2018-01-01

Credit Union Loan Rate Determinants during the Post-2009 Expansion

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Dedication

This thesis is dedicated to my family who has always encouraged me to keep going forward, and to my beloved husband whose love, support, and enthusiasm for life have helped me stand tall, even during stressful moments.

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by

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THESIS

Presented to the Faculty of the Graduate School of

The University of Texas at El Paso

in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE

Department of Economics and Finance

THE UNIVERSITY OF TEXAS AT EL PASO

December 2018

Acknowledgments

I would first like to thank my thesis advisor Dr. Thomas Fullerton who was always willing to assist and guide me throughout the whole process of my thesis completion.

Also, I would like to thank Adam Walke, an invaluable friend whose unconditional help and advice helped propel me to the finish line.

Abstract

Credit union deposits have grown substantially in recent years. Given that, an increasing number of consumers and small businesses are joining credit unions as members. This study investigates the determinants of credit union loan rates during a period of economic expansion in the United States using fourth quarter 2015 data for 5,942 credit unions. Five different interest rate categories are analyzed using nine potential loan rate determinants. The results indicate that credit union loan rates tend to be lower when economies of scale exist, while high ratios for net charge-offs and operating costs cause interest rates to increase. Opposite of what is expected, unemployment rates positively impact credit unions loan rates. A possible explanation for this outcome is that elevated loan delinquency rates accompany a weak labor market. Greater default risks then result in higher interest rates.

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Chapter 1: Introduction

Credit unions are not for profit financial institutions administrated by a committee nominated by each credit union member through a democratic election. Each member holds one vote to elect their representatives (Tokle et al., 2015; Anderson and Liu, 2013). Members must share a common bond to participate in this cooperative, also identified as credit union's "field of membership" (FOM). Frequently, members share workplace or occupation, place of residence (i.e., the same neighborhood, community, or rural district), or they are affiliated with the same organization. Because some associational credit unions admit anyone as a member, the number of potential members is limited only by total population (Anderson and Liu, 2013). According to the Credit Union Nacional Association, credit union membership in the United States expanded fairly rapidly after 2009 and surpassed 107 million people by 2016 (CUNA, 2016).

Credit unions are becoming increasingly important for consumer and small business loans (Wilcox, 2011). Credit unions are also an important source of fixed-rate first mortgage loans (CUNA, 2017). Because of the role that these organizations play in the financial sector at large, it is useful to understand how the loan rates charged behave at different stages in the business cycle. As noted by Smith (2012), credit union loan volumes tend to exhibit more stability than bank loans when economic fluctuations occur. One recent study examines interest rate patterns within the sector at the trough of the most recent recession (Tokle et al., 2015). This study analyzes loan rates during a period in which the national economy is expanding.

Fourth quarter 2015 data from all 5,942 credit unions in the United States form the heart of the sample information employed for this study. A brief review of the literature on credit union loan interest rates is provided in section 2. The theoretical model and methodology are explained in section 3, and the sample data are described in section 4. Empirical results are discussed in section 5 with concluding remarks in section 6.

Chapter 2: Literature Review

In 1982, the National Credit Union Administration (NCUA) expanded the concept of "field of membership" (FOM) and admitted multimember groups in credit unions. After policymakers amplified the definition of common bonds, credit unions were allowed to hold members joined by multi bonds and not only by a single bond; credit unions became more similar to commercial banks because anyone was now allowed to become a member. Currently, credit unions accept checking and savings account deposits and make a variety of loans to large numbers of customers. This similitude in offered services permits credit unions to compete closely with commercial banks (Chatterji et al., 2015). Following the recessions of 2001 and 2008, commercial bank loan growth was negative, while credit union growth was positive during both periods (Smith, 2012). Credit unions are becoming increasingly important in financial markets and provide numerous benefits to local economies and credit union members.

Several studies have examined the interest rates that credit unions charge on loans and pay on deposits. Kohers and Mullins (1988) find that larger credit unions offer lower loan rates and higher saving rates than smaller institutions in the sector. Tokle and Tokle (2000) report survey evidence that indicates that greater competition leads credit unions to offer a higher certificate of deposit rates to customers. Tokle and Tokle (2002) corroborate the hypothesis that reduced credit union competition is associated with higher loan rates. Tokle and Tokle (2008) analyze used vehicles loan rates and obtain similar outcomes. In general, there is an inverse relationship between credit union asset magnitudes and loan rates charged. Similarly, increases in the number of credit unions relative to state populations are also lead to reduced loan rates. Economies of scale have been found to work in favor of consumers. Loan rates are generally found to be negatively correlated with larger deposit bases (Feinberg and Rahman, 2006; Wilcox, 2006; Tokle and Tokle, 2008; Wheelock and Wilson, 2011).

The number of financial institutions, either banks or credit unions, in a market can also affect loan and deposit rates. As noted above, Tokle and Tokle (2000) find that local markets with

higher percentages of credit union membership encourage greater price competition among institutions. That competition stimulates banks to pay higher interest rates on certificates of deposit (CD) and to charge a lower rate on loans (Tokle and Tokle, 2008). Feinberg (2002) finds evidence of an inverse relationship between greater credit union competition and unsecured loan rates charged by those institutions. This conclusion is confirmed by Feinberg and Rahman (2006) using a combined sample of banks and credit unions. That study also documents inverse correlations between credit union competition and the interest rates charged on unsecured loans and new vehicle loans.

Credit unions respond to business cycle fluctuations differently than commercial banks. Evidence shows that deposits on credit unions expand in the presence of uncertainty in the financial market, suggesting that credit union members consider credit unions a safe place during an economic crisis (Rauterkus and Ramamonjiarivelo, 2010). Smith and Woodbury (2010) examine the financial stability of banks and credit unions during three different business cycles from 1986 to mid-2009. The results obtained also indicate that credit unions are much less sensitive to business cycle downturns than commercial banks. Although credit unions and banks deposits follow the business cycle, credit union deposits show smoother peaks and restricted bottoms. Changes in the regulatory landscape for credit unions have also been found to affect the collective behavior of how these institutions respond to recessions and expansions in recent years (Goenner, 2016); Goddard et al., 2016; Mckee and Kagan, 2016).

It is easy to see that loan rates charged by credit unions may be affected by the stages of business cycles. Tokle et al. (2015) quantify the impacts of different variables on credit union loan rates near the trough of the Great Recession period in the United States. The data employed are for 6,700 U.S. credit unions during the fourth quarter of 2009, roughly the nadir of that downturn. Multiple variables are found to affect the rates charged on five different loan categories. Coefficient magnitudes are also found to vary noticeably across loan categories. Risk-based pricing is found to increase aggregate lending while enabling credit unions to charge lower overall

loan rates. Results further suggest the presence of economies of scale and confirm that greater credit union competition leads to lower credit union loan rates.

Data for this study are collected for the fourth quarter of 2015. At that juncture, the national economy had grown for approximately 26 consecutive quarters. The model developed below is used to examine how the variables employed affect credit union loan rates during an expansionary phase of the business cycle.

