the factor model and also the following increase is captured better by including factors. However, one needs to also look at the various loss functions and significance tests. Summing up simply all residuals, the is the difference between forecasted and actual GDPC, the factor model yields a sum 5.304 which is smaller than the sum of the AR(4) model: 11.85. This qualitative finding is corroborated by looking at the most used loss function, the sum of squared errors, which is 23.93 for the factor model and 30.506 for the AR(4) model. Also for the sum of errors, the factor model better fit (28.497) than the AR(4) model (29.716). Figure 37 in the appendix also shows the individual squared losses for the different periods, which however shows that despite the stark difference in performance during the financial crisis, both forecasts perform similarily in magnitute of squared loss. This finding is ultimately corrobated by a Diebold-Mariano test, where the null hypothesis of an equal performance of forecasts can not be rejected ($t - value = -1.062 > t_{crit} = -2.0862$)

Table 4: Diebold-Mariano test comparing AR(4) with and without factors

	dt
Constant	−0.108 t = −1.062
Note:	*p<0.1; **p<0.05; ***p<0.01

A Additional graphs and figures

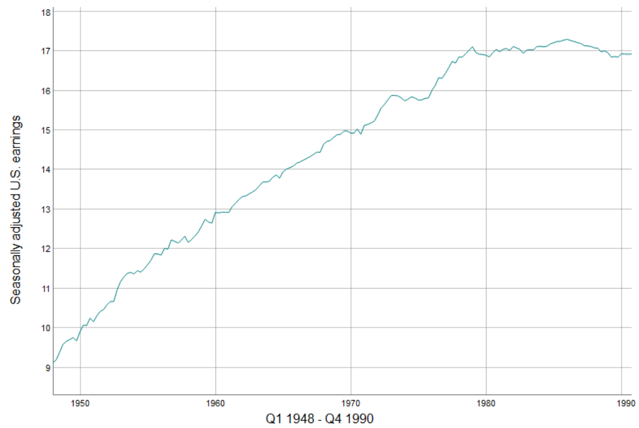

Figure 28: U.S. seasonally adjusted earnings

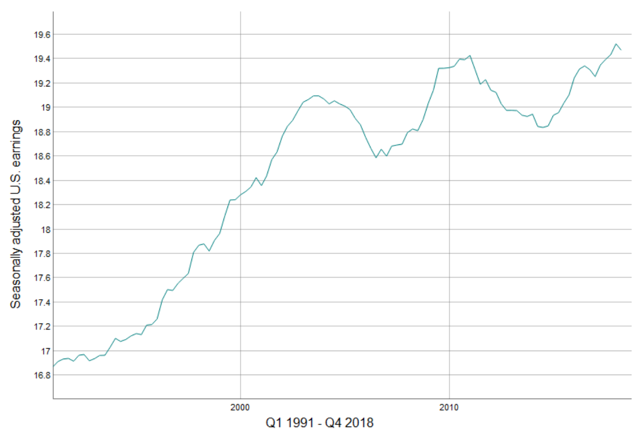

Figure 29: U.S. seasonally adjusted earnings

Table 5: Results 1

	Dependent variable:	
	earnings	d1.earnings
	(1)	(2)
logdefl_earning, 1)		-0.025
		t = -2.631
		p = 0.009***
time	0.005	0.00005
	t = 54.232	t = 0.937
	p = 0.000***	p = 0.350
time2	-0.00001	-0.00000
	t = -32.644	t = -0.605
	p = 0.000***	p = 0.546
Constant	2.303	0.066
	t = 389.846	t = 3.043
	p = 0.000***	p = 0.003***
Observations	282	281
R^2	0.971	0.193
Adjusted R^2	0.971	0.184
Residual Std. Error	0.033 (df = 279)	0.005 (df = 277)
F Statistic	4,652.574*** (df = 2; 279)	22.026*** (df = 3; 277)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6: Results for using first differences on earnings and extracting the time trend

