

MODELING VOLATILITY OF US CONSUMER CREDIT SERIES

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ABSTRACT

Consumer credit is one of the most important drivers of the economy. The time-series properties of consumer credit are examined in this paper. The Federal Reserve tracks consumer credit with three series: total consumer credit, revolving consumer credit, and nonrevolving consumer credit. Total consumer credit and nonrevolving consumer credit are found to exhibit heteroskedastic variance. Revolving consumer credit does not; it appears to be a white noise process. The findings here are important for modelling consumer credit and for forecasting it, as well as for developing theoretical models of consumer credit. *Keywords:* Credit, volatility, ARCH, GARCH

INTRODUCTION

One of the biggest drivers of the economy is credit. The Federal Reserve closely monitors credit in the economy and rightfully so, since the largest and most damaging recessions in the United States (US) economy have all started with problems in the credit markets. The Great Depression began with a banking crisis and the more recent Financial Crisis of 2007-2008 started with problems in the subprime mortgage market that soon spilled over into banking sector in general.¹ Credit itself, however, is not a simple variable; there are many types of credit. One type of credit closely followed by market participants is consumer credit. The Federal Reserve considers it to be the most important indicator of household finance.² There are two types of consumer credit: revolving and nonrevolving. The former are open-ended arrangements and thus can be rolled over (i.e. they revolve into a new agreement); generally, this category of credit refers to credit card loans, which are the most prominent and largest type of credit in this category. Nonrevolving consumer credit does not revolve into a new agreement; these are close-ended arrangements in which the loan follows a prearranged timetable. Car loans, education loans, boat loans, recreational vehicle loans, and personal loans are examples of nonrevolving consumer credit. This paper examines these series in a time-series framework. Specifically, the volatility of these series is the area of major concern. Some

¹ For an overview of the Great Depression, see Bernanke (1983); for the Financial Crisis of 2007-2008, see Cecchetti (2009).

² See <http://www.federalreserve.gov/econresdata/statisticsdata.htm>.

data exhibit volatility clustering where periods of calmness are coupled with turbulence. This type of variance makes it difficult to study and forecast these types of series.

While consumer credit is an important economic variable, most of the studies conducted on consumer credit are microeconomic studies. They include modelling consumer credit, risk assessment, and attitudes towards consumer credit, but of course, are not limited to these.³ Here the consumer credit series are examined with respect to their variance and the findings suggest that with consumer credit the answer is not straightforward. Total consumer credit and nonrevolving consumer credit exhibit heteroskedastic variance, or volatility clustering; revolving consumer credit does not. These findings are important. Understanding the behavior of the variance of a series is crucial for modelling that series and for forecasting. This finding could also help in theoretical models of credit. For example, any theoretical model of consumer credit would have to incorporate the different behaviors of the variance seen in nonrevolving and revolving consumer credit to explain the volatility clustering in the former and the lack of volatility clustering in the latter. This result also suggests that the two credit series must be treated differently. A possible implication of this result is that these two credit series have different effects on the economy; innovations in nonrevolving consumer credit may not have the same impact on the economy as those in revolving consumer credit. Of course, the variables that drive these two series are likely to be different as well. This result contributes to the literature by suggesting that while other macroeconomic studies use a one-size-fits-all cookie cutter approach to credit, a more detailed specification is necessary.

In section 2, a background on consumer credit is given as well as a statement of the hypotheses to be tested. Section 3 describes the data used in this paper and section 4 delves into the time series properties of the data. The methodology used here are described in section 5. In section 6 the results are given and in section 7 the robustness of these results is addressed. Section 8 concludes.

BACKGROUND ON CONSUMER CREDIT

While consumer credit has existed for thousands of years with its inception possibly occurring in the form of agricultural loans in the first urban society of Sumer, its present form has more recent origins.⁴ In fact, the Federal Reserve has only been keeping track of installment, or nonrevolving, consumer credit since 1943.⁵ Part of the reason being that it was not until the 1940's that this type of credit became widely used in the US. As manufacturers began producing more expensive, big-ticket items, consumers often had trouble paying for them without credit arrangements; in fact, usually only high-income households had this ability. Suppliers started offering credit to consumers in order to increase their market penetration. Sewing machines were one of the earlier examples of these types of expensive durables, but of course, with the advent of the automobile and

³ For examples of these, see Durkin (2000), Crook et al (2007), Thomas et al (2005).

⁴ See Homer & Sylla (1996), for example.

⁵ For a nice brief history of consumer credit in the US, see [<https://www.bostonfed.org/-/media/Documents/ledger/spring-summer2004/credhistory.pdf>] provided by the Boston Federal Reserve.

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home appliances, the need for credit arrangements grew. This growth started to take off in the 1930's and by the 1940's it was a common feature of the US economy. In 1968, the Federal Reserve began to track revolving credit. While revolving credit had existed for decades, it was limited in scope, principally found as credit for gas purchases. However, by the 1960's credit card use became prevalent among US consumers and hence the need to track revolving credit.