Chapter 3: Theoretical Model

The starting point for the model is credit union loan demand and credit union loan supply. Equation (1) specifies credit union loan demand (LD) as a function of the interest rate (INT) charged on that category of loans and the average unemployment rate (UR) for the region in which the institution operates. LD is hypothesized to be inversely correlated with each of the independent variables. Table 1 summarizes the variable descriptions and units of measure for each of the variables employed in Equation (1) and Equation (2).

$$LD = a_0 - a_1INT - a_2UR \tag{1}$$

Equation (2) specifies credit union loan supply as a function of nine variables. Eight of those regressors are continuous and include loan interest rates (INT); credit union membership to state population ratio (STM); credit union size (SIZE); total loan charge-offs to average total loans ratio during previous 12months (NCO); operating expense to average assets ratio (OXA); net worth to total assets ratio (NW); fees to total assets ratio (FEES); and costs of funds to average assets ratio (CF). The remaining explanatory variable RBL, a binary variable that indicates whether a credit union has adopted risk-based lending practices. Increases in INT, STM, SIZE, and NW are all expected to increase LS (Edelberg, 2006). LS is conjectured to be negatively correlated with NCO, OXA, and CF. The relationship between LS and both FEES and RBL may be positive or negative (Tokle and Tokle, 2008; Tokle et al., 2015). Table (2) summarizes all of the hypothesized signs for the parameters in Equations (1) and (2).

$$LS = b_0 + b_1INT + b_2STM + b_3SIZE - b_4NCO - b_5OXA + b_6NW \pm b_7FEES \pm b_8RBL - b_9CF \tag{2}$$

Table 1: Variable descriptions and units of measure.

Variable	Description
LD	Credit Union Loan Demand, US$
LS	Credit Union Loan Supply, US$
INT	Credit Union Interest Rate for Generic Loan Category, Percent
INTNV	Credit Union Interest Rate Charged for New Vehicle Loans, Percent
INTUV	Credit Union Interest Rate Charged for Used Vehicle Loans, Percent
INTMORT	Credit Union Interest Rate Charged for Mortgage Loans, Percent
INTUCC	Credit Union Interest Rate Charged for Unsecured Credit Card Loans, Percent
INTOU	Credit Union Interest Rate Charged for Unsecured Personal Loans, Percent
UR	Unemployment Rate, Percent
STM	Credit Union Membership to State Population Ratio, CUM / POP
SIZE	Credit Union Size Measured as Total Assets, US$, Thousands
NCO	Net Charge-Offs Ratio, 12 Month Total Loan Charge-Offs / Average Total Loans
OXA	Operating Expense to Assets Ratio, 12 Month Operating Expenses / Avg. Total Assets
NW	Net Worth Ratio, Credit Union Capital less Anticipated Charge Offs / Total Assets
FEES	Fees to Assets Ratio, Fee Revenues / Total Credit Union Assets
RBL	Binary Variable for Risk-Based Lending (RBL = 1 if used; RBL = 0 if no RBL occurs)
CF	Cost of Funds to Average Assets Ratio, Cost of Funds / Average Total Assets

Table 2: Expected coefficient signs for equation (1) and (2) explanatory variables.

Equation (1) Explanatory Variable	**Hypothesized Sign**
INT	(-)
UR	(-)
Equation (2) Explanatory Variable	**Hypothesized Sign**
INT	(+)
STM	(+)
SIZE	(+)
NCO	(-)
OXA	(-)
NW	(+)
FEES	(+ or -)
RBL	(+ or -)
CF	(-)

To develop an expression for the loan rates, Equations 1 and 2 are set equal to each other. Equation 3 is then solved for INT. The intermediate steps are shown below. For simplicity, the original coefficients from Equations 1 and 2 are substituted with reduced from coefficients in Equation 4.

$LD = LS$

$$a_0 - a_1 INT - a_2 UR = b_0 + b_1 INT + b_2 STM + b_3 SIZE - b_4 NCO - b_5 OXA + b_6 NW \pm b_7 FEES \pm b_8 RBL - b_9 CF \quad (3)$$

$$a_0 - b_0 - a_2 UR - b_2 STM - b_3 SIZE + b_4 NCO + b_5 OXA - b_6 NW \pm b_7 FEES \pm b_8 RBL + b_9 CF = INT\,(a_1 + b_1)$$

$$INT = ((a_0 - b_0) / a_1 + b_1)) - (a_2 / (a_1 + b_1))\, UR - (b_2 / (a_1 + b_1))\, STM - (b_3 / (a_1 + b_1))\, SIZE + (b_4 / (a_1 + b_1))\, NCO + (b_5 / a_1 + b_1)\, OXA - (b_6 / (a_1 + b_1))\, NW \pm (b_7 / (a_1 + b_1))\, FEES \pm (b_8 / (a_1 + b_1)\, RBL + (b_9 / (a_1 + b_1))\, CF$$

$$INT_i = c_0 - c_1 UR_i - c_2 STM_i - c_3 SIZE_i + c_4 NCO_i + c_5 OXA_i - c_6 NW_i \pm c_7 FEES_i \pm c_8 RBL_i + c_9 CF_i + e_i \quad (4)$$

In Equation 4, the subscript i is an integer designation for each credit union contained in the sample. Also, e is a stochastic disturbance term. This is the version of the model that is employed for parameter estimation.

Credit loan rates (INT) also affects the number of credit loans offered. Contrary to the effect of interest rates on credit loan demand, credit loan rates are directly correlated with credit loan supply. Higher loan rates allow a greater number of loans to be approved because loans with higher risk premia and servicing costs can be profitably issued (Edelberg, 2006).

A low unemployment rate (UR) usually reflects healthy economic conditions in the counties in which the credit unions headquarters are located. Under those circumstances, credit demand tends to increase. Greater loan demand will generally lead to higher loan rates. Following

this reasoning, it is possible to say that regional unemployment rates (UR) and credit union loan rates (INT) will be inversely correlated (Kiser, 2004).

The number of credit unions (STM) in a city may influence the credit loan supply. A large number of credit unions should increase the volume of loans offered relative to what occurs with only a small number of credit unions. A market with a greater number of competitors also leads to better prices for customers. Tokle and Tokle (2000) provide evidence that banks set higher interest rates on certificates of deposits in markets where thrift competition is more pronounced. Along those same lines, Feinberg (2001) reports that banks charge lower rates on new vehicle bank loans in local markets with more credit union competition. Feinberg and Rahman (2006) find similar results using a combined sample of banks and credit unions. In addition, Tokle and Tokle (2008) find that more credit union competition leads to lower credit union loan rates. Thus, the expected relationship between interest loan rate (INT) and number of credit unions (STM) in the model is negative.

The size of each credit union (SIZE) might also impact credit loan supply. Large credit unions may have economies of scales that allow offering a greater amount of loans for a lower cost than small credit unions. Wilcox (2006) reviews data that illustrate how larger credit unions enjoy lower non-interest costs that translate into lower loan rates, among other things. Other studies that find similar results include Kohers and Mullins (1988), Tokle and Tokle (2002), Feinberg and Rahman (2006), and Wheelock and Wilson (2011). The hypothesized sign for the coefficient estimated for SIZE in Equation 4 is, thus, negative.

