Bouncing Out of the Banking System: An Empirical Analysis of Involuntary Bank Account Closures

Dennis Campbell
Harvard Business School

Asís Martínez Jerez
Harvard Business School

Peter Tufano
Harvard Business School
NBER
D2D Fund

Draft: June 6, 2008

Bouncing Out of the Banking System:
An Empirical Analysis of Involuntary Bank Account Closures *

Using a new database, we document the factors that relate to the extent of involuntary consumer bank account closure resulting from excessive overdraft activity. Consumers who have accounts involuntarily closed for overdraft activity may have limited or no access to the formal banking system. In the period 2000 through 2005, there were approximately 30 million checking accounts reportedly closed for excessive overdrafting. Closure rates jointly reflect (a) financial mismanagement on the behalf of families and (b) bank forbearance policies regarding overdrawn customers. We focus on five factors to explain the incidence of involuntary closures: personal traits, community traits, economic trends, bank policies, and credit access through the alternative financial services sector. We find that involuntary closures are most frequent in U.S. counties with: high rates of households headed by single mothers; low levels of college education; high rates of property crime; a strong presence of multi-market vs. local banks; higher levels of competition among banks; and low rates of electoral participation. Negative shocks to income and rates of employment are also associated with increases in closure activity within counties over time. We interpret these results as consistent with involuntary consumer account closures being jointly driven by thin margins between income and expenditures; general consumer inability to budget and forecast; bank incentives; and community norms and social capital. Furthermore, using both national data and a natural experiment, we find that access to payday lending seems to lead to higher rates of involuntary account closure.

Dennis Campbell
Harvard Business School
Soldiers Field
Boston, MA 02163
dcampbell@hbs.edu

Asís Martínez Jerez
Harvard Business School
Soldiers Field
Boston, MA 02163
asis@hbs.edu

Peter Tufano
Harvard Business School
and NBER
and D2D Fund
Soldiers Field
Boston, MA 02163
ptufano@hbs.edu

We would like to thank eFunds for their cooperation with this research, in particular we benefited from assistance from Paul Bjerke, David Edwinsson, Barb McDonald, Benjamin Post, and Joshua Turnbull. We received excellent research support from Debbie Strumsky, Emily McClintock Ekins, and Jan-Emmanuel De Neve. We received helpful comments from Don Morgan and Anna Paulson and from seminar participants at the Yale School of Management and the Chicago Fed Bank Structure and Competition Conference. We thank Jim Fellows for sharing his data on alternative financial services with us. Financial support for this research project was provided by the Division of Research of the Harvard Business School. The findings and conclusions presented in this report are those of the authors alone, and do not reflect the opinions of eFunds or the Harvard Business School.

I. Introduction

Each year, millions of Americans have checking and debit accounts that are involuntarily closed by their banks.[1] The vast majority are closed because the account holder has demonstrated poor financial management through repeated overdraft or non-sufficient funds (NSF) activity. In common terms, they have bounced too many checks, writing checks or using debit cards for more than the balances available in their accounts. In some instances, the bank may have honored the overdrawn but presented payment requests, but expected the consumer to deposit the appropriate funds and pay additional overdraft fees in a timely manner. In other cases, the bank may not have honored the presented checks, but still charged the customer non-sufficient fund (NSF) fees. Up to a point, the bank may exhibit forbearance. However, at a certain point, recidivist check bouncers' accounts are involuntarily closed.

In the U.S., about 6.4 million accounts were involuntarily closed in 2005. Virtually all banks report involuntary closures to a private firm which maintains a database on the closure activity of the majority of the American banking population. While many people are familiar with credit bureaus and credit scores (e.g., FICO scores), fewer are familiar with the consumer reporting agency, ChexSystems[SM], that that maintains records of involuntary closures. Apart from Jacob, Post, Tescher and Turnbull (2006), there is no published empirical work on the incidence of involuntary closure. However, much as credit scores are used to determine who does and does not receive offers for and ultimately get credit, data from the ChexSystems database is used by

[1] Throughout the paper, we refer to "banks," but except where we identify them separately, our analysis considers not only commercial banks, but also other depository institutions such as savings and loans and credit unions.

virtually every large American bank to determine who will and will not have the right to open a checking account or to get a debit card.

While there is little formal research on how banks use ChexSystems data to determine who will have the right to open an account—nor is there research on bank forbearance, there is strong anecdotal evidence that evidence of prior financial mismanagement at another institution either leads banks to deny customers checking accounts, or only to offer them high cost or limited service accounts (Lamb and Leonard, 2007; Michael, 2004; Manning, 2000; Beckett, 2000; Caskey, 1994). Furthermore, many banks link the opening of a checking account with the right to open a savings account, so that denials of checking activity can mean that a person cannot open a savings account as well.

In essence, a customer that bounces too many checks can find themselves "bounced" out of the formal banking system and into the fee-based alternative financial service (AFS) sector. Many scholars, consumer advocates, and policy makers are troubled by the plight of these "unbanked" (or "self-banked," a term AFS providers prefer.) For example, on July 11th 2007, Jean Ann Fox of the Consumer Federation of America (CFA) testified before the U.S. House Subcommittee on Financial Institutions and Consumer Credit on how consumers with involuntary closures "may not be able to open a new bank account for years." These former bank customers may find themselves with only limited banking alternatives, or with access only to the fee-for-service check cashing or money service businesses.

Policy makers, consumer advocates and banking institutions can debate the social costs of the "unbanked" or the fairness of penalty charges or transaction fees paid by marginal customers. These emotionally charged debates should be informed by solid facts, and as a first step, this paper seeks to understand the characteristics of people whose bank accounts have been involuntarily closed. In particular, we construct a new national database to study the determinants of involuntary checking account closure activity. We have access to county-level closure statistics over the period 1999 through 2006, which we match to a variety of demographic, economic and industry data for these geographic units. Our study seeks to answer a simple question, “What types of people, communities, economic times, banks and other financial institutions lead to higher closure activity?”

As initial hypotheses, we look at a few broad classes of explanations. First, perhaps closure activity represents *individual traits*. Starting at first principal, overdrafts exist when expenses exceed current income, so we look at the level and volatility of both, as well as savings’ buffers to predict closures. Certain phenomena are related to the narrow income-expense margins, so for example, we examine poverty and unemployment as predictors of closure activity. Other non-economic personal traits may affect financial decision making, in this case, budgeting. For example, Campbell (2006) shows that poorly educated households are more likely to make apparent errors in refinancing decisions. Agarwal, Driscoll, Gabaix, and Laibson (2007) show that financial decision-making seems to be related to age in an inverse-U pattern, with poorer decisions by the young and old.

Second, while personal characteristics might be correlated to closure activity, *community structure* might affect the incidence of this activity too. In communities where there is greater social capital, individuals might be less likely to overdraw their accounts, banks might be more likely to give customers a second chance, or friends and family might band together to help families short of funds.

Third, the decision to close an account is a bank decision, and *bank policies* also play a role in determining how much NSF activity there is. "Free checking programs" that allow consumers to have checking accounts without monthly fees typically attract less financially stable customers. From a bank's perspective, the economics of these products is driven by customers with sloppy habits who pay courtesy overdraft fees. Certain bank policies permit (or perhaps even encourage) overdrafts, and overdraft fees have become an important component of bank profits. If banks induce more overdrafts that in turn leads to involuntary closure, then bank strategies and involuntary closures will be linked. We posit that banking markets that are more competitive might be ones in which banks reach deeper for new customers, leading to less financially secure customers and more closure. Some bank strategies might be more preconditioned on greater customer knowledge or greater forbearance. To test if "localness" affects rates of involuntary closure activity, we use data on the mix of single-market and multi-market banks.

Finally, while we are studying bank closures, banking activity is conducted in the context of a broader financial service sector. In particular, the availability of short-term unsecured loans, in the form of payday lending, could either help people forestall closures by giving them a way to remediate overdrafts, or could exacerbate closures by providing yet more short-term credit. We study the relationship between payday lending and closures, both using our national data, as well as by looking at a natural experiment in Georgia.

The remainder of the paper is divided in four sections. In Section 2, we provide institutional background critical to understanding the phenomena we are studying in this paper and develop our broad hypotheses. In Section 3, we describe our data and empirical methodology. We report aggregate data on the level of closure activity, discuss the empirical proxies we use for our analyses and discuss our methodological approach. In Section 4, we examine the empirical determinants of closure activity. In Section 5, we conclude, discussing implications of our work and additional research.

II. Background and Motivation: Involuntary Account Closures

In this paper, we study consumers whose financial mismanagement behaviors have led their banks to close their debit (checking and debit card) accounts. Our data, described below, come from an industry standard private database to which virtually all banks voluntarily report this type of closure information. This data is then shared with other participating banks that use it as part of their procedures to determine whether to accept new debit account applicants. Before we explain our data or the determinants of closure activity, we discuss what closure activity represents; and why studying closure activity may be interesting to economists, consumer advocates, bank executives, and policymakers.

What is involuntary closure? Our work studies *involuntary* closure of debit accounts. While voluntary closure may result from a consumer deciding to move or to do business with another bank, involuntary closure results from a bank decision to deny debit privileges to an existing consumer. The database we use maintains records of these denials which result from two main classes of activities: fraud and overdraft activities. Banks report the account closure and select the reason for the closure. In theory, reporting should represent all closures, but there is no way to assure this to be the case. Virtually all of the reported closures (97.5%) are from overdraft activities and only 2.5% reflect fraudulent activity. See Figure 1 for the time pattern of average monthly closure activity which shows that the general level of closure activity has been increasing over time. The seasonal patterns shown in Figure 1 reflect the ebb and flow of consumer spending patterns over the year.

Observed involuntary closure is the joint product of behavior by both an individual and a bank. First, overdraft closures reflect *consumer behavior*, in particular substantial and sustained overdraft activities which are not remediated by the consumer posting sufficient funds to her account to cover the charges and overdraft fees. Taken from the consumer perspective, overdrafts may reflect (a) poor financial management, (b) unexpected shocks, or (c) strategic defaults. Poor financial management would imply bank customers not balancing their checkbook and living beyond their means. Unexpected shocks to income or expenses, due to unemployment or health problems, could cause a consumer to overdraw even if she was a careful budgeter. Finally, strategic defaults could reflect consumers intentionally taking advantage of "courtesy pay" programs. Banks offer these programs where they honor debits where there are insufficient funds, but demand the payment of a fixed fee, often $25-35 along with posting of the debited amounts.[2] In functional terms, overdrafts are high-cost short term credit. For example, a $30 fee for a $100 overage remediated in two weeks would correspond to an APR of 780%, were it considered interest.

[2] For a description of an overdraft program, see Campbell, Martinez-Jerez, McClintock and Tufano (2007).

Involuntary account closings also reflect two *bank* decisions. First, banks set policies about which debit applicants to accept, and can choose to take more or less risky applicants. Second, in the face of overdraft activities, banks have discretion about when or whether to close accounts. For example, banks do not typically close accounts simply because someone has bounced a single check. If a person has an account closed, it implies that the bank perceived that the financial mismanagement was severe enough so that the bank no longer wished to extend debit banking privileges to the consumer. To the best of our knowledge, there is no public data on accounts that bank policy would dictate should be closed, but that the bank choose to keep open. To the extent that involuntary closures reflect bank behavior, we would look for factors that would make banks more likely to open riskier accounts or less likely to exhibit forbearance.

