ECONOMIC RESEARCH
FEDERAL RESERVE BANK OF ST. LOUIS

WORKING PAPER SERIES

The Impact of Local Predatory Lending Laws on the Flow of Subprime Credit

Authors	Giang Ho, and Anthony Pennington-Cross
Working Paper Number	2006-009A
Creation Date	February 2006
Citable Link	https://doi.org/10.20955/wp.2006.009
Suggested Citation	Ho, G., Pennington-Cross, A., 2006; The Impact of Local Predatory Lending Laws on the Flow of Subprime Credit, Federal Reserve Bank of St. Louis Working Paper 2006-009. URL https://doi.org/10.20955/wp.2006.009

Federal Reserve Bank of St. Louis, Research Division, P.O. Box 442, St. Louis, MO 63166

The Impact of Local Predatory Lending Laws on the Flow of Subprime Credit

A shorter version is forthcoming in the *Journal of Urban Economics*

Giang Ho &
Anthony Pennington-Cross*
Federal Reserve Bank of St. Louis
Research Division
P.O. Box 442
St. Louis, MO 63166-0442
Email: Pennington-cross@stls.frb.org
Tel: 314-444-8592, Fax: 314-444-8731

*Corresponding author: Anthony Pennington-Cross, Senior Economist. The views expressed in this research are those of the individual author and do not necessarily reflect the official positions of the Federal Reserve Bank of St. Louis, the Federal Reserve System, and the Board of Governors.

The Impact of Local Predatory Lending Laws on the Flow of Subprime Credit: North Carolina and Beyond

Abstract: Local authorities in North Carolina, and subsequently in at least 23 other states, have enacted laws intending to reduce predatory and abusive lending. While there is substantial variation in the laws, they typically extend the coverage of the Federal Home Ownership and Equity Protection Act (HOEPA) by including home purchase and open-end mortgage credit, by lowering annual percentage rate (APR) and fees and points triggers, and by prohibiting or restricting the use of balloon payments and prepayment penalties. Empirical results show that the typical local predatory lending law tends to reduce rejections, while having little impact on the flow (application and origination) of credit. However, the strength of the law, measured by the extent of market coverage and the extent of prohibitions, can have strong impacts on both the flow of credit and rejections.

JEL Classifications: G21, C25

Keywords: Mortgages, Predatory, Laws, Subprime

Introduction

The current mortgage market consists primarily of two segments – the prime market and the subprime market. The prime market extends credit to the majority of households. The subprime market provides more expensive credit to households who do not qualify for a prime mortgage. These households tend to be less financially secure and located in low-income areas and areas with a concentration of minorities. The combination of higher borrower costs and higher rates of delinquency and foreclosure have led to public policy concerns over fairness and accessibility of credit.

Subprime lending represents an opportunity for the mortgage market to extend the possibility of home ownership beyond traditional barriers. These barriers have existed because the prime segment of the mortgage market uses lending standards (credit scores and documented employment history, income, and wealth, among other factors) to accept or reject loan applicants. Applicants that are rejected or expect to be rejected can look to the more expensive subprime market. In this fashion the subprime market completes the mortgage market and can be welfare enhancing (Chinloy and MacDonald [4]) because it provides the opportunity of home ownership to a larger portion of the population.

Over the past ten years subprime lending has grown rapidly -- from $65 billion to $332 billion of originations from 1995 through 2003 (Inside Mortgage Finance [17]).[1] According to the Mortgage Bankers Association of America, the rate that loans were in foreclosure from the

[1] These numbers are derived from type B&C loans. B&C loans are loans with less than an A (or prime) rating. See the Mortgage Markets Statistics Annual published by Inside Mortgage Finance for more details on loan classification schemes.

first quarter of 1998 to the third quarter of 2004 rose by more than 400 percent for subprime loans while declining by approximately 25 percent for prime loans. In addition, during the same time period anecdotal evidence of predatory lending in the subprime market was gaining more public and regulatory attention.[2] Therefore, the welfare benefit associated with increased access to credit is believed to have been reduced by some unscrupulous lending in the subprime mortgage market.

In response to public concerns of predation in the subprime mortgage market, federal regulations generated under the Home Ownership and Equity Protection Act (HOEPA) restrict some types of high-cost lending. Many states, cities, and counties have used HOEPA as a template and have extended the restrictions on credit to an even broader class of mortgages. These restrictions include limits on allowable prepayment penalties and balloon payments, prohibitions of joint financing of various insurance products (credit, life, unemployment, etc), and requirements that borrowers participate in loan counseling.

By introducing geographically defined predatory lending laws, policymakers have conducted a natural experiment with well defined control and treatment groups. Since state boundaries reflect political and not economic regions, we can compare mortgage market conditions in states with a law in effect[3] (the treatment group) to those in neighboring states currently without a predatory lending law (the control group). However, instead of examining whole states we focus on households that are geographically close to each other (border counties) and as a result are in similar labor and housing markets.

---

[2] See HUD-Treasury report (HUD-Treasury [16]) and Federal Reserve HOEPA Final Rule (Federal Reserve [8]).
[3] Laws are first enacted by the local legislature and become effective typically at a later date. It is not until the law becomes in effect that lenders are required to follow the new rules and restrictions.

Data at the individual loan level are used to identify the impact of local predatory lending laws on subprime applications, originations, and rejections. Specifically, we find that there is substantial heterogeneity in the response of the mortgage market to local predatory lending laws. In fact, in contrast to previous research on the impact of the North Carolina law, the flow of subprime credit can increase, decrease, or be unaffected by the laws. To help understand this heterogeneity we create an index that measures the strength of the local predatory laws. This index measures the increase in market coverage and the extent that certain lending practices and mortgage types are restricted.

This paper provides at least four contributions to the literature: (i) a wide variety of local predatory lending laws are characterized, (ii) the question of whether the market response in North Carolina (reduce flow of credit) was typical or atypical is examined, (iii) the importance of the strength of the law on the flow of credit is examined and (iv) the probability of a state introducing a predatory lending law is treated as jointly determined with the flow of subprime credit.

A Simple Model of Application Outcomes

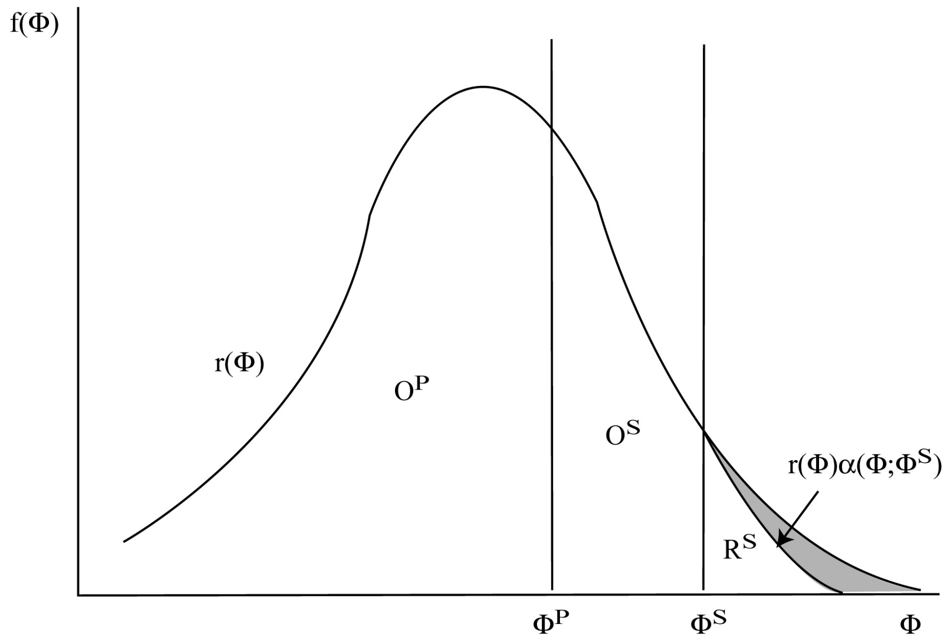
We present a highly stylized model of mortgage application outcomes to examine the potential effects of a predatory lending law on subprime applications, subprime originations, and subprime rejections. We assume that applicants understand that a subprime mortgage costs more than a prime mortgage and self-select their applications to the appropriate market. Following the approach of Ferguson and Peters [9] and Ambrose, Pennington-Cross and Yezer [2], we assume that all of the information included in the application can be summarized by a single number (mortgage credit score or credit risk). Each loan applicant has a credit risk represented by $\Phi \in [0,1]$. We interpret Φ as a monotonically increasing function of the borrower's likelihood of default, and the marginal probability density function of credit risk is given by $r(\Phi)$. Assuming mortgage lenders can observe the true credit risk of borrowers, they approve all loan applications with credit risk lower than a uniform underwriting cut-off, which we denote as Φ^P for the prime market and Φ^S for the subprime market, with $\Phi^P < \Phi^S$.

In this model the prime market is perfectly sorted; everyone who applies for a prime mortgage has credit risk $\Phi \leq \Phi^P$ and therefore is approved for a loan. While we do observe in the marketplace some rejections of prime applications, empirical research has shown that subprime loans are rejected at a much higher rate than prime loans: 33 percent versus 9 percent (Scheessele [24]). In addition, the assumption of perfect sorting or borrower self-selection does not affect the suggested impact of predatory lending laws on the outcome of subprime mortgage applications. Therefore, in Figure 1, prime applications and originations are given by the same integral of the marginal density function and are represented by the area O^P:

$$A^P = O^P = \int_0^{\Phi^P} r(\Phi) d\Phi \quad . \tag{1}$$

Applicants with credit risk higher than the prime underwriting standard, Φ^P, are subprime applications. However, applying for a subprime loan is costly, so that an individual will do so only if he/she thinks the chance of being accepted is sufficiently high.

Figure 1: Prime and Subprime Mortgage Outcomes



$r(\Phi)$ = marginal probability function of credit risk; $\alpha(\Phi;\Phi^S)$ = subprime application rate; Φ^P = prime underwriting standard; Φ^S = subprime underwriting standard; O^P = prime originations; O^S = subprime originations; R^S = subprime rejections.

This borrower self-selection implies that a fraction of individuals with credit risk higher than a certain level – we refer to these as the "marginal applicants" - will opt out of the subprime market, effectively altering the risk distribution. We define $\alpha(\Phi;\Phi^S)$ as the share of actual subprime applicants in the potential applicant universe; α is indexed by Φ, given the current subprime underwriting standard (Φ^S). For potential subprime applicants with $\Phi \leq \Phi^S$, $\alpha(\Phi;\Phi^S)$ equals unity. The probability of applying, $\alpha(\Phi;\Phi^S)$, continuous and decreasing for $\Phi > \Phi^S$ until it equals zero at some value Φ', where $\Phi^S < \Phi' \leq 1$. The applicants who opt out and do not apply are shown as the shaded area in Figure 1.

