Disposable Income, Debt, and Savings: Q1 1980 through Q3 2018

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Abstract

Background Over the past decade, American household debt spending has increased while contributions to personal savings have decreased. This analysis seeks to understand US household real per-capita disposable income, debt service payments, and personal savings over time, to understand trends in personal disposable income, and to determine whether savings can accurately be predicted from debt. ***Methods*** Seasonally adjusted quarterly data pertaining to disposable income, debt service payments as a percentage of disposable income, and savings as a percentage of personal income were obtained from the Federal Reserve Bank of St. Louis. Data were restricted to the common time horizon of first quarter 1980 through third quarter 2018, and each time series (TS) was explored by plotting the TS along with its autocorrelation and partial autocorrelation functions. A univariate ARIMA model was constructed for the disposable income data, and residuals were investigated for ARCH/GARCH behavior. The relationship between savings and debt was explored via scatterplot, crosscorrelation function (CCF), and an ARIMA model. For both models, forecasts were made and compared to known values, and percent error was calculated. ***Results*** Disposable income exhibited a generally increasing trend over time and was modeled as ARIMA(1,1,0) with ARMA errors. Forecast values showed good alignment with observed values, with percent error in predictions all below 1%. Savings showed a general decrease as debt increased, and the CCF plot suggested that lag-1 debt could be predictive of savings. Savings vs. lag-1 debt was modeled as ARIMA(1,1,0). Predictions were adequte, with percent error ranging between 1.8% and 10.4% in magnitude, and observed values falling within 95% prediction interval. ***Conclusion*** Modeling and forecasting performed well in the univariate case where a strong trend was observed, and performed acceptably in the bivariate case in which the TS data were more volatile and the CCF suggested weak cross-correlation between the two TS.

Background

Americans are on average spending more and saving less over the past decade. As of the fourth quarter 2018, total household debt in the United States has hit a ten-year high at $869B (Federal Reserve Bank of New York Center for Microeconomic Data (2019)). As debt increases, so does household spending, up from $9.7M in 2008 to $12.9M in 2017 (Organisation for Economic Co-operation and Development (2018b)). Total household savings is on the decline, decreasing from 9.1% in 2012 to 6.9% in 2017 (Organisation for Economic Co-operation and Development (2018a)). Wages have increased modestly during this time, and appears largely attributable to inflation (Federal Reserve Bank of St. Louis (2016)).

The objective of this study was to analyze US household real per-capita disposable income, debt service payments, and personal savings over time, to understand trends in personal disposable income, and to determine whether savings can accurately be predicted from debt.

Methods

Data pertaining to disposable personal income, household debt service payments, and personal savings informed the analytic dataset (Table 1). All variables were obtained from the Federal Reserve Bank of St. Louis, all share a common year of valuation ($US 2012), and all have already been seasonally adjusted. The data were limited to a common time horizon (Q1 1980 through Q3 2018), yielding 155 observations for each time series (TS).

Table 1. Analytic Dataset Contents

Variable	Description	Reference
`fred_disposable`	Per-capita disposable income, adjusted for inflation in chained $US 2012, seasonally adjusted	Federal Reserve Bank of St. Louis (2018c)
`fred_debt`	Household debt service payments as a percent of disposable personal income, seasonally adjusted	Federal Reserve Bank of St. Louis (2018a)

Variable	Description	Reference
`fred_savings`	Personal savings as a percentage of disposable personal income, seasonally adjusted	Federal Reserve Bank of St. Louis (2018b)

Data Exploration

Each TS was separately explored via the `forecast::ggtsdisplay()` function, which yields plots for the raw time series along with its autocorrelation (ACF) and partial autocorrelation (PACF) functions. Differencing was applied where needed. Classical decomposition was performed for each TS via `decompose()` to understand the seasonality, if any, of these time series. Where meaningful seasonality was suspected, a periodogram was generated to determine important frequencies. To understand how savings may be dependent on debt, the cross-correlation function (CCF) was computed and plotted for differenced `fred_savings` vs. differenced `fred_debt`.

Modeling Disposable Income

To model the disposable income data, the `fred_disposable` TS was subset to a "training" dataset capped at Q3 2017, and a suggested fit was obtained via `forecast::auto.arima()`. The suggested model was fit using `forecast::Arima()`, and model fit was assesed both through analysis of residuals using `forecast::checkresiduals()` and by checking p-values via `lmtest::coeftest()`. ACF plots of squared and absolute value residuals were assessed for ARCH/GARCH behavior. Finally, `forecast::forecast()` was used to predict the next three values (i.e., Q1 2018 through Q3 2018) along with a confidence interval, and these predictions were compared to the values found in the full dataset.

Modeling Savings vs. Debt

Since both debt service payments (`fred_debt`) personal savings (`fred_savings`) are expressed as a percentage of disposable personal income, it is reasonable to hypothesize that, as debt payments increase, personal savings may decrease. Under this hypothesis and using the same set of functions as described above, debt was used to predict savings for Q1 2018 through Q3 2018 using training datasets capped at Q3 2017 in an ARIMA model that incorporates both differencing and a lag offset informed by the CCF of differenced savings vs. differenced debt. Predictions were again compared to the observed values available in the full `fred_savings` dataset.

All analyses were performed in R (R v. 3.5.1, R Foundation for Statistical Computing, Vienna, Austria) using the `forecast` package (Hyndman et al. (2019)) for specialized time series calculations and plots. All statistical tests were evaluated against a significance threshold of $\alpha = 0.05$.

Results

Data Exploration

Figures 1-3 show the `ggtsdisplay()` output for the three time series. A generally increasing trend is seen in the plot of disposable income, and the ACF plot shows a slow linear decline in $\hat{\rho}(h)$ with increasing h, both of which suggest nonstationarity. The graphs of debt payments and savings (Figs. 2 and 3 respectively) do not exhibit any simple trend, but do fluctuate over time, though without any apparent seasonality (which is expected, because the data are provided in seasonally adjusted form). Additionally, the ACF plots for both debt payments and savings are suggestive of nonstationarity due to their slow decline, and thus these TS required differencing to achieve stationarity.