The net loan charge-offs to average loans ratio (NCO) is calculated as total lending charged off during the previous 12 month period divided by total loans. Higher charge-offs are correlated with higher costs which lead to a reduced supply of credit and higher interest loan rates. The expected sign for net loan charge off in the model is, thus, negative (Tokle and Tokle, 2002; 2008).

Like any other company, operating expenses influence how many products a firm can offer. For credit unions, higher operating expenses (OXA) will restrict the number of loans that can be approved as increase interest rates charged on those loans that are approved. Peterson and

Ginsberg (1976) provide evidence on how loan processing and service costs influence commercial bank credit provision.

The net worth ratio (NW) is calculated as capital minus anticipated charge-offs with that result divided by total assets. Higher NW ratios are hypothesized to lower loan rates because credit unions can use this source of funds without paying interest (Tokle and Tokle, 2008). A similar study finds that small companies and companies with no bond ratings tend to be charged higher interest rates by banks that have low levels of equity capital (Hubbard et al., 2002). Credit unions with higher net worth ratios should, therefore, provide lower cost credit to borrowers.

As pointed out in Tokle and Tokle (2008), the effect of the fees to assets ratio (FEES) on loan rates is ambiguous. As fee revenues grow, that might permit credit unions to set lower loan rates. However, greater dependence on fee revenues might reflect cash flow pressures. If that is the case, loan rates will be positively correlated with FEES.

Credit unions that offer risk-based loans (RBL) tend to supply a larger quantity of loans than credit unions that do not use this tiered pricing approach (Walke et al., 2018). RBL allows credit unions to approve loans to a variety of customers that would not otherwise qualify for standard loans. Offering risk-based loans does not mean that higher overall interest rates will be charged by credit unions since there will also be clients with good credit scores that qualify for lower interest rate loans (Tokle et al., 2015).

The cost of funds to average assets ratio (CF) is expected to have an inverse relationship with the supply of loans and a positive effect on loan rates. The reasoning is that higher costs reduce lending volumes and force credit unions to raise rates on those loans that do get approved. Studies such as Feinberg (2002) and Feinberg and Rahman (2006) confirm positive correlations between CF ratios and the interest rates charged on different categories of loans. Table 3 summarizes the expected parameter signs for each of the right-hand side variables appearing in the reduced form expression shown in Equation (4).

Table 3: Expected coefficient signs for equation (4) explanatory variables.

Explanatory Variable	**Hypothesized Sign**
UR	(-)
STM	(-)
SIZE	(-)
NCO	(+)
OXA	(+)
NW	(-)
FEES	(+ or -)
RBL	(+ or -)
CF	(+)

Chapter 4: Sample Data

Summary statistics for the fourth quarter 2015 sample data are reported in Table 4. Credit union interest rates charged for unsecured credit card loans (INTUCC) and credit union interest rates charged for unsecured personal loans (INTOU) are higher, on average, than the interest rates charged for new vehicle loans (INTNV), used vehicle loans (INTUV), and mortgage loans (INTMORT). INTUCC and INTOU range from 1.0 to 25 percent with double-digit averages of 10.0 and 11.0 percent, respectively. The range of the other three interest rates is 1.0 to 18.0 percent, with averages of 3.8 percent for INTNV, 5.1 percent for INTUV, and 4.5 percent for INTMORT. The three-vehicle loan and mortgage rates are (positively) right skewed, while more risky loan rates are distributed in fairly symmetric manners. The three less risky loan rates are leptokurtic, while the unsecured interest rates are fairly Gaussian.

Table 4: Summary statistics.

Variable	**Mean**	**Med.**	**Max.**	**Min.**	**Std. Dev.**	**Skew.**	**Kurt.**	**Obs.**
INTNV	3.8	3.4	16.2	1.0	1.6	1.7	7.6	5,682
INTUV	5.1	4.6	18.0	1.1	2.4	1.5	6.7	5,750
INTMORT	4.5	4.3	12.5	1.5	1.1	1.8	8.9	3,950
INTUCC	10.5	10.0	18.0	1.0	2.1	0.14	4.0	3,528
INTOU	11.1	11.0	25.0	2.0	2.8	0.4	3.3	5,842
UR	5.3	5.2	24.0	1.9	1.3	1.8	18.5	5,942
STM	33.3	28.7	124.0	0.0	27.7	0.6	2.2	5,942
SIZE	$204.4	$28.0	$73,279	$0.0	$1,227	40.2	2,208	5,942
NCO	0.6	0.3	121.8	-22.5	2.7	29.2	1,162.6	5,940
OXA	3.6	3.5	150.4	0.10	2.5	35.4	2,033.8	5,942
NW	13.2	11.5	66.3	0.8	6.0	2.5	12.5	5,942
FEES	0.7	0.53	24.0	-0.1	0.7	7.3	190.3	5,942
RBL	0.7	1.0	1.0	0.0	0.5	-0.9	1.7	5,942
CF	0.3	0.3	5.3	0.0	0.3	3.9	42.0	5,942

Notes:

Data are from NCUA and CUNA.
Sample data are for 2015Q4.
SIZE is measured in US$ millions for expository ease.
Only the variable SIZE is logarithmically transformed. Dependent variables are not transformed because of the sample size. According to the law of large numbers and the central limit theorem, the use of OLS remains valid when samples are large (Li et al., 2012).

During the fourth quarter of 2015, labor markets where the credit unions are located exhibited a wide variety of conditions. At 5.3 percent, the average unemployment rate (UR) across all of the institutions is slightly higher than the corresponding national rate of 4.7 percent. However, the credit union labor markets exhibit at least some heterogeneity with individual jobless rates ranging from a low of 1.9 percent in a farm region of western Nebraska to a high of 24.0 percent in an agricultural district of southeastern California. In spite of the latter, the UR standard deviation is 1.4 indicating that the jobless rates are generally clustered close together. Perhaps not surprisingly, given the latter, the UR data are also leptokurtic.

Credit union membership (STM) represents, on average, one-third of the state populations in which these intermediaries operate. In some states, only a few people are associated with a credit union while for some other states, a portion of credit union members is from nearby states. For example, in California, there is a credit union with a membership total that is 24 percent greater than the entire state population. Most credit unions are small with a median asset value (SIZE) of \$28.0 million. Given the presence of some very large institutions, as in prior studies, the distribution of total credit union assets (SIZE) is skewed to the right and also has very high kurtosis (Wheelock & Wilson, 2011).

On average, credit unions have a low net charge-off ratio of 0.6 percent. For some credit unions, the net charge-off ratio (NCO) is even negative. That may occur when the repayment of previously charged-off loans exceeds the charge off loans registered in the current period. It has also been documented in prior studies (Tokle et al., 2015).

Partially reflecting both an expanding national economy as well as careful management practices, the vast majority of the institutions in this sample are well capitalized. The Prompt Corrective Action requirement of the Federal Credit Union Act defines a well-capitalized credit union as one that has a net worth ratio (NW) of 7 percent or greater (NCUA, 2013). Only 2.0 percent of the credit unions in the sample have net worth ratios that are below 7 percent.