Given the current subprime underwriting standard, Φ^S, and the risk distribution, $r(\Phi)$, the number of applications, A^S, originations, O^S, and rejections, R^S, are shown in Figure 1 and given by

$$\text{Applications } A^S = \int_{\Phi^P}^{1} r(\Phi)\alpha(\Phi;\Phi^S)d\Phi\,;$$

$$\text{Originations } O^S = \int_{\Phi^P}^{\Phi^S} r(\Phi)d\Phi\,;$$

$$\text{Rejections } R^S = \int_{\Phi^S}^{1} r(\Phi)\alpha(\Phi;\Phi^S)d\Phi\,. \tag{2}$$

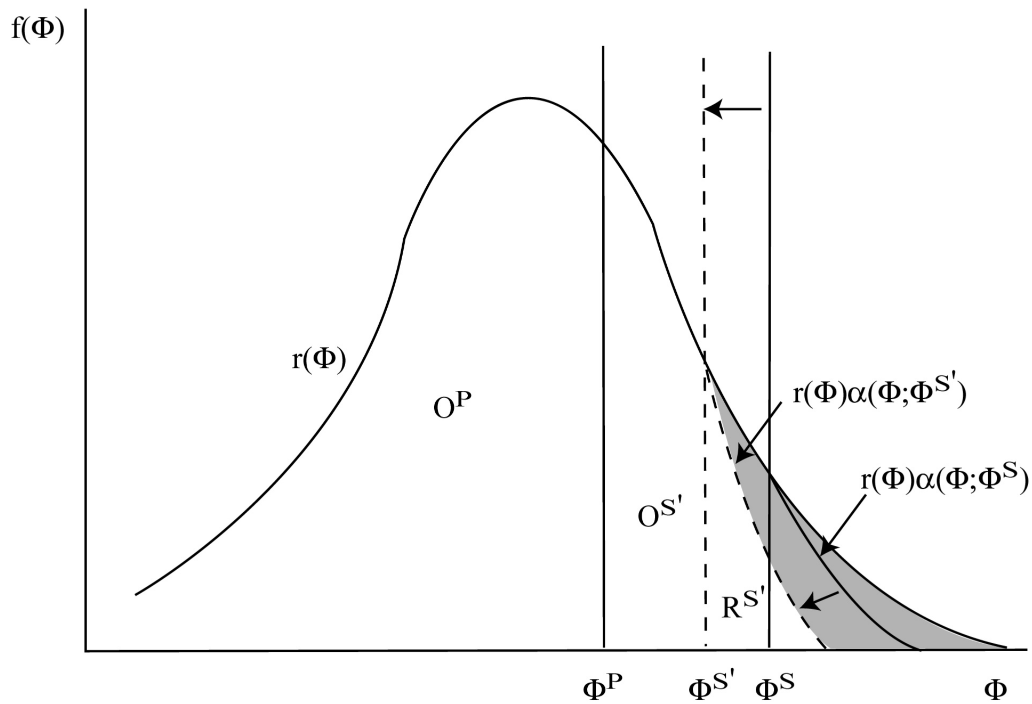
The number of applications can also be represented as the sum of originations and rejections, $A^S = O^S + R^S$.

Assume that a predatory lending law is introduced which imposes restrictions on subprime mortgage lenders in terms of information disclosure, allowable loan types, and required lending practices. In order to comply with the law's restrictions, lenders must tighten underwriting standards from Φ^S to $\Phi^{S'}$. This post-law scenario is illustrated in Figure 2. The law results in fewer subprime loans being originated due to the tighter minimum lending standards required to comply with the predatory lending law:

$$\int_{\Phi^P}^{\Phi^{S'}} r(\Phi)d\Phi = O^{S'} < O^S = \int_{\Phi^P}^{\Phi^S} r(\Phi)d\Phi\,. \tag{3}$$

The total number of subprime applicants also decreased after the law was implemented because more "marginal applicants", fearing higher probability of rejection, self-select out of the subprime market. For all values of $\Phi > \Phi^{S'}$, $r(\Phi)\alpha(\Phi;\Phi^S) > r(\Phi)\alpha(\Phi;\Phi^{S'})$, and, as a result, $A^S > A^{S'}$.

Figure 2: Post-law Scenario – Tightening Subprime Underwriting Standards



$r(\Phi)$ = marginal probability function of credit risk; $\alpha(\Phi;\Phi^{S'})$ = subprime application rate; Φ^{P} = prime underwriting standard; Φ^{S} = pre-law subprime underwriting standard; $\Phi^{S'}$ = post-law subprime underwriting standard; O^{P} = prime originations; $O^{S'}$ = post-law subprime originations; $R^{S'}$ = post-law subprime rejections.

Depending on the functional form of $\alpha(.)$ the number of rejected applications could increase or decrease if lending standards are tightened, especially if the propensity to apply is affected by the level of credit risk.[4]

$$\int_{\Phi^{S'}}^{1} r(\Phi)\alpha(\Phi;\Phi^{S})d\Phi = R^{S'} >,=,< R^{S} = \int_{\Phi^{S}}^{1} r(\Phi)\alpha(\Phi;\Phi^{S})d\Phi . \tag{4}$$

In addition, the rejection rate or the ratio of rejections to applications could either increase or decrease, again depending on the function from of $\alpha(.)$.

---

[4] However, if $\alpha(.)$ is a linear decreasing function of $\left(\Phi - \Phi^{j}\right)$, where is j indexes the lending standards S and S', the number of rejected applications will increase when lending standards are tightened.

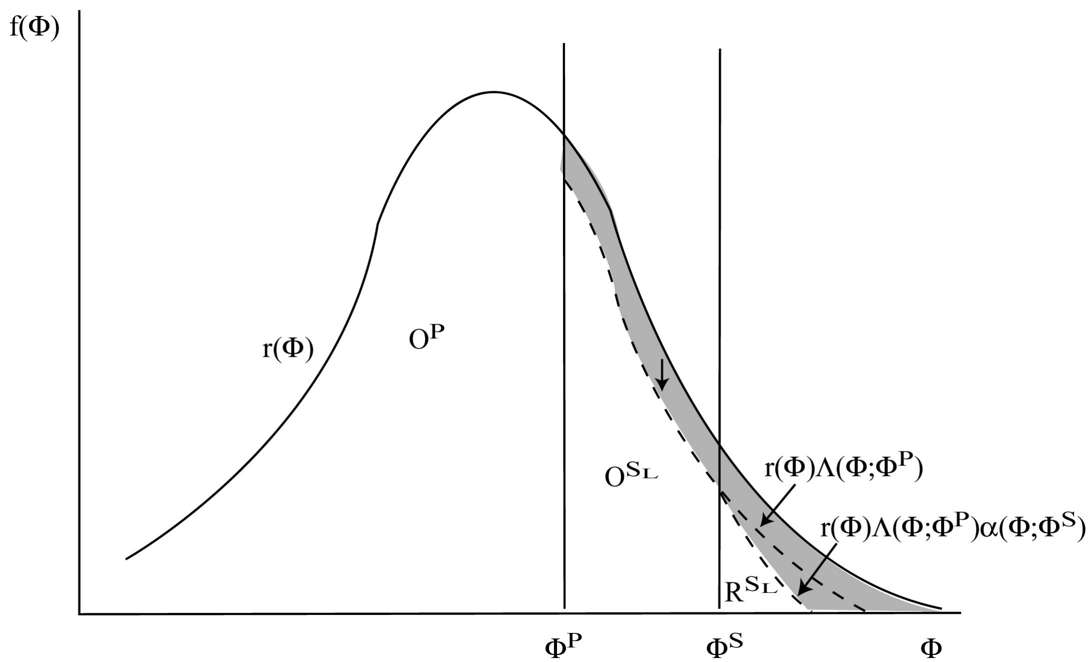
This analysis allows us to develop testable hypotheses regarding the impact of a predatory lending law on subprime mortgage outcomes. Specifically, we expect that the introduction of a law will reduce relative to prime market the number of subprime applications and originations. In addition, a law that tightens lending standards should also be associated with higher rates of subprime rejections.

Finally, we introduce what we call the "lemons effect," as pioneered by Akerlof [1], into the market for subprime mortgage. In this type of market loans can be sold honestly or dishonestly. The borrower attempts to sort the honest loans from the dishonest loans. Unfortunately, regulatory agencies (HUD and Treasury) and The Board of Governors of the Federal Reserve System (Board) did find some evidence from task force interviews and open meetings that some subprime borrowers, typically elderly or poorly educated households, have had difficulty sorting the honest loans from the dishonest loans (HUD-Treasury [16][5] and Federal Reserve [8]).

In a market with some dishonest loans, all borrowers must exert extra effort and time to screen the lender and loan documents, but this represents extra costs (transaction costs) for the borrowers. In addition, the press, government reports, and local nonprofit agencies, have informed the public about the presence of predatory lending, or dishonest loans, in the subprime market. This uncertainty in loan quality can have the effect of deterring subprime applications and is illustrated in Figure 3.

[5] The report recommended improved consumer literacy and disclosures, as well as prohibitions of loan flipping, lending without regard to ability to repay, and the sale of life credit insurance and other similar products. It was also recommended that potentially abusive terms and conditions such as balloon payments, prepayment penalties, excessive fees and points be restricted.

Figure 3: The "Lemons Effect"



$r(\Phi)$ = marginal probability function of credit risk; $\Lambda(\Phi;\Phi^P)$ = lemons shift function; $\alpha(\Phi;\Phi^S)$ = subprime application rate; Φ^P = prime underwriting standard; Φ^S = subprime underwriting standard; O^P = prime originations; O^{S_L} = subprime originations under the lemons effect; R^{S_L} = subprime rejections under the lemons effect.

Here we introduce a shift function $\Lambda(\Phi;\Phi^P)$ that equals zero for $\Phi \le \Phi^P$ and a constant *k*, $0 < k < 1$, for $\Phi^P < \Phi \le 1$. $\Lambda(.)$ can be interpreted as the fraction of potential subprime applicants that are deterred from applying for fear of falling prey to predatory lending or because of the additional transaction costs associated with identifying the dishonest loan or lender. Therefore, the risk distribution becomes kinked at Φ^P and shifts down for all applicants with credit risk above Φ^P. The resulting subprime originations and rejections are represented in Figure 3 by areas O^{S_L} and R^{S_L}, respectively, and subprime applications equal $O^{S_L} + R^{S_L}$.

Given the perception that predation has occurred in the subprime market and not in the prime market, the volume of lending as measured by the number of originations and applications may be lower than expected, given the distribution of credit risk, $r(\Phi)$. One of the primary purposes of predatory lending laws is to weed out the "lemons" in the subprime mortgage market. If households feel that the predatory lending law has been successful, there may be less need to spend time and energy to identify the dishonest loans and other households may feel more comfortable applying for a mortgage; in this scenario $\Lambda(.)$ is reduced to zero or much closer to zero. Therefore, if the subprime market is operating as a lemons market the introduction of the predatory lending law should have two countervailing forces. First, as illustrated in Figures 1 and 2, the law should reduce applications and originations because of tighter lending standards. Second, as illustrated in Figure 3, the law should induce potential applicants back into the market; If the law removes or heavily regulates the dishonest loans there would be little or no fear of being taken advantage of and no need to expend effort sorting honest loans from dishonest loans. Therefore, in markets with a substantial lemons problem, or big $\Lambda(.)$, the impact of a predatory lending law could be neutral or could increase the rate of subprime application and origination. In addition, if $\Lambda(.)$ is not strictly proportional, but has a larger impact on potential borrowers closer or farther away from Φ^S, then the introduction of a predatory lending law could also increase or decrease rejections rates.

National Lending Restrictions – Home Ownership and Equity Protection Act

Congress enacted HOEPA (Pub. L. 103-325, 108 Stat. 21600) by amending the Truth in Lending Act (TILA, 15 U.S.C 1601). In 1994, the Board of Governors implemented HOEPA through 12 CFR part 226 (Regulation Z), which articulates specific rules governing lending practices.

HOEPA and the regulations promulgated under it define a class of loans that are given special consideration. HOEPA-covered loans (loans where HOEPA applies) include only closed-end home equity loans that meet APR and finance fee triggers. Home purchase loans and other types of lending backed by a home, such as lines of credit, are not covered by HOEPA. The original version, in 1994, set out the framework and defined the triggers and restrictions. The second version, in 2002, adjusted some of the triggers and restricted some additional practices. In the 2002 version, HOEPA protections were triggered in one of two ways: (i) if the loan's APR exceeded the rate for Treasury securities of comparable maturity by 8 percentage points or more on the first lien and 10 percentage points or higher on higher liens or (ii) if finance charges, including points and fees paid at closing for optional insurance programs and other debt protection programs, were greater than 8 percent of the loan amount or a fixed $480 amount indexed annually to the consumer price index.

For HOEPA-covered loans, creditors were not allowed to provide short-term balloon notes, impose prepayment penalties greater than five years, use non-amortizing schedules, make no-documentation loans, refinance loans into another HOEPA loan in the first 12 months, or impose higher interest rate upon default. In addition, creditors were not allowed to habitually engage in lending that did not take into account the ability of the consumer to repay the loan.