	Dependent variable:		
	d1.earnings	d1.earnings	d1.earnings_detrend
	(1)	(2)	(3)
dif1_earning, 1)	−0.953 t = −15.871 p = 0.000***		
dif1_time2	−0.00001 t = −5.667 p = 0.00000***		
time		−0.00003 t = −6.455 p = 0.000***	
dif1_earning_detr, 1)			−0.953 t = −15.900 p = 0.000***
Constant	0.006 t = 7.969 p = 0.000***	0.006 t = 9.826 p = 0.000***	−0.00001 t = −0.022 p = 0.983
Observations	280	281	280
R^2	0.476	0.130	0.476
Adjusted R^2	0.472	0.127	0.474
Residual Std. Error	0.005 (df = 277)	0.005 (df = 279)	0.005 (df = 278)
F Statistic	125.949*** (df = 2; 277)	41.666*** (df = 1; 279)	252.805*** (df = 1; 278)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 7: Regression results for unemployment

	Dependent variable:	
	logdefl_earning	dif1_earning
	(1)	(2)
logdefl_earning, 1)		-0.025
		t = -2.631
		p = 0.009***
time	0.005	0.00005
	t = 54.232	t = 0.937
	p = 0.000***	p = 0.350
time2	-0.00001	-0.00000
	t = -32.644	t = -0.605
	p = 0.000***	p = 0.546
Constant	2.303	0.066
	t = 389.846	t = 3.043
	p = 0.000***	p = 0.003***
Observations	282	281
R^2	0.971	0.193
Adjusted R^2	0.971	0.184
Residual Std. Error	0.033 (df = 279)	0.005 (df = 277)
F Statistic	4,652.574*** (df = 2; 279)	22.026*** (df = 3; 277)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 8: Regression results for GNP

	Dependent variable:		
	gnp	d1.gnp	d1.gnpdetrend
	(1)	(2)	(3)
time	0.008	-0.00002	
	t = 168.484	t = -2.814	
	p = 0.000^{***}	p = 0.006^{***}	
dif1_gnp_detr)			-0.664
			t = -11.764
			p = 0.000^{***}
Constant	7.756	0.011	-0.00002
	t = 1,015.326	t = 9.381	t = -0.030
	p = 0.000^{***}	p = 0.000^{***}	p = 0.976
Observations	282	281	280
R^2	0.990	0.028	0.332
Adjusted R^2	0.990	0.024	0.330
Residual Std. Error	0.064 (df = 280)	0.009 (df = 279)	0.009 (df = 278)
F Statistic	$28,386.780^{***}$ (df = 1; 280)	7.920^{***} (df = 1; 279)	138.401^{***} (df = 1; 278)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9: Results from manual VAR(1) regressions: Full sample

	Dependent variable:		
	dif1_earning	dif1_gnp	dif1_unemp
	(1)	(2)	(3)
dif1_earning, 1)	0.136	−0.102	11.039
	t = 2.086	t = −1.002	t = 3.635
	p = 0.038	p = 0.318	p = 0.0004
dif1_gnp, 1)	0.078	0.245	−14.395
	t = 1.521	t = 3.047	t = −5.990
	p = 0.130	p = 0.003	p = 0.000
dif1_unemp, 1)	0.001	−0.005	0.444
	t = 1.200	t = −2.657	t = 7.702
	p = 0.231	p = 0.009	p = 0.000
Constant	0.002	0.006	0.082
	t = 3.377	t = 7.826	t = 3.508
	p = 0.001	p = 0.000	p = 0.001
Observations	280	280	280
R^2	0.037	0.152	0.500
Adjusted R^2	0.026	0.142	0.494
Residual Std. Error (df = 276)	0.006	0.009	0.262
F Statistic (df = 3; 276)	3.522**	16.450***	91.925***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 10: Results from manual VAR(1) regressions: 1948 - 1990

	Dependent variable:		
	dif1_earning	dif1_gnp	dif1_unemp
	(1)	(2)	(3)
dif1_earning, 1)	0.040	−0.232	9.806
	t = 0.454	t = −1.731	t = 2.436
	p = 0.651	p = 0.086	p = 0.016
dif1_gnp, 1)	0.056	0.232	−15.214
	t = 0.779	t = 2.085	t = −4.559
	p = 0.438	p = 0.039	p = 0.00001
dif1_unemp, 1)	−0.001	−0.007	0.402
	t = −0.330	t = −2.404	t = 4.914
	p = 0.742	p = 0.018	p = 0.00001
Constant	0.003	0.008	0.107
	t = 3.710	t = 6.184	t = 2.917
	p = 0.0003	p = 0.000	p = 0.005
Observations	170	170	170
R^2	0.021	0.165	0.478
Adjusted R^2	0.004	0.150	0.469
Residual Std. Error (df = 166)	0.007	0.010	0.304
F Statistic (df = 3; 166)	1.198	10.923***	50.745***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 11: Results from manual VAR(1) regressions: 1991 - 2018