Figure 1. Real Disposable Personal Income Per Capita

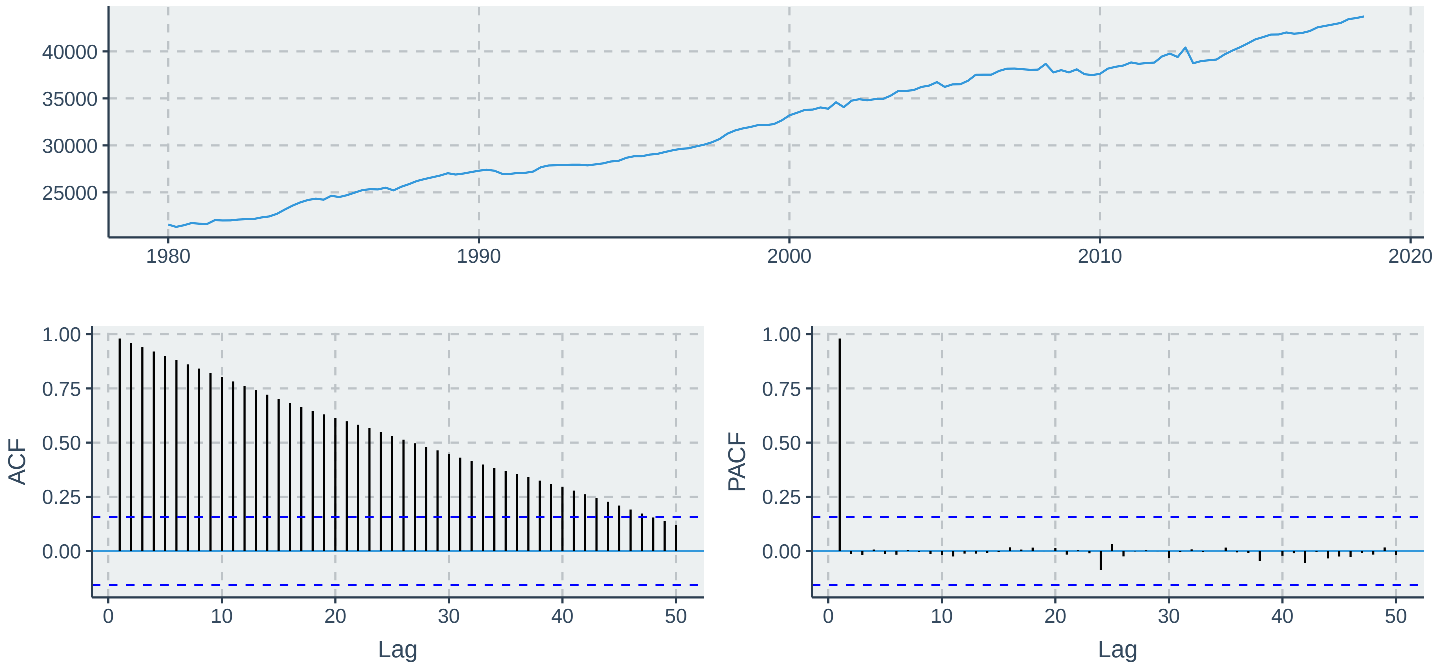


Figure 2. Household Debt Service Payments as a Percent of Disposable Personal Income

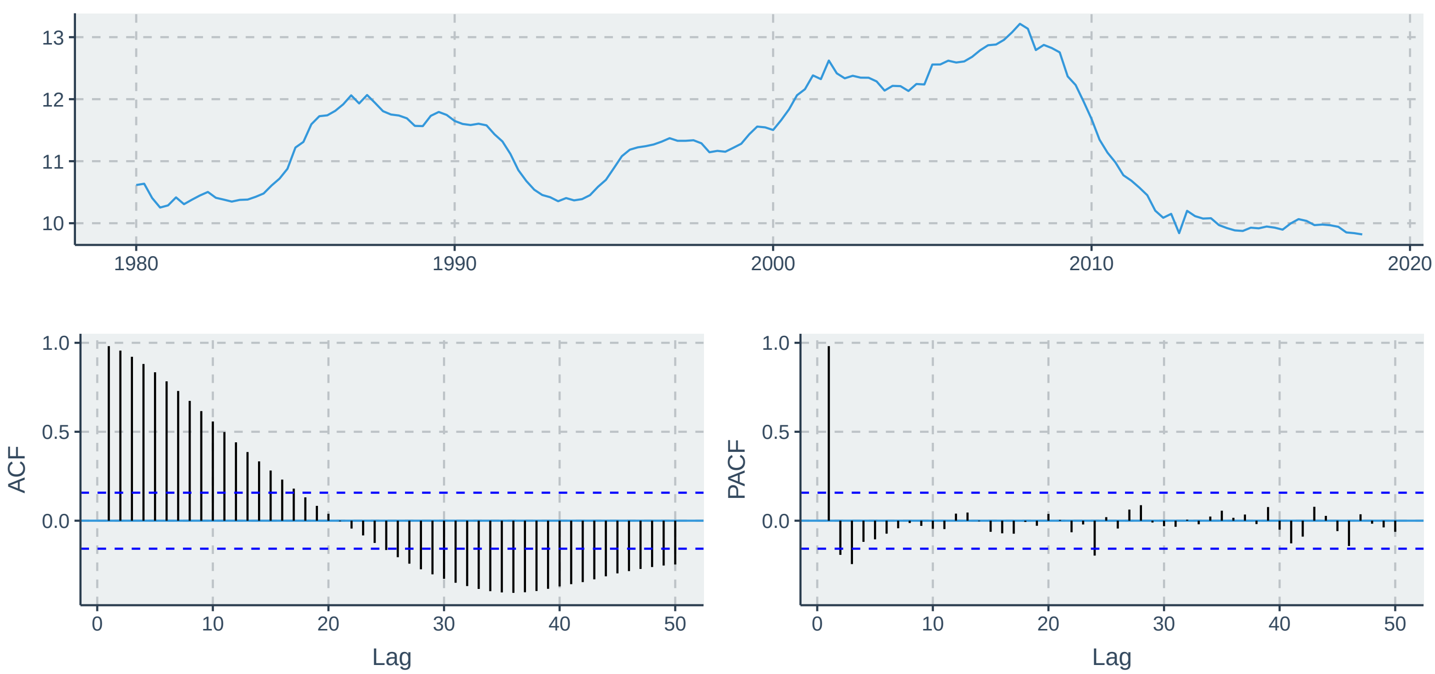
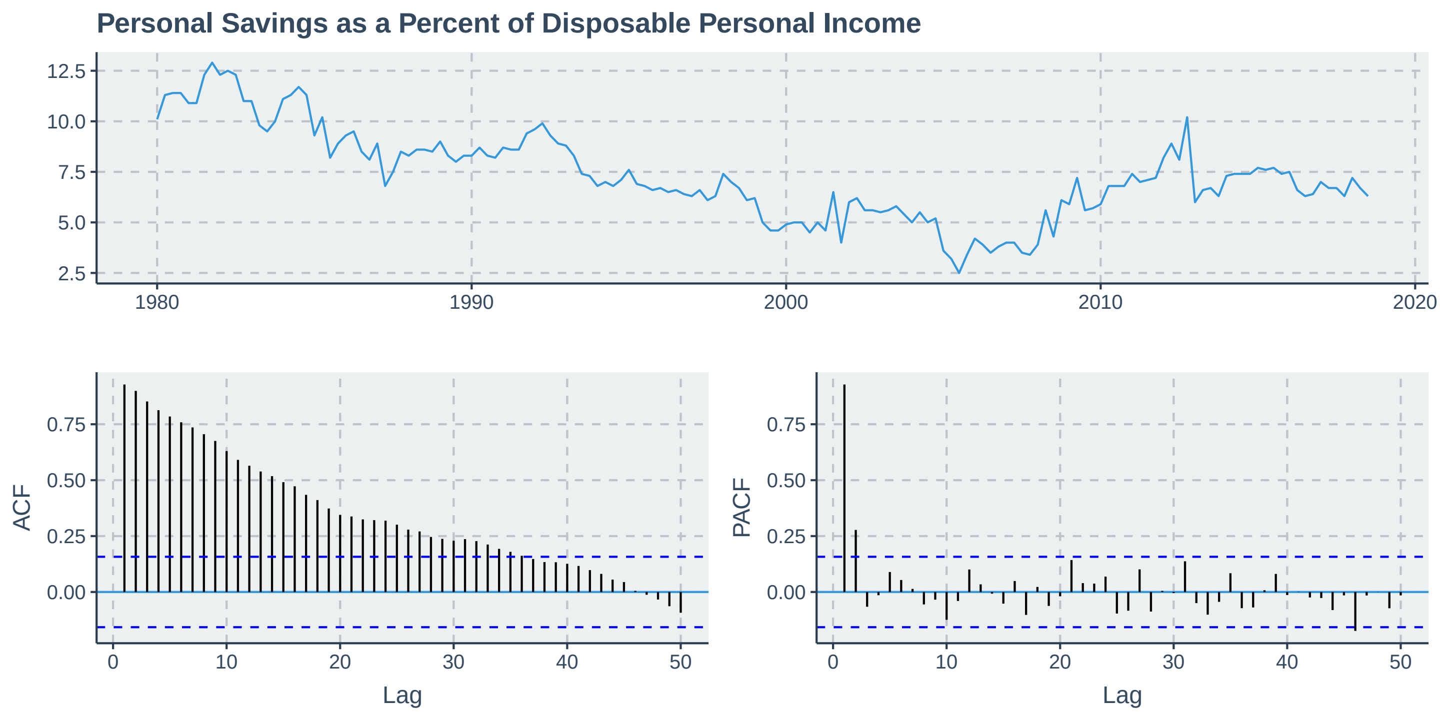


Figure 3. Personal Savings as a Percent of Disposable Personal Income



Figures 4-6 show the results of differencing. After differencing, stationarity appears to be met for all three TS. Figure 4 suggests that the disposable income data may be modeled as an AR(1) process. The output in Figs. 5 and 6 is of limited value beyond confirming stationarity since these plots pertain to each time series individually and the aim is to model savings as dependent on debt.