Regional Restrictions – State and Local Predatory Lending Laws

A number of states and local municipalities have sought to impose restrictions on predatory lending that reach further than HOEPA and Regulation Z. Ho and Pennington-Cross [15] provide a detailed description of each law in Appendix A.[6]

Beginning with North Carolina in 1999, at least 23 states have passed predatory lending laws that are currently in effect: including Arkansas, California, Colorado, Connecticut, Florida, Georgia, Illinois, Kentucky, Maine, Maryland, Massachusetts, Nevada, New Jersey, New Mexico, New York, North Carolina, Ohio, Oklahoma, Pennsylvania, South Carolina, Texas, Utah, and Wisconsin.

Both the original and the 2002 versions of HOEPA defined a class of high-cost refinance mortgages that were subject to special restrictions. The state laws tend to follow this lead and expand the definition of covered loans. For example, North Carolina – the first state to enact predatory lending restrictions -- includes both closed-end and open-end mortgages but not reverse mortgages and limits loan size to the conventional conforming limit (loans small enough to be purchased by Fannie Mae and Freddie Mac and therefore not considered part of the jumbo market). HOEPA covers only those closed-end loans that are not for home purchase (typically refinance and second mortgages). North Carolina did leave the APR triggers the same as the HOEPA triggers, although the points and fees triggers were reduced from the HOEPA 8 percent of total loan amount to 5 percent for loans under $20,000. For

[6] Every attempt was made to include all laws in effect by the end of 2004 that, similar to HOEPA, use triggers to define a class of loans eligible for restrictions and disclosures. Because other laws are likely to exist, those discussed here should be viewed as a sample of all the state and local predatory lending laws. Other states have laws that do not focus on high-cost or subprime lending and do not have any triggers (Idaho, Michigan, Minnesota, Mississippi, Nebraska, New Hampshire, Oregon, Tennessee, Washington, and West Virginia).

loans $20,000 or larger, the same 8 percent trigger is used or $1,000, whichever is smaller. The North Carolina law also prohibits prepayment penalties and balloon payments for most covered loans. But the law also prohibits the financing of credit life, disability, unemployment, or other life and insurance premiums, while HOEPA included them only as part of the trigger calculation.

While most states followed the North Carolina example by expanding the coverage and restrictions associated with HOEPA, there is substantial variation in the laws. In an attempt to quantify the differences in the local laws, we created an index. The higher the index, the stronger the law is. In addition, the index can be broken down into two components. The first component reflects the extent that the law extends market coverage beyond HOEPA. The second component reflects the extent that the law restricts or requires specific practices on covered loans. Table 1 summarizes the construction of the law index. The full index is the sum of all the assigned points as defined in Table 1 and the coverage and restrictions indexes are the sum of points assigned in each subcategory.

The coverage category includes measures of loan purpose, APR first lien, APR higher liens, and points and fees. In general, if the law does not increase coverage beyond HOEPA it is assigned zero points. Higher points are assigned if the coverage is broader. In each category the highest points are assigned when all loans are covered. For example, points assigned for loan purpose range from zero to four and the highest point total (four) indicates that the law covers all loan purposes. The points assigned for extending first lien APR trigger ranges from zero to three depending on how low the trigger is. For example, 7 percent triggers are assigned one point while 6 percent triggers are assigned two points. In addition, laws that do not have a first lien trigger are assigned three points. A similar scheme is used to assigned points for higher lien triggers and the points and fees triggers. In general, if the law includes multiple triggers within a category the most stringent trigger is used to assign the points. [7]

The restrictions index includes measures of prepayment penalty restrictions, balloon restrictions, counseling requirements, and restrictions on mandatory arbitration. If the law does not require any restrictions then zero points are assigned. Higher points indicate more restrictions. For example, laws that do not restrict prepayment penalties are assigned zero points, while laws that prohibit all prepayment penalties are assigned four points. Laws that prohibit or restrict the practice more quickly are assigned higher points. For balloon restriction, the points vary from zero for no restrictions to four when the law prohibits all balloons.[8] The last two restrictions measure whether the law requires counseling before the loan is originated or restricts fully or partially mandatory arbitration clauses.

Table 2 reports the calculated full (law) index, the coverage index, and the restrictions index for each law identified as being in effect by the end of 2004. The average law index is 10.16, varying from 4 in Florida, Maine, and Nevada to 17 in New Mexico and Cleveland. The coverage index and the restrictions index have a mean just over 5. The coverage and restrictions indexes are only modestly correlated at 0.19. This indicates that, while laws that increase coverage more also tend to increase the restrictions more, the relationship is very

[7] For example, some laws have different triggers depending on loan amount or other distinctions.
[8] The law in Cleveland was determined to be restrictive and was assigned four points despite not neatly falling into any of the categories.

noisy. Therefore, there are laws that increase coverage without increasing restrictions (Nevada) and other states that extend restrictions more than coverage (Florida).

Scaled indexes are created and reported in Table 3. This is necessary because the magnitude of each subcomponent of the index implicitly weights the index so that it represents some subcomponents more than others. To help correct for this, each subcomponent number is scaled so that the maximum value equals one (actual/max). It is then divided by the category mean value [(actual/max)/mean(actual/max)] so that each category has a mean of one. Therefore, the scaled index equally reflects each subcomponent in terms of marginal impacts and the level of the index. Since eight categories are used to create the law index the mean value of the index is by design eight. Zero also retains the appealing intuition of reflecting no increase in law strength beyond HOEPA. The scaled law index varies from 17.16 to 1.47 and the scaled and original law index are highly correlated (0.87).

Table 1: Law Index Definition

Category	Description of Law Index
Coverage:	
Loan Purpose	HOEPA equivalent=0, all loans except no government loans=1, all loans except no reverse or open loans=2, all loans except no reverse, business, or construction loans =3, and all loans with no exceptions=4
APR Trigger 1st Lien	8%, HOEPA equivalent =0, 7%=1, 6%=2, and no trigger=3
APR Trigger Higher Liens	10%, HOEPA equivalent =0, 9%=1, 8%=2, 7%=3, and no trigger=4
Points and Fees Trigger	8%,HOEPA equivalent =0, 6%-7%=1, 5%=2 , <5%=3, and no trigger=4
Restrictions:	
Prepayment Penalty Prohibitions	No restriction=0, prohibition or percent limits after 60 months=1, prohibition or percent limits after 36 months=2, prohibition or percent limits after 24 months=3, and no penalties allowed=4
Balloon Prohibitions	No restriction =0, no balloon if term<7 years (all term restrictions) =1, no balloon in first 10 years of mortgage =2, no balloon in first 10 years of mortgage and Cleveland=3, and no balloons allowed=4
Counseling Requirements	Not required=0, and Required=1
Mandatory Arbitration Limiting Judicial Relief	Allowed=0, partially restricted=1, and prohibited =2

Note: The law index is calculated by summing all categories. The coverage and restrictions indexes are created by summing the subcategories.

Table 2: The Law Index

State	Full Index	Coverage Index	Restrictions Index
Arkansas	8	5	3
California	11	7	4
Chicago, IL	15	10	5
Cleveland, OH	17	7	10
Colorado	13	8	5
Connecticut	10	5	5
Cook County, IL	15	10	5
Florida	4	0	4
Georgia	16	6	10
Illinois	13	6	7
Indiana	11	4	7
Kentucky	9	2	7
Maine	4	4	0
Maryland	8	7	1
Massachusetts	14	6	8
Nevada	4	4	0
New Jersey	10.5	5.5	5
New Mexico	17	7	10
New York	10	6	4
North Carolina	11	3	8
Ohio	6	4	2
Oklahoma	8	2	6
Pennsylvania	7	4	3
South Carolina	9	4	5
Texas	8	2	6
Utah	6	4	2
Washington, DC	15	8	7
Wisconsin	5	3	2
Average	10.16	5.13	5.04
Standard Deviation	4.03	2.39	2.82

Table 3: The Scaled Law Index

State	Full Index	Coverage Index	Restrictions Index
Arkansas	10.06	2.73	7.33
California	7.07	5.09	1.98
Chicago, IL	12.64	10.20	2.43
Cleveland, OH	15.19	4.35	10.84
Colorado	16.19	12.87	3.31
Connecticut	6.92	2.73	4.20
Cook County, IL	12.64	10.20	2.43
Florida	1.98	0.00	1.98
Georgia	14.88	4.13	10.76
Illinois	17.16	8.73	8.43
Indiana	7.55	2.36	5.19
Kentucky	4.95	0.74	4.22
Maine	1.47	1.47	0.00
Maryland	10.51	5.84	4.67
Massachusetts	9.68	4.13	5.55
Nevada	1.47	1.47	0.00
New Jersey	6.27	3.13	3.14
New Mexico	12.91	6.28	6.63
New York	6.82	4.13	2.69
North Carolina	5.07	1.11	3.96
Ohio	2.38	1.47	0.90
Oklahoma	4.59	0.74	3.85
Pennsylvania	2.92	1.47	1.44
South Carolina	8.83	2.36	6.47
Texas	3.79	0.74	3.06
Utah	2.55	1.47	1.08
Washington, DC	14.89	10.50	4.39
Wisconsin	2.63	1.55	1.08
Average	8.00	4.00	4.00
Standard Deviation	4.98	3.52	2.87

Note: The Coverage and Restrictions Indexes are modestly correlated (0.21).

Literature on Local Predatory Lending Laws

Research on the impact of predatory lending laws has been primarily focused on the impact of the North Carolina law. Various data sets, both publicly available and privately held, have been used for analysis. However, regardless of the method and author affiliations, the North Carolina law was found to have a significant impact on the flow of credit.

Papers by Ernst, Farris, and Stein [7] and Quercia, Stegman, and Davis [22, 23] use tables of mortgage conditions before and after the North Carolina law became effective, or in effect, and compares these metrics with growth rates in nearby states and the nation as a whole. Using the Home Mortgage Disclosure Act (HMDA) data set and a list of subprime lenders created by HUD, Ernst, Farris, and Stein [7] find that the volume of loans originated did decline relative to the rest of the U.S. However, using data leased from a private data vendor called LoanPerformance (LP), Quercia, Stegman, and Davis [22] find no volume impact on purchases or low credit score loans. However, they do find some evidence that interest rates are higher on average, refinance activity declines, and the prevalence of prepayment penalties is lower; but the impact on balloons and high loan-to-value loans is mixed. Using the same data, Quercia, Stegman, and Davis [23] find that the decline in volume in North Carolina was largely associated with refinancing loans. The LP data set differs greatly from the HMDA data because it provides much more detail about loan characteristics and is very expensive to lease for one year (over $100,000). In addition, the LP data likely does not provide a complete picture of the subprime mortgage market because it includes only loans that are securitized. If loans of better quality (A- rated) or pricing tend to have higher rates of securitization, then the LP data represent only one segment of the subprime market. Chomsisengphet and Pennington-Cross [5] show that the rate of foreclosures, as reported by the Mortgage Bankers Association of America (MBAA), shows different time series properties than the LP data and was on average almost three times the LP foreclosure rate. Therefore, for the purpose of volume comparisons, HMDA is the preferred source because of its better market coverage.

Harvey and Nigro [13, 14] and Elliehausen and Staten [6] go beyond univariate tables and estimate multivariate equations to identify the impact of the laws in North Carolina, Chicago, and Philadelphia. Since publication the Philadelphia law is no longer in effect. On both Harvey and Nigro papers a proprietary version of HMDA along with the HUD subprime lender list is used while Elliehausen and Staten use proprietary loan information provided by nine members of the American Financial Services Association (AFSA). AFSA has been an active participant in legal challenges of local predatory lending laws and represents some of the largest subprime lenders (Ameriquest Mortgage Company, Conseco Finance Corporation, Countrywide Home Loans, Equity One, CitiFinancial, Household Finance Corporation, Key Consumer Real Estate, Washington Mutual Finance and Wells Fargo Financial, Inc.). All three papers include explanatory variables that control for location and borrower characteristics, as available. Harvey and Nigro estimate at the loan level the probability of applying for a subprime loan, originating a subprime loan, and being rejected on a subprime application in a logit estimation. Elliehausen and Staten count the number of originations up to the county level and create a panel data set from 1995 through 2000 and estimate a negative binomial regression on all observed originations covering the whole U.S.