In this paper, the variance associated with consumer credit is examined. Also, the variance of the different consumer credit series will be compared. Specifically, the two hypotheses to be tested are:

H1: *Consumer credit exhibits homoskedastic variance.*

H2: *The different types of consumer credit exhibit the same type of variance.*

The literature does not provide any expectations as to what one would expect from the variance of these series. Fulford (2010) looks at credit limit effects on consumer credit. Fulford and Schuh (2015) and Fulford and Schuh (2017) look at how consumer credit varies over both life cycles and the business cycle. While these papers might be helpful in modelling consumer credit and answering the question of why consumer credit series might behave differently, they do not look at the macroeconomic time series properties of these series. So, the notion that behavior of the variance is dependent on the series type might at first seem puzzling, but given the differences in how these consumer credit series are constructed, it might not be after all. This paper does not attempt to address this issue. The goal is simply to expose this difference in behavior so that forecasters, analysts, and theorists can incorporate this finding in their work.

DATA

The Federal Reserve tracks three consumer credit series. They are total consumer credit (Total Consumer Credit Owned and Securitized, Outstanding – [TOTALSL]); revolving consumer credit (Total Revolving Credit Owned and Securitized, Outstanding – [REVOLSL]); and nonrevolving consumer credit (Total Nonrevolving Credit Owned and Securitized, Outstanding – [NONREVSL]). As previously mentioned, nonrevolving consumer credit consists of close-end credit arrangements such as car loans; revolving consumer credit is basically credit obtained through credit cards; and finally, total consumer credit is simply the sum of these two series. Nonrevolving consumer credit has been tracked since January 1943; revolving consumer credit has been tracked since January 1968, while total consumer credit has been tracked since January 1943. But, from January 1943 until January 1968, when revolving consumer credit began to be tracked, total consumer credit was equal to nonrevolving consumer credit since revolving consumer credit did not “exist”; after January 1968, total consumer credit is equal to the sum of revolving consumer credit and nonrevolving consumer credit. The data used in this paper is monthly. To convert the data to real terms the Consumer Price Index [Consumer Price Index for All Urban Consumers: All Items] was used; this series is given by the Federal Reserve as well and starts in January 1947. Therefore, the range of

the data goes from January 1947 through October 2017 for total consumer credit and for nonrevolving consumer credit; for revolving consumer credit the range is from January 1968 through October 2017. There are 850 observations for total consumer credit and for nonrevolving consumer credit each and there are 598 observations for revolving consumer credit. In order to measure growth rates the natural log of each series is used. The summary statistics for the variables are given in Table 1.

TIME SERIES PROPERTIES

In Figure 1 through Figure 3, the credit variables in real terms are graphed over time. All of the series appear to be nonstationary with a positive trend. In Figure 4 through Figure 6, the logarithmic differenced series are graphed over time as well. All appear stationary and covariance stationary.

In Figure 7, the autocorrelation and partial autocorrelation functions are given for total consumer credit. Both show a convergence to zero at a relatively quick pace. The functions suggest an AR(1), AR(2), or ARMA(1,1) process. In Figure 8, the autocorrelation and partial autocorrelation functions are given for nonrevolving consumer credit. Again, both display a quick convergence to zero, suggesting an AR(1), AR(2), or ARMA(1,1) process. Figure 9 shows the autocorrelation and partial autocorrelation functions for revolving consumer credit. Here, convergence to zero is immediate. It happens in the first lag for both functions, suggesting that this process is white noise and cannot be modelled as specified.

For the total consumer credit and nonrevolving consumer credit series, the following models are tested:

$$Credit_t = \alpha_0 + \alpha_1 Credit_{t-1} + \varepsilon_t \quad (1)$$

$$Credit_t = \alpha_0 + \alpha_1 Credit_{t-1} + \varepsilon_t + \beta_1 \varepsilon_{t-1} \quad (2)$$

$$Credit_t = \alpha_0 + \alpha_1 Credit_{t-1} + \alpha_2 Credit_{t-2} + \varepsilon_t \quad (3)$$

Equation (1) suggests that credit is dependent on its lag, or an AR(1) process. equation (2) models an ARMA(1,1) process; the series depends on its lag plus an error term today and residual from the previous period. Equation (3) is representative of an AR(2) process in which the series depends on its lag going back both one and two time periods.

Based on the statistical significance of the coefficients and the Akaike's and Schwarz's Bayesian information criteria as well as the log likelihood score, an ARMA(1,1) model seems most appropriate for total consumer credit and nonrevolving consumer credit. Again, given that revolving consumer credit displays characteristics of a white noise, or random, process, it cannot be modelled without further manipulation to the series. In Table 2, the results are given. The statistical significance of the coefficients α and β for each model are not reported, but with p-values equal to zero all are statistically

significant at the one-percent level. The resulting model for total consumer credit and for nonrevolving consumer credit are given in Table 3.