Why does involuntary closure matter to families, policymakers and consumer advocates? One of the key functions of a financial system is to facilitate the payments system that allows people to purchase goods and services, or to pay bills (Crane et al. 1995). From a consumer's perspective, one can buy goods or pay bills using a variety of means, including barter, cash, postal money orders, private money orders, personal checks, debit cards, ACH transfers, bank wires, checks, or stored value cards. Alternatively, a consumer can combine the payments function and borrowing to use products like credit cards or overdraft facilities. Given the many substitute payment mechanisms, and with more than 8,000 commercial banks, 1,400 savings banks, and 10,000 credit unions[3] in America, why would involuntary closure activity matter—especially at a single bank?

[3] Source: Hoovers. Available at http://www.hoovers.com/banks-and-credit-unions/--ID__111--/free-ind-fr-profile-basic.xhtml (accessed in October 2007)

While one needn't have a bank account to use barter, cash, postal money orders, or private money orders, the other means of effecting payments often require that a person have a bank account. A person's ability to open a bank account at *any* depository institution can depend on a closure event from a *single* other bank, given the way in which this information is shared with virtually all banks. Furthermore, while in theory, failure to have a payment account shouldn't affect your ability to get other financial services, in practice, there are often institutional links between payment services and other financial services.

To understand why an involuntary closure can lead to a near-complete closure of the formal banking payment system, one needs to consider how the account opening process works at banks.[4] In general, before approving an applicant for a debit account, banks and credit unions access the industry-standard ChexSystems database, which maintains records of involuntary and fraud closures over the prior five years. This information is collected from member banks, which include most depository institutions in America. A customer service representative can usually access this information electronically while a customer is waiting. Banks determining policies about who will and won't be accepted or for which accounts. Banks can either use raw information (e.g., has there been an involuntary closure in the last 5 years) or they can use a scored version of the debit information (called QualiFile®) that is analogous to a credit score. This score depends on debit and payment information (and can also use credit information) for current and past accounts. A major factor in the QualiFile score is the event of past

[4] See Campbell, Martinez-Jerez, McClintock and Tufano (2007) for a case study that details this process at a single bank.

involuntary closures. Neither ChexSystems nor its QualiFile product determines account opening, but rather are inputs to bank operating procedures.

While there is no public data on how banks use ChexSystems, various sources suggest that it is the norm for many banks to either turn down customers with previous debit problems altogether or offer them a limited set of products. For example, in a field experiment conducted by Beverly, Schneider and Tufano (2006), the bank not only denied applicants with involuntary closures checking accounts, but savings accounts as well. In the case study at another bank, Campbell, Martinez Jerez, McClintock, and Tufano (2007) found that the institution routinely turned down debit applicants with prior debit problems, turning away about 20% of applicants. Thus, a single bank's decision to involuntarily close an account can severely affect an individual's ability to get any account. It should be noted that some banks voluntarily (a) choose not to use ChexSystems[5]; (b) limit the time horizon over which they consider an involuntary closure relevant, and (c) offer a restricted product set to consumers with involuntary closure information. Furthermore, ChexSystems' parent has partnered with the University of Wisconsin Extension to develop a "Get Checking" program, whereby consumers who have prior negative debit events can enroll in a financial education program and be assured to being able to open an account. To date, this program is reported to have been completed by 11,000 participants.[6]

Many consumer groups have focused attention on the problems of those who have limited payment system options as a result of prior involuntary closure activities.

[5] For a list of these banks and credit unions, see http://chexsys.tripod.com/goodbanks.html (visited October 15, 2007). For a discussion of banks that have voluntarily limited their use of ChexSystem's data, see <>. For a discussion of "Fresh Start checking programs, see <>.
[6] See http://www.getchecking.org/ (visited October 29, 2007)

Consumer advocates and policymakers worry that individuals with prior negative debit events might have few options, all of which are costly. Either the consumer might be use AFS centers, commonly called check cashers. Desmond and Sprenger (2007) summarize studies of the costs of using these services, as well as the indirect costs of not having access to savings accounts and credit. Alternatively, bounced customers might be forced to use bank debit accounts with limited services and substantial overdraft penalties. These accounts might have monthly fees, but more importantly can charge substantial overdraft fees, which are likely important for customers who have already demonstrated a propensity to overdraft. Our paper does not measure the cost of involuntary closures, but rather the incidence of this activity.

What can academics learn by studying involuntary closures? Financial economists can use this new study of involuntary closures as a window into consumer and bank behavior. In the wake of increasing interest in behavioral factors affecting consumer decision making, our data provides a window into simple household financial management. A number of other studies examine more advanced financial decision making (e.g., whether to invest in a 401k; how to invest one's assets; whether to select a fixed or adjustable mortgage; or whether to borrow while maintaining a positive, but lower yielding, savings account). We examine a much simpler financial condition: the inability to balance cash inflows and outflows to avoid recurrent overdrafts. We study the household and community factors that make this problem more severe.

Secondly, a number of studies examine bank credit decisions (Agarwal and Hauswald 2007, DeGryse and Ongena 2005, DeYoung et. al. 2004, Hauswald and Marquez 2005). We study an element of bank debit decisions, in particular, how bank-level factors affect the decision to close accounts, independent of the characteristics of customers. For example, one might imagine that "local" banks might be more willing to show forbearance and not close accounts of customers they know or may have better "soft" information on their local markets and consumers than large banks that operate across multiple markets (Agarwal and Hauswald 2007).

III. Data and Methodology

Our primary approach to explaining the determinants of involuntary bank account closure activity is to examine how differences in this activity relate to empirical proxies for personal traits, community traits, economic trends, bank policies and other financial services both across counties and within counties over time. ChexSystems, the eFunds database, is our main source of information for account closures. eFunds is a Scottsdale, Arizona-based payment solutions company that helps firms manage risk through products that analyze customer data. Information on involuntary account closures is reported to ChexSystems by approximately 9,000 financial institutions representing over 100,000 locations (about 90% of U.S. commercial banks, credit unions, and savings institutions). Involuntary closures may be caused by delinquent payments or by fraud. The same financial institutions that provide client data to ChexSystems use the system to view the banking history of new account applicants.

In the case of new checking accounts, ChexSystems compares the data of account applicants with information from other banks in order to flag individuals who have recently experienced a negative, risk-enhancing event. The system notifies the bank if the customer has been forced to close an account or has left bills unpaid at a participating retailer. It also informs the bank of cases in which the given social security number and other identifying information do not seem to match, signaling a possible incidence of identity fraud or theft.

eFunds provided detailed frequency statistics of closure activity at the county level. The information was protected so that we did not have access to specific individual information such as identity or socio-demographic characteristics. Identifying information of the financial institutions reporting account closures or making customer inquiries was similarly excluded. Jacob et al. (2006) also use aggregated (census tract) data from eFunds, in their study of the Chicago market.

ChexSystems keeps a repository of historical information for seven years, allowing us to access information starting in the year 1999. However, the availability of other data sources led us to limit the period covered by our study to the years 2002-2004. (Jacob et al (2006) look at 2002.) Table 1 describes the geographic coverage of our analysis. Of the 3,141 counties in the United States, 3,138 reported account closures during the period analyzed. We discard 43 counties in the Northeastern United States because eFunds acquired a regional closure database for that area in 2004 that makes these observations incompatible with the rest of the database. We discard an additional 238 counties for which one or more of the data sources used in the study was not available. This leaves us with a total of 2,857 counties.

We consolidate monthly data by year in order to maintain consistency with our explanatory variables, most of which are available only on an annual basis or at an even lower frequency. To normalize for size differences across counties, we scale the closure measure by county population in thousands (*CLOSURES)*. Table 2 contains variable descriptions, data sources, and summary statistics for all variables. The annual number of account closures ranges from 0 to 61.4 per thousand people, with an average of 13.5. By way of comparison, in their study of Chicago, Jacob et al. (2006) tracked accounts opened in 2002 and found that by 2006, 7.6% were closed for cause. On an annual basis, this seems to 1.9% or 19 per thousand accounts.

We look at a number of different possible determinants of closure activity. Involuntary closure occurs when debit withdrawals exceed debit account deposits on a persistent basis, the overdrafts remain unremediated, and the bank chooses to close the account. The factors we study relate to levels of family income and expenses, shocks to income and expenses, the availability of cash assets as buffers, education as a measure of general ability to budget, crime, social capital connections in the community, the localness of banks, and other factors, as explained below and described more fully below. First, however, we discuss an important normalization measure: bank account activity.

Bank Account Activity: All else equal, involuntary closure activity should be higher when there are more open bank accounts. This is problematic for comparing closure activity across counties since many of the determinants we examine in this paper may be correlated with unobserved banking activity across geographic areas. For example, ceteris paribus, banking activity might be generally lower in economically distressed areas where we would predict involuntary closures to be higher (holding the level of banking activity constant). Without adequately controlling for the level of banking activity across counties, this could limit our ability to identify the predicted relationships between closure activity and its determinants. Ideally, we would like to measure the total number of active checking accounts in each county. However, we are not aware of a source that breaks down active checking account numbers at the county level. As an alternative measure, ChexSystems tracks the number of inquiries banks make about individuals during the account opening process. We use the detailed frequency statistics on account inquiries at the county level as a measure of banking activity. To avoid endogeneity between involuntary closures and account inquiries (e.g. consumers with involuntarily closed accounts at one bank inquiring at other banks about new accounts), we use the number of "clean" inquiries per capita (inquiries made by banks for customers who do not have any reported closures in the past five years) as our county-level measure of bank account activity (*INQUIRIES*). Table 2 shows that the number of inquiries per thousand people ranges from 0.16 to 441, with an average of 69.4.

For robustness, we also use an alternative measure of bank account activity, an estimate of the number of banked households per capita by county, which we obtain from a private firm (IXI), described below.

Finances Relative to Expenditures and Shocks to Income: Ceteris paribus, families with lower *income* should generally be more likely to overdraft. Similarly, families with lower financial assets should encounter more problems. Conversely, families with higher *expenses* should be more likely to overdraft. For families in poverty, the margin between income and expenses is thin by definition. Finally, certain family structures—in particular single mothers—typically have less income relative to expenses. All of these factors might lead to more overdrafting.

We gauge the margin between income and expenses for the average family in each county through per capita personal income (*PCPI*), unemployment levels (*UNEMPLOYMENT)*, population of single-mothers (*SINGLEMOM*), and poverty levels *(POVERTY)*. County PCPI data is obtained from the Bureau of Economic Analysis's Regional Economic Accounts and is updated annually. In constant 2000 dollars, the poorest county has a PCPI of $10,340 and the wealthiest has a PCPI of $88,800 as shown in Table 1. The average PCPI is $25,000.[7] Unemployment figures come from the Local Area Unemployment Statistics of the Bureau of Labor Statistics. Unlike PCPI, this source is updated monthly, but we use end-of-year observations for our analysis. These observations show that the average unemployment level is 5.8%. The lowest unemployment rate per county is 2.0%, and the highest, at more than three times the average, is 17.1%. The presence of single mothers is measured using 2000 Census data as the percentage of each counties population classified as a female head of household living with her own children and has a mean of 7.1% in our sample. Finally, we measure poverty as the percentage of all households in each county living below the federal poverty line (in 2000, about $17,603 for a four-person family).[8] These rates are estimated annually and range from 2.3% to 49.1% per county. The average percentage of households living in poverty is 13.7.

