# Macroeconomic Indicators of the U.S Credit Card Charge-off Rate

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The identification and monitoring of macroeconomic indicators of charge-off rates is essential in loan loss reserve allocation and more generally bank risk management. The empirical literature provides contradicting evidence on the significant macroeconomic indicators of charge-offs. The study shows that the trend in the credit-card charge-off rate shows variability over time coupled with extreme swings in the most recent periods. The paper then argues that failure to account for the inherent volatility in charge-off rates will lead to inconsistent guidance on its key indicators. The study demonstrates the usefulness of Autoregressive Conditional Heteroscedastic (ARCH) methods when accounting for the time-varying volatility of charge-offs. Once ARCH effects are controlled for the key macroeconomic indicators demonstrating a causal link to the charge-off rate are identified. The paper also demonstrates that there has been a fundamental change in the association of the key indicators with charge-off rates in recent times.

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## 1. Introduction

The movement in the rate of credit card charge-offs is one of the most commonly used measures of firm and industry performance. [1] Developing macroeconomic models of the charge-off rate and identifying key indicators of future realizations are also used to help determine the appropriate allocation of loan loss reserves in the firm's capital balance and for overall risk management objectives.

The paper applies autoregressive conditional heteroscedasticity (ARCH) econometric techniques to account for the time-varying volatility identified as a historical characteristic of the U.S credit card charge-off rate. A theoretically motivated econometric model of changes in the credit card charge-off rate that includes indicators of repayment ability is estimated with an ARCH specification. Once this volatility in charge-off is controlled for, measures of employment, asset values and the level of debt held are identified as the key indicators of the rate.

This work is important because the literature on the predictors of charge-off and delinquency in general, present contradicting evidence on the macroeconomic

[1] The charge-off rate measures the average percent of credit balances written-off by issuers, and indicates consumer conditions, banks' expected credit card revenues, and more broadly, funding risks.

variables best served as leading indicators. Measures of unemployment and income growth are the most commonly utilized. However the empirical support for these indicators are inconsistent. To date, the published literature on credit charge-offs has not recognized the instability in the variation of the rate. We argue that this inconsistency is due to the implicit volatility of the rate.

Given that there is inconsistency in the evidence provided in the literature the paper further tests whether significant changes can be identified in the relationship between the main indicators and charge-off rates over time. Time dummy variables are interacted with each indicator to facilitate this test. It is found that the magnitude of the association between employment and the charge-off rate was magnified before and during the period of the financial crisis.

The study provides a robust contribution to the literature by demonstrating that ARCH methods are a useful approach for accounting for the volatility in charge-off rates. More generally the study provides practical implications for banks and lending institutions given that throughout the year loan loss reserves are allocated to cover possible future charge-offs. Additional insight on useful macroeconomic indicators of expected charge-off rates and application of an ARCH approach as an additional estimation method will help organizations take a more informed approach in their reserve management.

**Some Background**

Total outstanding U.S credit card debt was approximately US$3,200 per credit card holder in 2010 (United States Census Bureau, 2012). The industry has experienced continued growth as purchase volume increased over the past decade from $1,241 billion in 2000 to $2,203 billion in 2011, representing an average annual growth rate of 3 percent in real dollar value. Figure i below presents the time trend of the number of cardholders and purchase volume.

Charge-offs are loan assets deemed uncollectible that are removed from the issuer's balance sheet. The credit card charge-off process first begins with the delinquent account on which there has been failure to receive the required payment by the due date. The card company seeks to collect on those delinquent accounts every thirty days, and since 1999, U.S law requires that accounts delinquent for 180 days must be charged-off.[2]

Figure ii shows the time trend in the U.S credit card charge-off rate and the unemployment rate. It can be observed that the charge-off rate generally reflects the trend of the unemployment rate, however the charge-off rate distinctly demonstrates more frequent episodes of volatility not reflected by the unemployment rate.

Generally, the charge-off rate demonstrates a cyclical trend over time. It is noteworthy however that after the first quarter of 2001 the charge-off rate begins to demonstrate more erratic behavior between cycles. For example, during the period of 1990 to 2000, the average credit card charge-off rate completed two cycles, while

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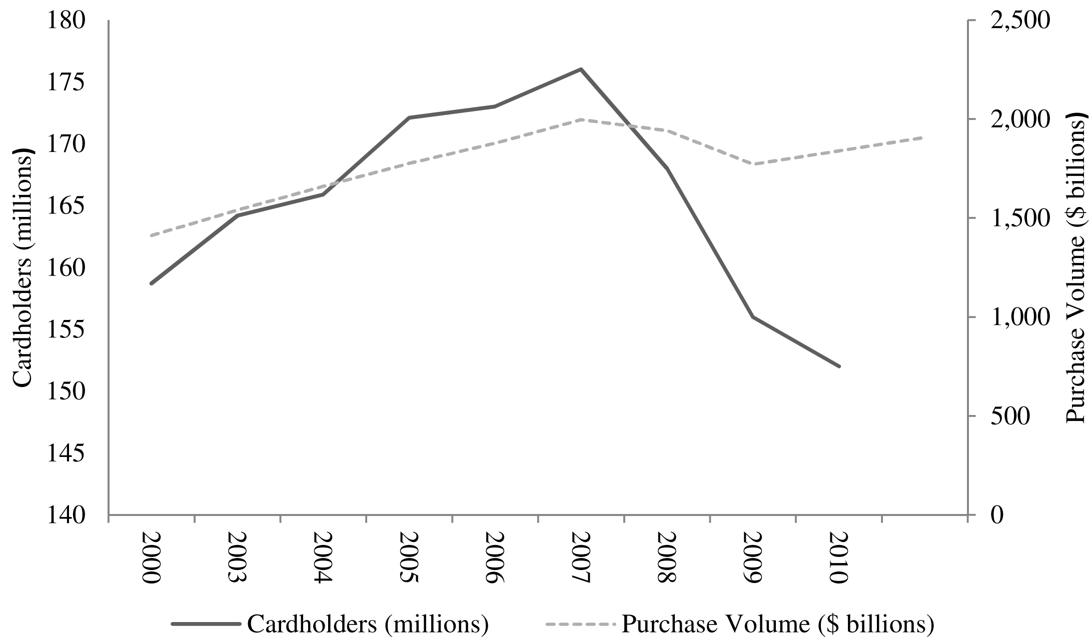
[2] See Furletti (2003) for detail on the charge-off accounting and reporting process.