Figure 4. Real Disposable Personal Income Per Capita, Differenced Once

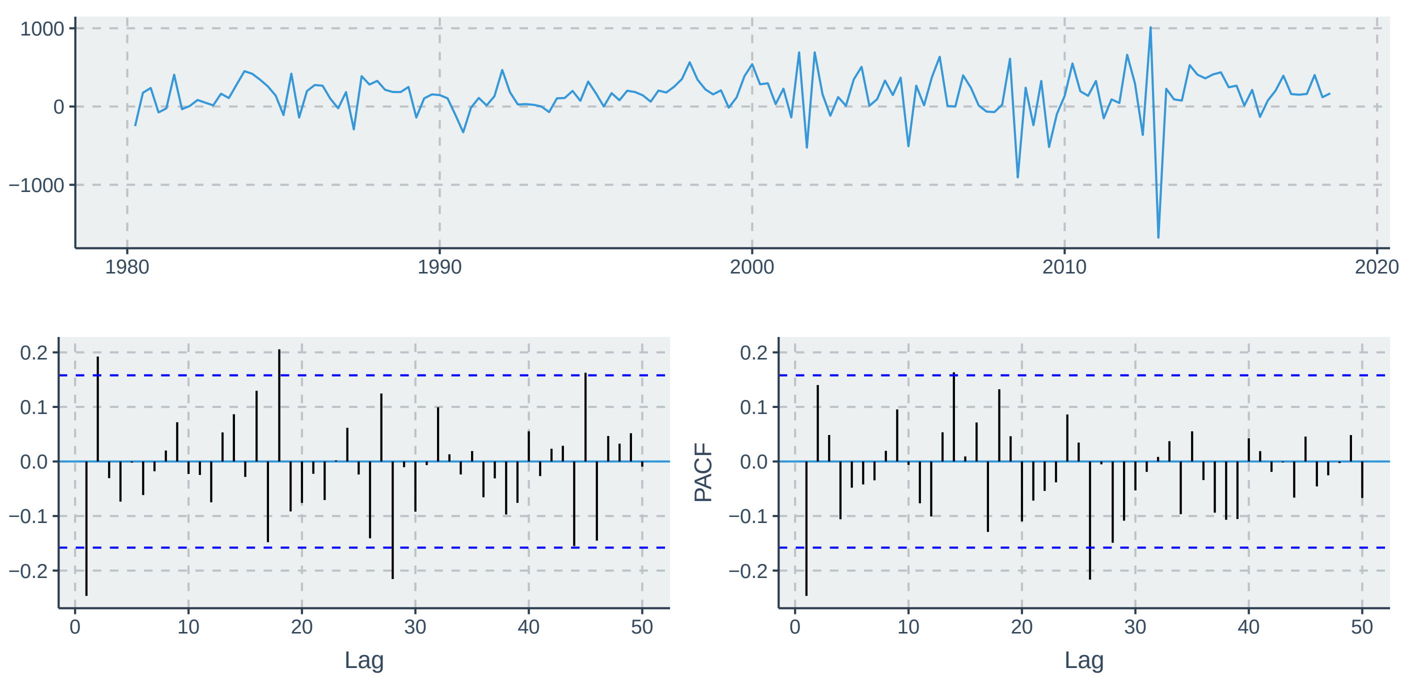


Figure 5. Household Debt Service Payments as a Percent of Disposable Personal Income, Differenced Once

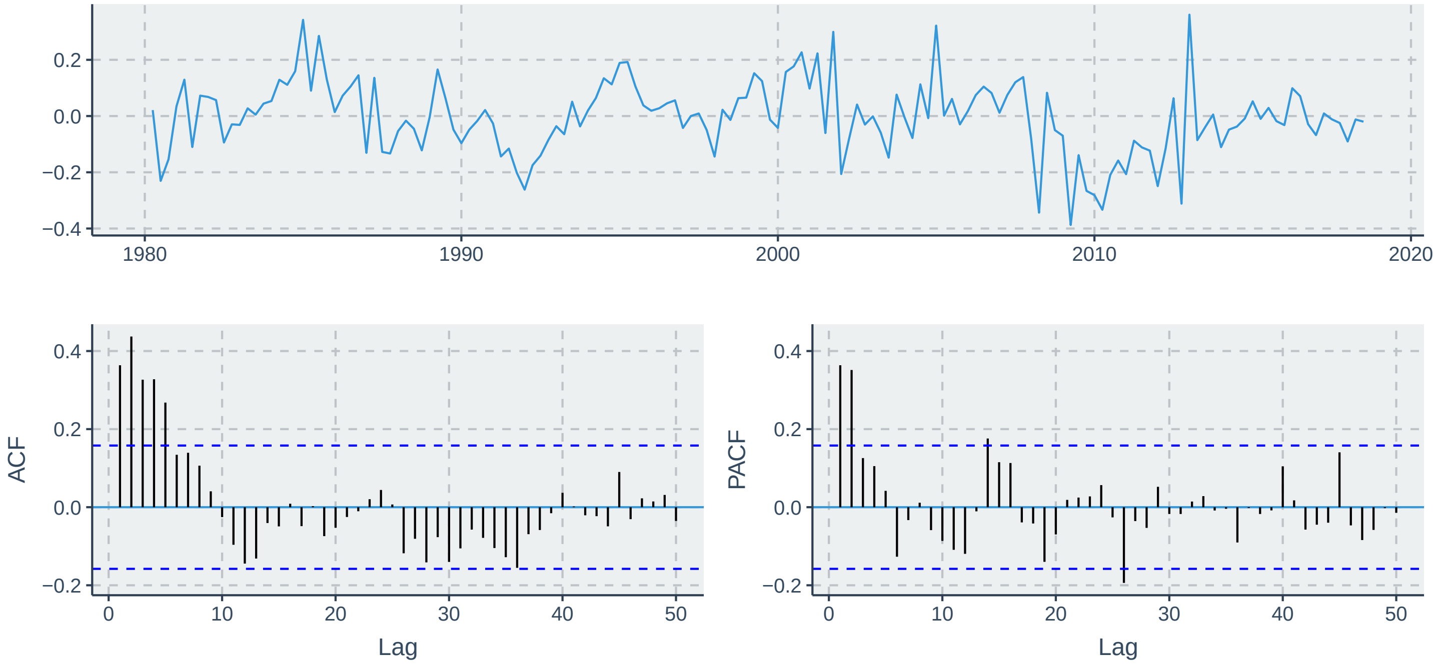
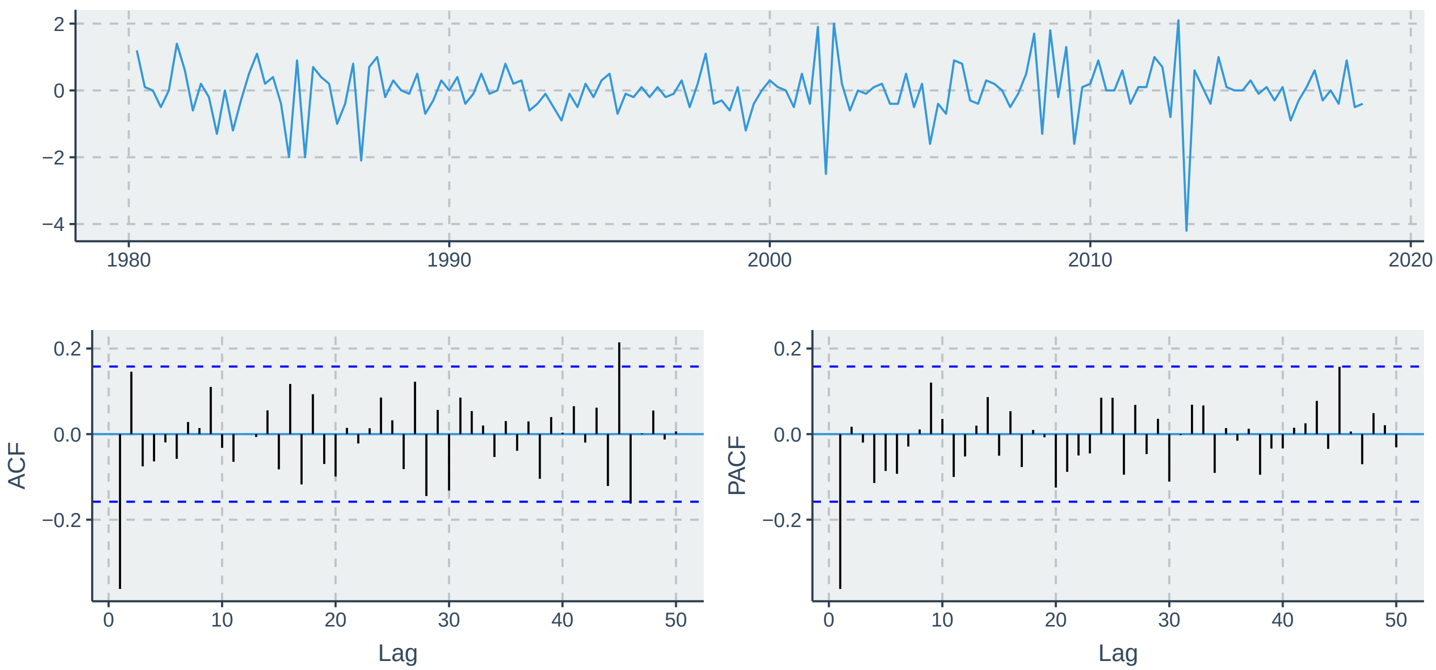


