EXPLAINING THE UNDERBANKED: REGULATION, POVERTY, AND CONSUMER CREDIT

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I. Research Question

As of 2013, the United States has a population of 24.8 million (20 percent of all U.S. households) underbanked households that have bank accounts, but still rely on alternative financial service providers (AFSPs) to meet their banking needs. Members of these households are patrons to check cashing stores, pawnshops, and payday lenders, as they cannot rely solely mainstream banking services that require minimum balances and have very few branches in urban areas. Some states have sought out to protect this vulnerable economic class by imposing a strict regulatory environment for AFSPs, while some have not. This paper will analyze the impact of regulation, poverty, and credit on the underbanked populations of each state.

II. Literature Review

The Office of Financial Empowerment, a branch of the CFPB, was created in 2012. There are 48 million people who live below the federal poverty line and 43.9 percent of households do not have adequate savings, defined as adequate liquidity to cover "basic expenses for three months if unemployment, a medical emergency, or other crisis leads to a loss of stable income" (Consumer Financial Protection Bureau, 2013, p. 15). Lack of access due to geographic proximity, public transportation, language, and financial obstacles (fees/minimum balances for accounts) are barriers to financial empowerment. It is estimated that 8.2 percent of U.S. consumers are unbanked and 20.1 percent are underbanked as of 2011 (*Ibid*., p. 23). "The average unbanked consumer spends five percent of [their] net income on financial service fees. For a low-to-moderate- income worker, this amounts to about $1,000 in fees annually, or $40,000 over an average working life" (*Ibid*., p. 24). Unfortunately, bank fees are not always presented clearly to consumers. Unbanked households do not like dealing with banks, and these households generally do not trust them.

The rapid growth of alternative financial service providers (AFSPs) has led to controversy surrounding their location decisions. Prager (2009) writes that most (90 percent) of urban counties had at least one AFSP in 2006 (Prager, 2009, p. 13). The largest number of payday lending stores per capita is in states that do not prohibit payday lending, which are Alabama, South Carolina, Tennessee, Mississippi, and Louisiana (*Ibid*., p. 14). Payday lenders are more prevalent in urban and rural counties where a larger share of the population is below the age of 40, whereas they are less prevalent in counties where a larger share of the population sits below the poverty line. AFSPs generally avoid areas with a large piece of the population living below the poverty line (*Ibid*., p. 19). Data also suggests that payday loan stores are more prevalent where a substantial share of the population may have difficulty accessing mainstream sources of credit (*Ibid*., p. 15). There is also no evidence that AFSPs concentrate in areas with large Hispanic populations. Population density is a strong predictor of locations per capita in the rural counties with significance levels at 0.01 levels for payday lending, pawnshops, and check cashers. However, OLS estimation results for urban counties are not significant for payday lenders and check cashers (*Ibid*., p. 20).

Birkenmaier et al. (2011) explores the composition (beginning credit score, family history, etc.) of IDA's – Individual Development Accounts are matched savings accounts intended to encourage capital accumulation among low-income residents. Since fringe-banking services are in high demand (roughly 50 percent of Los Angeles residents according to a 2010 Pew Study) and margins are high (payday lending netted $7b in 2008), IDAs attempt to bolster credit scores and improve credit history through homeowner education and credit counseling

(Birkenmaier et al., 2011, p. 69). Poor credit coupled with high debt is a common barrier to IDA participant saving (*Ibid*., p. 71). As a result, IDAs have developed programmatic responses to credit and debt problems (*Ibid*., p. 72). The empirical study found that IDA participants were mostly single, female, African-Americans. Only about one-third had some college education without a degree, whereas only 16 percent actually held a degree (*Ibid*., p. 75). Half of participants had used a payday lender, 69 percent had used a pawnshop, but only 20 percent had used a rent-to-own account. The average monthly debt was $399.23 with a standard deviation of $461.51, and the mean debt-to-income ratio was 52 percent. In terms of credit, 94 percent of participants had a credit score with the Experian and TransUnion mean credit scores sitting at 598 and 578, respectively, which is just below the low-end of a "good" credit score (*Ibid*., p. 76). When compared to two national samples (American Dream Demonstration Project and the Assets for Independence Act), Birkenmaier et al. (2011)'s sample was more educated, more likely to own a home, and more likely to be banked (*Ibid*., p. 77).

