Volatility in US bank credit series

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ABSTRACT

Bank credit and business loans are two of the most important variables in financial markets and the macroeconomy. The time-series properties of these two series are investigated in this paper. The Federal Reserve tracks both credit variable in two series: bank credit and commercial and industrial loans. Both variables are found to display heteroskedastic variance. The findings here are important for modelling and forecasting bank credit and business loans, as well as for developing theoretical models that incorporate bank credit and business loans.

Keyword: Credit, volatility, ARCH, GARCH, macroeconomy

INTRODUCTION

Nearly 900 US chartered banks report balance sheet data to the Federal Reserve on a weekly basis. The Federal Reserve then adjusts the data to control for large nonbank activity and off-balance-sheet activity.[1]

One of the biggest drivers of the economic activity is credit. The Federal Reserve follows credit data closely in the economy and rightfully so, since the largest and most punitive recessions in the United States (US) economy have all started with problems in the credit markets. The Great Depression started with a banking crisis and the Financial Crisis of 2007-2009 began with problems in the subprime mortgage market that soon spilled over into banking sector in general.[2] Credit itself, however, is not a simple variable; there are numerous types of credit. Two credit variables that are closely followed by market participants are bank credit and commercial and business loans.

This paper examines these series in a time-series framework. Specifically, the volatility of these series is the area of major concern. Some 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 both of these credit variables are important, most of the studies conducted on bank credit and commercial and industrial loans do not look at the volatility of these series. These studies tend to be theoretical or they are conducted to determine the importance of bank credit on other variables.[3] Here the bank credit and commercial and industrial loan series are examined with respect to their variance. The findings suggest that both series exhibit heteroskedastic variance, or volatility clustering. These findings are important. For modelling and for forecasting it is crucial to understand the behavior of the variance of a series. This finding could also help in theoretical models of credit. For example, any theoretical model of bank credit would have to incorporate the different behaviors of the variance seen in these series in order to describe the volatility clustering properly. This result contributes to the literature by suggesting that while many macroeconomic studies use a one-size-fits-all cookie cutter approach to credit, a more detailed specification is necessary.[4]

In section 2, a background on the credit series 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 looks at the time series properties of the data. The methodology used here are described in section 5. In section 6 the results are given and section 7 concludes.

BANK CREDIT AND COMMERCIAL AND INDUSTRIAL LOANS

Bank credit includes Treasury securities as well as securities issued by other US government agencies; it includes mortgage-backed securities issued by US government agencies or enterprises sponsored by the US government (Government National Mortgage Association, Federal National Mortgage Association, and Federal Home Loan Mortgage Corporation); it

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[1] Large, as per the Federal Reserve, is defined as over $5 billion.

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

[3] For examples of these, see Orr and Mellon (1961), Rajan (1994), Dell'Ariccia and Marquez (2004), Hirtle (2009) and Gorton and He (2008).

[4] See Heath (2018).

includes loans and leases in bank credit, but not loans to commercial banks nor federal funds bought or sold. Commercial and industrial loans are loans made to businesses. It is usually backed by collateral and short-term. They are very important for small businesses. Both of these series are thought to be pro-cyclical.[5]

In this paper, the variance associated with these credit series is examined and compared. Specifically, the three hypotheses to be tested are:

H1:   Bank credit exhibits homoskedastic variance.
H2:   Commercial and industrial loan series exhibits homoskedastic variance.
H3:   These credit series 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. Gorton and He (2008) and De Soto (2006) look at credit cycles using bank credit. Mulligan (2005) look at commercial and industrial loans as to how they relate to the business cycle. Melitz and Pardue (1973) look at the demand and supply of commercial bank loans. While these papers might be helpful in modelling bank credit and commercial and industrial credit as well as answering the question of how these two series behavior compares, they do not look at the macroeconomic time series properties of these series. The goal of this study is simply to explore the volatility of these series so that forecasters, analysts, and theorists can incorporate these findings in their work.

DATA

The Federal Reserve tracks two important business credit variables. The series are business loans (Commercial and Industrial Loans, All Commercial Banks [BUSLOANS]) and bank credit (Bank Credit, All Commercial Banks [TOTBKCR]). 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. Business loans have been tracked since January 1947 as well and bank credit since January 1973. For the purposes of this study, the range of the data goes from January 1973 through January 2021. Therefore, there are 577 observations. In order to measure growth rates the natural log of each series is used. The summary statistics for the variables are given as indicated in Table 1 (Appendix).