Despite these many methodological and data source differences, all three multivariate papers find evidence that the introduction of the North Carolina law substantially reduced the flow of credit in the subprime mortgage market. Consistent with the simple theory of a market without considering any lemons issues, the reduction in flow was attributed more to a reduction in applications than an increase in rejections. In addition, low-income areas and households tended to have larger declines.

Data Design, Identification, and Probit Estimation

To examine whether the experience in North Carolina is typical we use the publicly available version of HMDA in conjunction with the HUD subprime lenders list.[9] Any loan application or origination associated with a lender on the list is identified as a subprime loan. All other loans are treated as not-subprime, that is, as a conventional loan. Because it is impossible to fully characterize borrower and location characteristics, the sample is reduced to include only locations where a new predatory lending law has been introduced and other locations that are physically nearby. The locations where the law comes into effect can be viewed as the treatment group and locations where no new law comes into effect can be viewed as the control group.[10] Therefore, only counties that border other states without a local predatory lending law are used for the treatment group. The control group includes only counties in neighboring states that border the treatment state and do not have a predatory lending law in effect during the examined time period (the year before and after the introduction of the law). This contrasts with other studies (Harvey and Nigro [14], Elliehausen and Staten [6]) that have used the whole of the U.S. or regions to define both control and treatment groups. To help remove the impact of any temporary reaction to each law and any market reaction prior to the law coming into effect, only the year before and the year after the law is in effect are included in the sample. This approach should help to increase the comparability of the

---

[9] http://www.huduser.org/datasets/manu.html, accessed on 2/1/05. HUD generates a list of subprime lenders from industry trade publications, HMDA data analysis, and phone calls to the lender confirm the extent of subprime lending. Since this list is defined at the lender level, loans made by the subprime lenders may include both prime and subprime loans. In addition, subprime loans made by predominately prime lenders will also be incorrectly identified as prime lending. Therefore, an alternative interpretation of the loans identified using the HUD subprime lender list is that it identifies the extent of specialized subprime lending -- not full-service lending.

[10] This geographically based sampling does not create a "matched" sample, where one similar loan in the treatment location is matched with another loan in the control location. In short, all observed loans in the specified location and time periods are included.

treatment group and the control group because they are geographically closer and, as a result, likely to be more economically similar than full state and region comparisons.

This approach and HMDA availability reduce the sample to ten local predatory lending laws: California, Connecticut, Florida, Georgia, Maryland, Massachusetts, North Carolina, Ohio, Pennsylvania, and Texas.

Identification Strategy

To identify the impact of a local predatory lending law, the location and timing of the law becoming effective, along with borrower and location characteristics, are included. Table 4 describes the variables and data sources. Similar to Harvey and Nigro [13, 14], three separate dependent variables will be tested for impacts of local predatory lending laws -- the probability of applying for a subprime loan, the probability of originating a subprime loan, and the probability of being rejected on a subprime application.

The key variable of interest is *Ineffect*. This variable indicates that a loan is in a location when and where a predatory lending law is effective. It is defined as zero before the law is effective, even in the treatment location, and is always zero in the control location. *Ineffect* is constructed by interacting the variable *Law*, which indicates locations where the law will eventually be in effect, and *Postlaw*, which indicates the time period after a law has become effective. Therefore, *Law* identifies the treatment location and *Postlaw* identifies the time period the treatment is in effect. The reference group is defined as locations where the law will never be in effect in the time period before the law is in effect. There are no priors regarding the coefficients on *Law* or *Postlaw*, because they will capture prevailing probabilities associated with location and time that are not controlled for by other variables. Given the results from prior research we would expect *Ineffect* to be negative for the application and origination outcome and potentially insignificant for the rejection outcome.

Table 4: Identification Strategy and Control Variable Definitions

Variable	Definition	Source
Outcome		
Application	Indicator variable = 1 for subprime application; 0 for prime	HMDA & HUD subprime lender list
Origination	Indicator variable = 1 for subprime origination; 0 for prime	HMDA & HUD subprime lender list
Rejection	Indicator variable = 1 if subprime loan is denied; 0 if accepted	HMDA & HUD subprime lender list
Identification		
Law	Indicator variable = 1 if borrower is from a location with a law at some point; 0 otherwise	Working Paper : Appendix A*
Postlaw	Indicator variable = 1 for post-legislation time period; 0 otherwise	Working Paper : Appendix A*
Ineffect	Interaction of *Law* and *Postlaw* indicators indicating that the borrower is from a location with a law currently effective.	Working Paper : Appendix A*
Control Variables		
Income	Borrower's gross annual income ($ in thousands)	HMDA
Loan2inc	Ratio of requested loan amount to borrower's income	Calculated from HMDA
Relinc	Ratio of tract median family income to MSA median family income	HMDA
Minority	Tract's minority population percentage	HMDA
Vacant	County's percentage of vacant housing units	Census 2000
Population	County's population growth from the calendar year before and after the law became effective	Census Bureau
Unemployment	County's unemployment rate	Bureau of Labor Statistics

* Ho and Pennington-Cross [15] provide a detailed description of each law in Appendix A. The detailed descriptions of the laws are too long to include in this paper and have been summarized by the law index discussed above.

Both Harvey and Nigro [13, 14] and Elliehausen and Staten [6] include a series of control variables associated with the location of the loan or loan application and the borrower because they may impact the demand or supply of subprime credit. In general we expect that borrowers will be more likely to use/apply for subprime loans (and perhaps be rejected by subprime lenders in locations) with difficult economic conditions and when borrowers have lower income or are in minority areas (Calem, Gillen, and Wachter [3] and Pennnington-Cross [20]). Economic conditions are proxied by the county unemployment rate, housing vacancy rate, and population growth rate. Borrower characteristics are proxied by the percent of minority population in the census tract and borrower income. In general, we expect that applicants with more income relative to their loan amount will have an easier time meeting prime underwriting requirements. Underwriting requirements are proxied by the loan-to-borrower-income ratio. One important caveat to this analysis is that the borrower's credit history or credit score, which has been shown to be a very important determinant of mortgage performance for both subprime and prime loans (Pennington-Cross [21]), is not reported in the HMDA data and therefore cannot be included in this analysis. Lastly, perhaps due to minimum scale requirements, prime lending may be more available in locations with more households. As a result, subprime may be more prevalent in locations with a smaller population.

Probit Estimation

A probit model is estimated for each outcome and for each law sample (treatment and control location loans). Therefore, for each law, three probit models are estimated and a total of 30 model estimates are generated including 10 explanatory variables each for a total of 300 estimated coefficients excluding intercepts.

The probit specification is given by

$$\Pr(Y = 1 \mid x) = \Phi(x'\beta), \tag{5}$$

where Y is the outcome (application, origination, or rejection), x is a vector of explanatory variables, β is a vector of parameters, and $\Phi(.)$ denotes the standard normal distribution. The log-likelihood for the probit model is

$$L = \sum_{y_i=0} \ln[1 - \Phi(x_i'\beta)] + \sum_{y_i=1} \ln \Phi(x_i'\beta), \tag{6}$$

where y_i and x_i are, respectively, the observed values of outcome Y and explanatory variables x for observation i.

Due to the large number of coefficient estimates, instead of reporting all coefficients, summary information is provided.[11] To provide context for the marginal effects, Table 5 reports the mean of the dependent variables for each of the law samples (control and treatment loans). It shows that there is a wide variety in subprime application, origination, and rejection rates. For example, subprime applications ranged from almost 25 percent in California to just over 15 percent in Maryland. The relative magnitude of application and origination rates provides indirect support for the high rates of rejection on subprime applications. In fact, in some of the law samples, over 50 percent of subprime applications were rejected.

Table 6 reports the marginal impact of a local predatory lending law becoming effective for each state and each outcome. Consistent with prior literature, these results indicate that the North Carolina law did reduce the flow of subprime credit through a reduction in both application and origination probabilities. But the experience in terms of originations and applications in North Carolina is replicated in only one-half of the laws examined. In the

[11] Detailed results are available upon request.

other half the introduction of the law was associated with an increase in the flow (originations) of subprime credit. The results are also mixed in terms of applications, with some laws being associated with higher and other laws associated with lower probabilities of application. The impacts of the local laws on the probability of being rejected are a little more consistent, with seven of the ten laws being associated with lower rejection rates.

Table 5: Mean of Dependent (Outcome) Variables

Law sample (treatment and control loans)	**Application**	**Origination**	**Rejection**
California	0.249	0.153	0.354
Connecticut	0.245	0.119	0.397
Florida	0.177	0.063	0.574
Georgia	0.224	0.097	0.505
Massachusetts	0.174	0.080	0.357
Maryland	0.153	0.064	0.439
North Carolina	0.233	0.111	0.484
Ohio	0.241	0.092	0.551
Pennsylvania	0.261	0.109	0.476
Texas	0.242	0.104	0.550

Table 6: Marginal Effects of Ineffect Variable

Law Sample	**Application**	**Origination**	**Rejection**
California	0.032***	0.067***	-0.258***
Connecticut	0.014**	0.023***	0.013
Florida	-0.030***	0.008*	-0.057***
Georgia	-0.056***	-0.007**	-0.110***
Massachusetts	-0.074***	-0.032***	-0.030***
Maryland	0.029***	0.018***	-0.066***
North Carolina	-0.069***	-0.042***	-0.048***
Ohio	-0.005	-0.004	-0.022**
Pennsylvania	0.037***	0.032***	0.032***
Texas	0.189***	0.107***	0.148*

Note: *, **, *** indicate that the marginal effect is significantly different from zero at the 90%, 95%, and 99% levels respectively.

Table 7 provides a summary of coefficient estimates for the remaining control variables for the probit application, origination, and rejection models. The first four columns report the minimum, maximum, mean, and standard deviation of the estimated coefficients across the ten laws. The last column reports the mean t-statistic associated with the coefficients. There is no expected sign or even significance associated with the *Law* and *Postlaw* dummy variables since they control for unobserved impacts of location and time in each law sample. There are three measures of income included in the model (borrower income, the ratio of the requested loan amount to borrower income, and the ratio of tract to MSA median family income). As anticipated, on average, borrowers with higher income are less likely to apply for or get a subprime loan and are less likely to be rejected on a subprime application. However, as with most of the control variables, there is substantial variation in the sign and magnitude of the coefficient estimates. Consistent with the findings for borrower income, originations and applications are more likely to occur in locations with relatively lower incomes, and applications are more likely to be rejected when they come from locations with relatively lower incomes. Lastly, as anticipated, applicants requesting larger loans relative to their income are more likely to be rejected.

Higher unemployment rates are also associated on average with higher probabilities of application, origination, and rejection, but the coefficient estimates vary from being negative to positive. In addition, weaker housing markets, proxied by the vacancy rate and county population growth, are inconsistently associated with application, origination, and rejection probabilities. However, consistent with prior research, locations with more minorities are associated with higher subprime application, origination, and rejection probabilities.