METHODOLOGY

To model the volatility of the consumer credit series, an autoregressive conditional heteroscedasticity (ARCH) framework and a generalized autoregressive conditional heteroscedasticity (GARCH) framework are used.⁶ For the ARCH framework, the conditional mean is given by Equation (2) above and the conditional variance is specified by Equation (6) below:

$$Variance_t^{ARCH} = \varphi_0 + \varphi_1 \epsilon_{t-1}^2 + \varphi_2 \epsilon_{t-2}^2 + \dots + \varphi_m \epsilon_{t-m}^2 \quad (4)$$

In this model, the size of past changes that are unexpected are allowed to affect the variance. In the GARCH model, lagged values of the conditional variance are incorporated. While ARCH models are adequate in modelling heteroskedastic variance, GARCH models improve on handling this type of variance by not requiring the occurrence of this volatility clustering to follow a pattern. For the GARCH framework, the conditional mean is again reflected by Equation (2), but the conditional variance is given by Equation (7) below:

$$Variance_t^{GARCH} = \varphi_0 + \varphi_1 \epsilon_{t-1}^2 + \dots + \varphi_m \epsilon_{t-m}^2 + \delta_1 \sigma_{t-1}^2 + \dots + \delta_k \sigma_{t-k}^2 \quad (5)$$

RESULTS

Based on the statistical significance of the coefficients and the Akaike's and Schwarz's Bayesian information criteria as well as the log likelihood score, an ARCH(1) GARCH(1) model seems appropriate. Table 4 provides the results for both total consumer credit and nonrevolving consumer credit. The statistical significance of the coefficients ϕ and δ for each model are not reported, but with p-values equal to zero for almost all of the coefficients, statistical significance at the one-percent level is shown. The one exception is the δ coefficient for nonrevolving consumer credit. However, both coefficients together have a p-value of zero and therefore, the ϕ coefficient and the δ coefficient are jointly significant at the one-percent level. Table 5 gives these results.

ROBUSTNESS

The revolving consumer credit series does not behave the same as total consumer credit and nonrevolving consumer credit; unlike the latter two, it appears to be a white noise process. However, revolving consumer credit is a relatively new series when compared to total consumer credit and nonrevolving consumer credit. Revolving consumer credit

⁶ See Engle (1982) for original ARCH model and see Bollerslev (1986) for original GARCH model.

starts in January 1968 while the other two series start in January 1947.⁷ It is possible that all series behave in a similar fashion over the same time range. Figure 10 gives the autocorrelations and partial autocorrelations for total consumer credit starting from January 1968. Clearly, the process is very similar to the total consumer credit series over the entire time period and more importantly it behaves unlike the revolving consumer credit series. Figure 11 provides the autocorrelations and partial autocorrelations for nonrevolving consumer credit over the same range. As with total consumer credit, the series does not behave like white noise and therefore, does not behave like revolving consumer credit. The behavior of total consumer credit is looked at the period before the existence of revolving consumer credit as well.⁸ Figure 12 provides the autocorrelations and partial autocorrelations for total consumer credit from January 1947 through December 1967. Again, total consumer credit behaves as before and unlike revolving consumer credit.

However, testing for ARCH/GARCH properties for both series over the post-1968 range we see a slight change in our results. The results for the nonrevolving consumer credit series are similar, but the results for the total consumer credit series are not. Table 6 summarizes these results. The coefficient for ϕ_0 is not given since it is near zero in both cases. Both ϕ_1 and δ_1 for total consumer credit are not statistically significant; jointly ϕ_1 and δ_1 are statistically significant at the one-percent level. As before δ_1 for nonrevolving consumer credit is not statistically significant; however, jointly ϕ_1 and δ_1 are statistically significant at the one-percent level.

Testing for ARCH/GARCH in total consumer credit in the period before January 1968, we see that its behavior is similar to its behavior throughout the entire time range. Again, the coefficient for ϕ_0 is not given since it is near zero as before. Both ϕ_1 and δ_1 for total consumer credit are statistically significant at the one-percent level and jointly ϕ_1 and δ_1 are statistically significant at the one-percent level as well.

CONCLUSION

The Federal Reserve considers consumer credit to be the most significant indicator of a household's finances. Open-ended arrangements, which can be rolled over into a new agreement, are called revolving consumer credit. Close-ended arrangements, where the loan is paid back on a prearranged timetable, are called nonrevolving consumer credit. Total consumer credit is the sum of the two series.

In this paper the variance of these credit variables were examined since these series exhibit periods of calmness coupled with turbulence. Volatility clustering makes forecasting and modelling difficult. Here, heteroskedastic variance is apparent in total consumer credit and nonrevolving consumer credit exhibit. For revolving consumer

⁷ Again, as mentioned in section 3 of this paper, these two series actually start in January 1943, but the CPI was needed to convert them to real terms and that series starts in January 1947.

⁸ Also mentioned in section 3 of this paper, before January 1968, total consumer credit and nonrevolving consumer credit were the same given that revolving credit was not recorded before then since its use was minimal.

credit this is not the case. These findings are important for modelling the series, for forecasting, and for developing theoretical models of credit. An implication of this result is that these two credit series have individually unique effects on the economy. Changes in nonrevolving consumer credit may not affect the economy in the same manner as those in revolving consumer credit. More research is needed to tackle these issues revealed by the result in this paper.