Bars and supermarkets were the original check cashing stores, and they did not charge a fee – they simply relied on the additional business spurred from the convenience. Caskey (1991) found that only seven states (CT, DE, GA, IL, MN, NJ, NY) placed maximum fee restrictions on check cashing outlets (CCOs). Fees generally run about 1.0 to 3.0 percent with a mean of 1.75 percent, based on a 1989 study by the Consumer Federation of America. Personal checks, however, come with a higher default risk, and subsequently higher fees – a mean of 7.7 percent (Caskey, 1991, p. 94). Check cashing is dominated "mainly by local owner-operators," and regulations on the aforementioned states include minimum bonding/capital requirements, radius boundaries to prevent CCO concentration, and diligent bookkeeping and reporting (*Ibid*., p. 95). States are also required to report large sales of money orders – this prevents the proliferation of money laundering. The study found that the yellow pages count of CCOs underestimates the number of NY stores by 20 percent and GA stores by 50 percent. CCOs are disproportionately located in middle- and low-class urban neighborhoods: "In eight states fewer than 10 percent of the CCOs are located in cities of less than 100,000." New Jersey's number of CCOs grew less than 20 percent from 1988 to 1991, but Florida grew at 195 percent and Michigan at 293 percent (*Ibid*., p. 97). Banks are cheaper than CCOs – the gap widens as income increases because CCOs charge based on a percentage of check amount whereas bank fees are usually fixed. Despite high out-of-pocket expenses, convenience and ease of service lead one to believe that traditional banks and CCOs are not perfect substitutes.

Caskey (1991) also outlines a CBA survey, finding that CCO customers were young (ages 18-30), poor (less than $15k/year), and disproportionately racial and ethnic minorities – 47 percent black and 18 percent Hispanic (*Ibid*., p. 99). "In New Jersey, check-cashers are limited by law to charging 1.0 percent on in-state checks and 1.5 percent on out-of-state checks. Of 662 customers there who reported the amount of the check they cashed and the amount of fee they paid, 49 percent were charged more than the legal maximum" (*Ibid*., p. 99). However, NJ Dept. of Banking had only received one check-cashing complaint in over two years, confirmed by a Government Accountability Office report. Requiring very low fees could "kill the industry and hurt the low and moderate-income people who have no realistic alternatives" – the nature of the fee ceiling depends on the geographic area (*Ibid*., p. 102).

Surveys from Los Angeles and New York City say that check cashing stores patrons (vs. bank users) are more likely to be not working (40.6 percent vs. 18.5 percent), on welfare (29.4 percent vs. 5.4 percent), have income below $15,000 (41.9 percent vs. 7.9 percent), Latino (55 percent vs. 44 percent), and not have a deposit account (78.2 percent vs. 12.7 percent), Caskey

(2002) writes (Caskey, 2002, p. 6). The same generally holds for customers in Oklahoma City, Atlanta, and smaller urban Philadelphia area, where blacks use the service 55.4 percent vs. 26.2 percent (*Ibid*., p. 7). People use CCOs because money orders are cheaper there than at banks. Paying bills or buying stamps are also more convenient at CCOs, as people would prefer one-stop shopping. Some could argue that U.S. Post Offices cannot be considered reasonable substitutes to mainstream banks until they first offer the same extensive operating hours that CCOs do. A sample of unbanked North Carolina households felt that although CCOs were expensive (48.5 percent), many said they did not need a bank account (32 percent). Only 0.3 percent said that banks had bad locations/hours – more evidence that banks don't welcome the unbanked crowd (*Ibid*., p. 10).

Community Trust Prospera is a community organization that transitions fringe bank users from check cashing stores to credit unions, Choi (2013) explains. The Bank One Initiative provides starter accounts with special, specific features for the unbanked (Choi, 2013, p. 4). Unbanked individuals fluctuate from living paycheck to paycheck to having some savings, but banks can only accommodate users who have some constant liquid savings due to minimum balance requirements. Language barriers, lack of ID, distance, and "stickiness of current habits," are a deterrent for some (*Ibid*., p. 5). CT Prospera moves from transactional products (check cashing) to deposits (checking/savings accounts) to loans (auto/home). They originally opened at 10 am on Saturdays, but clients asked for an earlier opening time because payday fell on Friday. CT Prospera allows customers to have up to two unpaid balances (not to exceed $500 total on their accounts). Financial education is key to CT Prospera's mission. Of all their clients, 24 percent opened a bank account, whereas the rest never got past "transactional services." Check cashing was 56.3 percent of all transactions – the most popular service (*Ibid*., p. 6).