Figure 6. Personal Savings as a Percent of Disposable Personal Income, Differenced Once



Classical decomposition of the debt and savings TS is shown in Figs. 7-8. For both TS, the seasonal component was small in magnitude when compared to the raw TS, with personal savings having the more pronounced seasonal component.

Figure 7. Debt Service Payments, Decomposition

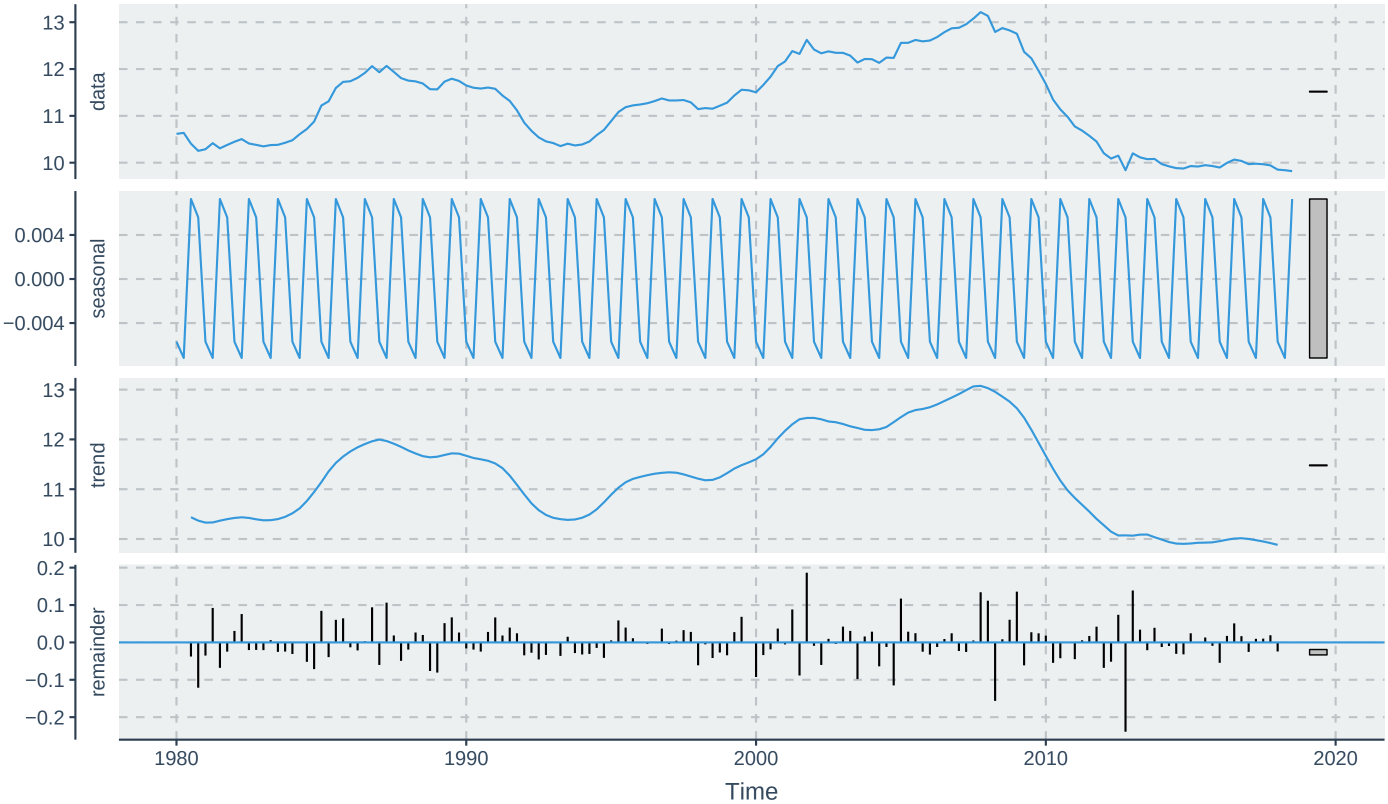
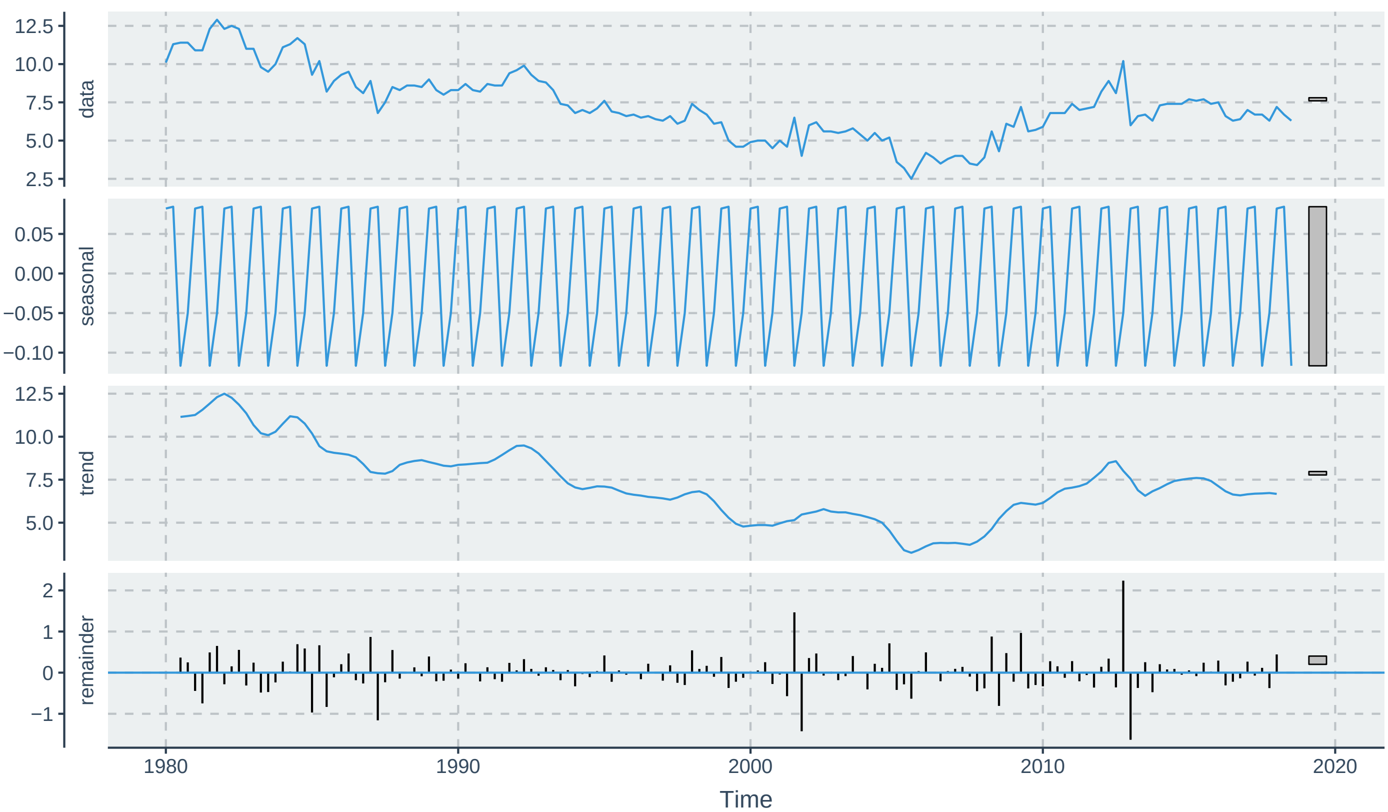