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Table 1

Credit Variable (in real terms)	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Total	850	590.6097	415.7035	45.4851	1541.61
Nonrevolving	850	432.4012	258.5784	45.4851	1131.489
Revolving	598	224.8782	161.0306	3.861583	477.2701
Credit Variable (logarithmic)					
Total	850	6.0758	0.8541	3.8174	7.3406
Nonrevolving	850	5.8623	0.6981	3.8174	7.0313
Revolving	598	4.9218	1.2238	1.3511	6.1681

Summary statistics for credit variable in real terms and in logarithmic form are given.

Table 2

Total	Number of Observations	Log Likelihood	AIC	BIC
Model 1	849	3167.661	-6331.322	-6321.834
Model 2	849	3252.639	-6499.278	-6486.046
Model 3	849	3223.671	-6441.342	-6427.11
Nonrevolving				
Model 1	849	2980.496	-5956.992	-5947.503
Model 2	849	3067.728	-6129.457	-6115.224
Model 3	849	3029.548	-6053.096	-6038.864

Model 1 represents an AR(1) process for total consumer credit and nonrevolving consumer credit; Model 2, an ARMA(1,1) process for each; and Model 3, an AR(2) process for each. The log likelihood score, as well as the Akaike's and Schwarz's Bayesian information criteria results, are given for each model.

Table 3

Total	Coefficient	P-value
$\alpha(0)$	0.0044	0.000
$\alpha(1)$	0.9373	0.000
$\beta(1)$	-0.6127	0.000
Nonrevolving		
$\alpha(0)$	0.0040	0.000
$\alpha(1)$	0.9420	0.000
$\beta(1)$	-0.6922	0.000

Table 3 gives the ARMA(1,1) regression results ($Credit_t = \alpha_0 + \alpha_1 Credit_{t-1} + \varepsilon_t + \beta_1 \varepsilon_{t-1}$) for total consumer credit and nonrevolving consumer credit.

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Table 4

Total	Number of Observations	Log Likelihood	AIC	BIC
ARCH(1)	849	3272.177	-6534.354	-6510.634
ARCH(2)	849	3277.027	-6542.053	-6513.589
ARCH(1) GARCH(1)	849	3280.781	-6549.561	-6521.097
Nonrevolving				
ARCH(1)	849	3110.695	-6211.390	-6187.670
ARCH(2)	849	3074.628	-6139.256	-6115.536
ARCH(1) GARCH(1)	849	3110.727	-6209.453	-6180.989

ARCH(1), ARCH(2) and ARCH(1) GARCH(1) are tested for total consumer credit and nonrevolving consumer credit; The log likelihood score, as well as the Akaike's and Schwarz's Bayesian information criteria results, are given for each model.

Table 5

Total	Coefficient	P-value
$\varphi(1)$	0.1301	0.003
$\delta(1)$	0.5826	0.000
Nonrevolving		
$\varphi(1)$	1.2072	0.000
$\delta(1)$	0.0050	0.827

Table 5 gives the ARCH(1) GARCH(1) regression results for the variance of an ARMA(1,1) process ($Variance_t^{GARCH} = \varphi_0 + \varphi_1 \epsilon_{t-1}^2 + \delta_1 \sigma_{t-1}^2$) for total consumer credit and nonrevolving consumer credit. The coefficient for φ_0 is not given since it is near zero in both cases. While δ_1 for nonrevolving consumer credit was not statistically significant, jointly φ_1 and δ_1 are statistically significant at the one-percent level.

Table 6

Total	Coefficient	P-value
$\varphi(1)$	0.0496	0.315
$\delta(1)$	0.4062	0.208
Nonrevolving		
$\varphi(1)$	1.9714	0.000
$\delta(1)$	-0.0104	0.380

Table 6 gives the ARCH(1) GARCH(1) regression results for the variance of an ARMA(1,1) process ($Variance_t^{GARCH} = \varphi_0 + \varphi_1 \epsilon_{t-1}^2 + \delta_1 \sigma_{t-1}^2$) for total consumer credit and nonrevolving consumer credit from January 1968 through October 2017. The coefficient for φ_0 is not given since it is near zero in both cases. Both φ_1 and δ_1 for total consumer credit were not statistically significant; jointly φ_1 and δ_1 are statistically significant at the one-percent level. While δ_1 for nonrevolving consumer credit was not statistically significant, jointly φ_1 and δ_1 are statistically significant at the one-percent level.