A 2006 study takes a forensic accounting approach to CCO analysis. Gottlieb (2006) writes that some 30 million people cash 180 million checks at CCOs annually (Gottlieb, 2006, p. 2). Clients generally need access to financial services after normal banking hours. CCOs generally spend little money on advertising, but increased competition from banks and convenience stores has led to heightened competition. Direct deposit accounts threaten the dominance of CCOs, since unbanked, low-income consumers often have a high opportunity cost of time (i.e. cannot afford to wait a week for a check to clear) (*Ibid*., p. 5).

Community Check Cashing is a non-profit, low-fee check cashing store that provides financial coaching for consumers. This pilot program found that lower fees did not compromise profitability – start-up capital of $400,000 was on track to be recovered in two years (Liebsohn, 2011, p. 10). The shop also started lower-cost small dollar loans, and kept fees low by initiating a "more careful screening and application process to help pick consumers who are more likely to repay." Demand was not high for financial coaching, and even after a crisis, low-income unbanked consumers have no interest in long-term planning (*Ibid*., p. 11).

Figart (2013) applauds Raskin's view that both regulatory framework and financial education efforts are required for total financial inclusion. Institutional prerequisites for financial inclusion consist of: 1) access to non-exploitative institutional arrangements for engaging in market transactions, 2) ability to save and access to credit, 3) institutionalization of social norms, 4) human diversity for enhancement of capabilities, 5) and focus on well-being of communities as well as individuals (Figart, 2013, p. 874). A capability approach, following Amartya Sen, should also include structural and cultural support for financial inclusion. The banking industry was heavily deregulated in the 1980's and 1990's, and fees were increased in low-income areas to compensate for both loss profit and future inflation (*Ibid*., p. 875). Table 2 (*Ibid*., p. 881) outlines why some households do not have a bank account – there is evidence that banks simply are not right for them and see no value in mainstream banking. At least a third of underbanked individuals use non-bank check cashing (*Ibid*., p. 882). Figart argues that stricter regulations, including caps on fees/interest rates, and community-oriented banking are required to advance the inclusion process. Regulations must stay innovative, or else the check cashing firms will out-smart the government agencies. Public-private partnerships should expand to areas where fringe banking is not profitable – all areas, especially poor, need at least fringe banking markets (*Ibid*., p. 885). An example of this would be post offices serving as offices as check cashing stores, as endorsed by Senator Elizabeth Warren (Warren, 2014).

The more sophisticated the financial products, the wider the gap between immigrant and native-born users. Zhan et al. (2014) explains that check cashing fees for immigrants in 2006 were a staggering $2 billion (Zhan et al., 2014, p. 4). Of native-born residents, 64.4 percent and 31.9 percent of natives use banks and check cashing outlets, respectively – immigrants use 48.4 percent and 38.3 percent, respectively. Of nationals, 3.7 percent of natives reported they did not know how to open a bank account, while nearly double the proportion (7.2 percent) of immigrants did not know. Of those born here, 29.6 percent of natives said check cashers are convenient, compared to 19.8 percent of immigrants (*Ibid*., p. 8). It can be concluded that bank operations and customer recruitment and retention do not seek out non-native inhabitants of urban areas, which may lead to a wider poverty gap between national and foreign residents.

III. Statement of Hypotheses

This paper will demonstrate to what extent several variables from statewide populations (consumers with subprime credit, households with savings accounts, check cashing and payday lending regulation, income poverty rate, and asset poverty rate) have an impact on that particular state's unbanked population. These multiple individual hypotheses (one-tailed T-tests at a significance level of $\alpha = 0.05$) are grouped into two different variable families. The first set of variables consist of variables expected to lead to an expanded underbanked population as the coefficients of those variables increase. Conversely, the second set of variables is expected to decrease the underbanked population as the coefficients of those variables increase.

H_o: β of LSUBPRIMES, LPOVERTY, & LASSETPOVERTY = 0

H_a: β of LSUBPRIMES, LPOVERTY, & LASSETPOVERTY > 0

N = 51 for most, 45 for Asset Poverty Rate

As seen above, the first set of null hypothesis state that three independent variables have an expected coefficient equal to zero, whereas the alternative hypothesis states that those three variables have a positive coefficient. If the null hypothesis is rejected for these three variables, it is concluded that the positive coefficients coincide with states with higher proportion of consumers with subprime credit, households in poverty, and households in asset poverty lead to a higher level of a particular state's underbanked population.