TIME-SERIES PROPERTIES

As indicated in Figure 1 and Figure 2 (Appendix), the credit variables in real terms are graphed over time. All of the series appear to be nonstationary with a positive trend.
As indicated in Figure 3 and Figure 4 (Appendix), the logarithmic differenced series are graphed over time as well. All appear stationary and covariance stationary.
As indicated in Figure 5 (Appendix), the autocorrelation and partial autocorrelation functions are given for business loans. The autocorrelation function shows a long gradual convergence to zero while the partial autocorrelation function shows a rapid convergence to zero. The functions suggest an AR(1), AR(2), or ARMA(1,1) process.

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[5] For more information of these series, see https://www.federalreserve.gov/releases/h8/current/.

As indicated in Figure 6 (Appendix), the autocorrelation and partial autocorrelation functions are given for bank credit. Again, both display convergences to zero in a similar manner as the business loans series. And as with the previous series, this suggests an AR(1), AR(2), or ARMA(1,1) process.

For the business loans and bank credit, the following models are tested:

$$Credit_t = \alpha_0 + \alpha_1 Credit_{t-1} + \varepsilon_t \tag{1}$$
$$Credit_t = \alpha_0 + \alpha_1 Credit_{t-1} + \varepsilon_t + \beta_1 \varepsilon_{t-1} \tag{2}$$
$$Credit_t = \alpha_0 + \alpha_1 Credit_{t-1} + \alpha_2 Credit_{t-2} + \varepsilon_t \tag{3}$$

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 ARIMA(1,1) model seems most appropriate for both business loans and bank credit. As indicated in Table 2 (Appendix), these results are given.

As indicated in Table 3 (Appendix) the ARMA(1,1) model is reported with its coefficients and p-values for each. For business loans, all coefficients are statistically significant at the one percent level, except for the constant term which is almost statistically significant at the five percent level. For bank credit, all coefficients are statistically significant except for the moving average one.

METHODOLOGY

To model the volatility of the bank credit series and the commercial and industrial loans 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 (4) below:

$$Variance_t^{ARCH} = \varphi_0 + \varphi_1 \epsilon_{t-1}^2 + \varphi_2 \epsilon_{t-2}^2 + \cdots + \varphi_m \epsilon_{t-m}^2 \tag{4}$$

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 (5) below:

$$Variance_t^{GARCH} = \varphi_0 + \varphi_1 \epsilon_{t-1}^2 + \varphi_2 \epsilon_{t-2}^2 + \cdots + \varphi_m \epsilon_{t-m}^2 + \delta_1 \sigma_{t-1}^2 + \delta_2 \sigma_{t-2}^2 + \cdots + \delta_k \sigma_{t-k}^2 \tag{5}$$

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

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) model seems appropriate for the business loans and an ARCH(1) GARCH(1) model seems to be a better fit for bank credit. As indicated in Table 4 (Appendix) the results are provided for both business loans and bank 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 bank 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. These results are given as indicated in Table 5 (Appendix).

CONCLUSION

The Federal Reserve considers bank credit to be a very important indicator of the financial market. Securities issued by the US Treasury or other US government agencies and mortgage-backed securities issued by the US government or entities sponsored by the US government are all included in bank credit. Separately, short-term loans backed by collateral made to businesses represent commercial and industrial loans. The former series is important for understanding credit in macroeconomy and the latter is especially important for credit as it relates to small businesses.

In this paper the variance of these credit variables is examined since these series exhibit periods of calmness coupled with turbulence. Volatility clustering makes forecasting and modelling difficult. Here, heteroskedastic variance is apparent in both credit series. These findings are important for modelling the series, for forecasting, and for developing theoretical models of credit.