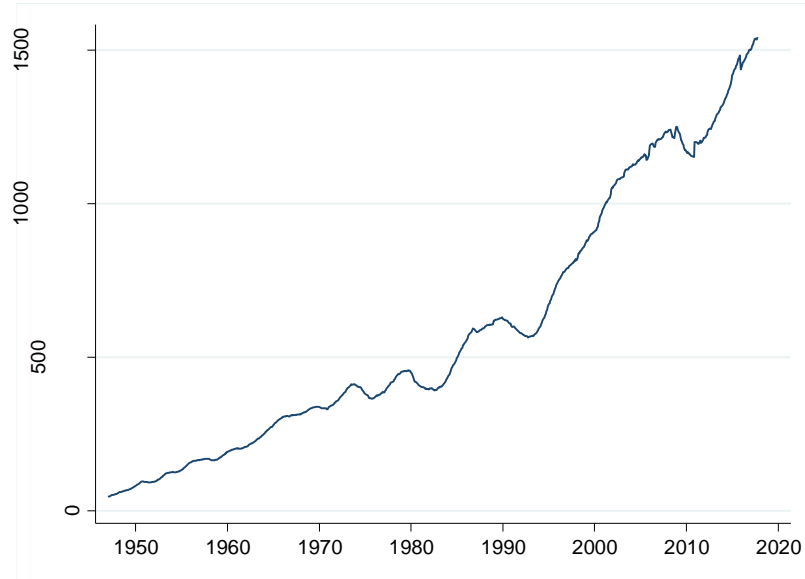
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Table 7

Total	Coefficient	P-value
$\varphi(1)$	0.1394	0.000
$\delta(1)$	0.8527	0.000

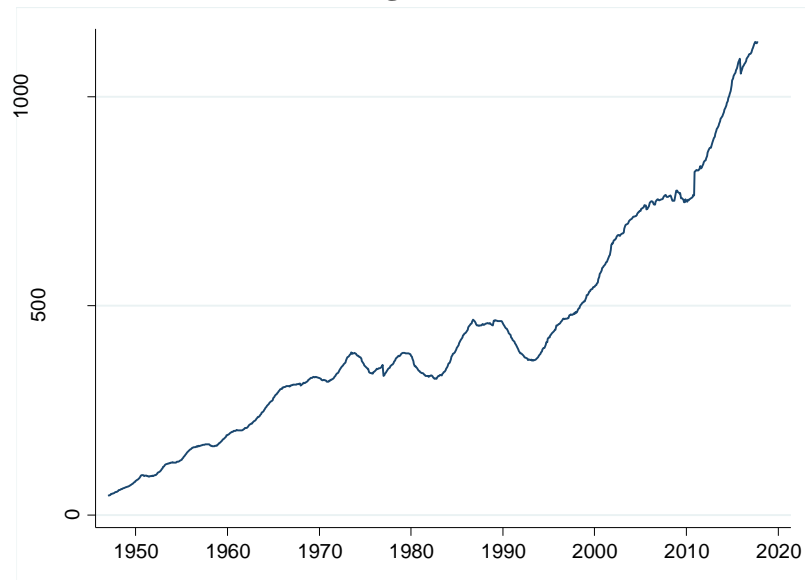
Table 7 gives the ARCH(1) GARCH(1) regression results for the variance of an ARMA(1,1) process ($Variance_t^{GARCH} = \varphi_0 + \varphi_1 \epsilon_{t-1}^2 + \delta_1 \sigma_{t-1}^2$) for total consumer credit from January 1947 through December 1967. The coefficient for φ_0 is not given since it is near zero. Jointly φ_1 and δ_1 are also statistically significant at the one-percent level.

Figure 1



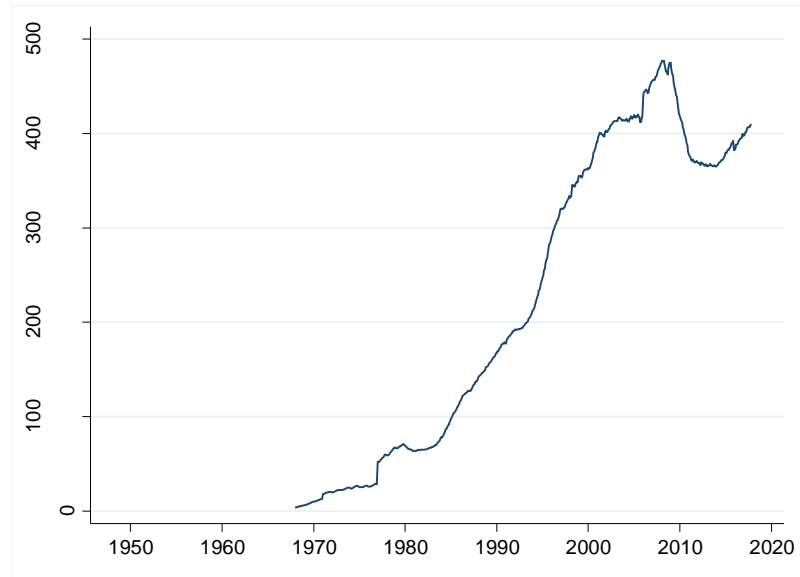
Total consumer credit in real terms over time.