Figure 8. Personal Savings, Decomposition



The scaled periodogram for differenced savings is presented in Figure 9. All peak values in this plot are quite small. Five peaks are seen; key frequencies observed are $\omega_1 = 0.123$, $\omega_2 = 0.377$, and $\omega_3 = 0.448$, with some possible clustering about ω_3, indicating it is not a fundamenal frequency. Because these data are already seasonally adjusted, none of these frequencies are expected to have real meaning; additionally, all peaks observed are of small magnitude, consistent with a weak seasonal component, and thus limiting the usefulness of the frequency domain approach.

Figure 9. Scaled Periodogram for Differenced Savings

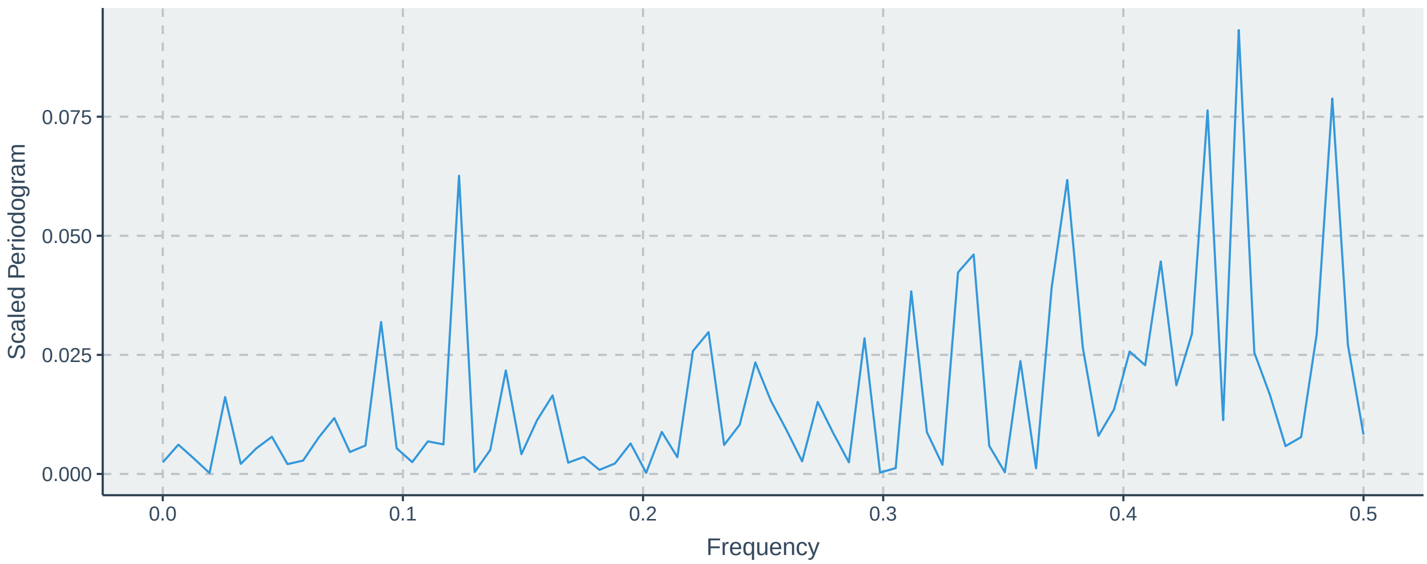
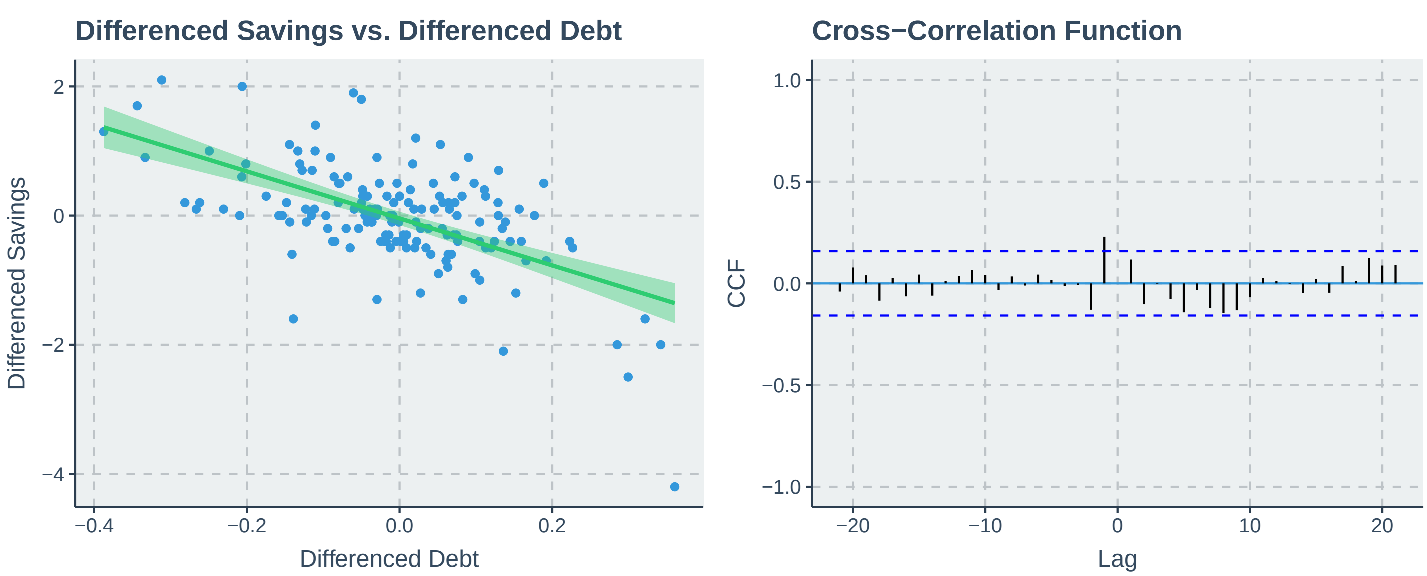


Table 2. Key Frequencies, Scaled Periodogram

Frequency
0.123
0.377
0.435
0.448
0.487

A scatterplot and the cross-correlation function for differenced savings vs. differenced debt are shown in Fig. 10. The scatterplot shows a general decrease in differenced savings as differenced debt increases, but a nontrivial degree of spread is seen in the plotted points. In the CCF plot, a cross-correlation is seen at lag $h = -1$; however, it is small in magnitude which suggests that differenced debt at $h = -1$ may only be weakly predictive of differenced savings.