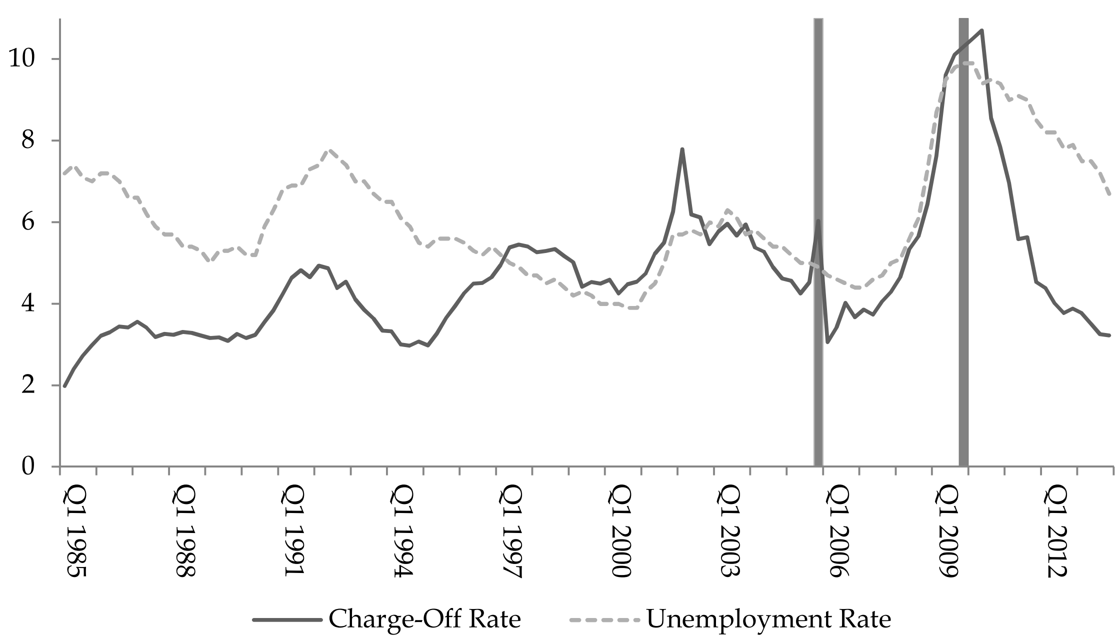
the unemployment rate demonstrated a steady downward trend. Laderman (1996) also comments on the unusual trend in charge-off during the period.

**Figure I Credit Card Usage over Time**




Source Census (2012a). Purchase volume in 2005 dollars.

**Figure II Quarterly Credit Card Charge-Off & Unemployment Rate (%)**



Moreover, there is a general increase in the average level of the charge-off rate, with ever increasing cyclical peaks over time. The beginning and reversion of the most noticeable spike coincides with the beginning of the Great Recession and also with significant regulatory changes within the industry. These changes are identified by the vertical bars in Figure ii. The first is the implementation of the Bankruptcy Abuse Prevention and Consumer Protection Act in 2005 that was aimed to protect creditors by tightening bankruptcy policy and credit eligibility criteria. The new law made it more difficult for consumers to file for bankruptcy thus holding them more accountable for repaying debt.[3]

Banks did not aggressively tighten credit standards until late 2007 amidst the exponential growth in charge-offs which peaked in 2009 reaching a rate of 10.12 percent (Office of the Comptroller of Currency, 2009). As a result, between 2006 and 2009, the return on assets of credit card banks fell from 3.34% to -3.01% (Board of Governors of the Federal Reserve System, 2013).

The second bar indicates the implementation of the Credit Card Accountability, Responsibility, and Disclosure Act of 2009. The legislation aimed to enhance the financial literacy of consumers, strengthen the oversight of the industry, and place more scrutiny on the actions of creditors. This act sought to protect the consumer by adding more transparency regarding the terms and conditions associated with credit cards, enhanced communication on interest rates and debt owed, and the elimination of fees deemed excessive.[4]

These observations show the importance of continued guidance on the empirical modeling of charge-off rates. This will aid in loan reserve management, provide more timely and effective strategic decisions using more effective models, and more generally should enhance the health of the credit services industry. The following section reviews the literature on the macroeconomic determinants of charge-off and further highlights the inconsistent evidence on the importance of the most frequently used macroeconomic indicators of credit charge-off and delinquency.

## 2. Prior Research

A credit charge-off represents the business outcome of debtor default. As such, related to work on macroeconomic indicators of the card charge-off rate is that on consumer bankruptcy and delinquency on debt. Total debt outstanding, which includes credit card and other forms of debt, such as medical and housing, has been found to exhibit the greatest predictive power for personal bankruptcy (Domowitz and Sartain, 2003). The effect of outstanding debt not only includes the level accumulated but also the bank specific repayment policies associated with card loans.

[3] In response to the forthcoming 2005 act there were 2 million personal bankruptcy filings in 2005 compared to only 600,000 the year after (White, 2007).

[4] Jiang and Dunn (2013) argue that regulatory measures of increasing monthly minimum required payments increased repayment rates in the industry. Agarwal et al. (2013) demonstrate that limits on credit card fees reduced average daily balances by almost 2.8%.

Subsequently, industry policy for debt repayment is an important determinant of delinquency (Dunn and Kim 1999; Stavins 2000). More specifically, the accounts most likely to charge-off are typically those associated with the level of debt relative to income.