The sample average for the operating expenses relative to total assets (OXA) ratio is 3.6 percent and the median is 3.5 percent. Reflective of the careful management practices in place at

most thrift institutions, OXA values for most of the credit unions are tightly clustered about the median. Less than one percent of the credit unions in the sample have OXA values that are more than two standard deviations above 3.5 percent.

For the period analyzed, credit unions have low fees to asset ratios (FEES). That is not surprising for tax-exempt organizations primarily seeking to provide services to members rather maximize profits. In some cases, the FEES ratios are negative due to fees charged being returned to members. The median value for this variable is 0.53 percent. It is positively skewed and fairly leptokurtic.

Almost 70 percent of the credit unions in the sample (4,146 out of 5,944) offer risk-based loans (RBL). Doing so allows these intermediaries to take advantage of modern technology to segment loan applicants into different risk categories. That may allow more borrowers to qualify for loans by reducing asymmetric information gaps confronting lenders (Edelberg, 2006; Einav et al., 2012).

The average cost of funds to assets ratio (CF) has mean and median values of only 0.3 percent. That reflects low costs associated with attracting deposits. More than 97 percent of the credit unions in the sample have CF ratios that are below 1.0 percent. Although the distribution tails off to the right, it is substantially leptokurtic.

Chapter 5: Empirical Results

Initial ordinary least squares (OLS) parameter estimation results indicate that heteroscedasticity is prevalent across the various loan categories. The output from the White (1980) Chi-squared test is shown in Table 5. With the exception of unsecured credit card interest rates (INTUCC), the null hypothesis of homoscedasticity is rejected for all of the equations. Consequently, generalized least squares (GLS) heteroscedasticity-consistent standard errors are reported for the final versions of each of the loan rate equations.

Table 5: White (1980) homoscedasticity test summary table.

Variable	**Test statistic (Obs*R^2)**	**5% critical χ^2 value**	**Conclusion**
INTNV	631.25	96.22	Reject H_0
INTUV	436.08	96.22	Reject H_0
INTMORT	378.76	96.22	Reject H_0
INTUCC	56.39	96.22	Do not reject H_0
INTOU	608.96	96.22	Reject H_0

Notes:

Null Hypothesis: Homoscedasticity
Obs*R^2 > Chi-squared Critical Value to Reject Null Hypothesis of Homoscedasticity.

Empirical analysis of credit union loan rates during the Great Recession indicates that values of the net worth ratio (NW) and the costs of funds ratio (CF) may be affected by changes in the dependent variables (Tokle et al., 2015). Given that, artificial regression tests are conducted to explore whether endogeneity is present among the sample data used in this study (Davidson and MacKinnon, 1989). The test outcomes displayed in Table 6 indicate that the null hypothesis of exogeneity cannot be rejected for INTNV, INTUV, and INTUCC. For the other two loan rates, however, endogeneity is found to be present. Those are the equations for mortgage rates (INTMORT) and unsecured personal loan rates (INTOU).

Table 6: Endogeneity test outcomes.

Variable	NW residual t statistic	CF residual t statistic	Joint F statistic	Conclusion
INTNV	0.256	1.119	0.726	Do not reject H_0
	(0.798)	(0.263)	(0.484)	
INTUV	-1.899	-1.098	2.990	Do not reject H_0
	(0.058)	(0.272)	(0.050)	
INTMORT	-1.046	-3.819*	11.298*	Reject H_0
	(0.296)	(0.000)	(0.000)	
INTUCC	0.176	1.450	1.213	Do not reject H_0
	(0.861)	(0.147)	(0.297)	
INTOU	-1.278	-4.176*	10.843*	Reject H_0
	(0.201)	(0.000)	(0.000)	

Notes:

Null Hypothesis: Exogeneity
Probability values are included in parentheses below each t and F statistic.
* indicates that the computed test statistic is statistically significant, $p < 0.05$.
NW stands for credit union net worth.
CF stands for credit union cost of funds ratio.

Based on the artificial regression test outcomes, the parameters for INTMORT and INTOU are re-estimated using two-stage least squares (TSLS). The instrumental variables used in this procedure are the purchase prices of single-family homes by state from 2015 (HP), a dummy variable for the change in real deposits (DEPOSITDUM) where 1 indicates a positive change and 0 indicates a negative change and the percentage of each state population that resides in rural areas (RURAL). The results of TSLS regressions for the INTMORT and INTOU equations are shown along with the GLS results for INTNV and INTUV, and the OLS results for INTUCC in Table 7.

Table 7: GLS and TSLS regression results.

Dependent Variable	**INTNV**	**INTUV**	**INTMORT**	**INTUCC**	**INTOU**
Method	**GLS**	**GLS**	**TSLS**	**OLS**	**TSLS**
Constant	2.221506	2.866220	4.078656	10.88390	4.987318
	(13.83995)*	(12.68042)*	(6.252261)*	(38.30984)*	(4.675176)*
UR	0.053390	0.112077	0.074688	0.012783	0.060597
	(3.719371)*	(5.725472)*	(3.437960)*	(0.477481)	(1.763984)
STM	0.000867	0.001146	-0.000495	-0.001371	-0.008901
	(1.017298)	(0.946332)	(-0.402438)	(-0.883022)	(-2.640549)*
LN(SIZE)	-0.215360	-0.420983	-0.379542	-0.244691	-0.144111
	(-15.08577)*	(-21.57117)*	(-5.877781)*	(-8.863494)*	(-1.761761)
NCO	0.278622	0.324395	0.007432	0.187602	0.035708
	(5.224718)*	(6.150597)*	(0.113459)	(2.655416)*	(2.283853)*
OXA	0.328331	0.417601	0.191965	0.070553	0.575285
	(10.73089)*	(8.336090)*	(4.842853)*	(1.567322)	(7.188835)*
NW	0.024153	0.046920	-0.013886	0.038782	0.150528
	(5.067697)*	(7.035979)*	(-0.263186)	(3.983397)*	(2.216048)*
FEES	-0.086641	0.060746	0.040956	0.004826	0.122320
	(-1.322324)	(0.475022)	(0.687137)	(0.057948)	(0.569229)
RBL	0.063676	0.166693	0.018676	-0.208615	0.489777
	(1.184428)	(2.218011)*	(0.253883)	(-2.008821)*	(2.925999)*
CF	1.144603	1.721326	3.354498	-0.058814	6.333090
	(12.06636)*	(12.94523)*	(3.407349)*	(-0.315978)	(3.779069)*
Observations	5682	5750	3934	3527	5824
R Squared	0.223176	0.292992	0.096258	0.051232	0.048112
S.E. of regression	1.423365	2.015583	1.219597	2.078148	3.148365
F-statistic	181.0582	264.3028	67.56321	21.10139	46.28800
Prob(F-statistic)	0.000000	0.000000	0.000000	0.000000	0.000000
Mean dependent var	3.770620	5.051529	4.540470	10.46417	11.13968
S.D. dependent var	1.613654	2.395237	1.141301	2.130794	2.832017
Sum Squared resid	11491.28	23319.19	5836.620	15188.86	57629.55
Second Stage SSR			4218.547		42572.99
J-statistic			1.441979		1.381959
Prob(J-statistic)			0.229819		0.239768
Instrument Rank			11		11

Notes:

Heteroscedasticity correction is used for calculating the regression parameters, except in the case of INTUCC.
Computed t statistics are in parentheses.
* $p < .05$

The Pseudo R Squared values shown in Table 7 for the TSLS regressions are calculated by squaring the correlation coefficients for the actual and predicted values of the INTMORT and

INTOU dependent variables. The second stage sum of squared residuals, J-statistics, and instrument ranks are also reported for those equations. J-statistics are used to test over-identifying restrictions. The number of restrictions to be tested is calculated by subtracting the number of endogenous regressors (two) from the number of instrumental variables (three). In this case, it is not possible to reject the null hypothesis that there is one valid over-identifying restriction. This is equivalent to the null hypothesis that the instruments are uncorrelated with the error term and therefore exogenous (Wooldridge, 2012). The instrument rank is the number of exogenous explanatory variables (seven) plus the number of instrumental variables (three).