Figure 10. Relationship between Differenced Savings and Differenced Debt

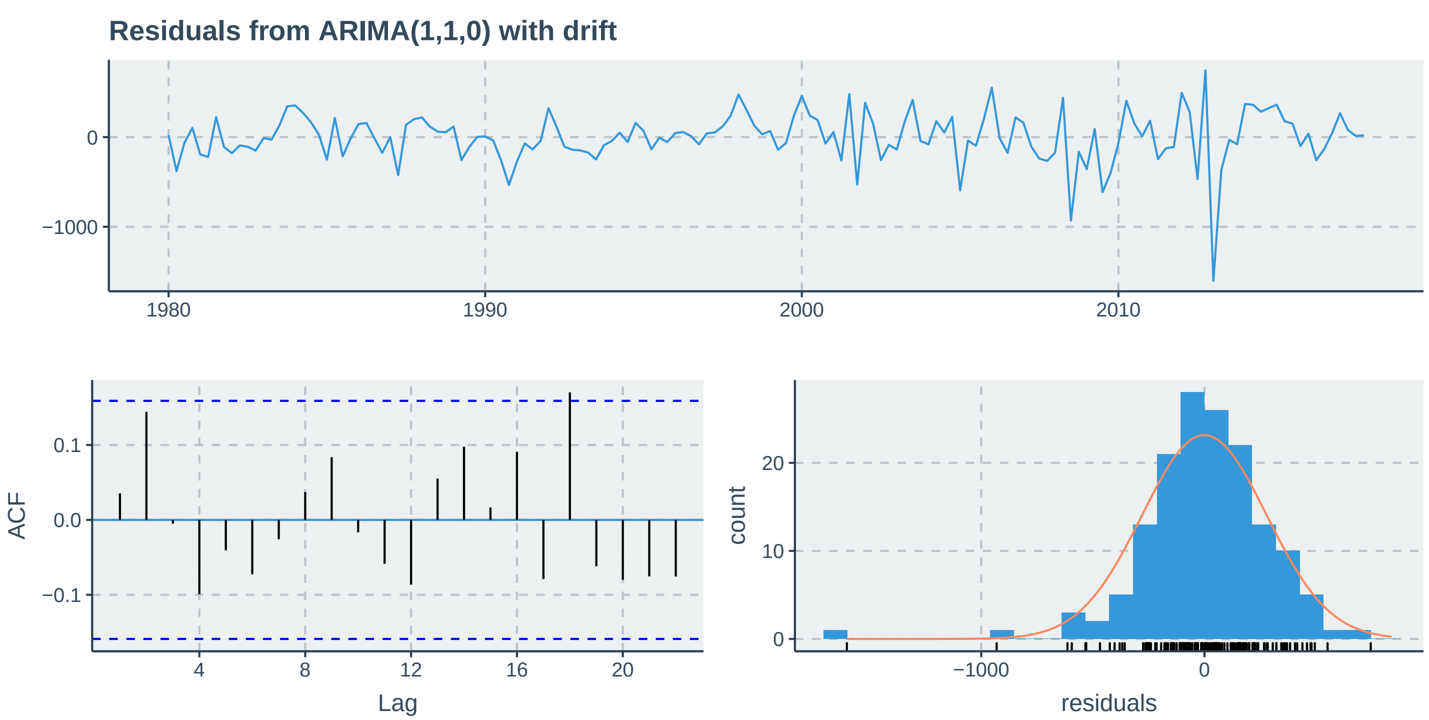


Modeling Disposable Income

For disposable income, the model suggested by `auto.arima()` was ARIMA $(1,1,0)$ with drift; `checkresiduals()` output for the fitted model is shown in Fig. 11. The Ljung-Box test (not shown in Fig. 11) yielded a p-value of 0.3746 over 8 lags, indicating that the residuals are consistent with white noise. This conclusion is supported by the plots in Fig. 11 - namely, the ACF plot looks like white noise, and the histogram demonstrates approximate normality of residuals with nontrivial deviation about the tails. Both the AR(1) and drift parameters in the model are significant at the $\alpha = 0.05$ threshold. Despite the suspected lack of normality in the residuals, this model fits the training dataset reasonably well. ARCH/GARCH behavior was not seen in the model residuals (Fig. 12), consistent with the `auto.arima()` fit, which indicated drift (i.e., ARMA errors).

```
## Series: fred_disposable_train
## ARIMA(1,1,0) with drift
##
## Coefficients:
##           ar1     drift
##       -0.2489  142.5335
## s.e.   0.0790   18.2321
##
## sigma^2 estimated as 79132:  log likelihood=-1064.84
## AIC=2135.67   AICc=2135.84   BIC=2144.73

##
## z test of coefficients:
##
##         Estimate Std. Error z value  Pr(>|z|)
## ar1    -0.248912   0.079026 -3.1497  0.001634 **
## drift 142.533522  18.232105  7.8177 5.379e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

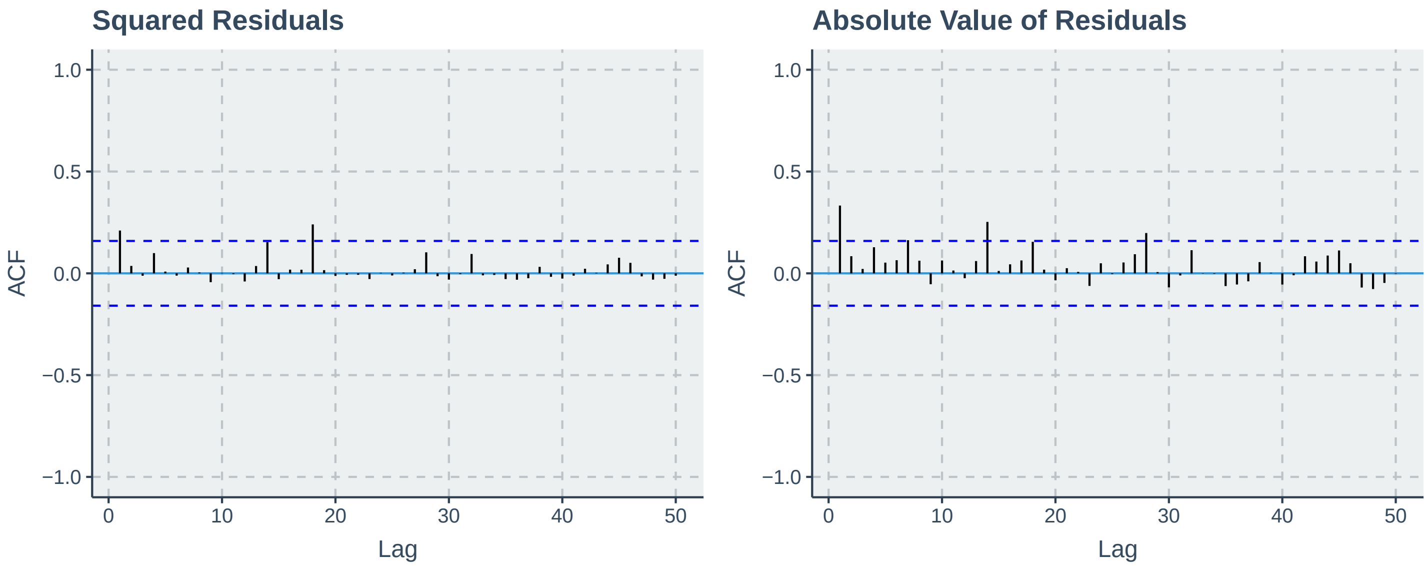
Figure 11. Residual Fit, Disposable Income Model: ARIMA(1, 1, 0) with Drift




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,1,0) with drift
## Q* = 6.4507, df = 6, p-value = 0.3746
##
```

```
## Model df: 2.   Total lags used: 8
```