Figure 2



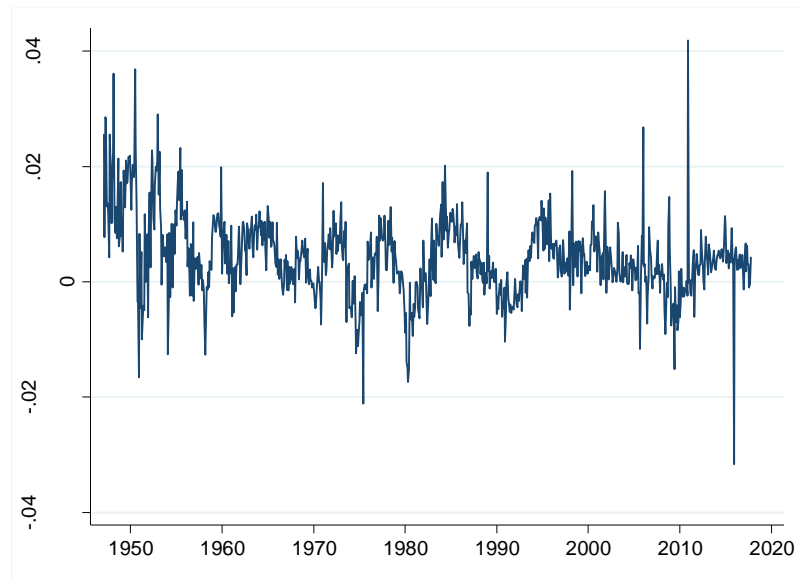
Nonrevolving consumer credit in real terms over time.

Figure 3



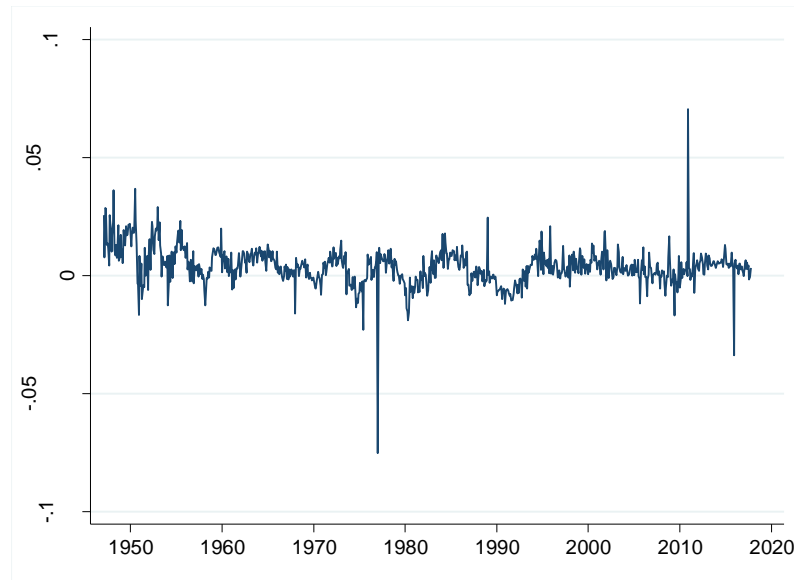
Revolving consumer credit in real terms over time.

Figure 4



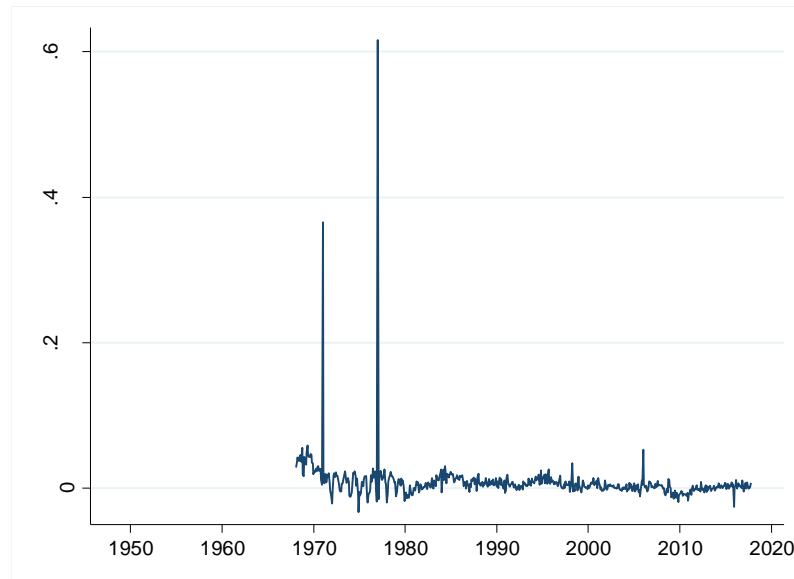
Logarithmic difference of total consumer credit over time.

Figure 5



Logarithmic difference of nonrevolving consumer credit over time.