A family can withstand income or expense shocks if it has a stronger household balance sheet, in particular if it has financial assets. We obtained a measure of county level financial assets (WEALTH) from IXI Corporation, a private data vendor to financial service firms. IXI has organized several financial services firms into a data

---

[7] We adjust PCPI numbers for inflation using the Chain Weighted Deflator.
[8] "Poverty Thresholds 2000," U.S. Census Bureau, http://www.census.gov/hhes/www/poverty/threshld/thresh00.html (accessed October 18, 2007).

sharing consortium with each member institution reporting detailed (anonymous) transaction, account, customer, and household level data. IXI collects data from 25 full service brokerage firms, 15 of the 20 largest banks in the U.S., and all of the largest 15 annuity issuers. IXI also collects data from several mutual fund groups and insurance firms. IXI uses direct measured data from these firms to estimate the total value of assets held in securities, deposits, and annuities within a geographic area (e.g. zip code or county). IXI also provides an estimate of households with deposit account which we divide by population (BANKEDHH). We have IXI data only for 2004.

General Ability to Budget and Forecast: A number of studies, such as Campbell (2006) and Massoud, Saunders, and Scholnick (2007) have found that certain factors, in particular education, are related to financial decision making. One might posit that more poorly *educated* individuals might be less able to carry out budgeting (or alternatively, it could be the case that less well educated people have lower or more variable income.) As cited earlier, Agarwal, Driscoll, Gabaix, and Laibson (2007) find that financial decisions may be related to age, with both younger and older persons making poorer decisions than those in between.

We capture measures of the education and age distribution of each county using variables from the 2000 Census of the U.S. Census Bureau. As shown in Table 2, the proportion of the adult population over the age of 25 that has completed high school but not attained a college degree (*HIGHSCHOOL)* or has attained a bachelors degree (*COLLEGE)* ranges from 9.9% to 55.7% and from 17.5% to 87% respectively. The distribution of the population across the age ranges of 20-34 (*AGE2034*), 35-64 (*AGE3564*), 65-74 (*AGE6574*), and over 75 (*AGE75*) also varies widely across counties.

As the Census is updated on a decennial basis, this data is non-variant across the annual observations used in the regression analyses. (In unreported analyses, we have also used median age as an alternative measure.)

Crime: Communities with higher *crime* could have higher overdraft and closure activity for a variety of reasons. First, the incidence of crime could indicate a generally weaker economic environment, and be a proxy for lower or more volatile household incomes. Second, while not fraudulent per se, intentional overdrafting that leads to closure could represent an economic response to bank practices which honor overdrafts.

The FBI Uniform Crime Report provides annual statistics on the number of crimes per 1,000 people. These statistics are divided into two groups, violent crimes and property crimes. In our analyses, we focus on rates of property crime (*PROPERTYCRIME*) as our primary measure since, to the extent involuntary closures are driven by fraudulent activity, we would expect this activity to be related primarily to the level of non-violent crime. Incidences of property crime vary widely across counties in our sample with a low of zero to a high of 84 per 1,000 people as shown in Table 2.

Community Norms and Social Capital: Social capital, as discussed by Putnam (2000) and others is the bond that links people together into communities. In communities with greater social capital, there could be norms that help families budget better, norms that discourage financial mismanagement, or norms that financial institutions should be more forgiving of some financial indiscretions by customers. In communities with stronger social capital, families might be able to borrow money from others in the network. To see if there is a link between social capital and involuntary closing, we examine two of the standard measures of community participation: *church* *attendance* and civic participation in the form of *voting turnout* (Guiso et. al. 2004, Irwin et. al. 1997, Greeley 1997, Hong et. al. 2004). Crime, as discussed above, could also be a negative measure of social capital.

We measure the strength of community bonds and social capital in communities by examining the total number of congregations of all denominations per 1,000 people (*CHURCHES*). This information is obtained from the Association of Religion Data Archives and is updated annually. The average concentration of congregations is 2.2 per thousand people, with a low of 0.15 and a high of 11.7. We also proxy for community norms and social capital using civic participation as measured by electoral turnouts during the 2004 general election (*VOTETURNOUT).* This measure captures the percentage of the adult population voting in the 2004 general election in a county and is obtained from the Congressional Quarterly Electronic Library. Ideally, as a measure of the level of civic engagement in a community, we would like to have a measure of electoral turnouts for *local* elections. However, this data does not appear to be widely available by geographic area.

Bank Characteristics: Some banks might be less likely or slower to close accounts which have experienced extensive overdraft activity. Consistent with prior studies on bank credit decisions (Agarwal and Hauswald 2007, DeGryse and Ongena 2005), "local" banks with substantial customer knowledge may be more likely to show forbearance than national banks with neither information nor a vested interest in a particular community or customer. To measure the *"localness"* of a banking organization, we measure the presence of multi-market and single-market banks in the county (Hannan 2006).

We characterize each county's banking environment by looking at year-end observations from the FDIC Summary of Deposits. First, we capture the proportion of bank branches in the county operated by multi-market (*MULTISHARE*) or single-market (*SINGLESHARE*) banks (the national averages in our sample are 57.6% and 23.0% respectively as shown in Table 2). Consistent with Hannan (2006) we define multi-market banks within a county as financial institutions that derive less than 30% of their deposits from that county and single market banks as those that derive at least 90% of their deposits from that county. A single market bank in one county can be a multi-market bank in another and vice versa. We would expect institutions to have better knowledge of customers in local markets where they have a strong presence. Due to their size, multi-market banks derive most of their competitive advantage from cost efficiency and capital strength and often limit the discretion of local branches. Single-market banks, on the other hand, rely on strong community links and deeper direct knowledge of customers for their strategic edge.

If banks open more accounts—and more marginal accounts, then one would expect closure rates to be higher. One might posit that banks in more competitive markets might be induced to open (and subsequently close) more marginal accounts in a struggle for customers. To see if bank competition affects closure activity, we measure the intensity of competition by the Herfindahl-Hirschmann Index (HHI) of the concentration of deposits, defined as the sum of the squares of the market shares of deposits of banks operating in the county (scaled to a range of 0 to 100). The HHI is an inverse measure of competition – lower levels of this measure signify less concentration, and more competition, among banking institutions in a county. The HHI sample average is 31.3 and varies from 4.4 to 100.

Alternative Financial Services (AFS) Credit: Consumers without access to credit cards, mortgages/equity lines of credit, and other banking products often obtain credit through the AFS sector from pawn shops, title lenders, and payday lenders. These organizations provide short-term, high-interest or high-fee loans to otherwise credit-constrained consumers. Consumers with goods or autos can utilize pawn shops and/or title lenders for collateralized borrowing. Others can use payday lenders. In the typical payday lending transaction, a borrower writes a postdated check to the lender. The lender, in return, provides the borrower a cash advance for the amount of the check less a finance charge. The lender holds the check for either deposit on the posted date or until cash is repaid by the borrower. The typical payday loan has a term of two weeks and an annual percentage rate (APR) in excess of 300% (Barr 2004). For example, a 2001 survey of payday lenders showed that, for the average loan size of $300 and loan term of two weeks, the average finance charge was $54 (Fox & Mierzwinski 2001).

There are at least two competing hypotheses about the influence of access to payday loans on involuntary bank account closures. First, critics argue that these expensive, short-term loans with balloon payments upon maturity force consumers into a "debt trap" in which they are unable to repay the original loan principal in full and repeatedly "roll over" any unpaid balances, plus finance charges, into new loans.[9] In this scenario, increased payday lending activity in a market could lead to higher rates of involuntary closure as some segments of consumers would face a reduction in financial flexibility due to servicing debt from payday lenders.

[9] Barr (2004) and Morgan & Strain (2008) discuss the "debt trap" argument in detail.

In contrast to the "debt trap" critique, expanded access to credit via payday lenders may help consumers smooth shocks to income and avoid adverse outcomes from defaulting on other financial obligations. From the perspective of a consumer facing the prospect of an overdrawn bank account, the availability of payday lending may help to maintain a positive balance leading to the avoidance of costly bounced check fees and reducing the likelihood of a forcibly closed account. In this scenario, expanded access to payday lenders in a market would lead to fewer involuntary closures as some segments of consumers would gain additional financial flexibility from the availability of this form of financing.

Evidence on which of these alternative explanations is likely to prevail is mixed. Morse (2007) finds evidence that a variety of measures of consumer welfare, including foreclosures and health outcomes, are enhanced by the availability of payday lending in communities which experience a natural disaster. Similarly, Morgan & Strain (2008) provide evidence that restricting the availability of payday lending leads to worse consumer outcomes. In their study, two states which banned payday lending, Georgia and North Carolina, experienced negative consumer outcomes, relative to other states, in the form of higher rates of bounced checks, complaints about lenders, and Chapter 7 bankruptcy filings after the ban. Melzer (2007) finds a different result, showing that expanded access to credit via payday lenders leads to worse health outcomes and increased financial difficulty among low income consumers.

We examine the effect of payday loan access on the rate of involuntary account closures in two ways. First, we capture a measure of the number of payday lenders per 1,000 people in a county (*PAYDAYLENDERS*) which allows us to link a proxy for the supply of payday loans to the rate of involuntary closures.[10] Data on payday lenders is only available during 2003. The mean (standard deviation) number of payday lending firms per 1,000 people in our sample of counties is 0.08 (0.11) and ranges from 0 to 0.84. Second, following Morgan & Strain (2008), we take advantage of a natural experiment in which the state of Georgia banned payday lending by statute in May 2004. We describe this experiment after we discuss our national results.

Race: A number of studies have found that financial decisions are related to race (Avery et. al. 2006, Rhine et. al. 2006, Jacob et. al. 2006). While empirical studies may find relations between race and certain outcomes, it is more difficult to trace out the path by which these effects work. Even after controlling for income, education and other measurable factors, certain ethnic groups may experience different closure rates due to a variety of differences. For example, certain ethnic groups also more frequently experience particular income shocks. Race could also have complicated relations with norms, familial experiences, discrimination, and a host of other factors. To control for potential race-related effects, we include in our county-level analysis the breakdown of the population by race. Data on the distribution of the population by race in each county is available from the 2000 census. On average, the population is 9.1% black, 5.3% Hispanic, 0.8% Asian, 1.8% Native American, and 0.9% non-white other in our sample of counties.