H_o: β of LSAVINGS, CHECKCASHING, & PAYDAYLENDING = 0

H_a: β of LSAVINGS, CHECKCASHING, & PAYDAYLENDING < 0

N = 51

The second set of hypotheses states a null hypothesis indicating that the coefficient for households with savings accounts, check cashing, and payday lending are zero. The alternative hypothesis states negative coefficients for households with savings accounts, check cashing, and payday lending. If the null hypothesis is rejected for the three variables, one can conclude that states with a higher proportion of households with savings accounts, the regulation of check cashing services, and the outlaw of payday lending will, on average, lead to a state with a lower underbanked population.

IV. Data Description and Research Methodology

The statistical model uses the logarithmic form (as indicated by the "L" preceding each variable) of the following dependent variable (**UNDERBANKED**), the logarithmic form of four independent variables, and two dummy variables. The logarithmic transformation of the dependent variable is to ensure consistent estimates; Logging the four continuous independent variables as well permits the interpretation of coefficients as the elasticity of response of **UNDERBANKED** to each. The following equation is used to estimate the dependent variable:

$$\mathbf{LUNDERBANKED} = \beta_0 + \beta_1 \text{*LSUBPRIMES} + \beta_2 \text{*LSAVINGS} + \beta_3 \text{*LPOVERTY} + \beta_4 \text{*LASSETPOVERTY} + \beta_5 \text{*CHECKCASHING} + \beta_6 \text{*PAYDAYLENDING} + \epsilon$$

- **LUNDERBANKED** (Log Underbanked 2013) is the log of the proportion of households in each state as of 2013 that are underbanked, which is defined as households that have traditional bank accounts, but still use AFSPs.
- **LSUBPRIMES** (Log Consumers with Subprime Credit Q3 2014) shows the log of the proportion of consumers in a state with a TransUnion score at or below 700 for the 3rd quarter of 2014.
- **LSAVINGS** (Log Households with Savings Accounts 2013) is defined as the log of the proportion of households with savings accounts in a state as of 2013.
- **LPOVERTY** (Log Income Poverty Rate 2013) refers to the log of the proportion of households as of 2013 with income below the federal poverty threshold, which is $23,550 for a family of four.

- **LASSETPOVERTY** (Log Asset Poverty Rate 2011) is the log of the proportion of households as of 2011 without sufficient net worth to subsist at the poverty level for three months in the absence of income. The data for the dependent variable and aforementioned five independent variables are provided by Pew Research Center's Assets & Opportunity Scorecard, which sources data from various FDIC reports.
- **CHECKCASHING** (Regulate Check Cashing) is a dummy variable where the value "1" is to assigned to a state with a regulatory environment for check cashing, whereas a "0" is assigned when a state has no special restrictions on check cashing. The Uniform Law Commission provides this data.
- **PAYDAYLENDING (**Allow Payday Lending) is another dummy variable where "1" is assigned to a state that allows payday lending, and "0" is assigned to a state that bans payday lending. Pew Trusts provides this data.

V. Statistical Methods and Interpretation of Results

The correlation matrix (Table 2) shows that **Households With Savings Accounts** and **Income Poverty Rate** are correlated, as seen by the simple correlation of -0.7734. Additionally, the correlation matrix also shows evidence of correlation among **Income Poverty Rate**, **Households With Savings Accounts**, and **Consumers With Subprime Credit**, giving evidence that these three metrics pertaining to poverty, savings, and credit help explain the same population of underbanked households on a state by state basis. All of these indicators capture part of a fundamental contributor to the underbanked: a low-income population.

Because of the potential overlap in these explanatory variables, a factor analysis (Table 3) was completed on the full model in order to see if the variability of the six independent variables can be well explained using fewer "unobserved" variables, referred to as factors. In other words, this analysis will indicate exactly how unique the variables are from one another. The results show that most of the variance in the full model is captured in the first factor, which is comprised heavily of **Consumers With Subprime Credit**, **Income Poverty Rate**, and **Consumers With Subprime Credit**. This means, these three variables are highly collinear, which anticipates there may be a problem of multicollinearity in the model. **Regulate Check Cashing** has the highest uniqueness figure of 0.8901[1]. That is, **Regulate Check Cashing** captures variance that none of the other variables capture, which provides interesting insight on the impact of government regulation on the model. Although not as strongly unique, **Allow Payday Lending** also provides a unique explanation of the model's variance.