An inverse correlation is hypothesized between the unemployment rate (UR) and each of the credit union loan rates (Kiser, 2004). However, all of the UR slope coefficients in Table 7 are greater than zero. That differs from what is reported for new vehicle, used vehicle, and mortgage rates in Tokle et al. (2015). Higher joblessness may signal greater loan delinquency risks (Agarwal and Liu, 2003). If that conjecture is true, then credit unions in areas with higher unemployment and loan delinquencies are likely to charge higher interest rates as a consequence of greater default risks.

As hypothesized, the ratio of credit union membership to state population (STM) is negatively correlated with three of the five loan rates. The only STM slope coefficient that satisfies the standard 5 percent significance criterion is that for unsecured personal loans (INTOU). That result confirms the hypothesis that higher credit union market shares raise competitive pressures in local financial markets and tend to suppress loan rates (Feinberg, 2002; Tokle and Tokle, 2008; Tokle et al 2015). Contrary to the hypothesis expressed for this regressor in Table 3, the new vehicle and used vehicle loans coefficients display positive signs. Neither of the latter parameter estimates, however, differ from zero in statistically reliable manners.

The regression parameters estimated for the natural logarithm of total credit union assets, LN(SIZE), indicate that larger credit unions tend to charge lower interest rates across all five loan categories. More specifically, for every 1% increase in total credit union assets, loan rates decline by roughly 0.14 to 0.42 percentage points. These results are similar to the evidence obtained by

Tokle et al. (2015). The negative signs for the LN(SIZE) coefficients are consistent with the economies of scale assertion that larger credit unions experience cost advantages that translate into lower loan rates (Feinberg and Rahman, 2006; Wilcox, 2006; Tokle and Tokle, 2008; Wheelock and Wilson, 2011).

Similar to Tokle and Tokle (2002; 2008), the results in Table 7 show that higher net charge-off ratios (NCO) raise credit union loan rates. The positive effect is probably reflective of the association between loan charge-off rates and risk levels. Higher levels of credit risk are correlated with more elevated delinquency rates, obligating lenders to charge higher interest rates whenever NCO ratios increase (Angbazo, 1997; Maudos & Fernandez de Guevara, 2004; Tokle et al., 2015).

Credit unions with high operating costs to average asset ratios (OXA) charge higher interest rates on all five types of loans. This is not surprising since higher operating expense ratios (OXA) reflect higher costs faced by these lenders. When credit unions face high operating costs, it is more likely that they will raise interest rates in order to maintain liquidity and solvency. The results in Table 7 indicate that loan rate responses to a 1 percentage point increase in OXA range from a low of 0.07 percentage points for unsecured credit cards, INTUCC, to a high of 0.57 percentage points for unsecured personal loans, INTOU. In an analogous setting, these outcomes confirm similar evidence provided by Peterson and Ginsberg (1976) on how loan processing and service costs influence commercial bank credit provision.

Results in Table 7 further indicate that higher net worth ratios (NW) lead to higher interest rates across four of the five loan categories. Those results are contrary to the null hypothesis that well-capitalized credit unions tend to charge lower interest rates because net worth can be used as an interest-free source of funds (Hubbard et al., 2002; Tokle and Tokle, 2008). The net worth coefficient is negative as hypothesized in the mortgage interest rate equation, but it does not surpass the conventional significance criterion. A possible explanation for the positive relationships between NW and the majority of the loan rates in the sample is that high net worth ratios may occur when credit unions are relatively insulated from competitive pressures. Low exposures to market competition potentially allow credit unions to charge higher rates than would

otherwise be observed (Tokle and Tokle, 2000; 2002). Tokle et al. (2015) also document similar outcomes in the aftermath of the 2008 financial crisis.

As noted by Tokle and Tokle (2008), the effect of the fees to assets ratio (FEES) on loan rates is ambiguous. One hypothesis is that higher fee revenues allow credit unions to reduce loan rates, while a second conjecture is that greater dependence on fee revenues may reflect cash flow pressures. In the latter case, the correlation between FEES and loan rates would be positive. Estimation results employing data from the trough of the 2008 recession indicate that higher FEES lead to increases in interest rates charged to credit union customers on mortgage loans and unsecured credit cards (Tokle et al., 2015). In Table 7, a positive relationship between FEES and four of the five loan rates is also documented using fourth quarter 2015 data. Those outcomes seemingly support the argument that a high fee ratio signals that a credit union is under pressure to increase revenues (Tokle and Tokle, 2008), but the four coefficient magnitudes are economically and statistically insignificant. The parameter estimate for the new vehicle (INTNV) interest rate is negative but, as with the rest of the coefficients, economically and statistically indistinguishable from zero.

As noted above, deployment of a risk-based loan pricing strategy has an ambiguous effect on credit union loan rates. That is because higher interest rates will be charged on loans approved for high-risk borrowers and lower rates will be assigned to loans approved for low-risk borrowers. In this sample, RBL is a binary variable that takes on a value of one if a credit union employs risk-based lending and zero if not. As in Tokle et al. (2015), one of the RBL coefficients in Table 7 is negative while others are positive.

In the cases of new vehicle (INTNV), used vehicles (INTUV), mortgage (INTMORT), and unsecured personal loans (INTOU), risk-based lending is associated with higher loan rates. While all of the parameter magnitudes are economically plausible, only those for INTUV and INTOU satisfy the 5 percent significance criterion. Those positive coefficients may reflect a predominance of high-risk borrowers among those particular customer categories, thus leading to numerically higher loan rates under RBL pricing. For unsecured credit card (INTUCC) loans, the RBL

coefficient is less than zero. The latter outcome probably indicates that RBL pricing encourages higher borrowing rates among lower-risk borrowers within the unsecured credit card customer category by offering low-risk customers relatively low-interest rates (Edelberg, 2006). The INTUCC parameter magnitude is economically plausible and surpasses the 5 percent critical value.

Consistent with results reported in Feinberg (2002) and Feinberg and Rahman (2006), the cost of funds to average assets ratio (CF) exerts a positive impact on four of the five interest rates. Those outcomes are consistent with the hypothesis that higher costs reduce the volume of loans that can be underwritten and force credit unions to raise rates on those loans that are approved. In the case of unsecured credit card rates (INTUCC), the CF coefficient is both statistically and economically indistinguishable from zero. That implies that unsecured credit card issuance is not really affected by credit union cost of fund developments relative to the overall asset positions of these lenders.