Multivariate Model: Our primary model for examining how each of these classes of variables relates to involuntary closure activity is the following empirical model

[10] Data on the number of AFS establishments were provided by Matt Fellowes formerly of Brookings institution and are based on underlying data from the FDIC, infoUSA, state licensing departments, and the U.S. Census Bureau. See Fellowes and Mabanta (2008).

$$
\begin{aligned}
CLOSURES_{it} = \beta_0 &+ \beta_1 INQUIRIES_{it} + \beta_2 PCPI_{it} + \beta_3 POVERTY_i + \beta_4 UNEMPLOYMENT_{it} + \beta_5 SINGLEMOM_i \\
&+ \beta_6 HIGHSCHOOL_i + \beta_7 COLLEGE_i + \beta_8 AGE2034_i + \beta_9 AGE3564_i + \beta_{10} AGE6574_i + \beta_{11} AGE75_i \\
&+ \beta_{12} PROPERTYCRIME_{it} + \beta_{13} MULTISHARE_{it} + \beta_{14} SINGLESHARE_{it} + \beta_{15} HHI_{it} \\
&+ \beta_{16} CHURCHES_i + \beta_{17} VOTETURNOUT_i \\
&+ \beta_{18} BLACK_i + \beta_{19} HISPANIC_i + \beta_{20} ASIAN_i + \beta_{21} NATIVE_i + \beta_{22} OTHER_i + \varepsilon_{it} \qquad (1)
\end{aligned}
$$

where 'i' and 't' index county and year respectively. Variables without a 't' subscript do not vary over the time period of our sample.

If shocks to income and thin-margins between income and expenses are determinants of closure activity, then we expect $\beta_2<0, \beta_3>0, \beta_4>0, \text{and } \beta_5>0$. If general ability to budget and forecast determine closure activity, we expect $\beta_6<0, \text{and } \beta_7<0$ as the relationship between education and closure activity will be measured relative to the population of non-high school graduates. Similarly, while we have no specific predictions on the distribution of closure activity by age group, if poorer financial decisions are made by both young and old, relative to the 35-64 year old population, rates of involuntary closure would be higher for the 20-34, 64-75, and 75 and over populations respectively which would suggest $\beta_8>\beta_9, \beta_{10}>\beta_9 \text{ and } \beta_{11}>\beta_9$. We expect $\beta_{12}>0$ consistent with higher rates of closure activity in geographies with higher incidences of non-violent crime.

Consistent with weaker (stronger) incentives for multi-market (local) banks to tailor customer-acquisition and forbearance polices based on market-specific information, we expect that $\beta_{13}>0 \text{ and } \beta_{14}<0$. In accordance with prior literature, our method for classifying banks as multi-market vs. single-market leaves a broad middle group of banks that are classified as neither (Hannan 2006). Thus, the relationship between closure activity and the presence of multi-market and single-market banks in a county is measured relative to this group. Since *HHI* is an inverse measure of competition, we expect β_{15}<0 reflecting a propensity for banks facing more competition to reach deeper for new customers, leading to less financially secure customers and more closure activity. If community norms and social capital are associated with reduced closure activity, we expect β_{16}<0 and β_{17}<0.

We also estimate a version of equation (1) with *PAYDAYLENDERS* as an additional explanatory variable using the subsample of county level data during 2003 which is the only year for which this data is available. This expanded specification allows us to test whether payday lending is associated with involuntary closure rates after controlling for factors which are expected to be associated with both closures and the supply of payday loans. In addition, for 2004, we estimate a form of equation (1) using the IXI wealth proxies by county.

We estimate equation (1) using both pooled-and year-by-year OLS. We also estimate a version of equation (1) using county fixed-effects regression on the set of time-varying variables. Pooled and year-by-year OLS allow us to exploit the significant variation that exists across counties in closure activity and its determinants in our empirical tests and to investigate determinants of closure activity that do not vary annually over our sample period.

In the long-run banks may adjust their customer acquisition and forbearance policies in response to economic conditions—in effect putting in place tighter restrictions on opening new accounts when anticipated closures are high. If this sort of adjustment occurs, then variables related to "shocks" to income (e.g. *UNEMPLOYMENT)* may not demonstrate a cross-sectional relationship with involuntary closure activity. Estimating equation (1) using county fixed-effects regression allows us to examine whether short-run shocks to income in the form of changes in *PCPI* and *UNEMPLOYMENT* are associated with changes in involuntary closure activity within counties over time.

IV. Empirical Results

A. Correlates of Involuntary Closure Activity

Table 3 contains basic univariate correlations between involuntary closures and other variables related to the four broad classes of factors we study (personal traits, community traits, economic trends, and bank policies). We report these in the spirit of offering simple descriptive statistics, rather than to test any proposition.

Somewhat surprisingly, involuntary closures are positively correlated with per capita personal income, albeit with a relatively small correlation coefficient of 0.07. This univariate correlation may simply reflect a higher level of banking activity in the form of deeper penetration of banking accounts in higher income populations.

Table 3 provides some evidence that closure activity is related to variables that capture shocks to income and thin margins between income and expenses. The rate of involuntary closures is positively and significantly correlated with poverty rates, unemployment rates, and the presence of higher populations of single-mothers. The correlation coefficient for *SINGLEMOM* is relatively high at 0.48 possibly reflecting a higher likelihood of thin margins between income and expenses in this family structure and/or perhaps less time to devote to financial management.

The extent to which our proxies for the general ability to budget and forecast are related to closure activity as predicted is unclear in Table 3. Involuntary closures are negatively correlated with *HIGHSCHOOL* but positively with *BACHELORS*. Similar to per capita personal income, this latter case may simply reflect higher rates of bank account penetration among college educated populations. The rate of involuntary closures is positively associated with the percentage of the population in the 20-34 age group and negatively with every other age category suggesting the possibility of relatively poor financial management in younger populations.

Correlations between involuntary closures and characteristics of the banking environment in counties are consistent with our predictions that closure activity is related to bank incentives and knowledge of customers. The significant presence of multi-market (single-market) banks is positively (negatively) correlated with the rate of involuntary closures. The Herfindahl-Hirschman index is negatively correlated with closure activity consistent with higher rates of closure activity in counties with more competition among banks. Bank characteristics appear to be relatively strong correlates of closure activity with the correlation coefficients on *MULTISHARE*, *SINGLESHARE*, and *HHI* at 0.296, -0.263, and -0.249 respectively.

The relatively strong negative correlations of closure activity with both *CHURCHES* and *VOTETURNOUT* (-0.39 and -0.22 respectively) are consistent with a link between social capital and rates of involuntary closure. The incidence rate of property crime, which may be a negative indicator of social capital, is positively correlated with closure activity with a relatively high correlation coefficient of 0.192. With the exception of *NATIVE*, all variables representing the racial distribution of a county's population are positively correlated with closure activity with the highest correlation coefficient of 0.33 on *BLACK*.

Finally, in the univariate results, closures are strongly positively related to payday lending activity (0.33), and in unreported results, with check cashing activity (.36) and pawnshops (.25).

While the univariate correlations reported in Table 3 provide some evidence consistent with our predictions on the determinants of closure activity, many of the variables are relatively highly correlated with each other making it difficult to tease apart their unique contribution to the rate of involuntary closures. We turn to this issue next through estimation of equation (1) and other specifications.

B. Multivariate Results

Table 4 presents a number of specifications using the national data. The column labeled "Pooled OLS" reports the results for the entire pool, where we use robust standard-errors adjusted for correlation within counties over time prior to inference.clustering at the county level. The next four columns report results for 2002, 2003 and 2004, where one specification for 2003 includes, and the other excludes, the payday lending information which is only available for this year. The sixth column contains results from county fixed-effects regression on the set of variables which vary annually over our sample period. The final column reports the 2004 cross section with additional controls for the number of banked households and financial assets per capita in the county.

The results in Table 4 provide mixed evidence in support of theory that closure activity is driven by the level of income relative to expenditures and/or shocks to income. In pooled and all year-by-year cross-sectional estimates, the coefficient on *PCPI* is *positive* and significant at the 1% level in all specifications. However, the coefficient is *negative* and significant at the 1% level in the fixed-effects specification. Similarly, the coefficient on *UNEMPLOYMENT* is insignificant in most specifications with the exception of the 2002 cross-section where it is *negative* and significant at the 1% level. However, the coefficient on *UNEMPLOYMENT* is positive and significant (at the 10% level) as expected in the fixed effects estimation.

It appears that differences in levels of per capita personal income across counties are positively associated with the level of closures per capita while "shocks" to income within counties are negatively associated with changes in closures per capita over time. The unemployment results show opposite results. One potential explanation for the discrepancy in the sign of the coefficients on income and unemployment between the OLS and fixed effects estimates is that, in the long-run, banks adjust their customer acquisition policies to more (less) aggressively open accounts in markets with higher levels of income (unemployment). Such adjustment is not likely to occur in the short-term so that shocks in the form of immediate changes in per capita income and unemployment rates are associated with short-term changes in rates of closure activity consistent with the results of our fixed effects estimates. An alternative explanation is that income and unemployment are partially capturing the effect of unobserved banking activity across counties that is not fully controlled for through scaling by population and the inclusion of *INQUIRIES*.[11] To the extent that such unobserved banking activity is relatively static over time, it is accounted for in our fixed effects estimates.

[11] In both univariate and multivariate tests, we find a positive coefficient on INQUIRIES, which we interpret as controlling for the level of account activity. Jacob et al., find that census tracts with greater inquiries have lower closure rates. However, this finding is a univariate result that does not control for other factors and is for Chicago alone.

Poverty rates are not significantly related to closure activity in any specification. This is consistent with impressions we have gathered by interviews with bankers, who report that financial mismanagement is not limited to the poor.

However a high proportion of single mothers in the population of a county is positively and significantly (at the 1% level) related to such activity. Moreover, the coefficient on *SINGLEMOM* is relatively large at 0.62 in the pooled OLS specification suggesting that each 1.5% increase in *SINGLEMOM* is associated with an increase in involuntary closures of one per 1,000 people – a result consistent with this family structure being particularly at risk for involuntary closure.

Turning to our proxies for the general ability to budget and forecast, the results in Table 4 paint a relatively consistent picture across specifications, and one that underscores other research on consumer financial decision making. After controlling for other determinants, involuntary closure activity is lower in counties with more college educated populations. The coefficient on *COLLEGE* is negative and significant at the 1% level in all specifications while the coefficient on *HIGHSCHOOL* is not significant at conventional levels in any specification. This result confirms findings from other research that education is related to financial decision making. (However, it is possible that education might also measure the level and volatility of income.)

Relative to the baseline of under 20 year olds, the coefficients on the age distribution variables show a pattern where the level of involuntary closures is higher for 20 to 34 year olds, reverts to baseline levels for the 35-64 year old population, is higher again in the 64 to 75 age range, and then sharply declines for the elderly population over 75 years of age. These patterns are consistent across years and provide some evidence for the U-shaped pattern documented by Agarwal et al. (2007) whereby financial decision-making is related to age with "poorer" decisions by the young and old, although the sharp decline in closures for the population over the age of 75 suggests that this pattern attenuates for older seniors.

Table 4 provides some evidence that the incidence of property crime is associated with increased involuntary closure activity even after controlling for other determinants. The coefficient on *PROPERTYCRIME* is positive and significant at the 10% level in the pooled OLS specification, but this result seems to be driven by the 2002 cross-section which is the only individual year in which the coefficient on crime is significant. Despite the instability of the coefficient across years, *PROPERTYCRIME* is positively and significantly related to closures in the fixed-effects specification at the 5% level.