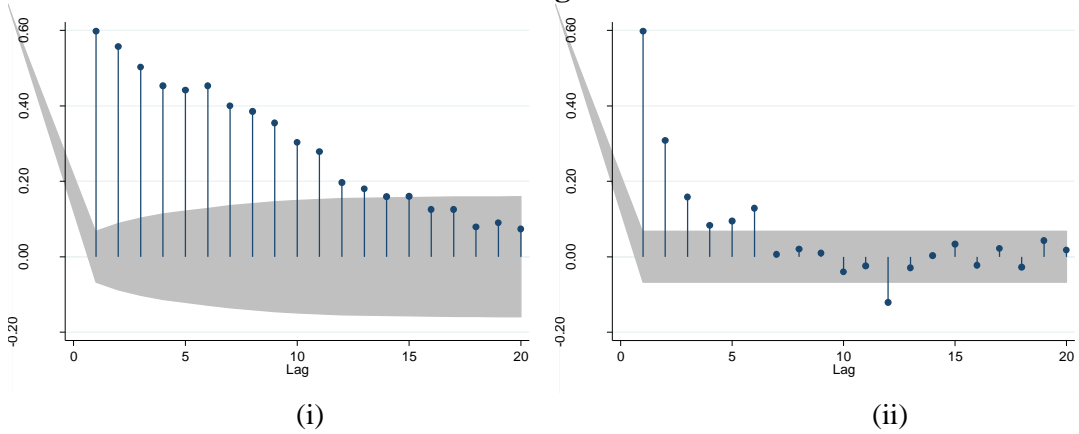
Figure 6



Logarithmic difference of revolving consumer credit over time.

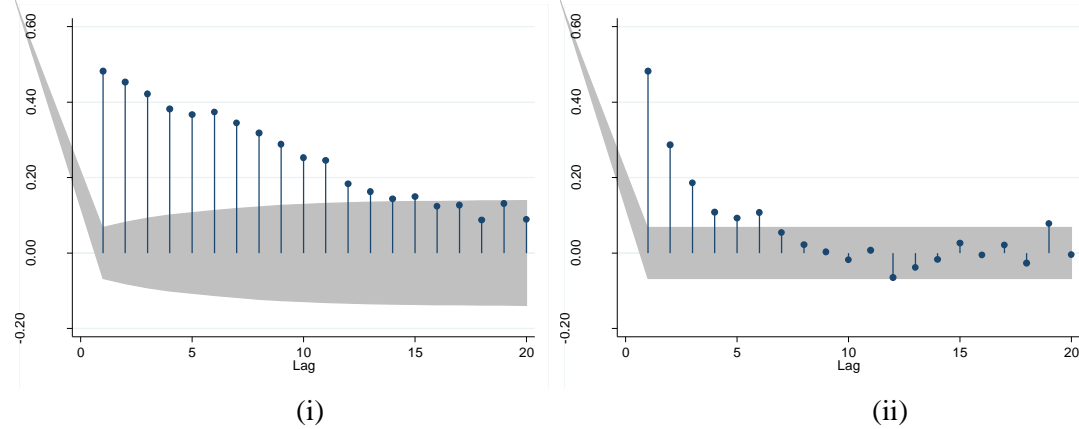
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Figure 7



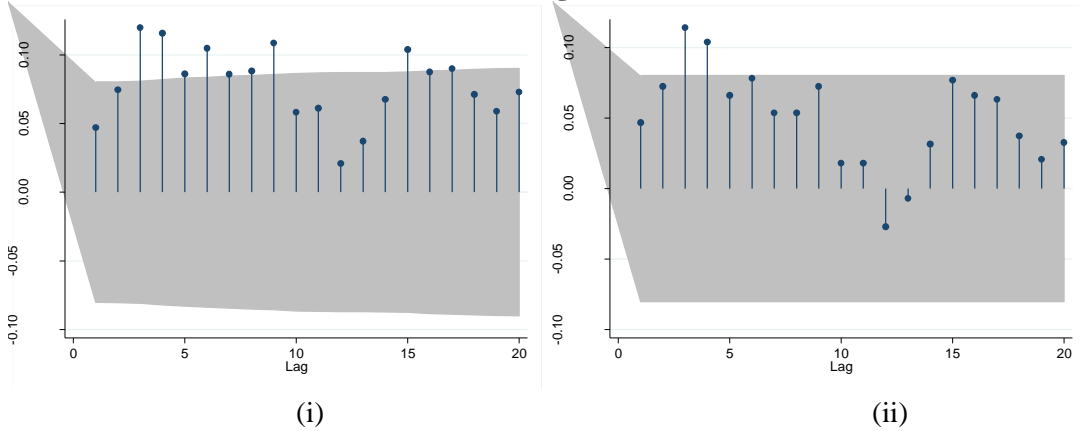
Autocorrelations and partial autocorrelations of logarithmic difference of total consumer credit over lag length in months. The shaded area represents the 95% confidence bands.

Figure 8



Autocorrelations and partial autocorrelations of logarithmic difference of nonrevolving consumer credit over lag length in months. The shaded area represents the 95% confidence bands.