In summary, the evidence in Table 7 provides substantial, although not universal, support for the hypotheses advanced in Table 3. No hypothesis is advanced for parameters associated with two of the variables listed in Table 3: fee revenues (FEES) and risk-based loans (RBL). Of the remaining seven explanatory variables, three have coefficients with signs that are always consistent with the respective hypotheses: credit union size (SIZE), net charge-offs (NCO), and operating expenses (OXA). Beyond that, the coefficient signs for the cost of funds (CF) regressor are consistent with the corresponding hypothesis for four of the five interest rate categories.

Results in Table 7 provide only weak evidence for an effect of increased membership relative to state population (STM) on credit union loan rates. Two of the five STM parameter signs run counter hypothesized inverse relationship and four of five coefficients are statistically indistinguishable from zero. The effects of the unemployment rate (UR) and the net worth ratio (NW) are not generally consistent with the hypotheses advanced for those variables. In the case of NW, the hypothesized negative coefficient is present only in the equation for mortgage loan rates (INTMORT) and not in a statistically reliable manner.

The results in Table 7 do, however, suggest some general inferences with regard to credit union business practices. Managers have varying degrees of influence over factors such as credit union size, customer risk levels, operating expense ratios, and cost of funds ratios. The negative coefficients for the SIZE variable indicate that efforts to attract more members may translate into secondary benefits in the form of lower loan interest rates for borders. Because net charge-offs depend primarily on borrower risk levels, credit unions have minimal capacity to influence NCO ratios. However, investments in financial literacy programs for credit union members may yield some benefits in this regard. The positive OXA coefficients suggest that adjusting operating expenses to streamline service provision may help credit unions reduce operating costs and permit offering reduced loan rates to members.

The cost of funds ratio (CF) is defined as the sum of dividends paid on shares, plus interest paid on deposits, plus interest paid on borrowed money, all divided by average assets. The positive coefficients suggest that credit unions that pay higher dividends and interest rates to members and depositors also tend to charge higher interest rates to borrowers. This correlation suggests that credit unions face a tradeoff between serving the interests of members that are borrowers and those that are savers. The distribution of benefits between borrowers and savers is a key element of many theoretical analyses of credit union behavior (McKillop and Wilson, 2011). The optimal balance between these competing interests is not uniform across credit unions and depends on local demand for loans and savings deposit levels, among other factors.

None of the FEES coefficients surpass the conventional significance level and it is, therefore, difficult to draw general inferences regarding the effects of fee revenues on interest rates. RBL results are statistically reliable for three out of five interest rate categories: INTUV, INTUCC, and INTOU. In two cases the impact of RBL is positive and in one case it is negative. The effects of risk-based loan pricing are relevant for managers because about 70 percent of credit unions have adopted this practice (Table 4). Walke et al. (2018) suggest that the adoption of risk-based loan pricing mainly benefits lower risk borrowers, who tend to pay lower interest rates under RBL. The coefficient for INTUCC is consistent with that hypothesis because it indicates that risk-based

pricing results in lower interest rates. However, the coefficients for INTUV and INTOU suggest that risk-based lending is associated with higher interest rates. The diversity of results obtained suggests that individual credit unions that adopt risk-based loan pricing will monitor borrower risk levels for each individual loan category.

The unexpected positive coefficients for NW provide some evidence that credit unions with high net worth ratios tend to offer higher loan rates. Maintaining unnecessarily large capital cushions may restrict credit union growth potential (Tokle and Tokle, 2008). Conversely, credit unions may be able to broaden their customer base by utilizing excess capital reserves to provide better interest rate terms to members. Finally, as mentioned previously, the unexpected positive impacts of UR presumably occur because weak job market conditions are accompanied by greater loan delinquency rates, thus adding to the risk premiums paid by borrowers (Agarwal and Liu, 2003). Credit unions in economically stressed regions might benefit from more advanced risk screening procedures in evaluating loan applicants. Though previous research suggests that such procedures would not necessarily result in lower loan rates, they might help improve credit union profitability (Edelberg, 2006; Einav et al., 2012).

Table 8: Null hypothesis outcomes for equation (4) parameter estimates.

Explanatory Variable	**Hypothesized Sign**	**Result Obtained**	**Statistically Significant**		**Statistically Insignificant**
			Positive	**Negative**	
UR	(-)	(+; rejects H_0)	3	0	2
STM	(-)	(-)	0	1	4
SIZE	(-)	(-)	0	4	1
NCO	(+)	(+)	4	0	1
OXA	(+)	(+)	4	0	1
NW	(-)	(+; rejects H_0)	4	0	1
FEES	(+ or -)	Neither	0	0	5
RBL	(+ or -)	(+ and -)	2	1	2
CF	(+)	(+)	4	0	1

Table 8 summarizes the null hypotheses outcomes associated with Table 7 estimation results. As noted above, the results in Table 7 largely corroborate most of the hypotheses advanced above and summarized in Table 2. However, the coefficient signs for the unemployment (UR)

and net worth (NW) regressors run counter to what is hypothesized for those variables. For labor market conditions and credit union loan rates, the alternative hypothesis advanced by Agarwal and Liu (2003) is supported. For net worth ratios and loan rates, it is possible that high net worth ratios may occur when credit unions are relatively insulated from competitive pressures and that may allow credit unions to charge higher rates than would otherwise be observed (Tokle and Tokle, 2000; 2002). Additional research on this topic appears warranted.

Chapter 6: Conclusion

Credit unions continue to grow as a source for consumer and small business lending. Given that, it is helpful to understand how credit union loan rates behave at the different phases of the business cycle. This study examines loan rates during a period of economic expansion. Fourth quarter 2015 data for 5,942 credit unions in the United States are employed for this study. Five categories of loan rates are analyzed.

To model the five interest rates, nine explanatory variables are included in the sample. Among other things, economies of scale appear to benefit borrowers. For every 1% increase in total credit union assets, loan rates decline by roughly 0.14 to 0.42 percentage points. Increased net charge-offs have the opposite effect on loan rates, implying that investing in financial literacy programs may be necessary to help borrowers make better decisions regarding debt. Similarly, weaker labor markets are generally associated with higher loan rates, potentially due to elevated loan delinquency rates and greater default risks faced by credit unions in those regions. Not surprisingly, more costly operating expenses also lead to higher loan rates.

Prior research using a similar approach was completed using data from close to the nadir of the 2008 recession. Many of the results reported above using data from an expansionary phase of the business cycle corroborate those of the earlier study. That implies that credit union loan pricing behavior holds steady under fairly different economic conditions. The largest departure from that pattern is how interest rates react to joblessness. In this study, higher unemployment rates lead to steeper loan rates. More research will be required to unravel why that is the case.