Differences across counties in bank characteristics are associated with closure activity as predicted. A strong presence of multi-market (single-market) banks in a county is associated with higher (lower) rates of closure activity after controlling for other determinants. The coefficients on *MULTISHARE* (*SINGLESHARE*) are positive (negative) and significant at the 1% level in the pooled and year-by-year cross-sectional OLS specifications. These results are consistent with "local" banks with substantial customer knowledge either being more informed (and less likely to inadvertently accept applications of riskier customers) or more likely to show forbearance than a multi-market bank with neither information nor a vested interest in a particular community or customer.

The negative and significant (at the 1% level) coefficients on *HHI* (an inverse measure of competition) across the pooled and year-by-year OLS specifications is consistent with the prediction that banks are more willing to accept risk—in the form of riskier debit accountholders—as they face increased competition for customers in a local market. This increased risk taking is related then to higher realized closure activity. The coefficients on the bank variables are generally not significant in the fixed-effects specification suggesting that short-term changes in the banking environment within a county do not immediately impact the rate of involuntary closures.

The evidence in Table 4 in support of our prediction that involuntary closure activity should be lower in communities with stronger social capital is mixed. When proxied by electoral participation rates, the level of social capital appears to be negatively related to closures after controlling for other determinants. The coefficient on *VOTETURNOUT* is negative and significant at the 1% level in all pooled and year-by-year OLS specifications. The coefficient on *CHURCHES* is not significant at conventional levels in any specification. However, in unreported specifications where we used median age instead of the distribution of age specification, CHURCHES was consistently and significantly negatively related to closures. Apparently, church location is highly correlated with age distributions more so than voting activity.

Turning to race, the evidence in Table 4 points to significant differences in closure activity across racial groups. Involuntary closure rates are higher in counties with high Black and non-white "Other" populations and lower in counties with high Hispanic, Asian, and Native American populations. With the exception of *NATIVE* in the 2004 OLS specification, all coefficients on the race distribution variables are significant at the 5% level or lower across specifications. These results may reflect many different phenomena—which we cannot explain, but given their size cannot be ignored.

The final column in Table 4 provides some evidence that our results are not due to the potentially omitted correlated variable of wealth. In the last column of Table 4, we include the additional control variable *WEALTH* measured as the per capita dollar value of total assets held in a county ($000's) using IXI's estimates.[12] We also include in this specification IXI's estimate of the number of households (per 1,000 population) in a county with any assets held in deposit accounts (*BANKEDHH*) as an alternative to *INQUIRIES* as a measure of the level of banking activity. As expected, *WEALTH* is negatively, while *BANKEDHH* is positively, related to closures. Our primary findings are robust to the inclusion of these alternative measures.

To facilitate comparability among the coefficients on the different determinants of closure activity, Table 5 presents standardized coefficient estimates from two of the specifications in Table 4. Panel A of Table 5 presents standardized coefficient estimates from the pooled OLS specification results in Table 4. Panel B of Table 5 presents standardized coefficient estimates from the fixed effects specification. In Panel B, each coefficient is standardized by the within-county standard deviation of its respective variable. We define the within-county standard deviation for each variable '*X*' as the standard deviation in $X_{it} - \overline{X_{i.}}$ where $\overline{X_{i.}}$ denotes the mean of *X* over the sample period for county 'i'.

The evidence in Panel A of Table 5 points to the economic significance of our findings. Relative to the mean level of closures per capita (13.45 per 1,000 people), a one-standard deviation increase in *SINGLEMOM* is associated with an increase in

[12] We were only able to obtain IXI data measured as of June 2006. Because the final year in our sample for which all county-level variables are available is 2004, we match the 2006 IXI wealth data to county-level closures during 2004. To the extent that differences across counties in per capita wealth are relatively constant over time, this mismatch in time periods should not lead to any systematic bias in our results.

closures of approximately 13% in a county. By this measure, differences in the age distribution across counties also appears to be an economically significant determinant of closure activity with closures increasing by 9-10% for each standard deviation increase in the percent of the population in the 20-34 of 65-74 age ranges respectively. Our crime and social capital variables appear to have a small effect on closure activity with one standard deviations in rates of property crime and electoral participation being associated with a modest 1% increase and 3% decline in the rate of involuntary closures respectively. Collectively, the bank variables show a modest relationship with closure activity with one-standard deviations in *MULTISHARE*, *SINGLESHARE*, and *HHI* being associated with changes in involuntary closures relative to the mean in the range of 4-7%.

Panel B of Table 5 provides some evidence on the magnitude of the relationship between short term changes in income, unemployment, and property crime on closure activity. The within-county standard deviations on *PCPI* and *UNEMPLOYMENT* are approximately $1,000 and 1% respectively. Closure activity appears to respond strongly to shocks to income. Each $1,000 decline in *PCPI* is associated with a 0.64% increase in closures relative to the mean county in our sample while each 1% increase in rates of unemployment is associated with a 0.79% increase in closures relative the mean. Increases in rates of property crime show a modest relationship with closure activity over time with each within-county standard deviation associated with a 0.39% increase over the mean level of closures.

Table 4, column 4 reports results relating the number of payday lending establishments per 1,000 people in a county to the rate of involuntary closures. Data on payday lenders is only available during 2003, so the results in Table 6 are restricted to cross-sectional analysis for that year. The results suggest that the number of payday lending establishments is positively related to the rate of involuntary closures after controlling for other county level determinants of involuntary closure rates. The coefficient on *PAYDAYLENDERS* shows that a one standard deviation increase in the per capita number of payday lending establishments is associated with an increase in closures per 1,000 people of 1.5. This represents an approximate 11% increase relative to the mean rate of involuntary closures per 1,000 people.

The number of payday lending establishments is likely to be endogenous: closure rates may depend on the prevalence of payday lending, but the supply of payday lending may also adjust as customers facing financial difficulty seek alternative sources of borrowing. To address this, we estimate a version of equation (1) using two-stage least-squares in which *PAYDAYLENDERS* is treated as endogenous. The ideal instrument would be correlated with *PAYDAYLENDERS* but not with the error in estimating equation (1). In 2003, we identify five states which did not allow payday lending including, Massachusetts, Maryland, New York, Pennsylvania, and Virginia. A suitable instrument for our purposes is an indicator for whether a county is in a state which does not allow payday lending. We treat this as an exogenous shifter of the supply of payday lending establishments. The results (available from the authors) do not vary from those in column 4: the number of payday lending establishments in a county remains positively associated with the rate of involuntary closures after controlling for the other factors.

C. A Natural Experiment on Payday Lending[13]

To further explore the link between access to payday lending and involuntary

[13] We thank Don Morgan for suggesting this line of inquiry.

closure activity, we following Morgan & Strain (2008) by taking advantage of a natural experiment in which the state of Georgia banned payday lending by statute in May 2004. We identify the effect of restricted access to payday loans on closures by comparing the rate of involuntary closures before and after the period of the payday lending ban for Georgia counties to that of counties in states bordering Georgia. Additionally, we provide further identification of the effects of the payday lending ban by exploiting geographic distance from state boundaries. Specifically, we compare changes in the rate of involuntary closures around the payday lending ban for counties in Georgia that are far from the border of a neighboring state that allows payday lending to those counties in Georgia that are close to such neighboring state borders. That is, we compare counties in Georgia for which consumers are likely to face prohibitive transactions costs in accessing credit from payday lenders after the ban to counties in which consumers are likely to face lower transactions costs due to access to payday lending in nearby states.

Our basis for identifying the effect of the Georgia payday lending ban on the rate of involuntary closures is the following fixed effects specification:

$$CLOSURES_{it} = \beta_1 POST_{it} + \beta_2 POSTGA_{it} + \beta_3 POSTGA_{it} xDISTANCE_i + \beta_4 UNEMPLOYMENT_{it} + \sum_{j=2}^{12} \gamma_j MONTH_t^j + \sum_{k=2000}^{2006} \lambda_k Year_t^k + \alpha_i + \varepsilon_{it} \qquad (2)$$

where 'i' and 't' index county and time respectively. We estimate this specification using monthly county-level data on closures over the full seven years of our sample period from September 1999 to August 2006. We scale monthly closures in each county by constant year 2000 population (per 1,000 people).[14] *POST* is an indicator variable taking

[14] Results are substantively unchanged when monthly closures are scaled by annual population during the year in which the observation occurs rather than constant year 2000 population.

on a value of 1 for time periods after the implementation of the Georgia payday lending ban (May 2004) and 0 otherwise. *POSTGA* is an indicator variable taking on a value of 1 for counties within Georgia during time periods after May 2004 and 0 otherwise. *DISTANCE* is a measure of the minimum distance in miles between any zip code within a Georgia county and the nearest zip code in a neighboring state.[15] *UNEMPLOYMENT* is the monthly county-level unemployment rate. $MONTH^j$ (j=2-12) and $YEAR^k$ (k=2000-2006) are calendar month and year indicators respectively and are included to control for monthly seasonality annual trends in closure rates. α_i represent individual county fixed effects.

In this specification, β_1 measures any change in average closure rates in non-Georgia counties after May 2004 conditional on unemployment rates in those counties and any general month or year-specific effects. The estimated treatment effect of the payday lending ban in Georgia in this specification is $\beta_2 + \beta_3 DISTANCE$ which captures the average change in closure rates in Georgia counties relative to non-Georgia counties after the payday lending ban conditional on the distance of the Georgia county to a neighboring state border.

During our sample period, all states which share a border with Georgia allowed payday lending.[16] Consumers in counties which are closer to neighboring state borders

---

[15] We use a measure of the minimum distance between any zip-code in a county and the nearest zip code in a neighboring state as this measure is most likely to adequately classify distant counties as those whose full geographic boundaries are far from neighboring states. Alternative distance measures, such as distance from each Georgia county centroid and the nearest neighboring state, can misclassify counties with large geographic boundaries as distant when large portions of these counties are close to neighboring states. While we choose to use this measure of distance, our results are robust to this alternative measure.

[16] North Carolina effectively banned payday lending in December 2005. After this time, Georgia consumers living near North Carolina would not be able to obtain payday loans in that state. Exclusion of counties within Georgia that are close to the North Carolina border (e.g. within 25 miles) does not alter our

would, on average, have easier access to payday loans after the Georgia payday ban than would consumers in counties which are far from neighboring states. Thus, any effects of restricting access to payday loans should be more prevalent in counties which are far from neighboring state borders. If payday lending leads to a "debt trap" and increased financial difficulties for consumers, then its absence after the ban should lead to a reduction in the rate of observed involuntary closures and we should see $\beta_2 \leq 0$ and $\beta_3 < 0$. Alternatively, if the predominant effect of the availability of payday lending is to increase the financial flexibility of consumers to smooth shocks to income or expenses, then the absence of this financing option after the ban should lead to increased rates of observed involuntary closures and we should see $\beta_2 \geq 0$ and $\beta_3 > 0$.