Figure 12. Autocorrelation Function for Residuals

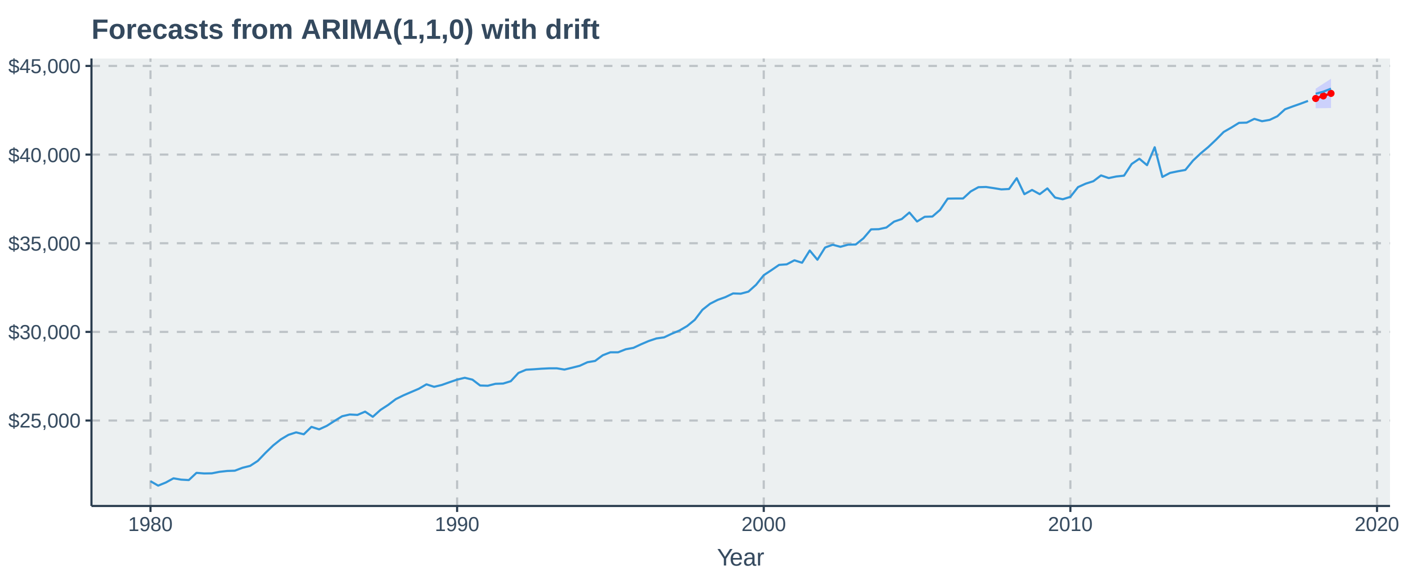


Predicted and observed disposable income values for Q1 through Q3 2018 are shown in Table 3. The observed values are marginally greater than predicted values in each case, and fall within the 95% prediction interval (Fig. 13).

Table 3. Predicted and Observed Values, Disposable Income, Q1 through Q3 2018

Timepoint	Predicted Values	Actual Values	Percent Error
Q1 2018	$43,165	$43,430	-0.61
Q2 2018	$43,309	$43,549	-0.55
Q3 2018	$43,451	$43,718	-0.61

Figure 13. Predicted vs. Actual Values, Disposable Income



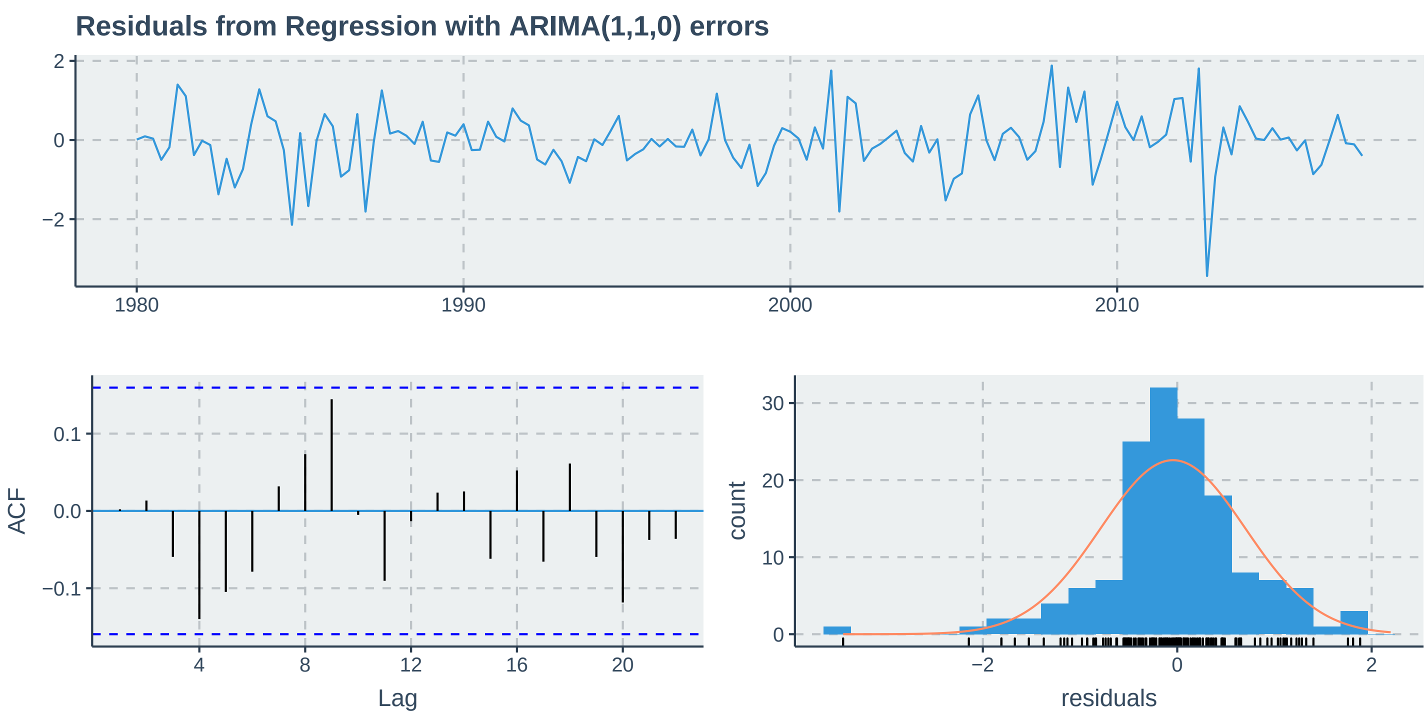
Modeling Savings vs. Debt

For predicting savings from lag-1 debt, the model suggested by `auto.arima()` was ARIMA(1,1,0). Residual fit diagnostics are presented in Fig. 14. The histogram of residuals is passably normal, although strong departure from normality is observed in the lower tail. The ACF plot shows all values within the blue boundaries, the Ljung-Box test is not statistically significant, and no ARCH/GARCH behavior is seen (Fig. 15); thus the residuals are consistent with white noise. However, when testing for predictor significance, lag-1 debt (`xreg` on output) is found not to be a significant predictor in the model.