	Dependent variable:		
	dif1_earning	dif1_gnp	dif1_unemp
	(1)	(2)	(3)
dif1_earning, 1)	0.265	0.265	11.925
	t = 2.979	t = 1.612	t = 2.274
	p = 0.004	p = 0.110	p = 0.026
dif1_gnp, 1)	0.018	0.189	−14.067
	t = 0.317	t = 1.839	t = −4.296
	p = 0.752	p = 0.069	p = 0.00004
dif1_unemp, 1)	0.004	−0.005	0.502
	t = 3.416	t = −2.137	t = 6.718
	p = 0.001	p = 0.035	p = 0.000
Constant	0.001	0.005	0.060
	t = 2.042	t = 5.694	t = 2.219
	p = 0.044	p = 0.00000	p = 0.029
Observations	109	109	109
R^2	0.228	0.138	0.578
Adjusted R^2	0.206	0.113	0.566
Residual Std. Error (df = 105)	0.003	0.006	0.182
F Statistic (df = 3; 105)	10.335***	5.597***	47.970***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 12: F-test on granger causality (earnings) using anova

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Res.Df	2	277.000	1.414	276	276.5	277.5	278
RSS	2	0.009	0.0001	0.009	0.009	0.009	0.009
Df	1	−2.000		−2.000	−2.000	−2.000	−2.000
Sum of Sq	1	−0.0001		−0.0001	−0.0001	−0.0001	−0.0001
F	1	1.193		1.193	1.193	1.193	1.193
Pr(>F)	1	0.305		0.305	0.305	0.305	0.305

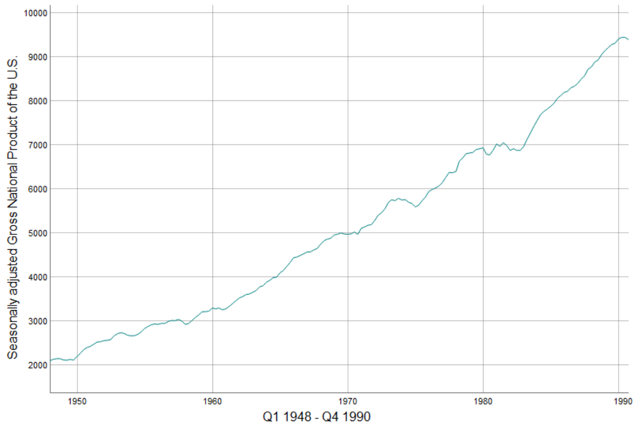

Figure 30: U.S. real gross national product

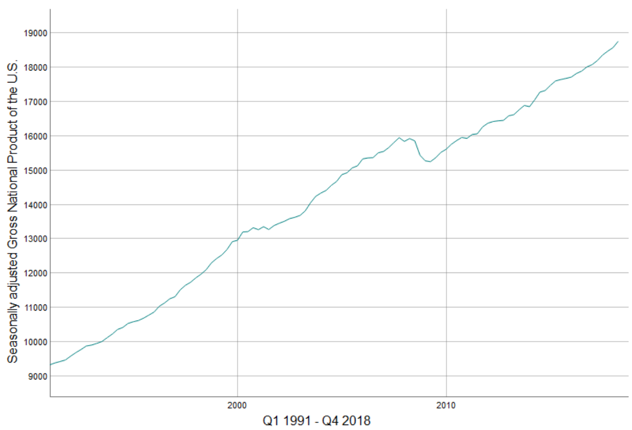

Figure 31: U.S. real gross national product

Table 13: F-test on granger causality (gnp) using anova

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Res.Df	2	277.000	1.414	276	276.5	277.5	278
RSS	2	0.021	0.0005	0.021	0.021	0.022	0.022
Df	1	−2.000		−2.000	−2.000	−2.000	−2.000
Sum of Sq	1	−0.001		−0.001	−0.001	−0.001	−0.001
F	1	4.322		4.322	4.322	4.322	4.322
Pr(>F)	1	0.014		0.014	0.014	0.014	0.014