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APPENDIX

Table 1

Credit Variable (in real terms)	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Business Loans	577	536.0577	170.7096	313.7782	1186.234
Bank Credit	577	2783.676	1295.745	1306.471	5802.276
Credit Variable (logarithmic)					
Business Loans	577	6.238855	0.2953622	5.748686	7.078539
Bank Credit	577	7.824439	0.4630642	7.175085	8.666005

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

Table 2

Business Loans	Number of Observations	Log Likelihood	AIC	BIC
Model 1	576	1914.615	-3823.229	-3810.161
Model 2	576	1938.097	-3868.194	-3850.769
Model 3	576	1929.981	-3851.962	-3834.538
Bank Credit				
Model 1	576	2183.238	-4360.476	-4347.408
Model 2	576	2183.378	-4358.756	-4341.332
Model 3	576	2183.343	-4358.686	-4341.261

Model 1 represents an AR(1) process for business loans and bank 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

Business Loans	Coefficient	P-value
$\alpha(0)$	0.0019812	0.052
$\alpha(1)$	0.3919508	0.000
$\beta(1)$	0.4478317	0.000
Bank Credit		
$\alpha(0)$	0.0025512	0.000
$\alpha(1)$	0.307647	0.006
$\beta(1)$	0.0682522	0.553

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 business loans and bank credit.

Table 4

Business Loans	Number of Observations	Log Likelihood	AIC	BIC
ARCH(1)	576	2010.911	-4011.821	-3990.041
ARCH(2)	576	1962.049	-3914.098	-3892.318
ARCH(1) GARCH(1)	576	1973.033	-4003.628	-3917.827
Bank Credit				
ARCH(1)	576	2217.538	-4425.075	-4403.295
ARCH(2)	576	2217.563	-4424.239	-4398.564
ARCH(1) GARCH(1)	576	2217.574	-4423.149	-4397.012

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

Business Loans	Coefficient	P-value
$\varphi(1)$	0.222611	0.000
Bank Credit		
$\varphi(1)$	0.7495715	0.000
$\delta(1)$	0.0099658	0.872