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Appendix A. OLS regressions

Table A.1. INTNV

Dependent Variable: INTNV
Method: Least Squares
Date: 04/29/18   Time: 13:46
Sample: 1 5942
Included observations: 5682

Variable	Coefficient	Std. Error	t Statistic	Prob.
C	2.221506	0.131669	16.87184	0.0000
UR	0.053390	0.014284	3.737834	0.0002
STM	0.000867	0.000804	1.078091	0.2810
SIZE	-0.215360	0.013098	-16.44216	0.0000
NCO	0.278622	0.023231	11.99360	0.0000
OXA	0.328331	0.019761	16.61543	0.0000
NW	0.024153	0.003756	6.430709	0.0000
FEES	-0.086641	0.038761	-2.235301	0.0254
RBL	0.063676	0.049501	1.286359	0.1984
CF	1.144603	0.077934	14.68673	0.0000

R-squared	0.223176	Mean dependent var	3.770620
Adjusted R-squared	0.221943	S.D. dependent var	1.613654
S.E. of regression	1.423365	Akaike info criterion	3.545682
Sum squared resid	11491.28	Schwarz criterion	3.557377
Log-likelihood	-10063.28	Hannan Quinn criter.	3.549755
F statistic	181.0582	Durbin Watson stat	1.879325
Prob(F statistic)	0.000000		

Table A.2. INTUV

Dependent Variable: INTUV
Method: Least Squares
Date: 04/29/18 Time: 13:49
Sample: 1 5942
Included observations: 5750

Variable	Coefficient	Std. Error	t Statistic	Prob.
C	2.866220	0.179175	15.99678	0.0000
UR	0.112077	0.019966	5.613475	0.0000
STM	0.001146	0.001129	1.015358	0.3100
SIZE	-0.420983	0.017927	-23.48303	0.0000
NCO	0.324395	0.031342	10.35016	0.0000
OXA	0.417601	0.024174	17.27482	0.0000
NW	0.046920	0.005269	8.904720	0.0000
FEES	0.060746	0.051585	1.177588	0.2390
RBL	0.166693	0.069382	2.402535	0.0163
CF	1.721326	0.105652	16.29237	0.0000

R-squared	0.292992	Mean dependent var	5.051529
Adjusted R-squared	0.291884	S.D. dependent var	2.395237
S.E. of regression	2.015583	Akaike info criterion	4.241432
Sum squared resid	23319.19	Schwarz criterion	4.253009
Log-likelihood	-12184.12	Hannan Quinn criter.	4.245461
F statistic	264.3028	Durbin Watson stat	1.916835
Prob(F statistic)	0.000000		

Table A.3. INTMORT

Dependent Variable: INTMORT
Method: Least Squares
Date: 04/29/18 Time: 13:50
Sample: 1 5942
Included observations: 3950

Variable	**Coefficient**	**Std. Error**	**t Statistic**	**Prob.**
C	4.337875	0.130978	33.11906	0.0000
UR	0.058244	0.012352	4.715186	0.0000
STM	0.001528	0.000726	2.103825	0.0355
SIZE	-0.247478	0.012294	-20.12937	0.0000
NCO	0.147146	0.031212	4.714460	0.0000
OXA	0.111554	0.020963	5.321440	0.0000
NW	0.019682	0.004197	4.689114	0.0000
FEES	0.115856	0.039455	2.936384	0.0033
RBL	-0.073537	0.048195	-1.525819	0.1271
CF	0.567251	0.070881	8.002843	0.0000

R-squared	0.186551	Mean dependent var	4.538539
Adjusted R-squared	0.184693	S.D. dependent var	1.141381
S.E. of regression	1.030602	Akaike info criterion	2.900692
Sum squared resid	4184.835	Schwarz criterion	2.916594
Log-likelihood	-5718.867	Hannan Quinn criter.	2.906333
F statistic	100.3972	Durbin Watson stat	1.786803
Prob(F statistic)	0.000000		

Table A.4. INTUCC

Dependent Variable: INTUCC
Method: Least Squares
Date: 04/29/18 Time: 13:51
Sample (adjusted): 1 5941
Included observations: 3527 after adjustments

Variable	**Coefficient**	**Std. Error**	**t Statistic**	**Prob.**
C	10.88390	0.284102	38.30984	0.0000
UR	0.012783	0.026771	0.477481	0.6330
STM	-0.001371	0.001553	-0.883022	0.3773
SIZE	-0.244691	0.027607	-8.863494	0.0000
NCO	0.187602	0.070649	2.655416	0.0080
OXA	0.070553	0.045015	1.567322	0.1171
NW	0.038782	0.009736	3.983397	0.0001
FEES	0.004826	0.083282	0.057948	0.9538
RBL	-0.208615	0.103849	-2.008821	0.0446
CF	-0.058814	0.186132	-0.315978	0.7520

R-squared	0.051232	Mean dependent var	10.46417
Adjusted R-squared	0.048804	S.D. dependent var	2.130794
S.E. of regression	2.078148	Akaike info criterion	4.303662
Sum squared resid	15188.86	Schwarz criterion	4.321151
Log-likelihood	-7579.508	Hannan Quinn criter.	4.309901
F statistic	21.10139	Durbin Watson stat	1.959824
Prob(F statistic)	0.000000		

Table A.5. INTOU

Dependent Variable: INTOU
Method: Least Squares
Date: 04/29/18 Time: 13:51
Sample: 1 5942
Included observations: 5840

Variable	Coefficient	Std. Error	t Statistic	Prob.
C	7.785192	0.230996	33.70268	0.0000
UR	0.086395	0.026545	3.254650	0.0011
STM	0.001272	0.001482	0.858814	0.3905
SIZE	-0.040578	0.022873	-1.774062	0.0761
NCO	0.045854	0.016214	2.828031	0.0047
OXA	0.470695	0.030507	15.42906	0.0000
NW	0.068551	0.006826	10.04259	0.0000
FEES	0.090946	0.066532	1.366958	0.1717
RBL	0.111759	0.091648	1.219435	0.2227
CF	0.663378	0.127345	5.209317	0.0000

R-squared	0.103242	Mean dependent var	11.13568
Adjusted R-squared	0.101858	S.D. dependent var	2.831387
S.E. of regression	2.683316	Akaike info criterion	4.813694
Sum squared resid	41977.07	Schwarz criterion	4.825120
Log-likelihood	-14045.99	Hannan Quinn criter.	4.817667
F statistic	74.57751	Durbin Watson stat	1.870283
Prob(F statistic)	0.000000		

Appendix B. Heteroscedasticity Test

Table B.1. INTNV

Heteroskedasticity Test: White			
F statistic	13.27161	Prob. F(53,5628)	0.0000
Obs*R squared	631.2498	Prob. Chi Square(53)	0.0000

Results:
Heteroscedasticity

Table B.2. INTUV

Heteroskedasticity Test: White			
F statistic	8.819483	Prob. F(53,5696)	0.0000
Obs*R squared	436.0780	Prob. Chi Square(53)	0.0000

Results:
Heteroscedasticity

Table B.3. INTMORT

Heteroskedasticity Test: White			
F statistic	7.796220	Prob. F(53,3896)	0.0000
Obs*R squared	378.7568	Prob. Chi Square(53)	0.0000