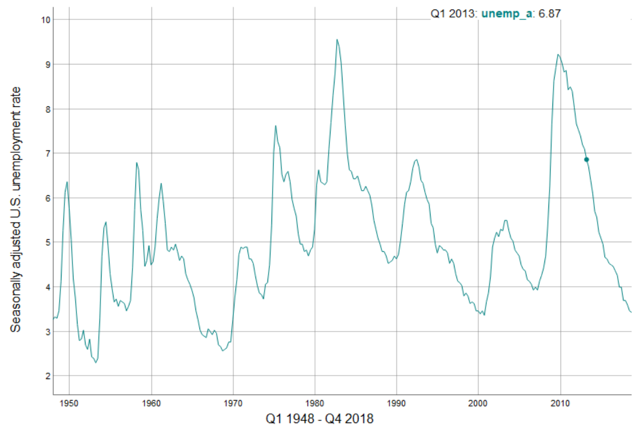

Figure 32: U.S. unemployment rate (20 years and older)

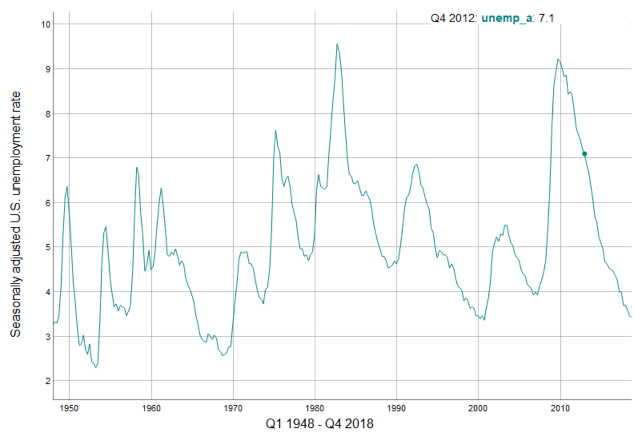

Figure 33: U.S. unemployment rate (20 years and older)

Table 14: F-test on granger causality (unemp) using anova

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Res.Df	2	277.000	1.414	276	276.5	277.5	278
RSS	2	20.254	1.854	18.943	19.599	20.910	21.566
Df	1	−2.000		−2.000	−2.000	−2.000	−2.000
Sum of Sq	1	−2.623		−2.623	−2.623	−2.623	−2.623
F	1	19.105		19.105	19.105	19.105	19.105
Pr(>F)	1	0.00000		0.00000	0.00000	0.00000	0.00000

