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

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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.

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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 are less financially secure and tends to occur in low-income areas and areas with a concentration of minority population. The subprime market identifies a large menu of products depending on mortgage and borrower information. Each classification charges a different risk-based price (interest rate and fees) which typically varies from one to four percentage points above the prime mortgage interest rate. This combination of higher borrower costs and the associated higher rates of delinquency and foreclosure have led to public policy concerns over fairness and accessibility of credit.

At the federal level, through regulations generated under the Home Ownership and Equity Protection Act (HOEPA), Congress has determined that it is socially preferable to 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[1] (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 in similar labor and housing markets.

[1] 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.

Individual loan level data is 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 three 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 (accept, reject, or apply) of subprime credit.

Background on the Growth of Subprime

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 evaluate 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, 2005) because it provides the opportunity of home ownership to a larger portion of the population.

However, despite only anecdotal evidence predatory lending has been predominantly associated with subprime lending and not prime lending[2]. Therefore, the welfare benefit

[2] See HUD-Treasury report and Federal Reserve HOEPA Final Rule (Federal Reserve, 2002)

associated with increased access to credit is believed to have been reduced by some unscrupulous lending in the subprime mortgage market.

Table 1 shows the substantial growth of the subprime market that has set the stage for predatory lending laws. Inside Mortgage Finance (Inside Mortgage Finance, 2004) reports in the Mortgage Market Statistics Annual that subprime lending has grown from $65 billion to $332 billion from 1995 through 2003.[3] In addition, during this period of rapid growth lenders in the subprime market have been consolidating. For example, from 1995 through 2003 the top 25 originators have grown from a market share of 39 percent to 93 percent of the subprime market. This rapid growth is at least part of the impetus behind the broadening of the HOEPA standards in 2002 and the introduction of local predatory lending laws.

Another facet of the subprime market, beyond its recent growth, is that subprime mortgages cost more than prime mortgages. Table 2 shows the average interest rate charged at origination for fixed-rate loans in the prime and subprime markets. The interest rate shown does not include any estimated fees and points paid or other upfront costs wrapped into the mortgage. However, the price differential is substantial. For example, the spread between prime and subprime was on average as high as 2.98 percentage points in 2000.

To justify such high interest rates for subprime borrowers, lenders must experience much larger rates of termination -- particularly foreclosures -- than in the prime market. Figure 1 provides evidence using data from the Mortgage Bankers Association of America (MBAA) that subprime loans do in fact experience substantially higher rates of foreclosures than both prime mortgages and loans insured by the Federal Housing Authority (FHA). The figure also provides at least indirect evidence that subprime loans did not perform very well during the recession beginning in March 2001. In contrast, FHA loans were only moderately affected and prime loans seemed almost completely unaffected by the recession. For example, at their peak less than one percent of prime loans were in foreclosure, compared to more than nine percent for subprime loans.

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

Table 1: Subprime Origination Growth

Year	Total B&C Originations (Billions)	Top 25 B&C Originations (Billions)
1995	$65.0	$25.5
1996	$96.8	$45.3
1997	$124.5	$75.1
1998	$150.0	$94.3
1999	$160.0	$105.6
2000	$138.0	$102.2
2001	$173.3	$126.8
2002	$213.0	$187.6
2003	$332.0	$310.1