Not only is total accumulated debt an important determinant of debtor default, but also the circumstances associated with debtors' environment, such as fluctuations in income and the value of assets owned. Negative shocks to both will reduce the likelihood of meeting consistent debt repayment. Fluctuations of these factors are often independent of debtor behavior, but are largely influenced by the macro-economy, such that personal financial changes will not affect the credit environment as much as the broader economic environment (Bernanke, 1993). In line with this view, empirical studies have modeled credit card delinquency and charge-off as being influenced by underlying factors such as aggregate income and unemployment (Dunn and Kim 1999; Gross and Souleles 2002; Agarwal and Chunlin 2003; Breeden and Thomas 2008; Sissoko 2011).

The association of these macroeconomic indicators with credit card charge-off and default is not without doubt. Anecdotally, historical data has demonstrated periods of a low unemployment and sound GDP growth, coupled with increasing credit card default (Ausubel, 1997). Based on empirical analysis, Dunn and Kimm (1999) and Grieb, Hegji, & Jones (2001) do not find any evidence that unemployment or income level significantly impact delinquency. However, subsequent research by Agarwal & Chunlin (2003) demonstrate the significance of the unemployment rate as a macro determinant of credit card delinquency and bankruptcy. Adding further discord to the empirical evidence of the association of unemployment rates and credit default, Lopes (2008) shows that the unemployment rate is negatively correlated with default.[5]

To account for the business cyclicality demonstrated in charge-off rates empirical models have been expanded to include additional macroeconomic indicators such as lending rates and those representing the housing sector (Jiong and Xu 2003; Rösch and Harald 2004). For example, volatility in the housing sector can indicate uncertainty in asset value and future debtor income. Declining home values can increase the debt burden, subsequently increasing the likelihood of a charge-off. On the contrary, a decrease in the home values may concern consumers to an extent that they are unwilling to undertake credit card spending (Incekara-Hafalir and Loewenstein, 2009). Still there is inconsistency in the relationship between macroeconomic housing sector variables and charge-offs. Gross and Souleles (2002) provide evidence that credit default is a function of housing prices, but demonstrated that default only explained a small portion of risk. Further empirical disagreement is

[5] Lopes (2008) interprets this result as an expectations effect. In which if high unemployment is expected, the consumer reduces borrowing and spending, and hence default.

created as Grieb et al. (2001) demonstrate that market interest rates are observed to be insignificant for predicting bankcard default.

The main indicators used in the empirical literature include the unemployment rate, GDP growth, debt costs, and changes in asset values. There is however incongruent empirical evidence on the association of these indicators with the health of the credit card industry. Further, it is shown in Figure ii that the credit card charge-off rate demonstrated periods of large increases and decreases over time, with no clear reversion to a long-run mean. This paper contributes to the body of work by explicitly accounting for this observed variability in charge-off rate over time while presenting further evidence in identifying key macroeconomic determinants of U.S credit card charge-off rates.

## 3. Volatility in the Charge-off Rate

Table 1 below demonstrates the heteroscedastic nature of U.S credit card charge-off rates. These is no consistent mean or variance over time.[6] The mean rate has increased while its variance is statistically different over the segmenting time periods.

**Table 1 Mean and Variance of U.S Commercial Banks' Charge-Off Rates**

| | 1985-1994 | 1995-2004 | 2005-2014 |
|---|---|---|---|
| Mean | 3.52 | 5.03* | 5.53 |
| Variance | 0.45 | 0.76* | 5.23* |

Two-sample t-tests were used to test the null of equal means. F-tests were used to test the null that the variance proportions are equal to one. * indicates significant difference from the previous period at the 5% level of significance.

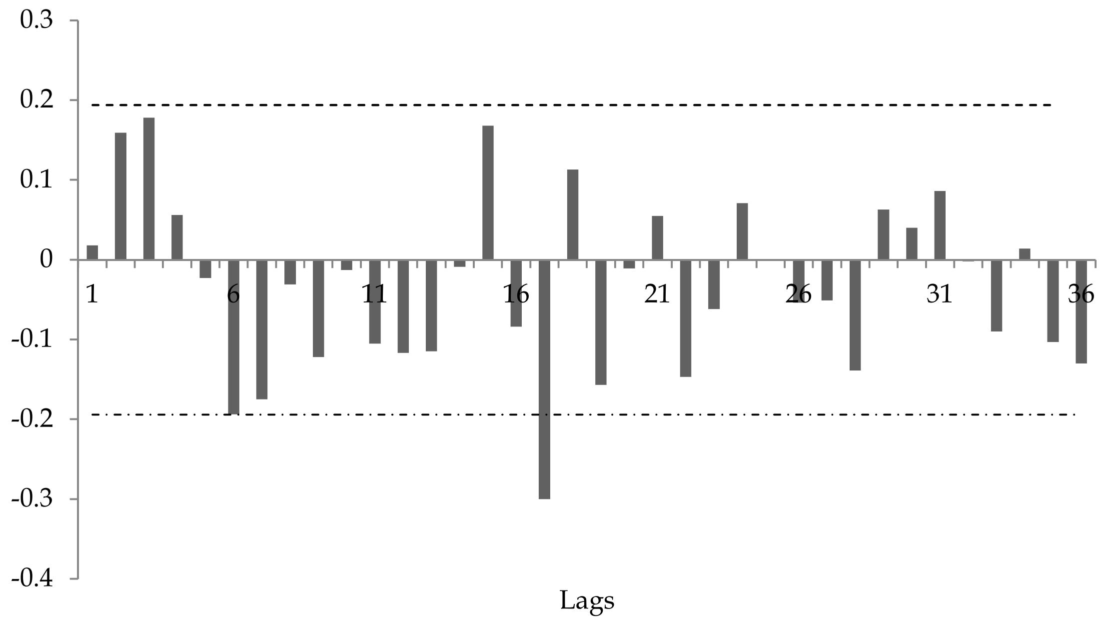
Historical volatility in the charge-off rate is also demonstrated by graphing partial autocorrelations of its squared variance and by calculating and graphing its one-year and four-year rolling standard deviation. The estimated partial autocorrelation function will indicate the extent to which past changes in the charge-off rate correlate with current changes, if so significant partial autocorrelations are expected, reflecting some predictability in the variance of the rate. Figure iii shows no significant correlation between any of the squared variances, demonstrating further its volatile nature.