Table 5 gives the ARCH(1) regression results for the variance of an ARMA(1,1) process ($Variance_t^{ARCH} = \varphi_0 + \varphi_1 \epsilon_{t-1}^2$) for business loans. 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 bank credit is also given. While δ_1 was not statistically significant, jointly φ_1 and δ_1 are statistically significant at the one-percent level. The coefficient for φ_0 in each regression are not given since they are near zero in both cases.
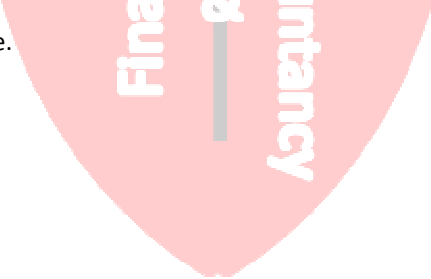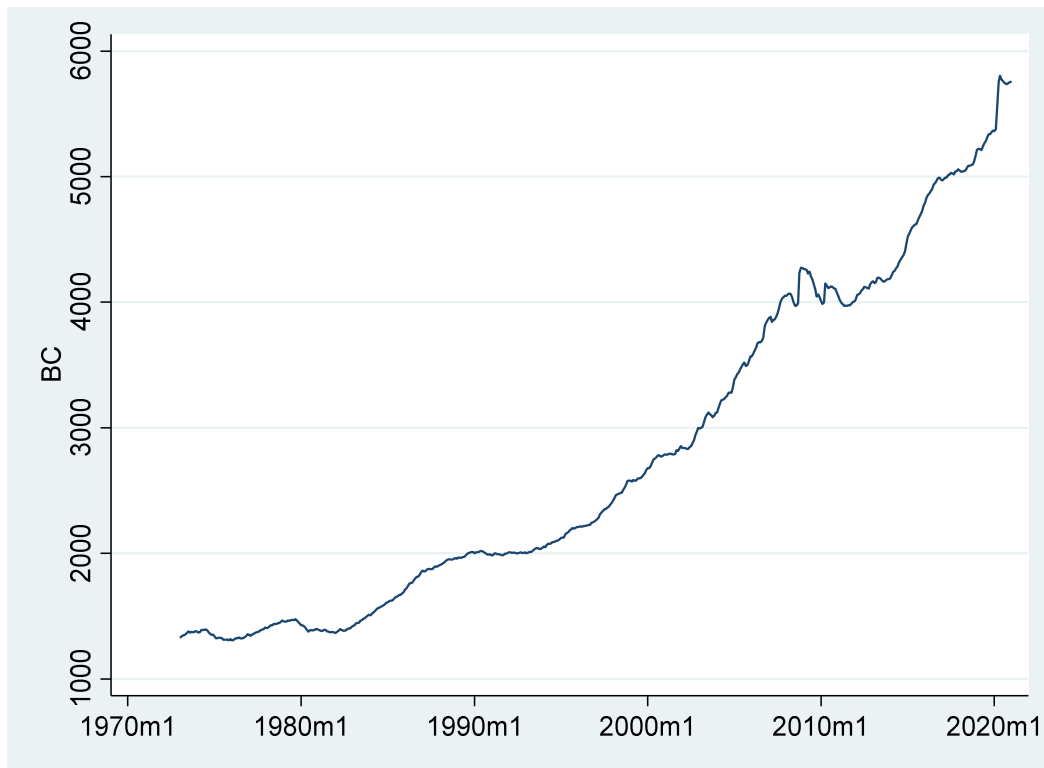
Figure 1
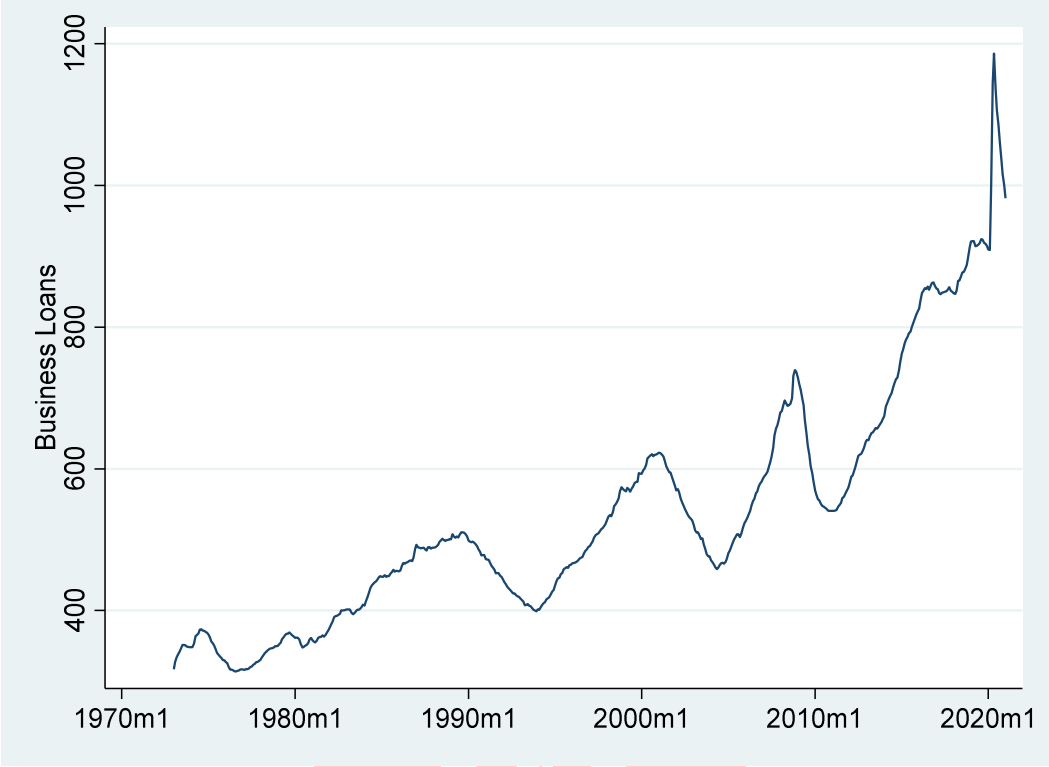
Business Loans in real terms over time.
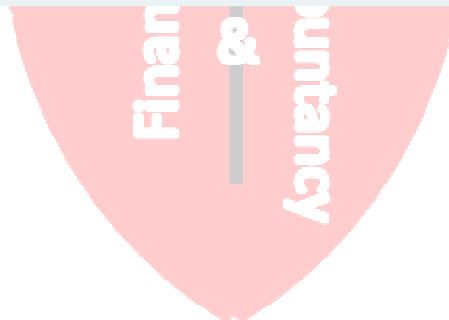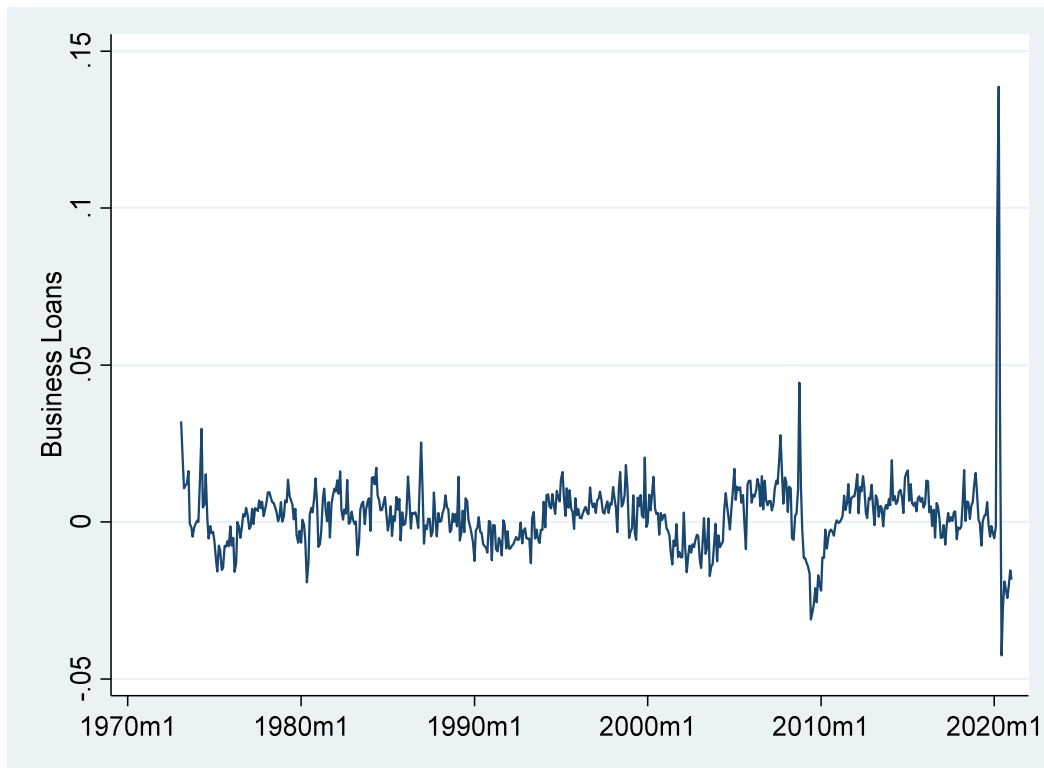
Figure 2