Table 7: Summary of Control Variable Coefficient Estimates

Variable	Coefficient Min	Coefficient Max	Coefficient Mean	Coefficient Std. Dev.	T-stats Mean
Application Results					
Law	-1.191	0.500	-0.032	0.447	2.621
Postlaw	-0.254	0.156	-0.078	0.120	-8.530
Ineffect	-0.288	0.765	0.031	0.299	-1.639
Income	-0.319	-0.058	-0.176	0.083	-34.463
Loan2inc	-0.001	0.032	0.012	0.012	9.622
Relinc	-0.617	-0.215	-0.431	0.165	-41.554
Minority	0.274	0.819	0.550	0.153	35.074
Vacant	-10.514	15.820	-0.207	6.704	-3.124
Population	-0.119	0.059	-0.018	0.053	-5.243
Unemployment	-5.393	16.539	7.503	6.453	13.972
Origination Results					
Law	-0.807	0.230	-0.079	0.293	-1.223
Postlaw	-0.509	0.067	-0.158	0.170	-8.510
Ineffect	-0.229	0.759	0.103	0.279	1.999
Income	-0.497	-0.039	-0.213	0.159	-19.529
Loan2inc	-0.033	0.031	-0.002	0.018	-2.871
Relinc	-0.615	-0.141	-0.388	0.156	-22.270
Minority	0.384	0.820	0.605	0.141	24.624
Vacant	-9.833	4.701	-1.604	3.791	-4.108
Population	-0.128	0.026	-0.022	0.055	-2.545
Unemployment	-5.246	18.093	6.891	6.623	9.131
Rejection Results					
Law	-0.377	1.837	0.197	0.599	3.088
Postlaw	-0.263	0.321	-0.006	0.168	-0.194
Ineffect	-0.469	0.373	-0.084	0.223	-3.927
Income	-0.082	0.051	-0.031	0.043	-4.660
Loan2inc	0.001	0.055	0.022	0.017	7.779
Relinc	-0.395	-0.018	-0.190	0.108	-9.553
Minority	-0.038	0.242	0.125	0.087	3.447
Vacant	-18.268	6.909	0.736	7.194	3.552
Population	-0.033	0.098	0.016	0.040	0.407
Unemployment	-7.209	26.239	1.147	9.270	-0.646

These results do not provide any indication that predatory lending laws systematically reduce the flow of subprime credit. However, the results do show that predatory lending laws may be associated with lower rejection rates of subprime mortgage applications. It can be expensive just to apply for a mortgage: the non-refundable application fee usually runs from $200 to $300, not to mention other hidden or non-pecuniary costs. Thus, while reducing rejection rates may not have been the primary purpose of the laws, a reduction in rejections can represent substantial savings to consumers.

Understanding the Heterogeneity of Market Responses

The previous section followed prior literature and estimated the impact of a local lending law one law at a time. While the findings for the North Carolina law sample were largely replicated the results showed that other laws did not always have the same impact. In fact, some laws were associated with relative increases in the flow of credit. This section tests to see if the heterogeneity in market responses is related to the nature or strength of the local law.

Table 8 presents the correlation between the impact of a local law, measured as the percent change in the probability of the outcome, and the scaled law indexes described previously. Stronger laws are correlated with reductions in application, origination, and rejection probabilities. In addition, law coverage is more highly correlated with declines in rejection rates than the extent of restrictions. This provides some preliminary evidence that stronger laws may be associated with larger declines in the flow of credit, while simultaneously being associated with lower rejection rates.

Table 8: Correlation of Law Strength and Outcome

	Percent Change When Law Becomes In Effect		
Scaled Law Index	Application	Origination	Rejection
Full Index	-0.35	-0.30	-0.08
Coverage Index	-0.30	-0.26	-0.58
Restrictions Index	-0.30	-0.26	-0.08

This section provides a more complete analysis by pooling all the law samples together and including the scaled law indexes as explanatory variables.[12] To maintain the identification strategy, law sample (each law's treatment and control loans) dummies are included and the variables *Law* and *Postlaw* are interacted with each law sample, with the North Carolina law sample as the excluded group. The impact of the average law can then be interpreted directly from the *Ineffect* variable.

If the outcome (subprime application, subprime origination, or subprime rejection) and the treatment are jointly determined, we must also be concerned with factors that could impact the probability of a location choosing to enact a predatory lending law. The HUD-Treasury report indicated that predatory lending primarily is found in subprime lending and not prime lending. Therefore, we would expect states with more subprime lending to be more likely to elicit requests from victims of predation and consumer advocacy groups for legislative remedies. In addition, predatory lending has also been associated with urban and African-American populations. Therefore, again we should expect that locations with more urban populations and nonwhite populations would be more likely to seek legislative restrictions on subprime lending. Lastly, since the predatory lending laws are crafted by state legislatures,

[12] To enhance computational feasibility, we only include a 10 percent random sample of each location in the pool sample. We also estimate using the 25 and 50 percent random samples and find that results are robust across sample sizes.

either Republicans or Democrats may be more or less likely to respond to predatory lending concerns through legislation. Table 9 provides a description of the variables used to identify whether the state where the property is located will enact a local predatory lending law.

Table 9: Variable Definitions – Treatment Equation

Variable	Definition	Source
Law	Indicator variable = 1 if borrower is from a location with a law at some point; 0 otherwise	Working paper : Appendix A*
Mktshare	State's market share of subprime loans, lagged one year	Calculated from HMDA and HUD's subprime lender list
Urban	State's urban population percentage	Census 2000
Nonwhite	State's nonwhite population percentage	Census 2000
Politics	Ratio of democrats to republicans in state legislatures, 2000	2002 Statistical Abstract of the US

* Ho and Pennington-Cross [15] provide a detailed description of each law in Appendix A.

Tables 10a and 10b provide descriptive statistics of the variables by outcome. The application sample includes over 590,000 prime and subprime loan applications; the origination sample includes over 390,000 prime and subprime originations; and the rejection sample includes over 89,000 subprime applications, which are either accepted or rejected.[13]

As shown in Table 10, just over 20 percent of the applications were subprime, while only 9.7 percent of the originations were subprime. Consistent with the relative magnitude of applications and originations, the average rejection rate is very high for our sample of subprime loans: 42.9 percent. The states in the sample are best described as urban, majority white, and predominately with the Democratic Party in the state legislature. The borrowers and applicants typically have loans approximately twice the size of their income. In addition, as expected, the income of subprime applicants (rejection sample includes rejects and accepts

[13] The rejection sample excludes loans whose application was withdrawn by applicant or whose file was closed for incompleteness.

of subprime loans only) is substantially lower than for the overall sample (application and origination samples include both subprime and prime loans), and subprime applications come from census tracts with a higher concentration of minority households. The law sample dummy variables indicate that the Maryland sample is the largest proportion of the pool sample and the Texas sample is the smallest. In addition, the number of loans either before or after a law becomes effective varies by location and approximately 40 percent of the overall sample has a law in effect.

Table 10a: Descriptive Statistics – Dependent and Control Variables

	Application sample		**Origination sample**		**Rejection sample**	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Application	0.205	0.404	---	---	---	---
Origination	---	---	0.097	0.296	---	---
Rejection	---	---	---	---	0.429	0.495
Mktshare	10.0%	2.8%	9.7%	2.7%	10.5%	2.7%
Urban	81.7%	12.4%	82.0%	12.1%	82.2%	12.6%
Nonwhite	26.6%	10.8%	26.6%	10.7%	27.4%	11.1%
Politics	2.370	1.790	2.415	1.818	2.232	1.673
Income (thousands $)	80.8	109.5	87.4	108.5	64.0	65.4
Loan2inc	2.054	3.993	2.043	2.057	2.062	2.548
Relinc	1.106	0.321	1.134	0.326	1.019	0.287
Minority	24.5%	24.1%	23.5%	23.1%	30.3%	27.4%
Vacant	8.5%	7.0%	8.2%	7.1%	9.1%	6.2%
Population	1.9%	2.0%	1.9%	2.0%	2.0%	1.9%
Unemployment	4.7%	2.3%	4.6%	2.3%	5.0%	2.3%

Table 10b: Descriptive Statistics – Identification Variables

Variable	Application sample		Origination sample		Rejection sample	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Law	0.631	0.482	0.627	0.484	0.666	0.472
Postlaw	0.623	0.485	0.646	0.478	0.597	0.490
Ineffect	0.397	0.489	0.410	0.492	0.407	0.491
ca	0.215	0.411	0.208	0.406	0.277	0.447
ct	0.039	0.193	0.037	0.188	0.041	0.199
fl	0.040	0.196	0.039	0.192	0.036	0.186
ga	0.052	0.221	0.049	0.216	0.060	0.238
ma	0.186	0.389	0.199	0.399	0.143	0.350
md	0.289	0.453	0.318	0.466	0.214	0.410
nc	0.070	0.254	0.059	0.235	0.085	0.279
oh	0.060	0.238	0.054	0.226	0.071	0.258
pa	0.039	0.193	0.030	0.171	0.059	0.236
tx	0.011	0.105	0.008	0.090	0.014	0.116
lawca	0.197	0.398	0.190	0.392	0.261	0.439
lawct	0.010	0.100	0.009	0.097	0.010	0.099
lawfl	0.029	0.166	0.027	0.163	0.026	0.159
lawga	0.024	0.154	0.024	0.152	0.026	0.160
lawma	0.135	0.342	0.148	0.356	0.094	0.292
lawmd	0.144	0.351	0.152	0.359	0.122	0.327
lawnc	0.029	0.168	0.023	0.150	0.038	0.192
lawoh	0.036	0.186	0.031	0.174	0.047	0.212
lawpa	0.026	0.160	0.021	0.143	0.040	0.196
lawtx	0.002	0.040	0.001	0.035	0.001	0.038
postlawca	0.136	0.343	0.133	0.340	0.188	0.391
postlawct	0.025	0.157	0.025	0.157	0.025	0.155
postlawfl	0.024	0.153	0.024	0.153	0.021	0.143
postlawga	0.029	0.167	0.029	0.167	0.031	0.175
postlawma	0.128	0.334	0.143	0.350	0.085	0.278
postlawmd	0.185	0.389	0.207	0.405	0.133	0.339
postlawnc	0.036	0.186	0.032	0.177	0.041	0.198
postlawoh	0.032	0.176	0.029	0.169	0.037	0.189
postlawpa	0.021	0.143	0.017	0.129	0.029	0.169
postlawtx	0.007	0.081	0.005	0.073	0.007	0.086
Sample size	590,543		394,198		89,536	

Estimation Strategy

For each of the outcomes, the dependent variable is binary. We use the probit model specification, which limits the estimated probabilities between zero and one and assumes a standard normal probability distribution. However, we must also consider the possibility that the probability of the outcome occurring is jointly determined with the probability of the state enacting a law. As noted by Greene [11] one approach is to estimate a bivariate probit model and allow the error terms to correlate between the two equations. Specifically, we jointly model the probability of the loan being in a location that enacts a predatory lending law and the probability of subprime application/origination/rejection. The model specification is given by

$$\pi_i^{*1} = X_i^1\beta^1 + \varepsilon_i^1, \qquad \pi_i^1 = 1 \text{ if } \pi_i^{*1} > 0, 0 \text{ otherwise} \tag{7a}$$

$$\pi_i^{*2} = X_i^2\beta^2 + \pi_i^1\gamma + \varepsilon_i^2 \qquad \pi_i^2 = 1 \text{ if } \pi_i^{*2} > 0, 0 \text{ otherwise} \tag{7b}$$

and

$$E[\varepsilon_i^1] = E[\varepsilon_i^2] = 0,$$
$$Var[\varepsilon_i^1] = Var[\varepsilon_i^2] = 1,$$
$$Cov[\varepsilon_i^1, \varepsilon_i^2] = \rho. \tag{8}$$

Equation (7a) models the probability of loan *i* being in a state that enacts a predatory lending law (π_i^{*1}) as a function of state characteristics, X_i^1. Equation (7b) models the probability of the outcome (application, origination, or rejection) for loan *i* (π_i^{*2}) as a function of loan and borrower characteristics, X_i^2, and the endogenous law indicator variable, π_i^1. The error terms ε_i^1 and ε_i^2 are correlated with correlation coefficient ρ.

Maddala [18] and Greene [12] showed that in the bivariate probit model, if the two dependent variables are jointly determined, the inclusion of an endogenous variable on the right-hand side of the second equation can be ignored when constructing the log-likelihood. The log-likelihood function for our seemingly unrelated bivariate probit is given by

$$L = \sum_i \ln \Phi_2\left(w_i^1, w_i^2, \rho\right), \qquad (9)$$

where $\Phi_2(.)$ denotes the standard bivariate normal cumulative density function, $w_i^1 = \left(2\pi_i^1 - 1\right)X_i^1\beta^1$, and $w_i^2 = \left(2\pi_i^2 - 1\right)\left(X_i^2\beta^2 + \pi_i^1\gamma\right)$. The function is maximized by choosing the parameters $\beta^1, \beta^2, \gamma,$ and ρ in SAS version 9.1 for Windows.