The standard deviation between time-periods provides a measure of the variability of a time series. Following Engle (2004) figure iv compares the standard deviation of the credit charge-off rate for one year intervals with that over four-year intervals. If the time series is stable, four-year rolling standard deviations should show a consistent slope in its trend over time, compared to standard deviations over shorter periods. The level of the four-year rolling standard deviation is generally

[6] These three segmenting periods provide sufficient time to account for transitions through the business cycle.

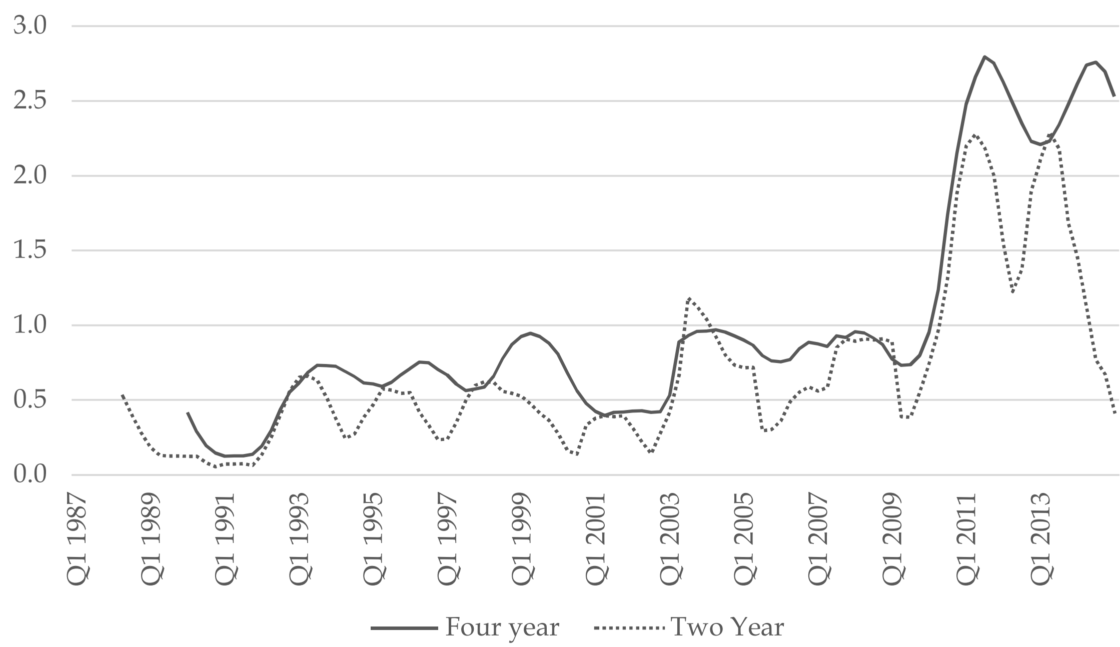
greater than the yearly value demonstrating further the changing variability of the charge-off rate.

**Figure III Partial Autocorrelation of the Change in Commercial Banks' Charge-off Rates**




Note: Significance is measured at the 10% level of significance.

**Figure IV Rolling Standard Deviation of Commercial Banks' Charge-Off Rate**



The trend of the credit card charge-off rate demonstrates an increasing mean plus varying levels of volatility over time. Do the commonly utilized macroeconomic indicators sufficiently account for these characteristics? Can an ARCH specification serve as alternative empirical framework? The following section provides the theoretical motivation used in specifying the econometric model.

## 3. Theoretical Motivation

The previous section demonstrated the changing volatility of credit-card charge-off over time. To assist with the identification of fundamental factors of bank charge-off rates we draw on partial equilibrium models of Bouvatier and Lepetit (2012) and Lawrance (1995). A representative bank i is specialized in loan type i and faces an exogenous business cycle. The bank's balance sheet at time t can be described as:

$$L_{i,t} - LLR_{i,t} + S_{i,t} = D_{i,t} + K_{i,t} \tag{1}$$

The left hand side of the equation represents assets comprised of loans, L, loan loss reserves, LLR, and safe assets, S. The liability side is given by debt, D, and equity, K. Bank profit can be described as:

$$\pi_{i,t} = r_{i,t}^{L} L_{i,t}\big(1 - J(y_t) - G(y_t)\big) + r_t^m S_{i,t} - r_t^m D_{i,t} - LLP_{i,t} - \delta L_{i,t} G(y_t) \tag{2}$$

Where $r_{i,t}^{L}$ is the interest rate on loans, $r_t^m$ is risk free interest rate, $y_t$ is economic output, $J(y_t)$ *and* $G(y_t)$ represent the fraction of non-performing loans and charge-off loans respectively. $LLP_{i,t}$ represents loan loss provisions and $\delta L_{i,t} G(y_t)$ represents unanticipated charge-offs. Bank profits are derived from interest on loans less that interest lost non non-performing loans and charge-offs. Banks pay interest on debt, and loan loss provisions and charged-off loan balances are charged against earnings.

$$J(y_t) = j_0 \left({}^{y_t}/_{y}\right)^{-w} z_t \tag{3}$$

$$G(y_t) = g_0 \left({}^{y_t}/_{y}\right)^{-\theta} v_t \tag{4}$$

Non-performing loans and charge-off is given as a function of the average income gap over the business cycle $j_0$ and $g_0$. The output gap is represented by ${}^{y_t}/_{y}$ , $w$ and $\theta$ represent elasticities, and $z_t$ and $v_t$ represents respective shocks. The output gap negatively impacts non-performing loans and charge-offs. Shocks imply that non-performing loans and charge-off are not fully explained by the output gap. Further profits are shared between equity, K, and dividend payments, Δ.