Table 6 contains results from estimation of equation (2). The first column of Table 6 includes counties in all U.S. states (with the exception of New England states where we do not have complete coverage over the sample period). This specification also excludes *POSTGAxDISTANCE*, so the control group consists of counties in states outside of Georgia. The coefficient on *POSTGA* is negative but not significant suggesting no change in the rate of involuntary closures in Georgia after the payday ban relative to counties in other states. Column 2, which only includes counties in Georgia's neighboring states as the control group, shows a different picture. Relative to counties in neighboring states, the rate of involuntary closures declined after the payday lending ban (coefficient on *POSTGA*=-0.154, p<0.05). One potential explanation for the discrepancy between the results in columns 1 and 2 is that there was a regional effect on closures in the Southeast United States around the same time as the payday lending ban occurred. In

results. This is likely due to the fact that payday lending was allowed in North Carolina over the majority of our sample period and shares a relatively small border with Georgia.

fact, one can see by looking at the higher coefficient on *POST* in column 2 versus column 1 (.23 compared to .12), that counties in states bordering Georgia experienced a larger increase in involuntary closure rates after May 2004 than did counties in other non-Georgia states.

Turning to column 3, which includes counties in Georgia's neighboring states as the control group and also includes the variable *POSTGAxDISTANCE*, the results demonstrate that the decline in closures after the payday lending ban is concentrated in counties which are further from the state border. The coefficient on *POSTGAxDISTANCE* is negative and significant (coefficient=-0.003, p<.05). The results in column 4 look at the interaction with *DISTANCE* in a different way. In place of *POSTGAxDISTANCE*, we include two indicator variables which capture whether a Georgia county after the payday ban is between 30 and 60 miles of a state border (*POSTGAxDISTANCE3060)* or is more than 60 miles from the state border (*POSTGAxDISTANCE60*). The coefficient on *POSTGA* is negative and significant (coefficient=-0.113, p-value<.05) while the coefficient on *POSTGAxDISTANCE3060* is not significantly different from that on *POSTGA*. This provides evidence of a decline in closures in Georgia counties after the payday lending ban that does not vary for counties that are less than 30 miles from a state border versus those that are between 30 and 60 miles from the state border. However, the coefficient on *POSTGAxDISTANCE60* is negative and significant (coefficient=-0.156; p<.05) suggesting that the decline in closures around the payday ban is stronger for counties which are very distant from state borders. The results in the final column in Table 6 exclude the two counties which contain the Atlanta metro area and show that our results our not driven solely by the effects of the payday ban in this one area of Georgia.

To put these estimates in perspective, consider the coefficient estimates reported in column 4. The average monthly closure rate in Georgia counties prior to the payday lending ban is approximately 1 per 1,000 people. The coefficient estimates in column 4 show that, relative to counties in border states, Georgia counties within 60 miles of a neighboring state border experienced an 11.3% decline in the mean rate of closures. Georgia counties which are more than 60 miles from a neighboring state border experienced a larger decline in the mean closure rate of 15.6%. Overall, the cross-sectional results reported in Table 6 along with the estimates of the effects of the payday lending ban in Georgia reported in Table 6 provide evidence consistent with the the notion that the availability of payday lending leads to increased rates of involuntary bank account closure. While our results are consistent with the "debt trap" critique of payday lending, we note that they are in contrast to those of Morgan & Strain (2008). It is not clear whether this is due to the use of county level vs. state-level data (as in Morgan & Strain); differences in control groups used (all states as in Morgan & Strain vs. only neighboring states and counties close to state borders as in our paper); differences in consumer outcomes investigated (e.g. closures as opposed to bounced checks, complaints against lenders, and bankruptcy filings as in Morgan & Strain); or some combination of these or other factors.

IV. Conclusions and Implications

Involuntary debit account closure is a frequent occurrence in America with over 30 million accounts closed over six years. Involuntary account closure is an issue for policymakers and consumer advocates because people becoming “unbanked,” “underbanked,” or “self-banked” with any of these terms referring to having access to a limited et of payment system options with high fees. Our paper provides the first look at the incidence of involuntary closure using county-level data for the U.S. taken from an industry-standard database maintained by ChexSystems.

While one might think that involuntary closures are primarily driven by poverty, this is not the explanation. Our analysis of ChexSystems' data reveals that differences in the rate of involuntary account closures across and within counties are only partially explained by negative shocks to income and proxies for populations where margins are thin between income and expenses (e.g. poverty rates and the presence of single mothers). Even after controlling for income, financial assets, poverty, family structure, and unemployment, we find that rates of involuntary account closure are explained by other measures related to consumers’ ability to budget and forecast (education and age); bank incentives (local vs. multi-market banks and competition); community norms and social capital (electoral participation); and the availability of credit through payday lending.

Most of these results deserve substantial additional study and suggest a variety of questions. For example, to the extent that involuntary closure is the endogenous outcome of bank policies to allow liberal opening of so-called “free” accounts (which might be better described as overdraft “fee” accounts), has the banking system exacerbated closures to increase fees from penalty charges? Is this a sustainable business strategy and good public policy? If there is a link between social capital and closures, what is the mechanism by which this link is made? Can social capital explain other financial decisions? If closures are more severe among certain demographic groups, what can or should be done about this situation? If account closure is the simplest example of failure to budget, is it a leading indicator of subsequent other financial problems?

Bibliography

Agarwal, S. and Hauswald, R. (2007) "Distance and Information Asymmetries in Lending." Available at SSRN: http://ssrn.com/abstract=996602

Agarwal, S., Driscoll, J., Gabaix, X. and Laibson, D. (2007) "The Age of Reason: Financial Decisions Over the Lifecycle." MIT Department of Economics Working Paper No. 07-11 Available at SSRN: http://ssrn.com/abstract=973790

Avery, R., Brevoort, K., and Canner, G. (2007) "The 2006 HMDA Data." *Federal Reserve Bulletin*, 93.

Barr, Michael S. "Banking the Poor." Yale Journal on Regulation, 2004, 121, pp. 121-237.

Beckett, P. (2000) “It's Not in the Mail: Bounce a Check, and You Might Not Write Another for 5 Years --- Banks Are Using Database To Blacklist Customers For Even Small Slip-Ups --- Do the Poor Get Hurt More?” *The Wall Street Journal*, 1 August 2000.

Beverly, S., Schneider, D., and Tufano, P. (2006) “Splitting Tax Refunds and Building Savings: An Empirical Test.” *NBER Tax Policy and the Economy*, 20, 111-161.

Caner, Asena and Wolff, Edward N. (2004) "Asset Poverty in the United States, 1984-99: Evidence from the Panel Study of Income Dynamics." *Review of Income and Wealth*, Vol. 50, No. 4, pp. 493-518, December 2004

Campbell, J. (2006) “Household Finance.” *The Journal of Finance*, Vol. LXI, No. 4, August.

Campbell, D., Martinez-Jerez, A., McClintock-Ekins, E., and Tufano, P. (2007) "Central Bank: The ChexSystems QualiFile Decision." Harvard Business School Case 208-029.

Caskey, J. (1994) *Fringe Banking: Check Cashing Outlets, Pawnshops, and the Poor*. Russell Sage.

Crane, D. B., K. A. Froot, S. P. Mason, A. F. Perold, R. C. Merton, Z. Bodie, E. R. Sirri, and P. Tufano (1995) *The Global Financial System*. Boston: HBS Press.

Degryse, H. and S. Ongena (2005), “Distance, Lending Relationships, and Competition.” *The Journal of Finance*, 60, 231-266.

Desmond, T. and Sprenger, C. (2007) “Estimating the Cost of Being Unbanked.” *Federal Reserve Bank of Boston*, Communities & Banking, Spring issue, 24-26. Available at bos.frb.org/commdev/c&b/2007/spring/article9.pdf (accessed in October 2007)

DeYoung, R., D. Glennon and P. Nigro, (2004), “Borrower-Lender Distance, Credit Scoring, and the Performance of Small Business Loans.” mimeo, Federal Reserve Bank of Chicago.

Fellowes, M. and M. Mabanta (2008), “Banking on Wealth: America’s New Retail Banking Infrastructure and Its Wealth-Building Potential” Brookings Institution Metropolitan Policy Program Research Brief.

Fox, JA and Mierzwinski, E., Consumer Federation of America, & U.S. Public Interest Research Group, (2001) “Rent-A-Bank Payday Lending: The 2001 Payday Lender Survey and Report”

Greeley, A. 1997. "Coleman Revisited: Religious Structures as a Source of Social Capital." *American Behavioral Scientist*, 40, 587-94.

Guiso, L., Sapienza, P., and Zingales, L. (2004) "The Role of Social Capital in Financial Development," *The American Economic Review*, 94, 3, pg. 526.

Hannan, T. (2006) "Retail deposit fees and multimarket banking." *Journal of Banking & Finance*, Elsevier, vol. 30(9), pages 2561-2578

Hauswald, R. and R. Marquez, (2005), “Competition and Strategic Information Acquisition in Credit Markets.” forthcoming in *Review of Financial Studies*.

Hong, H., Kubik, J., and Stein, J. (2004) "Social Interaction and Stock-Market Participation." *The Journal of Finance*, Vol. LIX, No. 1.

Irwin, Michael D., Charles M. Tolbert, and Thomas A. Lyson. 1997. "How to Build Strong Home Towns." *American Demographics* 19:42-48.

Jacob, K., B. Post, J. Tescher, and J. Turnbull (2006) “A Case Study of Checking Account Inquiries and Closures in Chicago.” Center for Financial Services Innovation Research Paper (November 2006). Available at http://www.cfsinnovation.com/research-paper-detail.php?article_id=2790

Lamb, J. and Leonard, R. (2007) *Credit Repair*. Nolo Publications.

Manning, R. (2000) *Credit Card Nation: The Consequences of America’s Addiction to Credit*. Basic Books.

Melzer, B. (2007). “The Real Costs of Credit Access: Evidence from the Payday Lending Market”. Working Paper.

Morgan, D. & Strain, M. 2008. “Payday Holiday: How Households Fare after Payday Credit Bans”. *Federal Reserve Bank of New York Staff Reports*.

Morse, A. (2007). “Payday Lenders: Heroes or Villains?”. Working Paper.

Massoud, N., Saunders, A. and Scholnick, B. (2007) "Who Makes Credit Card Mistakes." Unpublished manuscript, accessed October 31, 2007 at http://www.philadelphiafed.org/econ/conf/consumercreditandpayments2007/papers/Scholnick_Who_Makes_Credit_Card_Mistakes.pdf

Michael, J. (2004) *Repair Your Credit and Knock Out Your Debt*. McGraw-Hill Professional.

Putnam, R. (2000) *Bowling Alone: The Collapse and Revival of American Community*. Simon and Schuster.

Rhine, S. and Greene, W. (2006) "The Determinants of Being Unbanked for U.S. Immigrants," *Journal of Consumer Affairs*, summer, Vol. 40 Issue 1, p. 21-40.