Results

We estimate the model specified in equations (7), (8), and (9) using maximum likelihood. Table 11 provides the estimated coefficients, the standard error of the estimate, and the marginal impact of each variable at a specified interval and evaluated at the mean of all other variables.[14] Table 11 contains four panels (a-d). To aid comparison across outcomes, each panel provides the results for all three outcomes (application, origination, and rejection). Panel (a) provides the results for the treatment equation. Panel (b) provides the results for the control variables in the outcome equations. Panel s(c) and (d) provide the results for the identification variables used in the outcome equations.

In panel (a), consistent with the HUD-Treasury report, the results show that states are more likely to introduce and pass legislation in locations with more urban and nonwhite households. States with Republican dominated legislatures have tended to be more likely to be states with predatory lending laws. Locations with more subprime lending are also associated with a higher probability of enacting a law. In addition, the results are consistent across the three samples associated with each outcome.

[14] See Appendix for details on the calculation of marginal effects in the bivariate probit model.

Table 11: Bivariate Probit Results – Base Model
Panel (a): Treatment (Law) Equation

Variable	Coeff.	Std. Err.	Marg. Eff.	Unit
	Application Model			
Intercept	-12.300***	0.043	---	---
Mktshare	3.467***	0.101	0.0463	10%
Urban	14.744***	0.055	0.1450	10%
Nonwhite	2.670***	0.035	0.0359	10%
Politics	-0.197***	0.002	-0.0266	1
	Origination Model			
Intercept	-13.533***	0.059	---	---
Mktshare	3.701***	0.131	0.0241	10%
Urban	16.039***	0.075	0.0734	10%
Nonwhite	3.128***	0.046	0.0205	10%
Politics	-0.188***	0.003	-0.0125	1
	Rejection Model			
Intercept	-10.290***	0.098	---	---
Mktshare	1.073***	0.254	0.0176	10%
Urban	12.964***	0.126	0.1369	10%
Nonwhite	2.158***	0.083	0.0344	10%
Politics	-0.258***	0.005	-0.0449	1

Note: Marginal effects are estimated as the discrete change in probability as a variable deviates from its sample mean by an appropriate unit. The chosen units are reported in the last column.

The results in panel (b) largely meet expectations that location, borrower, and mortgage information indicting economic stress are positively associated with the probability of applying for a subprime loan. For instance, subprime applications are positively associated with lower borrower income, higher loan-to-income ratios, lower-income census tracts, higher concentrations of minority populations, lower population growth rates, and higher unemployment rates. However, subprime applications are negatively associated with higher vacancy rates. This may partly reflect the need of many subprime applications to have substantial equity in their home to compensate for weak credit history.

Table 11: Bivariate Probit Results – Base Model (continued)
Panel (b): Outcome Equation – Control Variables

Variable	Coeff.	Std. Err.	Marg. Eff.	Unit
	Application Model			
Intercept	-0.409***	0.021	---	---
Income	-0.165***	0.004	-0.0047	$10,000
Loan2inc	0.001**	0.000	0.0000	10%
Relinc	-0.420***	0.008	-0.0120	10%
Minority	0.431***	0.012	0.0127	10%
Vacant	-0.346***	0.101	-0.0099	10%
Population	-0.012***	0.002	-0.0034	1%
Unemployment	1.740***	0.243	0.0051	1%
Corr. Coeff. (ρ)	-0.329***	0.014	---	---
Log likelihood	-368,685			
	Origination Model			
Intercept	-0.895***	0.033	---	---
Income	-0.131***	0.007	-0.0022	$10,000
Loan2inc	-0.016***	0.002	-0.0003	10%
Relinc	-0.335***	0.013	-0.0056	10%
Minority	0.546***	0.019	0.0096	10%
Vacant	-0.707***	0.166	-0.0115	10%
Population	0.004*	0.002	0.0007	1%
Unemployment	1.450***	0.389	0.0025	1%
Corr. Coeff. (ρ)	-0.236***	0.021	---	---
Log likelihood	-183,048			
	Rejection Model			
Intercept	-0.011	0.048	---	---
Income	-0.048***	0.008	-0.0019	$10,000
Loan2inc	0.020***	0.003	0.0008	10%
Relinc	-0.256***	0.020	-0.0101	10%
Minority	0.007	0.026	0.0003	10%
Vacant	0.855***	0.246	0.0340	10%
Population	-0.017***	0.004	-0.0068	1%
Unemployment	1.189**	0.579	0.0047	1%
Corr. Coeff. (ρ)	-0.134***	0.030	---	---
Log likelihood	-68,018			

Note: Marginal effects are estimated as the discrete change in probability as a variable deviates from its sample mean by an appropriate unit. The chosen units are reported in the last column.

The results for originations are very similar to the application results. Again, in general, indicators of economic stress (borrower income, lower-income census tracts, minority status, and unemployment rates) are associated with higher probabilities of originating a subprime loan. However, higher vacancy rates, lower population growth rates, and higher loan-to-income ratios are all negatively associated with subprime origination probabilities. Again, the vacancy results may indicate the need for housing equity in the underwriting of subprime loans to compensate for other weaknesses in the loan application. In addition, consistent with the population growth results, Pennington-Cross [20] found that subprime loans were the largest part of the mortgage market in locations where economic conditions were stressful but improving.

The results for the rejection equation also show that in general more adverse economic conditions (lower borrower income, higher loan-to-income ratio, lower-income census tracts, higher property vacancy, declining population growth, and higher unemployment rates) are all associated a higher probability of rejection. In addition, the results cannot find a statistically significant relationship between minority presence and the probability of being rejected.

Panel (c) includes control variables for the time period before and after the law is in effect as well as indicators of each law sample (control and treatment loans or applications). The excluded law sample is North Carolina so that coefficients should be interpreted as relative to the North Carolina law sample. However, there are no priors on the sign, magnitude, or statistical significance of these variables. The coefficients on law sample dummy variables (for example, *ca*, *ct, fl, ga*, and others) are additive with the intercept, which represents the intercept for the North Carolina law sample. In addition, all the interactions of each state's law sample with the variables *Law* and *Postlaw* (for example, *lawca, postlawca, lawct*, *postlawct*, *lawfl*, *postlawfl*, and others) are additive relative to the variables *Law* and *Postlaw*, which represents the North Carolina law sample. While all the variables included in panel (b) do control for many factors, the variables in panel (c) control for all unobserved characteristics associated with the time period (pre-law versus post-law), law sample (law sample dummy variables), and the endogenously determined location (control locations versus treatment locations).

The main variable of interest is the *Ineffect* variable. This coefficient indicates whether the introduction of the law has had any impact on the application, origination, or rejection of subprime loans on average. The coefficient estimates are negative and significant at the 99 percent level in the application equation and rejection equation, and insignificantly different from zero in the origination equation.

To aid in economic interpretation, panel (d) provides estimates of the marginal impact of each of the identification variables. The marginal impacts can be interpreted as percentage point changes from the mean. Therefore, the impact of the variable *Law* is a 12.4 percentage point (coefficient = 0.124) increase in the probability of applying for a subprime loan relative to the average application rate of 20.5 percent. The average impact of a local predatory lending law, using the variable *Ineffect*, is a reduction of 4.9 percentage points in the probability of being rejected (mean = 42.2 percent), and a decrease of 1.7 percentage points in applying (mean = 20.3 percent). These results indicate that the average local predatory lending law is associated with only a small or statistically insignificant change in the probability of applying for or originating a subprime loan, while at the same time a substantial reduction in the probability of being rejected on a subprime loan. Therefore, the previously observed substantial reduction in the flow of credit found in North Carolina is not typical.

Table 11: Bivariate Probit Results – Base Model (continued)
Panel (c): Outcome Equation – Identification Variables

	Application		Origination		Rejection	
Variable	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Law	0.973***	0.058	0.941***	0.098	0.091	0.120
Postlaw	-0.051**	0.021	-0.267***	0.035	0.279***	0.048
Ineffect	-0.034***	0.011	0.000	0.017	-0.119***	0.026
ca	-0.686***	0.033	-0.665***	0.052	-0.065	0.074
ct	-0.073***	0.028	-0.133***	0.045	-0.079	0.060
fl	-0.089***	0.033	-0.204***	0.055	0.067	0.078
ga	0.155***	0.026	-0.049	0.042	0.309***	0.057
ma	0.069***	0.022	0.063*	0.035	-0.093*	0.049
md	-0.380***	0.019	-0.443***	0.031	-0.009	0.045
oh	-0.167***	0.024	-0.309***	0.040	0.234***	0.054
pa	0.038	0.028	0.141***	0.045	-0.093	0.057
tx	0.047	0.034	0.131**	0.060	0.104	0.073
lawca	-0.157***	0.056	-0.230**	0.095	0.089	0.111
lawct	-0.574***	0.050	-0.685***	0.084	0.254**	0.112
lawfl	-0.861***	0.065	-0.855***	0.110	0.181	0.140
lawga	-0.533***	0.050	-0.572***	0.084	0.135	0.113
lawma	-0.781***	0.049	-0.864***	0.084	-0.050	0.107
lawmd	-0.502***	0.051	-0.679***	0.087	0.249**	0.103
lawoh	-0.325***	0.049	-0.400***	0.083	0.012	0.109
lawpa	-0.343***	0.047	-0.465***	0.080	0.129	0.104
lawtx	-0.883***	0.080	-0.748***	0.134	0.135	0.181
postlawca	0.175***	0.025	0.459***	0.040	-0.579***	0.056
postlawct	-0.067**	0.031	0.244***	0.050	-0.564***	0.072
postlawfl	0.157***	0.032	0.246***	0.054	-0.107	0.074
postlawga	-0.020	0.031	0.261***	0.052	-0.487***	0.069
postlawma	-0.157***	0.026	0.060	0.042	-0.393***	0.059
postlawmd	0.045*	0.024	0.317***	0.039	-0.461***	0.054
postlawoh	0.078***	0.028	0.306***	0.047	-0.252***	0.063
postlawpa	0.051*	0.029	-0.053	0.049	0.001	0.064
postlawtx	-0.015	0.047	-0.024	0.082	-0.311***	0.102

Table 11: Bivariate Probit Results – Base Model (end)
Panel (d): Outcome Equation – Marginal Effect for Identification Variables

Variable	Application	Origination	Rejection
Law	0.124	0.084	-0.052
Postlaw	-0.015	-0.048	0.110
Ineffect	-0.017	-0.032	-0.049
ca	-0.166	-0.088	-0.026
ct	-0.021	-0.021	-0.031
fl	-0.025	-0.031	0.026
ga	0.047	-0.008	0.123
ma	0.020	0.011	-0.037
md	-0.103	-0.068	-0.003
oh	-0.045	-0.044	0.093
pa	0.011	0.026	-0.036
tx	0.014	0.024	0.041
lawca	-0.104	-0.089	0.036
lawct	-0.148	-0.094	0.101
lawfl	-0.191	-0.103	0.072
lawga	-0.145	-0.087	0.053
lawma	-0.207	-0.128	-0.018
lawmd	-0.152	-0.122	0.099
lawoh	-0.102	-0.077	0.004
lawpa	-0.099	-0.072	0.051
lawtx	-0.201	-0.103	0.054
postlawca	0.038	0.073	-0.221
postlawct	-0.017	0.044	-0.209
postlawfl	0.046	0.044	-0.042
postlawga	-0.008	0.046	-0.192
postlawma	-0.046	0.006	-0.152
postlawmd	0.015	0.059	-0.179
postlawoh	0.022	0.054	-0.099
postlawpa	0.015	-0.018	-0.002
postlawtx	-0.005	-0.012	-0.122

Note: Marginal effects are estimated as the discrete change in probability as the variable is increased from 0 to1, while holding all other variables at their mean.