$$\pi_{i,t} = K_{i,t+1} - K_{i,t} + \Delta_{i,t} \tag{5}$$

Risk based capital requirements are always binding and is given as:

$$K_{i,t+1} \geq k_0 L_{i,t+1} \tag{6}$$

Where $k_0$ is the regulatory threshold. The model then defines the provisioning rules that are set by the banking regulator which are based on current level of non-performing loans. Loan loss provisions are then defined as:

$$LLP_{i,t} = h_0 L_{i,t} J(y_t) \tag{7}$$

Where $h_0$ is the average fraction of non-performing loans over the business cycle. This specification demonstrates a counter-cyclical evolution of loan loss provisions. Realized bad loans underestimate expected loan losses during economic expansion. It is assumed that bank i operates in a monopolistic market and each bank faces a specific demand for its type of loan given by.

$$L_{i,t} = \left(\frac{r_{i,t}^L}{r_t^L}\right)^{-\tau} \mu L_t \tag{8}$$

Here L is the aggregate demand for loans, r is the average interest rate on loans, τ is the elasticity with respect to interest rate on loans, and μ is the bank market share. The bank maximizes expected dividend payments over time such that the maximization problem becomes

$$\max E_t \sum_{j=0}^{\infty} \beta^{t+j} \Delta_{t+j} \tag{9}$$

Subject to equations (1), (3), (4), (6) and (8). Household borrowing can be explained using a two period life-cycle model in which aggregate debt is determined by the expected path of future wage earnings, income from assets, and real interest rates.

$$V(C_1, C_2) = U(C_1) + \frac{1}{1+\delta} E[U(C_2) \tag{10}$$

Where $C_i$ is consumption in period i, δ the rate of time preference, and U is the constant relative risk aversion utility function. Consumption is linked by uncertain income in the second time period. Income Y is governed by a stochastic process with probability q second period income is low $Y_L$ and a probability 1-q a high income level $Y_H$ in period 2. Consumers can borrow at interest rate r such that borrowing conditions in period one consumption can increase by $x_1$ units by giving up $x_2$ units in the second period. The maximization problem with respect to borrowing becomes:

$$V(x_1, x_2) = U(Y_1 - I_L + x_1) + \frac{1}{1+\delta}[qU(Y_L) + (1-q)U[(Y+I)_H + x_2)] \tag{11}$$

subject to the budget constraint $x_2 = (1+r)x_1$.

Here $x_1$represents the amount borrowed if positive or the amount lent if negative. It is assumed that a share of the loan may be used for investment I and is negative in the first period. Negative investment reflects the portion of income that is not consumed, and therefore provides no utility. The first order condition with respect to loan amount becomes:

$$MRS = \frac{(1+\delta)U'(Y_L - I_L + x_1)}{(1-q)U'[(Y+I)_H + x_2)} = 1 + r \tag{12}$$

It is possible to derive the probability of default such that

$$q = \frac{(1+r)U'[(Y+I)_H+x_2] - U'(Y_L - I_L + x_1)(1+\delta)}{(1+r)U'[(Y+I)_H+x_2]} \quad (13)$$

The study associated this probability of default with the likelihood or rate of charge off. It is a function of income and wealth and bank lending rates. Implicit in the model is the dependence of income on unemployment and trends in asset prices. We next describe the approach taken to account for the historical instability in charge-off rates.

## 4. Empirical Approach and Data

### Methodology

The study aims to demonstrate the significance of the time varying volatility of credit card charge-off rates when identifying macroeconomic indicators. Equation (14) is first estimated as a base model, and then is re-specified to include ARCH effects, equations (15) & (16). Further, recognizing the inconsistency in empirical evidence on the key macro indicators of the system-wide health of the credit card industry, a third model is estimated to identify possible changes in the association with these key indicators with charge-off rates over time. This specification is provided in equation (17).

The base model of the conditional mean of the change in U.S credit card charge-off rate is presented below.

$$\Delta Chargeoff_t = \beta_0 + \beta_1 \Delta Unem_t + \beta_2 Income\ Growth_t + \beta_3 \Delta Financial\ Obligation_t + \beta_4 \Delta Asset\ Value_t + \varepsilon_t \quad (14)$$

Charge-off$_t$ is the credit card charge-off rate at time period t; defined as net charge-offs divided by the average level of loans outstanding. Equation (1) specifies macroeconomic indicators of the charge-off rate most often used in the literature, each of which is a proxy the aggregate ability to repay on credit card debt (Agarwal and Chunlin 2003; Dunn and Kimm 1999; Grieb et al. 2001; Stavins 2000).

These measures include the unemployment rate, *Unem*. A higher unemployment rate is expected to result in higher rates of charge-off. *Income Growth* is the growth rate of real disposable income per capita, indicating that increased income per capita is expected to result in lower levels of credit card charge-off. *Financial obligation* captures household debt payments as a share of disposable income. Larger debt payments relative to income are expected to indicate larger rates of charge-off. *Asset Value* proxies wealth and expected future income, and is measured as the house prices as a share of disposable income per capita. It is expected that increases in asset values are associated with lower expected rates of credit card charge-off. All variables, excluding income growth, are included as first differences, such that the model specifies expected changes in charge-off rates as a function of changes in the macroeconomic environment. Equation (14) is first estimated using OLS methods.

The major issue the study identifies in the body of work on the macroeconomic indicators of the health of the credit card industry is the lack of consistent evidence on the significance of the association with charge-off or delinquency. Most of the empirical work in this area utilizes OLS techniques. However, OLS estimation of models such as equation (14) assume that the error variance is constant over time, or that this error variance is completely predicted by the realized values of the exogenous variables. The basic premise of this paper is to understand whether an empirical approach that relaxes this assumption may serve as a useful alternative when modeling the macroeconomic indicators of charge-off rates.