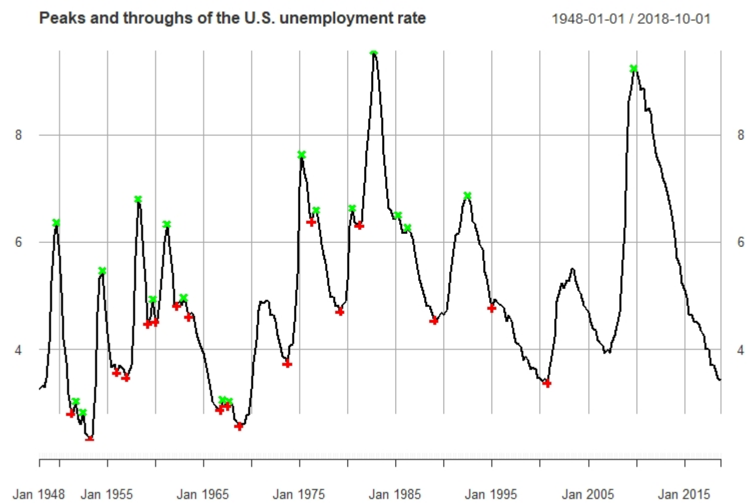

Figure 34: Peaks and throughs for unemployment with strict inequality

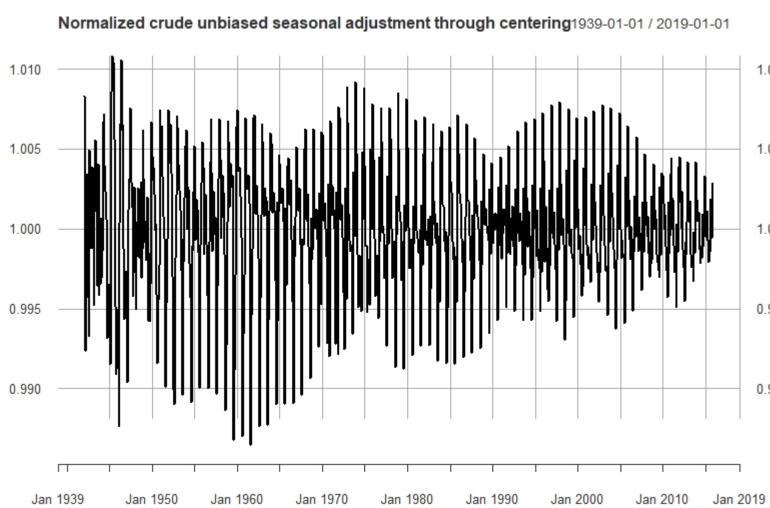

Figure 35: Normalization of the crude trend-cycle

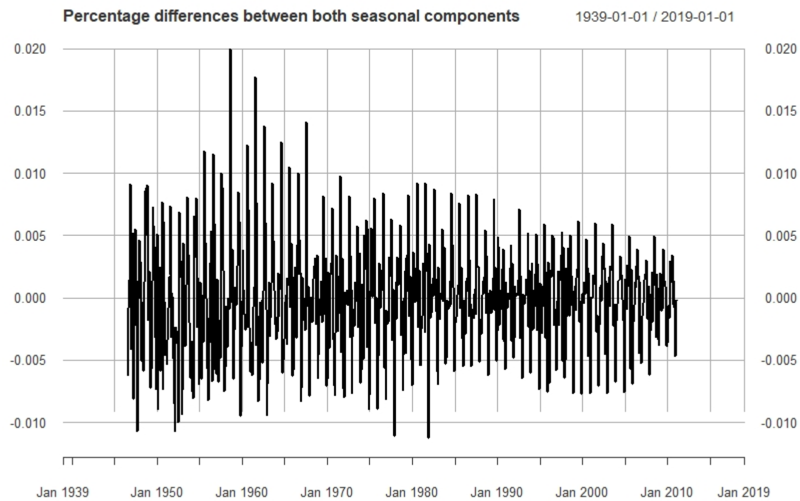

Figure 36: Percentage differences between both U.S. earnings seasonal component: Self-conducted ARIMA X11 and official FRED series

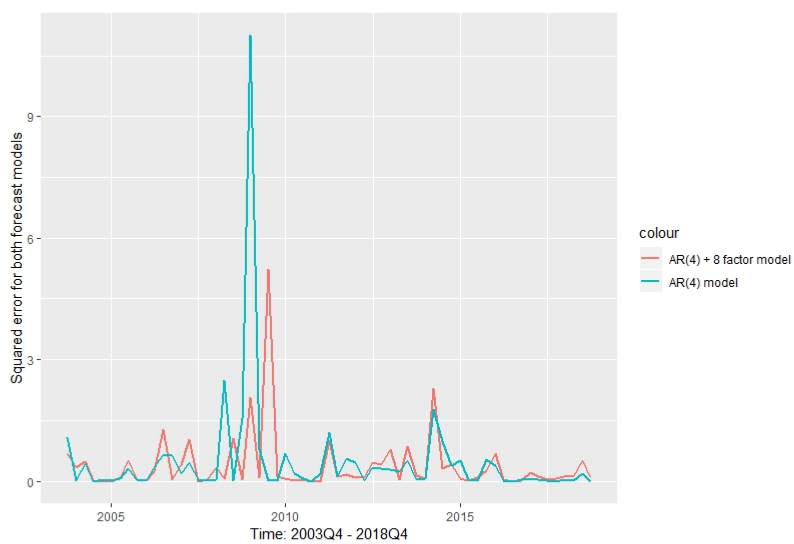

Figure 37: Squared loss for both types of forecast