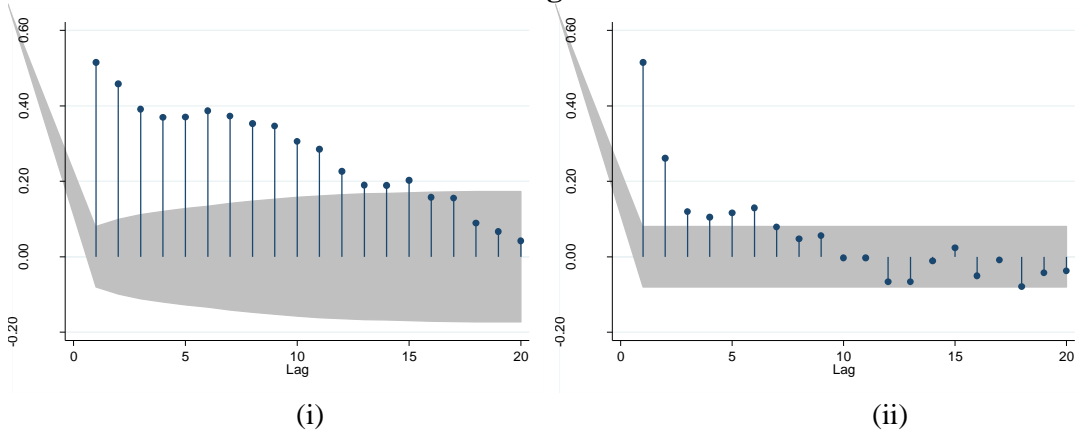
Figure 9



Autocorrelations and partial autocorrelations of logarithmic difference of revolving consumer credit over lag length in months. The shaded area represents the 95% confidence bands.

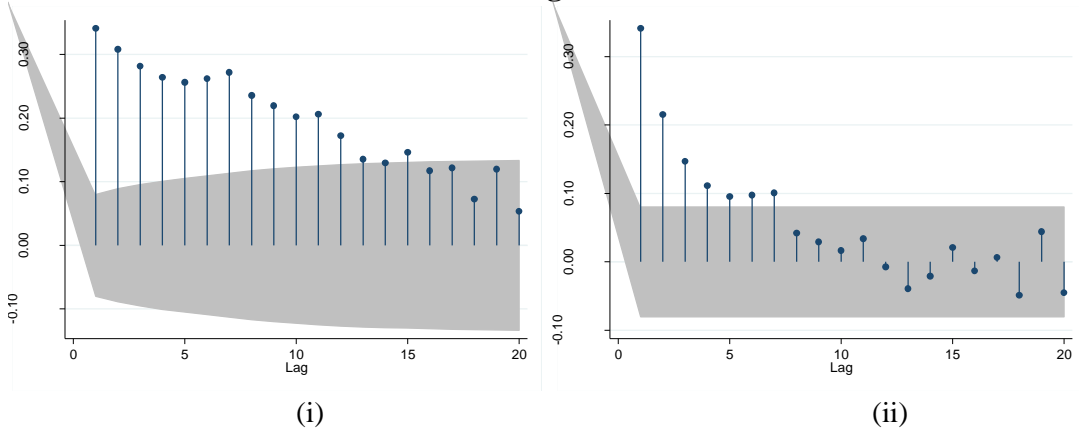
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Figure 10



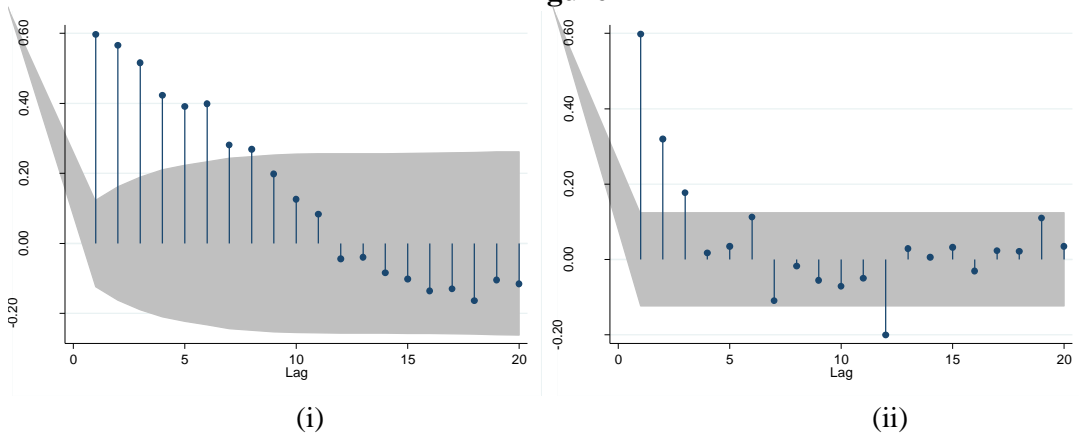
Autocorrelations and partial autocorrelations of logarithmic difference of total consumer credit over lag length in months from January 1968 through October 2017. The shaded area represents the 95% confidence bands.

Figure 11



Autocorrelations and partial autocorrelations of logarithmic difference of nonrevolving consumer credit over lag length in months from January 1968 through October 2017. The shaded area represents the 95% confidence bands.

Figure 12



Autocorrelations and partial autocorrelations of logarithmic difference of total consumer credit over lag length in months from January 1947 through December 1967. The shaded area represents the 95% confidence bands.

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