A separate set of regressions are subsequently estimated that include ARCH effects. The ARCH specification tests if the error variance of equation (15) is constant over time and whether this variability can be identified in a pre-determined manner. The model is presented below.

$$\Delta Chargeoff_t = \beta_0 + \beta_1 \Delta Unem_t + \beta_2 Income\ Growth_t + \beta_3 \Delta Financial\ Obligation_t + \beta_4 \Delta Asset\ Value_t + \varepsilon_t \qquad (15)$$

$$\sigma_t^2 = w + \alpha \varepsilon_{t-1}^2 \qquad (16)$$

The ARCH model represented by equations (15) and (16) allows both the conditional mean charge-off rate and its variance to vary over time (Engle 1982; Engel 2004). Equation (15) has the same structure as the base equation (14), but the model additionally describes the error variance of the charge-off rate, $\sigma_t^2$, as being conditioned on a constant, w, and on its past volatility. Here past volatility is measured as the lagged squared error of equation (15), $\varepsilon_{t-1}^2$. The coefficients estimates of equations (15) and (16) are obtained via maximum likelihood estimation.

ARCH methods are common when modeling financial time series. For example, Berkowitz & O'Brien (2002) and Gatev, Schuermann, & Strahan, (2009) both use ARCH methods in assessing bank performance. To date no study has been found utilizing this approach when assessing credit card charge-off or delinquency rates. Significant ARCH effects are expected, which will indicate that accounting for the conditional volatility in these measures will serve as a useful tool in charge-off management.

Figure ii demonstrated that anomalies in charge-off rates were observed between 2006 and 2009. To test whether the effect of the macroeconomic indicators change over time, a dummy variable identifying this period is used to create interaction terms with each variable. The model including time period interaction terms is given below.

$$\Delta Chargeoff_t = \beta_0 + \beta_1 \Delta Unem_t + \beta_2 Income\ Growth_t + \beta_3 \Delta Financial\ Obligation_t + \beta_4 \Delta Asset\ Value_t + (\beta_5 \Delta Unem_t + \beta_6 Income\ Growth_t + \beta_7 \Delta Financial\ Obligation_t + \beta_8 \Delta Asset\ Value_t) * time\ dummy + \varepsilon_t \qquad (17)$$

$$\sigma_t^2 = w + \alpha \varepsilon_{t-1}^2 \qquad (18)$$

Two dummy variables are created and are included separately in equation (17). The first D1 holds a value of 0 for periods prior to 2006 and a value 1 from 2006 to the end of the sample period. The second dummy variable D2 holds a value of 1 during the period 2006-2009, and 0 otherwise. Significance of the coefficients on the interaction terms will identify differences in the association of each macroeconomic indicator with charge-off subsequent to 2006, and between 2006 and 2009.

**Data**

Quarterly data between 1985Q1 and 2014Q4 is used in all models resulting in 115 observations. The source of each variable is given below:

- Charge-off rate (Federal Institutions Examinations Council, 2014)
- Unemployment rate (Bureau of Labor Statistics, 2014)
- Disposable personal income per capita (Bureau of Economic Analysis, 2014)
- Financial Obligation – Federal Reserve's financial obligation ratio which captures total household debt payments as a share of total disposable income (Federal Reserve, 2014)
- Asset Value – U.S house price index (Federal Housing Finance Agency, 2014)

For robustness measures separate alternative proxies of the independent variables are utilized, resulting in 4 estimates for each specification. These alternative measures are employment growth (Bureau of Labor Statistics, 2014), real GDP per capita growth (Bureau of Economic Analysis, 2014a), and the growth in S&P500 index (Federal Reserve, 2014b), which proxies for the unemployment rate, disposable income per capita growth, and the change in house price index respectively.

The U.S credit card charge-off rate has demonstrated periods of relative stability coupled with moments of extreme swings. The empirical procedure tests whether the variance of the error in a model of the charge-off rate is stable over time. If not, the ordinary least squares approach, that is most commonly used in the empirical literature, may not produce the most efficient parameter estimates of the causal effect of macroeconomic indicators. The following section tests this assumption providing summary statistics, a correlation matrix, and the estimation results.

**5. Results**

Table 2 below presents the mean and range of each variable over the sample period. The charge-off rate demonstrates a total spread of as much as 8.3 percentage points over the period, with a maximum one quarter change 2.93%. This variability exceeds that of any of the macroeconomic indicators. As expected the credit card charge-off rate is positively correlated with the unemployment rate and financial obligation, and inversely correlated with income growth and asset value. The magnitude of the correlation is largest with the unemployment rate.

The results of the OLS estimates of equation (1) and of the MLE estimates that include the possibility of conditional variation in the error variance are provided below. The usefulness of the ARCH model is assessed by testing whether significant ARCH effects are found after controlling for the independent variables.

**Table 2 Summary statistics and Correlation Matrix**

| | Δ Charge-off | Δ Unemployment Rate | Disposable Income Growth | Δ Financial Obligation Ratio | Δ House Price Index |
|---|---|---|---|---|---|
| Mean | 0.011 | -0.003 | 0.424 | -0.009 | 0.018 |
| Maximum | 2.150 | 1.400 | 2.187 | 0.410 | 0.197 |
| Minimum | -2.930 | -0.500 | -2.554 | -0.470 | -0.259 |
| Std. Dev. | 0.617 | 0.281 | 0.798 | 0.163 | 0.067 |
| **Correlation Matrix** | | | | | |
| Δ Charge-off | 1.000 | | | | |
| Δ Unemployment Rate | 0.474 | 1.000 | | | |
| Disposable Income Growth | -0.068 | -0.239 | 1.000 | | |
| Δ Financial Obligation Ratio | 0.052 | -0.027 | -0.562 | 1.000 | |
| Δ House Price Index | -0.086 | -0.132 | -0.401 | 0.602 | 1.000 |