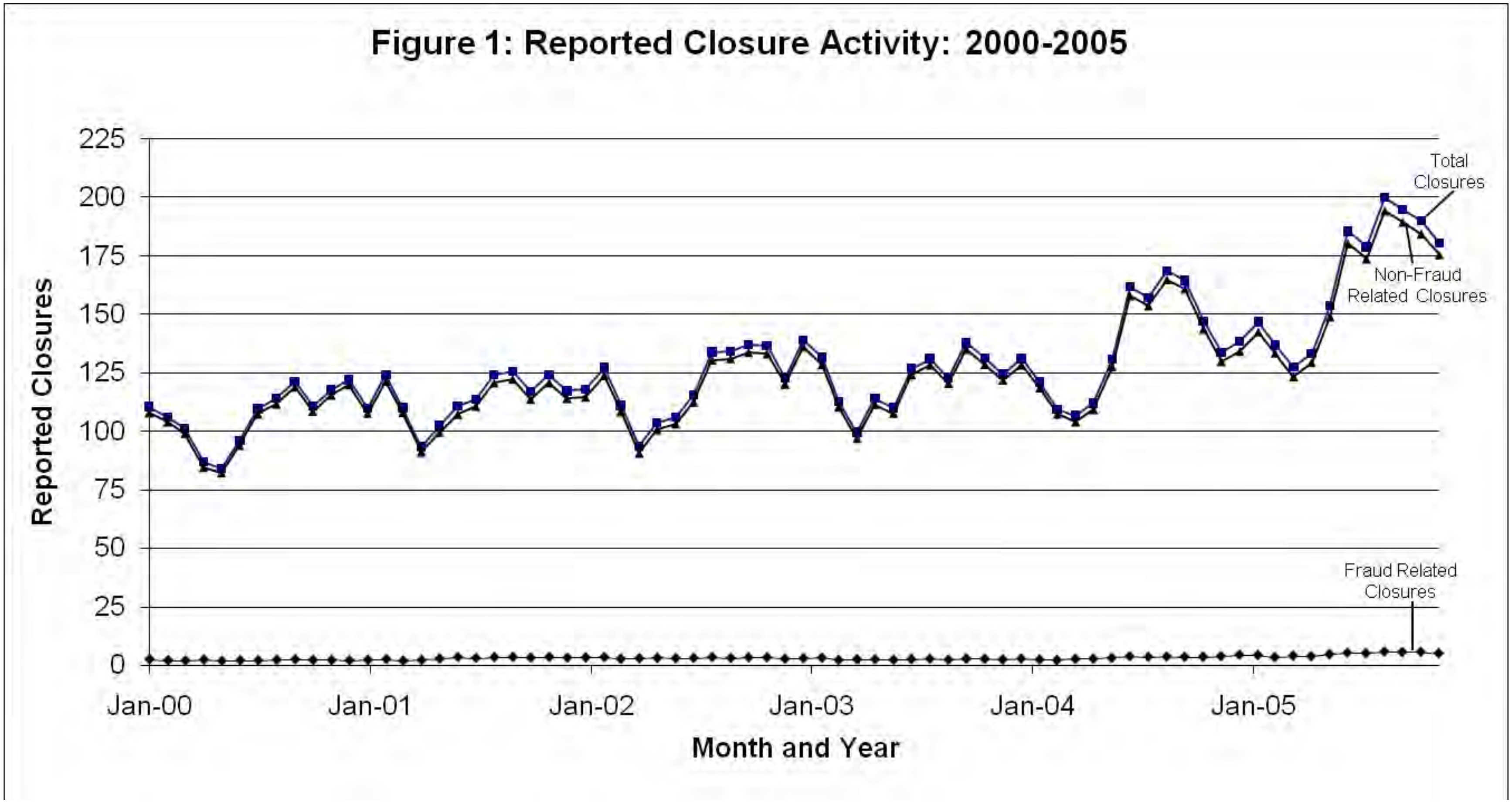
Figure 1: Reported Closure Activity: 2000-2005
Reported Closures
225
200
175
150
125
100
75
50
25
0
Jan-00
Jan-01
Jan-02
Jan-03
Jan-04
Jan-05
Month and Year
Total Closures
Non-Fraud Related Closures
Fraud Related Closures

Table 1: Sample Selection

Number of Counties in U.S.	3,141
Number of Counties with Reported Closures	3,138
Less: Counties in MA, NH, RI, and VT	43
Less: Counties with missing data for any variable	238
Number of Counties in Final Sample	2,857

Table 2: Descriptive Statistics (2002-2004)

Variable	Description	Source	Mean	Std. Dev.	Min	Max
CLOSURES	Number of involuntary consumer bank account closures per capita reported on the ChexSystems database for the county	eFunds ChexSystems database	13.45	7.09	-	61.38
INQUIRIES	Number of inquiries per capita for new consumer bank accounts for consumers without prior closure activity reported on ChexSystems database for the county.	eFunds ChexSystems database	69.42	47.36	0.16	441.4
PCPI	Per capita personal income ($000's per person).	Bureau of Economic Analysis Regional Economic Accounts	24.99	5.90	10.34	88.80
POVERTY	Percent of all households in county living below the poverty line	2000 Census	13.70	5.51	2.30	49.10
UNEMPLOYMENT	Unemployment rate for the county	Bureau of Labor Statistics Local Area Unemployment Statistics	5.80	1.85	2.00	17.10
SINGLEMOM	Percent of all households with female head of household living with own children	2000 Census	7.11	2.75	0.20	23.53
HIGHSCHOOL	Percent of population age 25 and over with high school diploma and no college	2000 Census	35.35	6.77	9.88	55.70
COLLEGE	Percent of population age 25 and over with bachelors degree or higher	2000 Census	44.62	11.25	17.47	87.08
AGE2034	Percent of population age 20 to 34	2000 Census	18.80	3.84	7.62	48.50
AGE3564	Percent of population age 35 to 64	2000 Census	39.19	3.03	17.07	53.72
AGE6574	Percent of population age 65 to 74	2000 Census	7.60	1.82	0.96	17.40
AGE75	Percent of population age 75 and over	2000 Census	7.29	2.46	0.47	21.19

Table 2 (Cont.): Descriptive Statistics						
Variable	**Description**	**Source**	**Mean**	**Std. Dev.**	**Min**	**Max**
PROPERTYCRIME	Property crimes per capita (per 1,000 people)	FBI Uniform Crime Reports	5.51	5.68	-	83.79
MULTISHARE	Percent of bank branches in county operated by multi-market banks	FDIC Summary of Deposits	57.56	29.11	-	100.00
SINGLESHARE	Percent of bank branches in county operated by single-market banks	FDIC Summary of Deposits	23.01	24.63	-	100.00
PAYDAYLENDERS	Number of payday lending establishments per capita (per 1,000 people)	FDIC, infoUSA, state licensing departments, and the U.S. Census Bureau	0.08	0.11	0	0.84
HHI	The Herfindahl-Hirschman index of concentration, defined as the sum of squared market shares of deposits	FDIC Summary of Deposits	31.31	20.16	4.36	100.00
CHURCHES	Total number of congregations per capita across all denominations	Association of Religion Data Archives	2.17	1.34	0.15	11.73
VOTETURNOUT	Percent adult population casting votes in the 2004 general election	Congressional Quarterly Electronic Library	59.77	10.78	4.53	98.34
BLACK	Percent black populaton in county	2000 Census	9.13	14.86	-	86.55
HISPANIC	Percent hispanic populaton in county	2000 Census	5.83	10.80	0.13	92.00
ASIAN	Percent asian populaton in county	2000 Census	0.92	2.13	-	46.84
NATIVE	Percent native american populaton in county	2000 Census	1.64	5.88	-	3.61
OTHER	Percent non-white, non-black, non-Asian, non-native american populaton in county	2000 Census	0.95	1.34	-	38.28
WEALTH	Value of financial assets (in $000s, per capita)	IXI	39.15	36.76	1.15	590.58
BANKEDHH	Number of households with checking/debit accounts per 1000 households	IXI	272.99	93.12	12.68	868.95

Notes: Closures, inquiries, property crimes, and churches per capita are measured per thousand people.

Table 3: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(1) *CLOSURES*																						
(2) *INQUIRIES*	0.3128*																					
(3) *PCPI*	0.0700*	0.4385*																				
(4) *POVERTY*	0.0839*	-0.3139*	-0.6108*																			
(5) *UNEMPLOYMENT*	0.1644*	0.0119	-0.3620*	0.4895*																		
(6) *SINGLEMOM*	0.4776*	0.0507*	-0.1617*	0.4310*	0.3448*																	
(7) *HIGHSCHOOL*	-0.1703*	-0.3346*	-0.3958*	-0.0175	0.0938*	-0.2330*																
(8) *COLLEGE*	0.0346*	0.4518*	0.6547*	-0.5309*	-0.3998*	-0.1236*	-0.6820*															
(9) *AGE2034*	0.3813*	0.1837*	0.0147	0.1360*	0.0686*	0.4286*	-0.3055*	0.1220*														
(10) *AGE3564*	-0.1281*	0.0385*	0.2763*	-0.3229*	-0.0708*	-0.2837*	0.1578*	0.0411*	-0.5281*													
(11) *AGE6574*	-0.3055*	-0.2432*	-0.2125*	0.0888*	0.0141	-0.4658*	0.3227*	-0.2460*	-0.7018*	0.2523*												
(12) *AGE75*	-0.4238*	-0.2351*	-0.0578*	-0.0711*	-0.1390*	-0.5981*	0.3105*	-0.0902*	-0.6651*	0.0923*	0.7950*											
(13) *PROPERTYCRIME*	0.1924*	0.1523*	0.0122	0.0791*	0.0864*	0.2289*	-0.0651*	0.0014	0.1010*	-0.0574*	-0.0639*	-0.1176*										
(14) *MULTISHARE*	0.2963*	0.4017*	0.0945*	-0.0536*	0.1036*	0.1493*	-0.1948*	0.1677*	0.1001*	0.0304*	-0.0889*	-0.1747*	0.1114*									
(15) *SINGLESHARE*	-0.2634*	-0.3136*	-0.0894*	0.0433*	-0.1044*	-0.1309*	0.1445*	-0.1237*	-0.0778*	-0.0252*	0.0655*	0.1319*	-0.1067*	-0.6608*								
(16) *HHI*	-0.2485*	-0.2591*	-0.3368*	0.3196*	0.0436*	-0.0996*	0.0976*	-0.2487*	-0.2549*	0.1289*	0.2479*	0.0965*	-0.0518*	-0.0603*	0.0215*							
(17) *CHURCHES*	-0.3905*	-0.4224*	-0.3744*	0.2620*	-0.0634*	-0.4012*	0.3041*	-0.3505*	-0.4611*	0.0679*	0.5088*	0.5226*	-0.1384*	-0.2234*	0.2081*	0.4658*						
(18) *VOTETURNOUT*	-0.2155*	0.0911*	0.2726*	-0.4214*	-0.2651*	-0.3499*	-0.0018	0.3785*	-0.2993*	0.2630*	0.1414*	0.2474*	-0.0992*	-0.0147	0.0148	0.0309*	0.1675*					
(19) *BLACK*	0.3285*	-0.1282*	-0.1282*	0.4615*	0.2904*	0.6873*	-0.1411*	-0.2126*	0.2541*	-0.1962*	-0.2090*	-0.2529*	0.1753*	0.0750*	-0.0812*	0.0396*	-0.1169*	-0.2776*				
(20) *HISPANIC*	0.0213*	0.1661*	0.0048	0.1903*	0.1196*	0.1557*	-0.3703*	0.0702*	0.1076*	-0.2568*	-0.1481*	-0.1755*	0.0275*	0.0581*	-0.0571*	0.0154	-0.1652*	-0.2961*	-0.0887*			
(21) *ASIAN*	0.0800*	0.3240*	0.4242*	-0.1628*	-0.0450*	0.0688*	-0.3892*	0.3654*	0.2436*	-0.0454*	-0.2813*	-0.1963*	0.0313*	0.1253*	-0.1271*	-0.2102*	-0.3133*	-0.0503*	0.0198*	0.1854*		
(22) *NATIVE*	-0.0041	-0.0305*	-0.1379*	0.2549*	0.0792*	0.1866*	-0.0708*	0.0306*	-0.0407*	-0.1618*	-0.0537*	-0.0827*	-0.0074	0.0227*	0.0148	0.1107*	0.0879*	-0.008	-0.1020*	0.0204*	-0.0441*	
(23) *OTHER*	0.1810*	0.1974*	0.1373*	-0.0473*	0.0134	0.1089*	-0.2228*	0.2519*	0.1550*	-0.0639*	-0.1684*	-0.1830*	0.0531*	0.0675*	-0.0635*	-0.1551*	-0.2330*	-0.0515*	-0.0932*	0.0717*	0.5622*	0.2425*