Results – Strength of the Law

While the average law may have only modest impacts on the flow of credit, it may be that relatively more stringent laws may have a larger impact. In general it is expected that stronger laws should be associated with larger reductions in applications and originations due to tighter lending standards. In addition, stronger laws may reduce rejections by deterring marginal applications or through increased screening by lenders to ensure law compliance.

To gauge the potential relevance of a law's strength, we estimated two additional models. Model II replaces the *Ineffect* variable with the scaled law index as an explanatory variable in the outcome equation, and Model III replaces the full law index with the disaggregated law index along the dimensions of coverage and restrictions. The results (coefficient, standard error, and marginal effects) are reported in Table 12. [15]

Table 12: Bivariate Probit Results – Augmented Models with Scaled Local Law Index

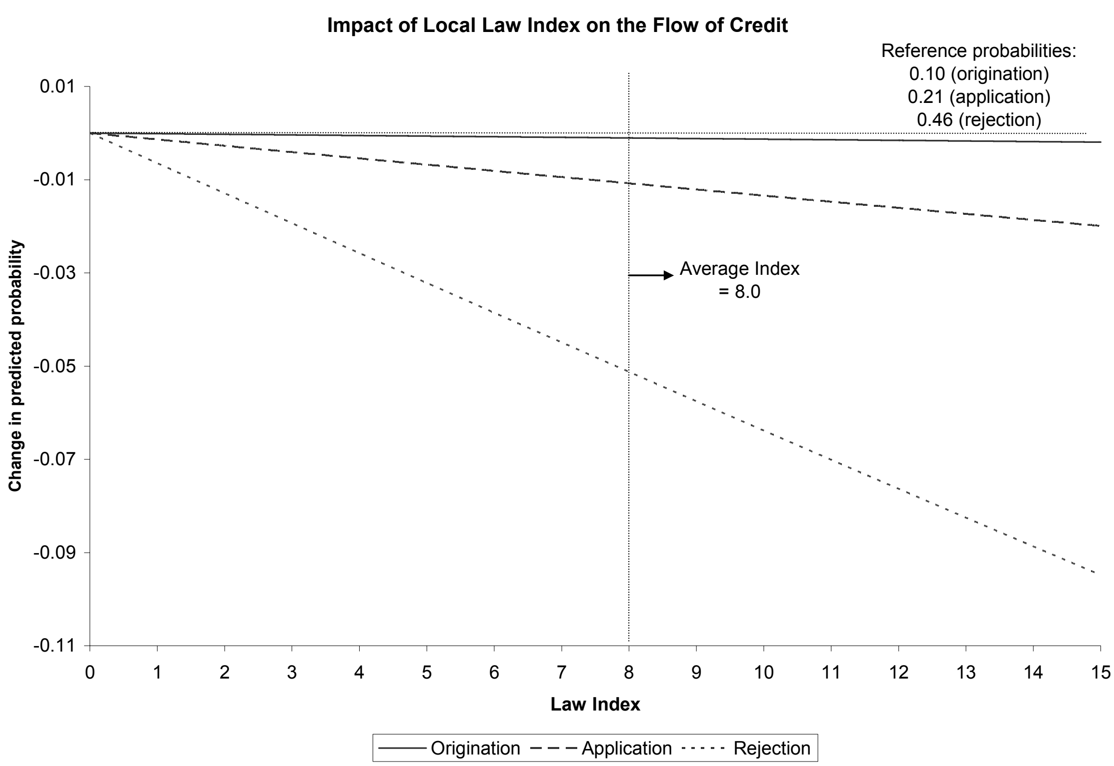
	Model II			**Model III**		
Variable	Coeff.	Std. Err.	Marg. Eff.	Coeff.	Std. Err.	Marg. Eff.
				Application Results		
Law index	-0.005***	0.001	-0.0067	---	---	---
Coverage index	---	---	---	0.054***	0.005	0.0584
Restriction index	---	---	---	-0.059***	0.005	-0.0454
				Origination Results		
Law index	-0.001	0.002	-0.0006	---	---	---
Coverage index	---	---	---	0.050***	0.009	0.0337
Restriction index	---	---	---	-0.049***	0.008	-0.0218
				Rejection Results		
Law index	-0.016***	0.003	-0.0318	---	---	---
Coverage index	---	---	---	-0.016	0.013	-0.0215
Restriction index	---	---	---	-0.017	0.011	-0.0191

Note: Marginal effects for the indexes are estimated as change in probability as an index deviates from its mean by one standard deviation. Means and standard deviations are as reported in Table 3.

[15] To conserve space all the control variables are not reported, but are available on request. In addition, specification tests were conductied including both the variable *Ineffect* and the laws indexes. In all cases the *Ineffect* variable was insignificant and is not reported.

In Model II, the coefficient estimates indicate that stronger laws are associated with lower probabilities of applying for a subprime loan and being rejected on a subprime application. However, law strength had no impact on the probability of originating a subprime loan. Again, the magnitude of the impact on the probability of applying is very small. For example the marginal impact, measured by a one-standard-deviation increase in the index from the mean, is only -0.67 percentage points in the application equation. In contrast, the marginal impact is much larger for rejection (-3.18 percentage points). This is highlighted in Figure 4, which plots the change in the probability of the outcome (apply, originate, and reject) relative to the strength of the law.

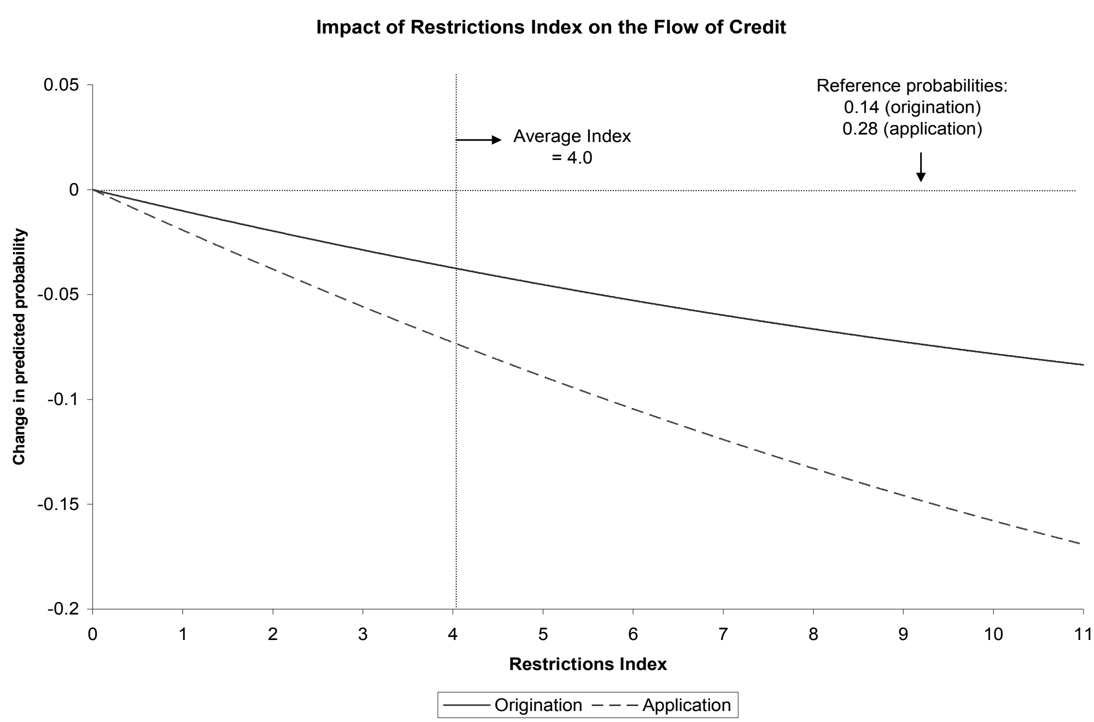
Figure 4



Note: All other variables are set to their mean and the law index is increased from 0 to the maximum observed value using Model II. Probabilities are indicated by fractions so that 0.05 is a 5 percent probability.

The strength of the law can also be measured along the dimensions of coverage and restrictions. Assuming the market does not have a significant lemons problem, the impact of restrictions should be unambiguous. If appropriate substitutes cannot be found, more restrictions on allowable lending should lead to less lending because lenders are required to tighten lending standards, which reduces the number of eligible applicants. Therefore, originations should be lower for stronger laws and likely applications will be deterred due to the reduced availability of loan types. In Model III, as illustrated in Figure 5, the coefficients results indicate that laws with more restrictions are associated with reduced probabilities of applying and originating subprime loans. For example, a one-standard-deviation increase in the scaled restrictions index reduces the probability of applying by 4.5 percentage points and the probability of originating by 2.2 percentage points.

Figure 5

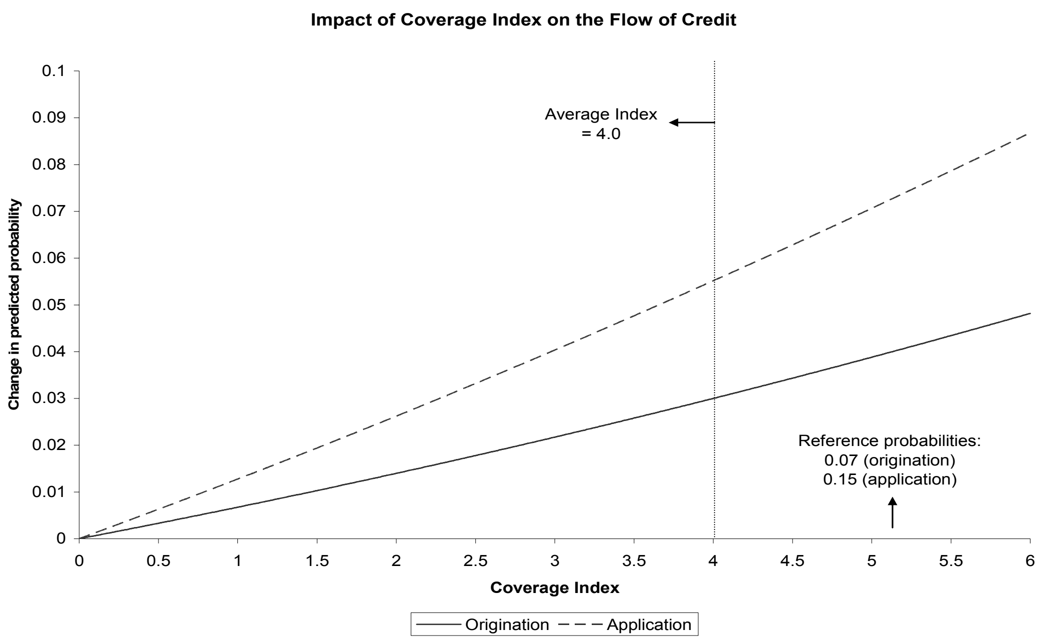


Note: All other variables are set to their mean and the restrictions index is increased from 0 to the maximum observed value using Model III. Probabilities are indicated by fractions so that 0.05 is a 5 percent probability.

The impact of increased coverage of a law, after controlling for restrictions, is largely an empirical question. If there is no lemons problem in the subprime market, more coverage should unambiguously reduce applications and originations. However, if potential applicants are deterred from applying because of fear of being taken advantage of by dishonest lenders or do not apply because of the cost of sorting the honest from the dishonest, then the introduction of a law that covers more application may help to increase applications by reducing the fear of predation and the cost of detection. Model III in Table 12 reports that laws with broader coverage tend to be associated with increased originations and applications. In fact, the coefficient estimates are very similar in magnitude, although they have the opposite signs, to the impact of stronger restrictions. The marginal impact of a one-standard-deviation increase in coverage increases the probability of applying for a subprime loan by 5.8 percentage points and the probability of originating a subprime loan by 3.4 percentage points. This result provides some support for the theory that negative press on predatory lending in the subprime market has suppressed demand for the product due to fear of being taken advantage of. As illustrated in Figure 6, when a law is passed that covers your loan application, even if it restricts lending very little, the household is more willing to make an application. In other words, consistent with a market with a lemons problem, as illustrated in Figure 3, the demand for subprime credit can actually increase when a predatory lending law is enacted. The largest increase is possible for laws with few restrictions but broad market coverage.