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**Table 3 Empirical Results**

| | Base Equation (1) | | | | ARCH | | | |
|---|---|---|---|---|---|---|---|---|
| | Base | Employment Growth$_a$ | GDP per Capita Growth$_b$ | S&P Growth$_c$ | Base | Employment Growth$_a$ | GDP per Capita Growth$_b$ | S&P Growth$_c$ |
| Constant | -0.005 | 0.123* | 0.002 | -0.042 | 0.049 | 0.154*** | 0.061** | -0.033 |
| ΔUnemployment Rate$_a$ | 1.089*** | -0.452*** | 1.124*** | 1.187*** | 0.71*** | -0.417*** | 0.769*** | 0.697*** |
| Income Growth$_b$ | 0.093 | 0.078 | 0.083 | 0.100 | 0.060 | 0.109** | 0.047 | 0.127* |
| ΔFinancial Obligations | 0.694 | 0.743 | 0.512 | 0.566 | 0.993*** | 1.235*** | 0.868*** | 0.619** |
| ΔAsset Value$_c$ | -0.749 | -1.106 | -0.996 | 0.009 | -2.534*** | -2.774*** | -2.557*** | 0.006 |
| Variance Equation | | | | | | | | |
| Constant | | | | | 0.046*** | 0.063*** | 0.041*** | 0.113*** |
| Sqaured Lagged Residual | | | | | 1.524*** | 1.299*** | 1.771*** | 0.846*** |
| R-squared | 0.244 | 0.108 | 0.239 | 0.249 | 0.201 | 0.084 | 0.204 | 0.198 |
| Durbin-Watson statistic | 2.417 | 2.178 | 2.416 | 2.496 | 2.271 | 2.120 | 2.279 | 2.311 |

Notes: This table presents the OLS estimates of equation (1) and MLE estimates of equations (2) and (3) over three sample periods; The p-value of the null hypothesis that the parameter estimates = 0 are reported in parenthesis.*** significant at the 1% level, **significant at the 5% level, * significant at the 10% level. The Durbin Watson statistics are used to test the null of no serial correlation of the error which was not rejected for each estimate. Column headings and subscripts $_{a,b,c}$ indicate the alternate variable used in the respective specification. Equations using past lagged values of independent variables provided insignificant parameter estimates.

This implies that the variance of the disturbance term of the base model is not constant but is determined by past variation. A t-test is used to assess significance of this ARCH effect against the null hypothesis $\alpha = 0$.

There is evidence of significant ARCH effects in the charge-off rate. The coefficient on the squared residual term is positive and significant at the 1% level. When controlling for ARCH effects measures of unemployment, financial obligation, and asset values have a significant causal effect on the charge-off rate.

The direction of association of each indicator is as expected. The coefficient on the unemployment rate is positive across all estimates and negative when employment growth is used as a proxy. These results indicate that measures of labor market conditions are an important indicator of credit card charge-off. As the charge-off rate will deteriorate with increases in unemployment.

The aggregate level of financial obligations also shows a positive and significant coefficient across specifications, indicating that increases in debt payments relative to disposable income will indicate increases in charge-off rates. The charge-off rate will be adversely impacted as debt obligations mount. The ARCH estimates also show that asset value is a significant indicator of the charge-off rate, as the coefficient on both measures are negative and significant at the 99% confidence level. Measures of income growth shows weak association with charge-offs, only in one specification does it show significance at the 95% level of confidence.[7] Generally the estimated model accurately identifies impact of income and asset value conditions on commercial banks charge-off.

The trend in charge off rates showed rapid growth between 2006 and 2009 and a possible reversion to the long run mean by 2014. Dummy variables were created for these sample periods and interacted with the independent variables. The coefficient on these interaction terms can then be used to assess whether there were changes in the relationship between the key macroeconomic indicators and the charge-off rate. Tables 4 and 5 present the results.

ARCH effects remain significant after including dummy variables accounting for the periods that demonstrate the largest volatility in the charge-off rate. The coefficient estimates support the main results provided previously. Changes in employment, the extent of financial obligations, and measures of asset value are strong predictive indicators of changes in the charge-off rate. Charge-off rates will remain low with improvement in the macroeconomy based on employment and asset value. However increases in total debt burden on average will generally increase bank charge-offs.

Measures of employment and asset values demonstrate significant changes in their impact on the charge-off rate for both the 2006-2009 and the 2006-2014 time periods. The coefficient on the interaction term when using the unemployment rate

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[7] Additional macroeconomic variables representing the cost of credit and the personal savings rate were considered and included in other specifications. These however are endogenous to charge-offs and their coefficient estimates were insignificant.

was negative, while that when using employment growth was positive. These results imply that during these periods the relationship of employment with charge-off rates were magnified. Based on the base equation labor market conditions indicate a multiplicative impact on charge-off. During the 2006 to 2014 period each one percent change would contribute on average a 1.18% increase to bank charge-off rates.

**Table 4 ARCH Estimates of Equation (4) and (5) with Time Period (2006-2014) Interactions**

| | Base | Employment Growth$_a$ | GDP per Capita Growth$_b$ | S&P Growth$_c$ |
|---|---|---|---|---|
| Constant | 0.083** | 0.088** | 0.095** | -0.020 |
| ΔUnemployment Rate$_a$ | 0.759*** | -0.264*** | 0.849*** | 0.633** |
| Income Growth$_b$ | 0.028 | 0.088* | 0.082 | 0.124 |
| ΔFinancial Obligations | 0.872*** | 0.537** | 0.931*** | 0.654* |
| ΔAsset Value$_c$ | -2.91*** | 1.808*** | -3.447*** | 0.000 |
| ΔUnemployment Rate$_a$*D1 | 0.425*** | -0.76*** | -0.064 | 0.857*** |
| Income Growth$_b$*D1 | 0.053 | 0.058 | -0.57*** | 0.125 |
| ΔFinancial Obligations*D1 | -0.103 | 0.144 | -0.547 | 0.047 |
| ΔAsset Value$_c$*D1 | 1.623*** | -3.549* | 2.159* | 0.031** |
| Variance Equation | | | | |
| Constant | 0.041** | 0.029* | 0.038*** | 0.11*** |
| Sq Res (-1) | 1.759*** | 0.981*** | 1.376*** | 0.706*** |
| R-squared | 0.223 | 0.133 | 0.243 | 0.245 |
| DW | 2.342 | 2.148 | 2.241 | 2.427 |

Notes: MLE estimates of equations (4) and (5) over three sample periods; The p-value of the null hypothesis that the parameter estimates = 0 are reported in parenthesis.*** significant at the 1% level, **significant at the 5% level, * significant at the 10% level. The Durbin Watson statistics are used to test the null of no serial correlation of the error which was not rejected for each estimate. Column headings and subscripts $_{a,b,c}$ indicate the alternate variable used in the respective specification. D1 is a dummy variable with a value of one for time periods after 2006. Equations using past lagged values of independent variables provided insignificant parameter estimates.