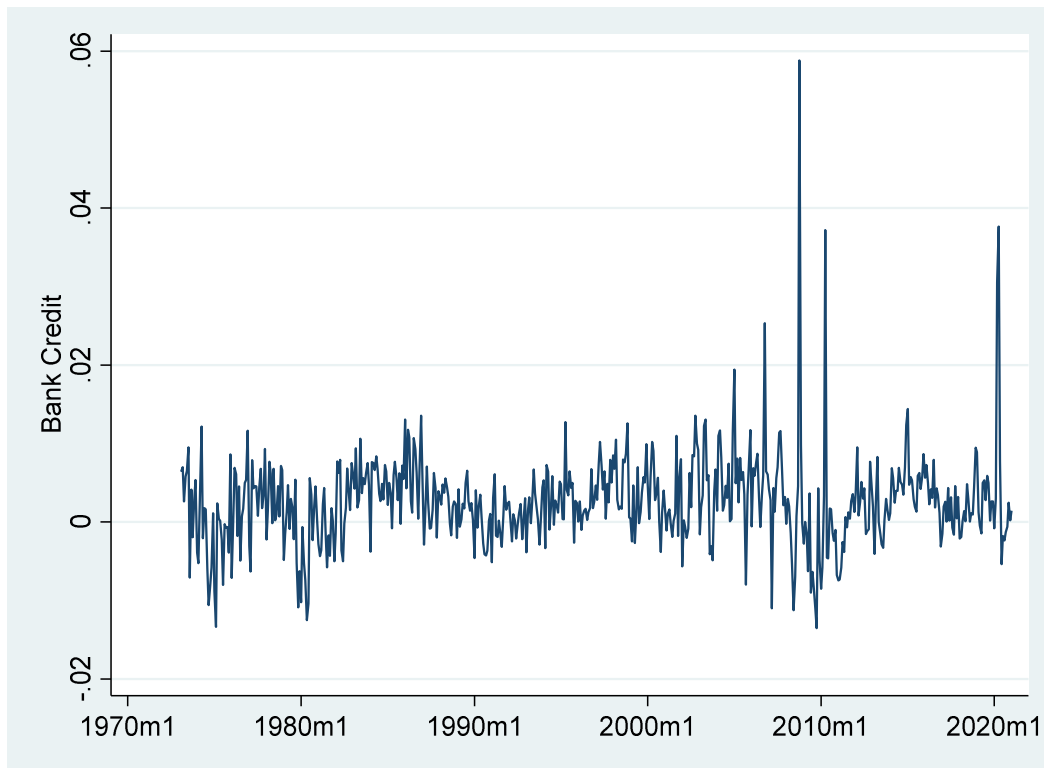Bank Credit in real terms over time.