A multiple regression of the underbanked (Table 4, Column 1) for the entire logged model was conducted and produced robust, highly significant F-test results. The adjusted R-squared suggests that the model explains roughly 62 percent of the variance in the dependent variable (**Underbanked**). Many of the individual independent variables are not significant at the 0.05 level; however, **Consumers With Subprime Credit** and **Regulate Check Cashing** are significant individual predictors and garner the hypothesized sign.

The lack of uniqueness in the factor analysis among **Households With Savings Accounts**, **Income Poverty Rate**, and **Asset Poverty Rate** coupled with the lack of significance in the multiple logged regression model supports the concern that the variables suffer from the problem of multicollinearity. As seen above when regressing **Households With Savings Accounts** as the dependent variable against **Income Poverty Rate** and **Asset Poverty Rate**

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[1]In factor analysis, uniqueness is the variance that is 'unique' to the variable and not shared with other variables. It is equal to 1 minus communality, where communality is defined as variance that is shared with other variables. (Torres-Reyna)

(Table 4, Column 2), the adjusted R-squared of 0.5826 shows a significant amount of explanatory power from just two independent variables, given the significant F-statistic for the equation. **Income Poverty Rate** is highly significant at the 0.05 level in the model, whereas **Asset Poverty Rate** is not.

Since **Asset Poverty Rate** was not significant in the previous regression, a simple regression was run on **Households With Savings Accounts** as the dependent variable and **Income Poverty Rate** as the independent variable (Table 4, Column 3). The model shows highly-significant T-test results and an improved adjusted R-squared of 0.617, concluding that there is significant overlap in the variance explained by the two variables together.

Although many of the individual predictors were insignificant, the group of independent variables as a whole is a good predictor of a state's underbanked population (Table 4, Column 1). Two variables in particular – **Consumers with Subprime Credit** and **Regulate Check Cashing** – are significant in the model. **Consumers with Subprime Credit**'s coefficient of 1.29 may contain explained variance from **Households with Savings Account**, **Income Poverty Rate**, and **Asset Poverty Rate**, since there is evidence that all four variables overlap in explaining the same portion of the population. However, with **Regulate Check Cashing**'s statistically significant coefficient of -0.05 indicates states that impose regulations on check cashing businesses may see a 5 percent reduction in the state's overall underbanked population. One postulation is that these state-imposed consumer protections minimize fees, which allows poor residents to amass enough savings to justify the sole usage of mainstream banking services.

A multiple regression was conducted using **Regulate Check Cashing**, **Allow Payday Lending**, and the first factor (**Factor** 1) from Table 3 constructed as an explanatory variable. The factor was selected as an independent variable to help simplify the four individual measures of poverty and consumer credit into one simpler variable with less overlapping variance. Additionally, the single variable as compared to the four separate measures mitigates the likely problem of multicollinearity, since there is reasonable assurance that consumers with subprime credit also experience asset poverty, and so forth. The findings, outlined in Table 5, shows **Factor 1** significant at the 0.01 level. The adjusted R-squared, however, is only 0.49, as compared to 0.62 in the full regression model using all six explanatory variables to explain the underbanked. Although there is evidence that using **Factor 1** as an explanatory variable helps provide a statistically significant coefficient upon which one can make conclusions about the population, the lower explanatory power in this partial model is less helpful than the full model in illustrating the impact of poverty and consumer credit on the population of underbanked households per state.

The test for heteroskedasticity (Table 6) shows mild evidence that error variances are a multiplicative function of one or more variables in the model as shown by the probability of 0.33, but the low chi-square value of 0.91 gives evidence that heteroskedasticity is not a problem in the complete model. The results of previous estimations stand.

VI. Conclusion

With over 20 percent of U.S. households classified as “underbanked,” meaning they use both mainstream banking services as well as fringe banking services (check cashers and payday lenders), there must be some questions raised as to why consumers fall in-between markets for banking services. The model outlined in this paper includes metrics of consumer poverty and credit, as well as the regulations imposed by the states on check cashing shops and payday lenders. Although it can be concluded that these metrics together explain a large portion of the variance in state underbanked populations, the confounding nature of these variables make it difficult to draw conclusions on the impact of individual predictors in the model.