However, there is no statistically significant evidence that the make-up of the law has any impact on the probability of being rejected. Instead, it is the overall strength that is associated with lower rejection probabilities.

Figure 6



Note: All other variables are set to their mean and the coverage index is increased from 0 to the maximum observed value using Model III. Probabilities are indicated by fractions so that 0.05 is a 5 percent probability.

Conclusion

Starting with North Carolina in 1999, states and other localities across the U.S. have introduced legislation intended to curb predatory and abusive lending in the subprime mortgage market. These laws usually extend the reach of the Home Ownership and Equity Protection Act (HOEPA) by including home purchase and open-end mortgage credit, lowering annual percentage rate (APR) and fees and points triggers and prohibiting and/or restricting the use of balloon payments and prepayment penalties on covered loans.

While prior literature found evidence that the North Carolina law did reduce the flow of credit, the results in this paper indicate that the typical law has little impact on the flow of subprime credit as measured by loan origination and application. However, rejections do decline by over 10 percent for the typical law. The reduction in rejections may reflect less aggressive marketing, additional pre-screening by lenders, increased self-selection by borrowers, or other factors. While a reduction in rejection rates may not have been the intent of the predatory lending law, it does indicate that borrowers are benefiting by saving non-refundable application costs when rejected for a subprime loan.

However, not all local predatory lending laws are created equal. The results indicate that the heterogeneity in law strength can help further explain the mechanisms that make one law decrease the flow of credit and another actually increase the flow of credit. The strength of the law is measured along two dimensions – coverage and restrictions. Some laws provide broad coverage of the subprime market (Colorado) and others very little coverage (Texas). Some have substantial restrictions (Georgia) on allowable lending, while others have very few restrictions (Maine). The results indicate that coverage and restrictions tend to have opposite impacts. In general, laws with more extensive restrictions are associated with larger decreases in the flow of credit. In fact, laws with the strongest restrictions can decrease applications by over 50 percent. In contrast, laws with broad coverage can increase applications by even more than 50 percent. Therefore, although on the surface local predatory lending laws seem to have little impact, the design of the law can stimulate the subprime market, depress the subprime market, or leave volumes relatively steady but with lower rejection rates. As a result, the design of the law can have economically important impacts on the flow and make-up of the mortgage market.

In future research it would be helpful to determine how product mix adjusts to the introduction of these laws. For example, the laws make no distinction between initial interest rates on fixed rate and adjustable interest rate loans. But adjustable rate loans tend to have lower initial rates, resulting in substitution rather than fewer loans, and can include teaser terms that temporarily reduce the rate below the benchmark. Therefore, adjustable rate loans may be one way to avoid the trigger APR levels in predatory lending laws and shift a borrower out from under the protective coverage of the regulations. There also may be a regulatory burden associated with these laws that needs to be passed on to consumers through higher interest rates and upfront fees. Lastly, these laws may reduce the availability of the secondary market leading to liquidity issues in the subprime market, which may also increase the cost of credit.

References

1. G. Akerlof, The Market for “Lemons”: Quality Uncertainty and the Market Mechanism, *Quarterly Journal of Economics,* **84**(3), 488-500 (1970).

2. B. W. Ambrose, A. Pennington-Cross, and A. M. Yezer, Credit Rationing in the U.S. Mortgage Market: Evidence from Variation in FHA Market Shares, *Journal of Urban Economics*, **51**, 272-294 (2002).

3. P. Calem, K. Gillen., and S. Wachter, The Neighborhood Distribution of Subprime Mortgage Lending, *Journal of Real Estate Finance and Economics,* **29**(4), 393-410 (2004).

4. P. Chinloy and N. MacDonald, Subprime Lenders and Mortgage Market Completion, *Journal of Real Estate Finance and Economics,* **30**(2), 153-165 (2005).

5. S. Chomsisengphet and A. Pennington-Cross, Borrower Cost and Credit Rationing in the Subprime Mortgage Market, Presented at the American Real Estate and Urban Economics Association Mid-Year meetings in Washington D.C. (2004).

6. G. Elliehausen and M. E. Staten, Regulation of Subprime Mortgage Products: An Analysis of North Carolina's Predatory Lending Law, *Journal of Real Estate Finance and Economics,* **29**(4), 411-434 (2004).

7. K. Ernst, J. Farris, and E. Stein, North Carolina’s Subprime Home Loan Market after Predatory Lending Reform, Durham, NC: Center for Responsible Lending, University of North Carolina at Chapel Hill, (2002).

8. Federal Reserve, Truth in Lending, Final Rule, 12 CFP part 226, Regulation Z; Docket No. R-1090, Board of Governors of the Federal Reserve System (2002).

9. M. Ferguson and S. Peters, What Constitutes Evidence of Discrimination in Lending? *Journal of Finance*, **50**(2), 739-748 (1995).

10. W. H. Greene, Marginal Effects in the Bivariate Probit Model, Leonard N. Stern School of Business working paper (1996).

11. W. H. Greene, Gender Economics Courses in Liberal Arts Colleges: Comment, Leonard N. Stern School of Business working paper (1998).

12. W. H. Greene, Econometric Analysis, Fifth Edition, Prentice-Hall, Inc., Upper Saddle River, New Jersey (2003).

13. K. D. Harvey and P. J. Nigro, How Do Predatory Lending Laws Influence Mortgage lending in Urban Areas? A Tale of Two Cities, *Journal of Real Estate Research* **25**(4), 479-508 (2003).

14. K. D. Harvey and P. J. Nigro, Do Predatory Lending Laws Influence Mortgage Lending? An Analysis of the North Carolina Predatory Lending Law, *Journal of Real Estate Finance and Economics,* **29**(4), 435-456 (2004).

15. G. Ho and A. Pennington-Cross, The Impact of Local Predatory Lending Laws, Federal Reserve Bank of St. Louis working paper No. 2005-049B (2005). Available at http://research.stlouisfed.org/wp/2005/2005-049.pdf

16. HUD-Treasury, Curbing Predatory Home Mortgage Lending, United States Department of Housing and Urban Development and the United States Treasury Department (2000). Available at huduser.org/publications/hsgfin/curbing.html.

17. IMF, Mortgage Market Statistics Annual, Inside Mortgage Finance Publications, Inc., Bethesda Maryland (2004). Available at www.imfpubs.com.

18. G. S. Maddala, Limited-Dependent and Qualitative Variables in Econometrics, Cambridge University Press (1983).

19. E. C. Norton, H. Wang, and C. Ai, Computing Interaction Effects and Standard Errors in Logit and Probit Models, *The Stata Journal,* **4**(2), 103-116 (2004).

20. A. Pennington-Cross, Subprime Lending in the Primary and Secondary Markets, *Journal of Housing Research,* **13**(1), 31-50 (2002).

21. A. Pennington-Cross, Credit History and the Performance of Prime and Nonprime Mortgages, *Journal of Real Estate Finance and Economics,* **27**(3), 279-301 (2003).

22. R. Quercia, M. A. Stegman, and W. R. Davis, The Impact of North Carolina's Anti-predatory Lending Law: A Descriptive Assessment, Durham, NC: Center for Community Capitalism, University of North Carolina at Chapel Hill (2003).

23. R. Quercia, M. A. Stegman, and W. R. Davis, Assessing the Impact of North Carolina's Predatory Lending Law, *Housing Policy Debate,* **15**(3), 573-601 (2004).

24. R. Scheessele, 1998 HMDA Highlights, Housing Finance Working Paper Series, U.S. Department of Housing and Urban Development, HF-009 (1998).

Appendix: Marginal Effects in the Bivariate Probit Model

As Greene [10] documented, the calculation of marginal effects in the general bivariate probit model is quite involved. It is further complicated by the presence of an endogenous variable on the right hand side of the second equation as well as interaction terms. We consider marginal effects for various types of variable in the model.

First, consider the treatment equation (7a). In our model all the variables in X^1 are continuous. Marginal effects are estimated by the discrete change in expected probability as a variable deviates from its mean by an appropriate unit. The bivariate probability is:

$$P(\pi^1 = 1, \pi^2 = 1 \mid X^1, X^2) = \Phi_2(X^1\beta^1, X^2\beta^2 + \gamma, \rho) \tag{10}$$

Second, consider the outcome equation (7b). The conditional mean function is:

$$\begin{aligned} &E[\pi^2 \mid X^1, X^2] = P(\pi^1 = 1)E[\pi^2 \mid \pi^1 = 1, X^1, X^2] + P(\pi^1 = 0)E[\pi^2 \mid \pi^1 = 0, X^1, X^2] \\ &= \Phi_2(X^1\beta^1, X^2\beta^2 + \gamma, \rho) + \Phi_2(-X^1\beta^1, X^2\beta^2, -\rho) \end{aligned} \tag{11}$$

For a binary variable q in X^2, the marginal effect of q on π^2 is the discrete change in predicted values of π^2 as q switches from 0 to 1:

$$Meff = E[\pi^2 \mid X^1, X^2, q = 1] - E[\pi^2 \mid X^1, X^2, q = 0] \tag{12}$$

For a continuous variable z in X^2, again, marginal effects are calculated as discrete change in probability, using the formula for expected probability specified in (10).

For the endogenous binary variable π^1, the marginal effect on π^2 is the difference between two conditional probabilities.

$$
\begin{aligned}
(13) \qquad & Meff = E[\pi^2 \mid X^1, X^2, \pi^1 = 1] - E[\pi^2 \mid X^1, X^2, \pi^1 = 0] \\
& = \frac{P(\pi^1 = 1, \pi^2 = 1 \mid X^1, X^2)}{P(\pi^1 = 1 \mid X^1)} - \frac{P(\pi^1 = 0, \pi^2 = 1 \mid X^1, X^2)}{P(\pi^1 = 0 \mid X^1)} \\
& = \frac{\Phi_2(X^1\beta^1, X^2\beta^2 + \gamma, \rho)}{\Phi(X^1\beta^1)} - \frac{\Phi_2(-X^1\beta^1, X^2\beta^2, -\rho)}{\Phi(-X^1\beta^1)}
\end{aligned}
$$

Now we consider interaction terms of the form $\pi^1 * q$, where q is a binary variable in π^2. According to Norton, Wang, and Ai [19], the full interaction effect is the double difference.

$$
\begin{aligned}
(14) \qquad & Meff = [E[\pi^2 \mid \pi \; = 1, X^1, X^2, q = 1, \pi^1 * q = 1] - E[\pi^2 \mid \pi^1 = 1, X^1, X^2, q = 0, \pi^1 * q = 0]] \\
& -[E[\pi^2 \mid \pi^1 = 0, X^1, X^2, q = 1, \pi^1 * q = 0] - E[\pi^2 \mid \pi^1 = 0, X^1, X^2, q = 0, \pi^1 * q = 0]]
\end{aligned}
$$

Intuitively, we first set π^1 to zero and calculate the change in probability as q changes its value from zero to one. We then do the same with π^1 set to one. The full interaction effect is the difference between these two quantities. The conditional probabilities are as in (13).

Lastly, for the interaction terms of the form $q^1 * q^2$, where q^1 and q^2 are both binary variables in X^2, the full interaction effect is the double difference:

$$
\begin{aligned}
(15) \qquad & Meff = [E[\pi^2 \mid X^1, X^2, q^1 = 1, q^2 = 1, q^1 * q^2 = 1] - E[\pi^2 \mid X^1, X^2, q^1 = 1, q^2 = 0, q^1 * q^2 = 0]] \\
& -[E[\pi^2 \mid X^1, X^2, q^1 = 0, q^2 = 1, q^1 * q^2 = 0] - E[\pi^2 \mid X^1, X^2, q^1 = 0, q^2 = 0, q^1 * q^2 = 0]]
\end{aligned}
$$

$E[\pi^2 | X^1, X^2]$ is the conditional mean function specified in (7).