Results:
Heteroscedasticity

Table B.4. INTUCC

Heteroskedasticity Test: White			
F statistic	1.064671	Prob. F(53,3473)	0.3496
Obs*R squared	56.38877	Prob. Chi Square(53)	0.3494

Results: NO
Heteroscedasticity

Table B.5. INTOU

Heteroskedasticity Test: White			
F statistic	12.70878	Prob. F(53,5786)	0.0000
Obs*R squared	608.9609	Prob. Chi Square(53)	0.0000

Results:
Heteroscedasticity

Appendix C. GLS Regressions

Table C.1. INTNV

Dependent Variable: INTNV
Method: Least Squares
Date: 05/10/18   Time: 11:08
Sample: 1 5942
Included observations: 5682
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t Statistic	Prob.
C	2.221506	0.160514	13.83995	0.0000
UR	0.053390	0.014355	3.719371	0.0002
STM	0.000867	0.000852	1.017298	0.3091
SIZE	-0.215360	0.014276	-15.08577	0.0000
NCO	0.278622	0.053328	5.224718	0.0000
OXA	0.328331	0.030597	10.73089	0.0000
NW	0.024153	0.004766	5.067697	0.0000
FEES	-0.086641	0.065522	-1.322324	0.1861
RBL	0.063676	0.053761	1.184428	0.2363
CF	1.144603	0.094859	12.06636	0.0000

R-squared	0.223176	Mean dependent var	3.770620
Adjusted R-squared	0.221943	S.D. dependent var	1.613654
S.E. of regression	1.423365	Akaike info criterion	3.545682
Sum squared resid	11491.28	Schwarz criterion	3.557377
Log-likelihood	-10063.28	Hannan Quinn criter.	3.549755
F statistic	181.0582	Durbin Watson stat	1.879325
Prob(F statistic)	0.000000	Wald F statistic	86.59458
Prob(Wald F statistic)	0.000000		

Table C.2. INTUV

Dependent Variable: INTUV
Method: Least Squares
Date: 05/10/18 Time: 11:09
Sample: 1 5942
Included observations: 5750
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t Statistic	Prob.
C	2.866220	0.226035	12.68042	0.0000
UR	0.112077	0.019575	5.725472	0.0000
STM	0.001146	0.001211	0.946332	0.3440
SIZE	-0.420983	0.019516	-21.57117	0.0000
NCO	0.324395	0.052742	6.150597	0.0000
OXA	0.417601	0.050096	8.336090	0.0000
NW	0.046920	0.006669	7.035979	0.0000
FEES	0.060746	0.127881	0.475022	0.6348
RBL	0.166693	0.075154	2.218011	0.0266
CF	1.721326	0.132970	12.94523	0.0000

R-squared	0.292992	Mean dependent var	5.051529
Adjusted R-squared	0.291884	S.D. dependent var	2.395237
S.E. of regression	2.015583	Akaike info criterion	4.241432
Sum squared resid	23319.19	Schwarz criterion	4.253009
Log-likelihood	-12184.12	Hannan Quinn criter.	4.245461
F statistic	264.3028	Durbin Watson stat	1.916835
Prob(F statistic)	0.000000	Wald F statistic	156.9039
Prob(Wald F statistic)	0.000000		

Appendix D. TSLS regressions

Table D.1. INTMORT
Dependent Variable: INTMORT
Method: Two Stage Least Squares
Date: 06/20/18 Time: 16:32
Sample: 1 5942
Included observations: 3934
White heteroskedasticity-consistent standard errors & covariance
Instrument specification: UR STM SIZE NCO OXA FEES RBL PRICE_HOUSING DEPOSITDUM RURAL
Constant added to instrument list

Variable	Coefficient	Std. Error	t Statistic	Prob.
C	4.078656	0.652349	6.252261	0.0000
UR	0.074688	0.021725	3.437960	0.0006
STM	-0.000495	0.001229	-0.402438	0.6874
SIZE	-0.379542	0.064572	-5.877781	0.0000
NCO	0.007432	0.065505	0.113459	0.9097
OXA	0.191965	0.039639	4.842853	0.0000
NW	-0.013886	0.052760	-0.263186	0.7924
FEES	0.040956	0.059604	0.687137	0.4920
RBL	0.018676	0.073561	0.253883	0.7996
CF	3.354498	0.984489	3.407349	0.0007

R-squared	-0.139298	Mean dependent var	4.540470
Adjusted R-squared	-0.141911	S.D. dependent var	1.141301
S.E. of regression	1.219597	Sum squared resid	5836.620
F statistic	67.56321	Durbin Watson stat	1.788811
Prob(F statistic)	0.000000	Second Stage SSR	4218.547
J statistic	1.441979	Instrument rank	11
Prob(J statistic)	0.229819		

Table D.2. INTOU
Dependent Variable: INTOU
Method: Two Stage Least Squares
Date: 05/10/18 Time: 10:37
Sample: 1 5942
Included observations: 5824
White heteroskedasticity-consistent standard errors & covariance
Instrument specification: UR STM SIZE NCO OXA FEES RBL
PRICE_HOUSING DEPOSITDUM RURAL
Constant added to instrument list

Variable	**Coefficient**	**Std. Error**	**t Statistic**	**Prob.**
C	4.987318	1.066766	4.675176	0.0000
UR	0.060597	0.034353	1.763984	0.0778
STM	-0.008901	0.003371	-2.640549	0.0083
SIZE	-0.144111	0.081799	-1.761761	0.0782
NCO	0.035708	0.015635	2.283853	0.0224
OXA	0.575285	0.080025	7.188835	0.0000
NW	0.150528	0.067926	2.216048	0.0267
FEES	0.122320	0.214887	0.569229	0.5692
RBL	0.489777	0.167388	2.925999	0.0034
CF	6.333090	1.675833	3.779069	0.0002

R-squared	-0.233976	Mean dependent var	11.13968
Adjusted R-squared	-0.235886	S.D. dependent var	2.832017
S.E. of regression	3.148365	Sum squared resid	57629.55
F statistic	46.28800	Durbin Watson stat	1.926543
Prob(F statistic)	0.000000	Second Stage SSR	42572.99
J statistic	1.381959	Instrument rank	11
Prob(J statistic)	0.239768		

Vita

Esmeralda Patricia Muñiz was awarded academic scholarships throughout her undergraduate education at *Universidad Autónoma de Ciudad Juárez*. While an undergraduate student, she worked as a Research Assistant for two different professors in the Department of Economics. In addition to her research duties, she helped organize a national mathematical economics and econometrics symposium, and was assigned instructional activities such as course material preparation and examination grading.

Esmeralda moved to El Paso, Texas in the summer of 2015 and applied for admission to the University of Texas at El Paso. In June 2015, she was admitted to the Masters of Science program in Economics. She was named a James Foundation Scholar by the Economics Graduate Faculty for the 2017 academic year. While pursuing her M.S. Economics degree, Esmeralda worked as a Graduate Research Assistant at The Hunt Institute for Global Competitiveness and, later, at the Border Region Modeling Project. At the latter organization, Ms. Muñiz was a co-author of the ***Borderplex Business Barometer*** and participated in a variety of different data collection and econometric research efforts.

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This thesis was typed by Esmeralda Patricia Muñiz.