* significant at 10%

Table 4: Determinants of Closure Activity

	Pooled OLS	OLS 2002	OLS 2003	OLS 2003 w/ Payday Lenders	OLS 2004	County Fixed Effects	OLS 2004 Wealth and Banked HH
BANKEDHH							0.006***
							(0.002)
WEALTH							-0.011*
							(0.006)
PAYDAYLENDERS				13.648***			
				(1.233)			
INQUIRIES	0.034***	0.036***	0.029***	0.039***	0.037***	0.017***	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	
PCPI	0.140***	0.143***	0.161***	0.107***	0.123***	-0.086***	0.201***
	(0.032)	(0.032)	(0.031)	(0.032)	(0.030)	(0.030)	(0.041)
POVERTY	-0.02	-0.048	-0.009	-0.049	-0.026		-0.028
	(0.040)	(0.039)	(0.038)	(0.043)	(0.040)		(0.042)
UNEMPLOYMENT	-0.075	-0.186***	-0.052	-0.105	0.013	0.106*	0.136*
	(0.069)	(0.072)	(0.067)	(0.075)	(0.074)	(0.059)	(0.076)
SINGLEMOM	0.618***	0.762***	0.610***	0.392***	0.531***		0.519***
	(0.094)	(0.082)	(0.078)	(0.089)	(0.077)		(0.080)
HIGHSCHOOL	-0.014	-0.04	-0.009	0.032	-0.004		-0.002
	(0.030)	(0.031)	(0.031)	(0.031)	(0.032)		(0.033)
COLLEGE	-0.067***	-0.063***	-0.074***	-0.051**	-0.073***		-0.040*
	(0.022)	(0.021)	(0.022)	(0.023)	(0.023)		(0.023)
AGE2034	0.324***	0.392***	0.356***	0.259***	0.266***		0.251***
	(0.053)	(0.053)	(0.055)	(0.060)	(0.060)		(0.063)
AGE3564	-0.01	0.037	-0.003	0.023	-0.032		-0.055
	(0.055)	(0.054)	(0.053)	(0.054)	(0.056)		(0.057)
AGE6574	0.733***	0.750***	0.815***	0.648***	0.694***		0.773***
	(0.100)	(0.111)	(0.111)	(0.108)	(0.114)		(0.122)
AGE75	-0.565***	-0.459***	-0.594***	-0.541***	-0.604***		-0.725***
	(0.090)	(0.100)	(0.098)	(0.094)	(0.099)		(0.102)
PROPERTYCRIME	0.030*	0.149***	0.038	0.011	0.011	0.015**	0.011
	(0.018)	(0.040)	(0.025)	(0.015)	(0.013)	(0.008)	(0.014)
MULTISHARE	0.020***	0.018***	0.020***	0.023***	0.022***	0.004	0.036***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
SINGLESHARE	-0.024***	-0.019***	-0.026***	-0.024***	-0.027***	0.003	-0.029***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
HHI	-0.046***	-0.031***	-0.044***	-0.041***	-0.059***	0.018	-0.058***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.012)	(0.007)
CHURCHES	-0.001	0.087	-0.021	-0.083	-0.002		-0.153
	(0.108)	(0.121)	(0.120)	(0.123)	(0.126)		(0.130)
VOTETURNOUT	-0.036***	-0.026**	-0.032***	-0.057***	-0.048***		-0.042***
	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)		(0.013)
BLACK	0.060***	0.028**	0.039***	0.118***	0.105***		0.090***
	(0.014)	(0.013)	(0.012)	(0.014)	(0.013)		(0.013)
HISPANIC	-0.039***	-0.041***	-0.035***	-0.012	-0.041***		-0.024*
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)		(0.013)
ASIAN	-0.734***	-0.784***	-0.720***	-0.626***	-0.699***		-0.652***
	(0.087)	(0.070)	(0.069)	(0.074)	(0.071)		(0.073)
NATIVE	-0.058***	-0.078***	-0.053**	0.01	-0.036		-0.035
	(0.022)	(0.022)	(0.022)	(0.022)	(0.023)		(0.023)
OTHER	1.227***	1.324***	1.143***	1.069***	1.191***		1.221***
	(0.184)	(0.114)	(0.115)	(0.164)	(0.120)		(0.124)
Constant	2.596	-2.274	0.597	2.217	5.956	12.468***	4.401
	(3.989)	(4.034)	(4.124)	(4.275)	(4.351)	(0.937)	(4.681)
Adjusted R2	0.43	0.43	0.41	0.49	0.46	0.11	0.43
Observations	8,566	2,853	2,856	2,855	2,857	8,710	2,855

Standard errors in parentheses (robust standard errors corrected for clustering at the county-level are reported in the pooled OLS specification); * significant at 10%;** significant at 5%; *** significant at 1%

Table 5: Economic Significance of Determinants of Closure Activity

Panel A: Pooled OLS Estimates*	Standardized Coefficient Estimate	Relative to Mean Closures per capita
INQUIRIES	1.59	11.82%
PAYDAYLENDERS	1.50	11.15%
PCPI	0.84	6.25%
SINGLEMOM	1.70	12.66%
COLLEGE	-0.75	-5.58%
AGE2034	1.25	9.26%
AGE6574	1.33	9.92%
AGE75	-1.39	-10.32%
PROPERTYCRIME	0.17	1.27%
MULTISHARE	0.59	4.39%
SINGLESHARE	-0.59	-4.40%
HHI	-0.94	-6.97%
VOTETURNOUT	-0.39	-2.87%
BLACK	0.89	6.63%
HISPANIC	-0.42	-3.11%
ASIAN	-1.56	-11.61%
NATIVE	-0.34	-2.52%
OTHER	1.65	12.27%

***Standardized coefficient estimate for *PAYDAYLENDERS* is computed using the 2003 cross-sectional OLS results from Table 4**

Panel B: Fixed Effects Estimates	Standardized Coefficient Estimate	Relative to Mean Closures per capita
INQUIRIES	0.34	2.53%
PCPI	-0.086	-0.64%
UNEMPLOYMENT	0.106	0.79%
PROPERTYCRIME	0.0525	0.39%

Panels A and B report standardized coefficient estimates from the pooled OLS and Fixed Effects models reported in Table 4. The last column in each panel reports the standardized coefficient relative to the mean level of closures per capita. In Panel A, coefficients are standardized by each variable's sample standard deviation. In Panel B, coefficients are standardized by each variable's *within-county* standard deviation. Only variables with significant coefficients in Table 4 are reported in Panels A and B of Table 5.

Table 6: Involuntary Closures after the Georgia Payday Lending Ban

	All States	Border States	Border States	Border States	Border States w/o Atlanta Counties
POST	0.122***	0.230***	0.230***	0.230***	0.231***
	(0.006)	(0.017)	(0.017)	(0.017)	(0.017)
POSTGA	-0.004	**-0.154*** **	-0.056	**-0.113** **	**-0.113** **
	(0.030)	(0.034)	(0.054)	(0.048)	(0.048)
POSTGAxDISTANCE			**-0.003** **		
			(0.001)		
POSTGAxDISTANCE3060				-0.011	-0.028
				(0.065)	(0.065)
POSTGAxDISTANCE60				**-0.156** **	**-0.156** **
				(0.075)	(0.075)
UNEMPLOYMENT	0.012***	0.019***	0.019***	0.019***	0.018***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Year2000	0.094***	0.191***	0.191***	0.191***	0.188***
	(0.006)	(0.013)	(0.013)	(0.013)	(0.013)
Year2001	0.172***	0.341***	0.341***	0.341***	0.338***
	(0.007)	(0.017)	(0.017)	(0.017)	(0.017)
Year2002	0.245***	0.401***	0.401***	0.401***	0.399***
	(0.009)	(0.022)	(0.022)	(0.022)	(0.022)
Year2003	0.270***	0.412***	0.412***	0.412***	0.410***
	(0.009)	(0.020)	(0.020)	(0.020)	(0.020)
Year2004	0.295***	0.444***	0.444***	0.444***	0.442***
	(0.010)	(0.021)	(0.021)	(0.021)	(0.021)
Year2005	0.450***	0.618***	0.618***	0.618***	0.615***
	(0.011)	(0.025)	(0.025)	(0.025)	(0.025)
Year2006	0.471***	0.658***	0.658***	0.658***	0.654***
	(0.012)	(0.026)	(0.026)	(0.026)	(0.026)
February	0.003	-0.007	-0.007	-0.007	-0.008
	(0.005)	(0.009)	(0.009)	(0.009)	(0.009)
March	-0.137***	-0.173***	-0.173***	-0.173***	-0.174***
	(0.005)	(0.009)	(0.009)	(0.009)	(0.009)
April	-0.249***	-0.273***	-0.273***	-0.273***	-0.273***
	(0.005)	(0.010)	(0.010)	(0.010)	(0.010)
May	-0.171***	-0.166***	-0.166***	-0.166***	-0.166***
	(0.005)	(0.009)	(0.009)	(0.009)	(0.009)
June	-0.062***	-0.007	-0.007	-0.007	-0.007
	(0.004)	(0.009)	(0.009)	(0.009)	(0.009)
July	0.072***	0.114***	0.114***	0.114***	0.114***
	(0.005)	(0.010)	(0.010)	(0.010)	(0.010)
August	0.035***	0.014	0.014	0.014	0.014
	(0.005)	(0.010)	(0.010)	(0.010)	(0.010)
September	0.149***	0.210***	0.210***	0.210***	0.209***
	(0.005)	(0.011)	(0.011)	(0.011)	(0.011)
October	0.119***	0.188***	0.188***	0.188***	0.186***
	(0.005)	(0.010)	(0.010)	(0.010)	(0.010)
November	0.070***	0.123***	0.123***	0.123***	0.122***
	(0.005)	(0.010)	(0.010)	(0.010)	(0.010)
December	0.037***	0.107***	0.107***	0.107***	0.106***
	(0.005)	(0.009)	(0.009)	(0.009)	(0.010)
Number of County-Months	248,614	44,822	44,822	44,822	44,654
R-Squared	0.17	0.25	0.25	0.25	0.25

Robust standard errors corrected for clustering at the county-level in parentheses; *, **, *** significant at 10%, 5% and 1% respectively