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VIII. Statistical Tables

Table 1
Variable Summary Table

Full Series Name	*Abbreviated Name*	*Mean*	*Sample Standard Deviation*	*Sample Size*
Log Underbanked 2013	**LUNDERBANKED**[2]	-0.71	0.10	51
Log Consumers with Subprime Credit Q3 2014	LSUBPRIMES[2]	-0.27	0.05	51
Log Households with Saving Accounts 2013	LSAVINGS[2]	-0.16	0.06	51
Log Income Poverty Rate 2013	LPOVERTY[2]	-0.85	0.09	51
Log Asset Poverty Rate 2011	LASSETPOVERTY[2]	-0.62	0.08	45
Regulate Check Cashing	CHECKCASHING[3]	0.41	0.50	51
Allow Payday Lending	PAYDAYLENDING[4]	0.71	0.46	51

[2] Source: http://scorecard.assetsandopportunity.org/latest/issue-area/finance
[3] Source: http://www.uniformlaws.org/shared/docs/money%20services/ndpnbfi.pdf
[4] Source: http://www.pewtrusts.org/en/multimedia/data-visualizations/2014/state-payday-loan-regulation-and-usage-rates

Table 2
Correlation Matrix

	UND~2013	CONSUM~Q	HOUSEH~S	INC~2013	ASS~2011	REGULA~G	ALLOWP~G
UNDERBA~2013	1.0000						
CONSUMERSW~Q	0.7648	1.0000					
HOUSEHOLDS~S	-0.7125	-0.7754	1.0000				
INCOMEP~2013	0.6089	0.7583	-0.7734	1.0000			
ASSETPO~2011	0.1847	0.3242	-0.0958	0.2111	1.0000		
REGULATECH~G	-0.3647	-0.1738	0.1918	-0.2248	0.0758	1.0000	
ALLOWPAYDA~G	0.0975	0.2276	-0.0471	0.2135	-0.1686	-0.2810	1.0000

Table 3
Factor Analysis

Factor analysis/correlation Number of observations = 45
Method: principal factorsRetained factors = 3
Rotation: (unrotated) Number of parameters = 15

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	2.98	2.34	0.79	0.79
Factor 2	0.64	0.31	0.17	0.96
Factor 3	0.32	0.16	0.09	1.05
Factor 4	0.17	0.12	0.04	1.09
Factor 5	0.05	0.21	0.01	1.10
Factor 6	-0.17	0.05	-0.05	1.06
Factor 7	-0.22	-	-0.06	1.00

Variable	Factor 1	Factor 2	Factor 3	Uniqueness
LSUBPRIMES	0.87	-0.01	0.15	**0.22**
LSAVINGS	-0.87	0.02	0.28	**0.17**
LPOVERTY	0.85	-0.04	0.07	**0.28**
LASSETPOVERTY	0.24	0.51	0.24	**0.62**
CHECKCASHING	-021	0.24	0.07	**0.89**
PAYDAYLENDING	0.02	-0.53	0.26	**0.65**

Table 4
OLS Estimation Results

	LUNDERBANKED	**LSAVINGS**	**LSAVINGS**
LSUBPRIMES	1.29** (3.78)	-	-
LSAVINGS	-0.44 (-1.32)	-	-
LPOVERTY	-0.21 (-1.05)	-2.38** (-7.92)	-2.27** (-9.04)
LASSETPOVERTY	-0.05 (-0.37)	0.13 (0.77)	-
CHECKCASHING	-0.05* (-2.54)	-	-
PAYDAYLENDING	-0.03 (-1.26)	-	-
INTERCEPT	-0.61** (-3.06)	1.01** (18.19)	1.02** (27.87)
Adjusted R^2	0.62	0.58	0.62
n	45	45	51
F-statistics	12.77** [6, 38]	31.71** [2, 42]	81.64** [1, 49]
T-statistics in parentheses. F-statistic degrees of freedom in brackets.			
* and ** indicate statistical significance at the 0.05 and 0.01 levels, respectively.			

Table 5
Regression Analysis with Factor Construction

	LUNDERBANKED
CHECKCASHING	-0.49 (-7.07)**
PAYDAYLENDING	-0.03 (-1.18)
FACTOR 1	0.45 (6.94)**
INTERCEPT	-0.16 (-1.93)
Adjusted R^2	0.49
N	51
F-statistic	16.79 (3, 47)**
T-statistics in parentheses. F-statistic degrees of freedom in brackets.	
* and ** indicate statistical significance at the 0.05 and 0.01 levels, respectively.	

Table 6
Test for Heteroskedascity

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Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of lunderbanked2013

         chi2(1)      =     0.91
         Prob > chi2  =   0.3396
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