The coefficient on the interaction terms between the time period dummy variables and measures of financial obligation and asset value did not provide strong consistent evidence on differences in the magnitude of their association with changes in charge-off rates. Differences in the size of the relationship between changes in financial obligation and changes in charge-off were obtained when comparing the 2006-2009 period to all other time periods, but not when comparing the coefficient estimates for 2006-2014 to all periods prior. Similarly, significant differences in the size of the effect of changes in asset values on changes in charge-off rates were found when comparing the 2006-2014 time period to all prior periods, but not when comparing the coefficient estimates for the time period 2006-2009.

**Table 5 ARCH Estimates of Equation (4) and (5) with Time Period (2006-2009) Interactions**

| | Base | Employment Growth$_a$ | GDP per Capita Growth$_b$ | S&P Growth$_c$ |
|---|---|---|---|---|
| Constant | 0.065** | 0.13*** | 0.069* | -0.063 |
| ΔUnemployment Rate$_a$ | 0.810*** | -0.233*** | 0.84*** | 0.623*** |
| Income Growth$_b$ | 0.039 | 0.13*** | 0.061 | 0.163** |
| ΔFinancial Obligations | 0.969*** | 1.717*** | 0.975*** | 0.897*** |
| ΔAsset Value$_c$ | -2.707*** | -3.452*** | -2.895*** | 0.004 |
| ΔUnemployment Rate$_a$*D1 | 0.384* | -0.282*** | 0.345 | 0.787** |
| Income Growth$_b$*D1 | 0.147** | 0.052 | 0.010 | 0.048 |
| ΔFinancial Obligations*D1 | -1.437** | -1.021* | -1.994*** | -1.142 |
| ΔAsset Value$_c$*D1 | 3.593 | 1.129 | 2.536** | 0.013 |
| Variance Equation | | | | |
| Constant | 0.036*** | 0.043** | 0.036*** | 0.104*** |
| Sq Res (-1) | 1.671*** | 1.589*** | 1.75*** | 0.719*** |
| R-squared | 0.205 | 0.085 | 0.222 | 0.261 |
| DW | 2.339 | 2.139 | 2.316 | 2.504 |

Notes: MLE estimates of equations (4) and (5) over three sample periods; The p-value of the null hypothesis that the parameter estimates = 0 are reported in parenthesis.*** significant at the 1% level, **significant at the 5% level, * significant at the 10% level. The Durbin Watson statistics are used to test the null of no serial correlation of the error which was not rejected for each estimate. Column headings and subscripts $_{a,b,c}$ indicate the alternate variable used in the respective specification. D2 is a dummy variable with a value of one for time periods 2006 and 2009. Equations using past lagged values of independent variables provided insignificant parameter estimates.

The study demonstrates that credit card charge-off rates has historically demonstrated instability and argues that failure to account for this implicit variability is possible reason for the inconsistency provided in the empirical literature on its key macroeconomic indicators. The main contribution of this paper is the demonstration that significant ARCH effects are found in the credit card charge-off rate. These results provide support for the need to account for the heteroscedastic nature credit delinquency and default. Empirical models that do not account for these effects might provide inefficient parameter estimates of the association with the macro-economy. The study further identifies key indicators useful for credit card charge-off rates. These include measures of the employment landscape, the extent of financial obligations, and movement is asset values.

## 6. Conclusion

Credit card products are a substantial portion of the financial services market in the U.S.. Credit card companies dedicate significant resources toward the development of statistical models in an effort to predict potential losses in loan portfolios. Analysts make adjustments to their predictive models based on economic trends or attempt to calibrate existing account-level models using macroeconomic data. In so doing the initial and most fundamental task is to understand the relationship between the macro-economy and industry performance (Mester, 1997).

The paper highlights the ARCH model as an additional econometric approach to consider when identifying relationships between macroeconomic variables and credit card charge-offs. ARCH methods can be used to relax the empirical assumptions present in the OLS methods by estimating a system of equations that explicitly account for the unexplained changing volatility in the credit charge-off rate. ARCH methods will improve empirical efficiency as the parameter estimates obtained using different sample periods will be more closely aligned with the true value of the causal impact.

The paper further finds that the key macroeconomic indicators of the credit card charge-off rate in the U.S are changes in measures of employment, financial obligation relative to income, and asset values relative to income. Each demonstrate a significant causal effect on the credit card charge-off rate. Further it is found that even though the income growth and the rate of charge-off have some correlation, the empirical results show no evidence of a significant causal effect of aggregate income growth once the other indicators are included.

As credit issuers and regulatory bodies continue to use macroeconomic indicators to set expectations specific on firm and industry health, specific indicators along with the utilization of an ARCH specification is recommended for the modeling of credit card risk. This is done for the continued effort of moving away from the often used discretion in loan loss reserve management (Beatty et al. 2002; Liu and Ryan 2006; Laeven amd Majnoni 2003). Sound empirical approaches to the identification of macroeconomic indicators of charge-off rates will assist financial institutions to better anticipate future credit losses. Future research should aim to better understand why the association between employment and charge-off rates fundamentally shifted during the period of 2006-2014.

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