CONTINUE HERE AND THINK ABOUT HOW TO EXPLAIN THIS

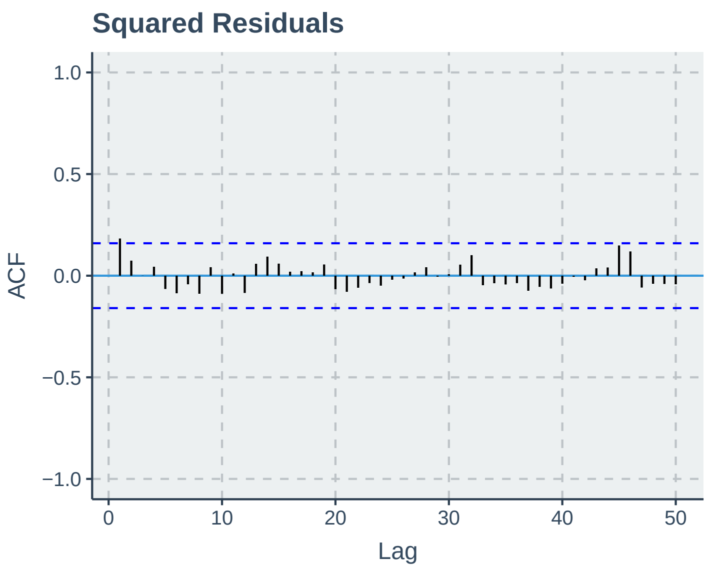
```
## Series: savdebt_ts[, 2]
## Regression with ARIMA(1,1,0) errors
##
## Coefficients:
##           ar1     xreg
##       -0.3639  -0.0066
## s.e.   0.0858   0.4440
##
## sigma^2 estimated as 0.5671:  log likelihood=-169.36
## AIC=344.72   AICc=344.89   BIC=353.76

##
## z test of coefficients:
##
##        Estimate Std. Error z value  Pr(>|z|)
## ar1  -0.3638799  0.0857849 -4.2418 2.218e-05 ***
## xreg -0.0065701  0.4439923 -0.0148    0.9882
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

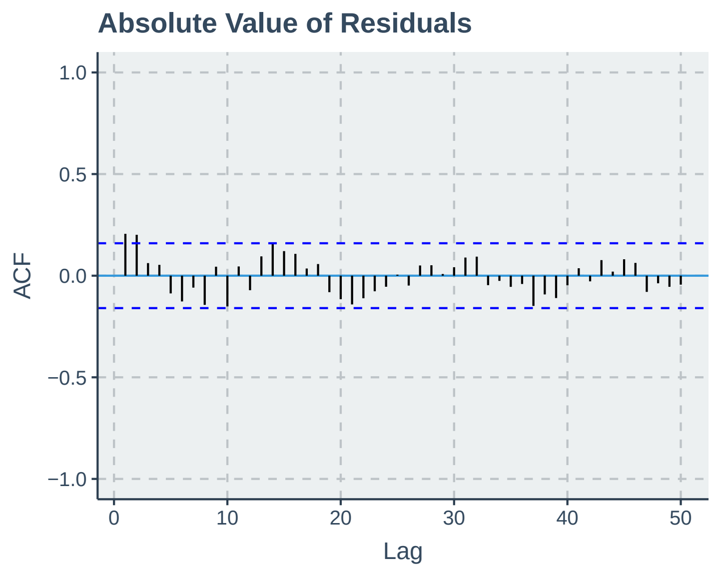
Figure 14. Residual Fit, Lagged Regression of Differenced Savings on Differenced Debt




```
##
##  Ljung-Box test
##
## data:  Residuals from Regression with ARIMA(1,1,0) errors
## Q* = 7.4125, df = 6, p-value = 0.2844
##
## Model df: 2.   Total lags used: 8
```

Figure 15. Autocorrelation Function for Residuals



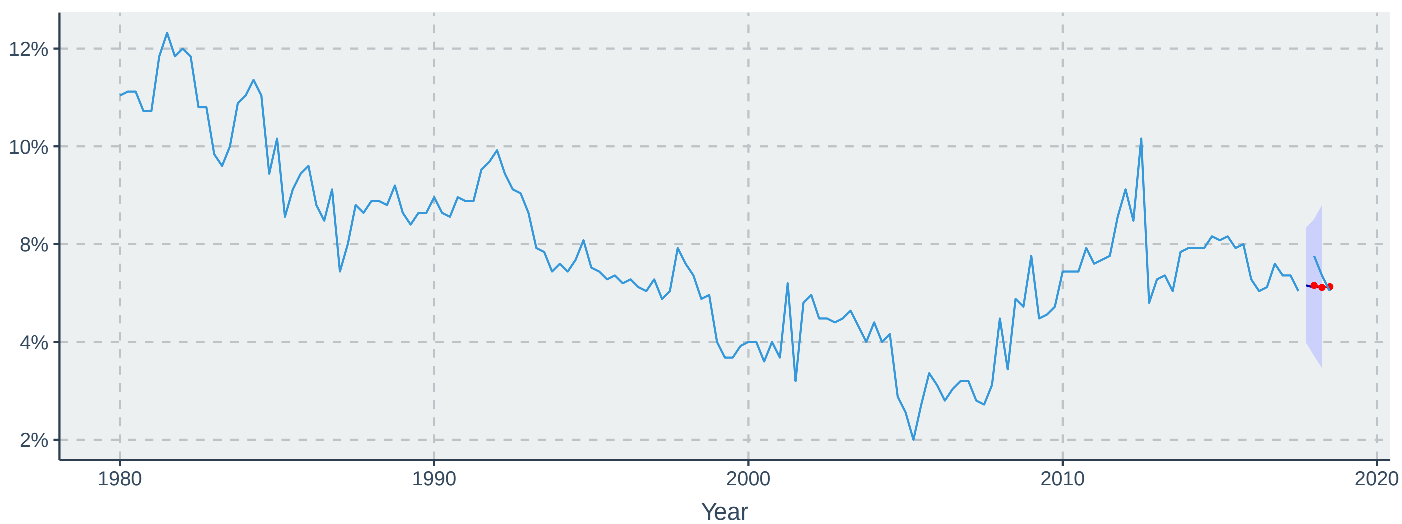


Predicted vs. observed values for the savings vs. debt model are shown in Table 4. Agreement is adequate, with percent error ranging between 1.75 and 10.42 in magnitude, and all observed values falling within the 95% prediction interval (Fig. 16).

Table 4. Predicted and Observed Values, Savings, Q1 through Q3 2018

Timepoint	Predicted Values	Actual Values	Percent Error
Q1 2018	6.45	7.2	-10.42
Q2 2018	6.39	6.7	-4.63
Q3 2018	6.41	6.3	1.75

Figure 16. Forecast Savings, Lagged Debt Model



Discussion

The model for disposable personal income worked quite well, with forecast values very close to observed values. This is not surprising because the disposable income data showed a strong trend without much volatility. Conversely, the model for predicting savings from debt worked adequately but agreement between predicted and observed values was poorer than for the disposable income model. This suggests that the savings vs. debt model may require an additional predictor - for example, quarterly nonessential or recreational spending. Additionally, the savings and debt data are somewhat volatile, and predictions may be improved by applying smoothing to these data, especially when predicting at or near turning points in the data.

Limitations

The major limitation to this analysis is that the data were obtained in seasonally adjusted form. This limits the ability to incorporate additional datapoints when they become available because the data are not static, and thus the models may change depending on the degree of adjustment in the data. Further, seasonally adjusted data limits the usefulness of the frequency domain approach. Although some seasonality was observed in each TS, in each case it was small in magnitude as compared to the scale of the raw data. Frequencies noted on the scaled periodogram are not believed to have real-world meaning, and are suspected to represent random noise, particularly because the magnitudes of periodogram peaks were small.

Conclusion

Modeling and forecasting performed very well in the univariate case where a strong trend was observed, and performed acceptably in the bivariate case. Future work includes incorporating additional predictor(s) into the savings vs. debt model and applying smoothing techniques to reduce the impact of volatility.

References

Federal Reserve Bank of New York Center for Microeconomic Data. 2019. "Quarterly Report on Household Debt and Credit - 2018 Q4." https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf//HHDC_2018Q4.pdf.

Federal Reserve Bank of St. Louis. 2016. "Consumer Price Index - Total All Items for the United States [Cpaltt01usm661s]." https://fred.stlouisfed.org/series/CPALTT01USM661S.

———. 2018a. "Household Debt Service Payments as a Percent of Disposable Personal Income." https://fred.stlouisfed.org/series/TDSP.

———. 2018b. "Personal Saving as a Percent of Disposable Personal Income." https://fred.stlouisfed.org/series/A072RC1Q156SBEA.

———. 2018c. "Real Disposable Personal Income - Per Capita." https://fred.stlouisfed.org/series/A229RX0Q048SBEA.

Hyndman, R, G Athanasopoulos, C Bergmeir, G Caceres, L Chhay, M O'Hara-Wild, F Petropoulos, S Razbash, E Wang, and F Yasmeen. 2019. "Forecast - Forecasting Functions for Time Series and Linear Models. R Package Version 8.5." http://pkg.robjhyndman.com/forecast.

Organisation for Economic Co-operation and Development. 2018a. "Household Savings." https://data.oecd.org/hha/household-savings.htm.

———. 2018b. "Household Spending." https://data.oecd.org/hha/household-spending.htm.