Figure 3

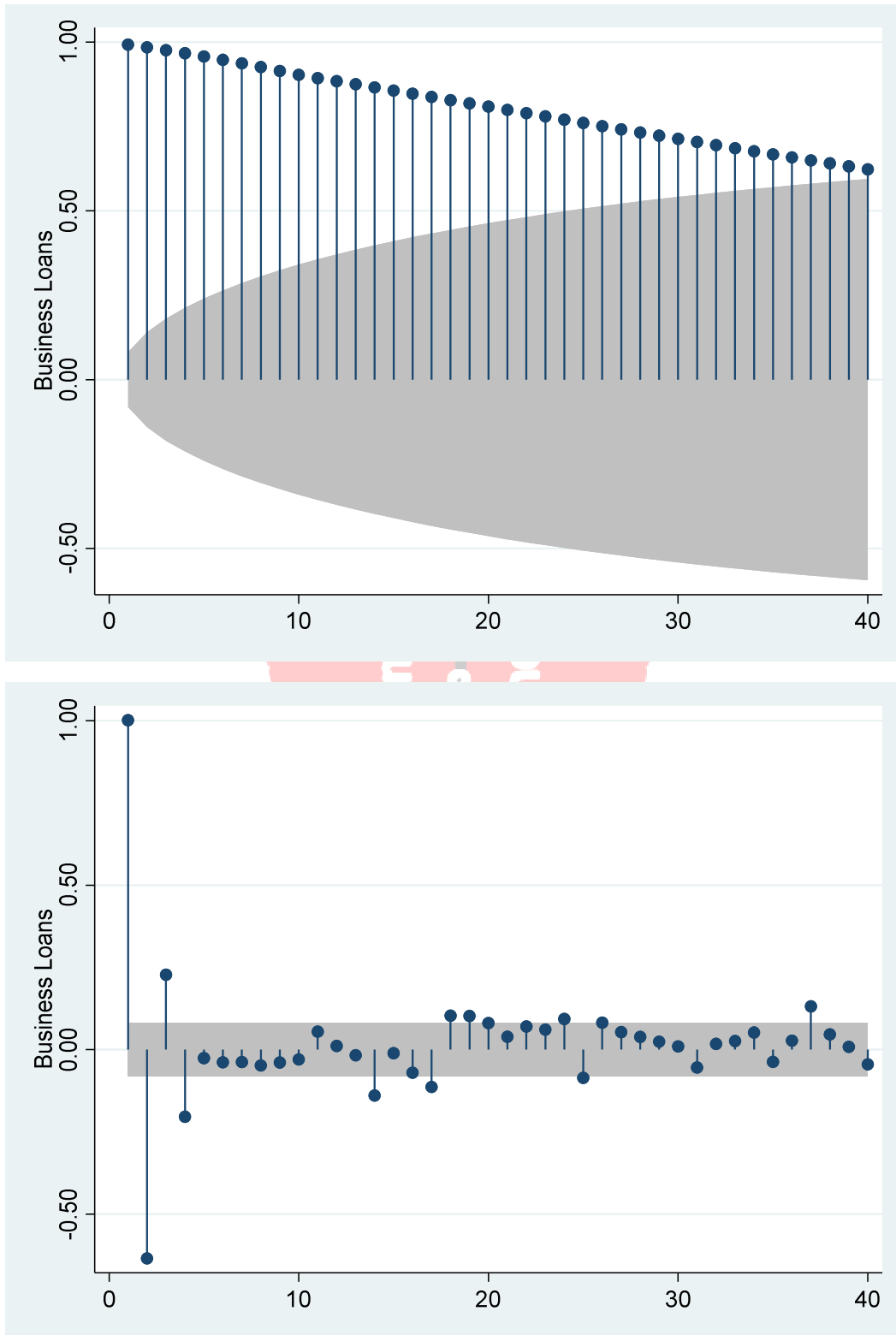Logarithmic difference of business loans over time.
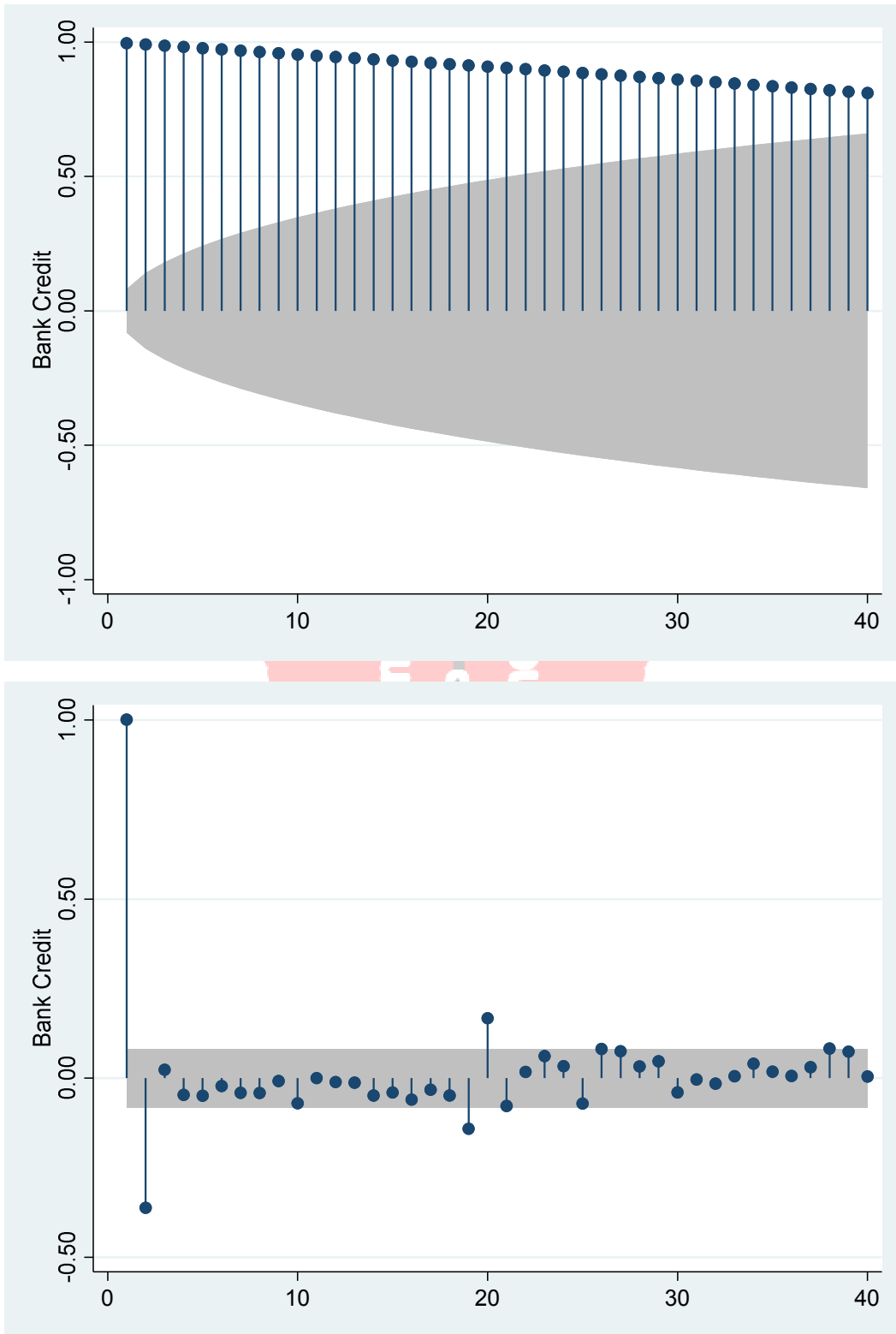
Figure 4

Logarithmic difference of bank credit over time.

Figure 5

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

Volatility in US bank credit series

Figure 6

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

Volatility in US bank credit series