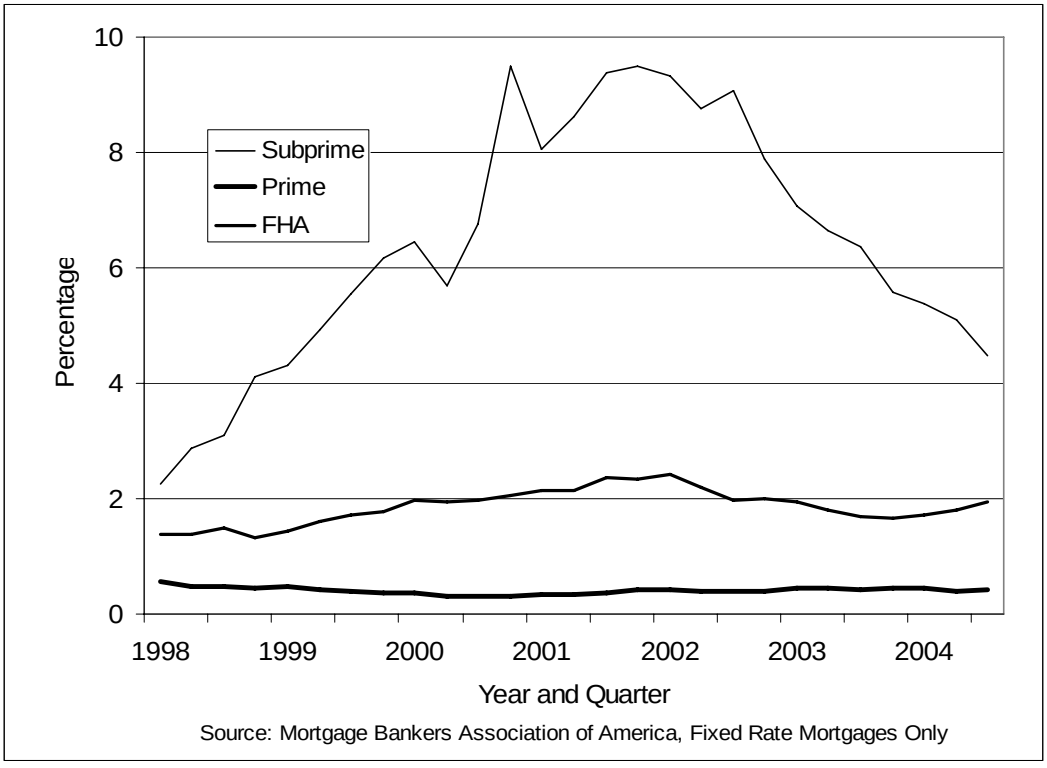
Source: Inside Mortgage Finance 2004 Annual Data Book. B&C is defined as including loans with less than A quality non-agency paper secured by real estate. Individual firm data are from Inside B&C Lending, which is another publication of Inside Mortgage Finance, and are generally based on security issuance or previously reported data.

Table 2: The Cost of Credit – Fixed Rate Origination Interest rate

Year	Subprime	Prime
1995	9.77	7.65
1996	9.78	7.64
1997	9.73	7.38
1998	9.26	6.83
1999	10.05	7.31
2000	10.92	7.95
2001	9.50	6.84
2002	8.38	6.35
2003	7.25	5.69
2004	7.13	5.79

Source: Freddie Mac's Primary Mortgage Market Survey for Prime loans and author's calculations using LoanPerformance ABS data set for Subprime loans (fixed rate loans only).

Figure 1: Foreclosures In-Progress Rate



Understanding Predatory Lending

In any document discussing predatory lending one of the first statements is usually similar to that found in the HUD-Treasury report (2000, p.17): "Defining the practices that make a loan predatory, however, is problematic." This difficulty arises because predatory lending depends on the inability of the borrower to understand the loan terms and the obligations associated with them. For example, some borrowers may be willing to accept a prepayment penalty in exchange for lower interest rates or fees because they do not expect to move in the near future. Or, the borrower may plan to diversify her portfolio away from a home and therefore would like an interest-only loan with a balloon payment in ten years. But interviews held by HUD, Treasury, and the Federal Reserve Board indicate that some, perhaps many, borrowers using high-cost loans may not have understood that the loan had a prepayment penalty or did not amortize through time, leading to a balloon payment.

HUD-Treasury Report

HUD and Treasury published an influential report in 2000 entitled "Curbing Predatory Home Mortgage Lending". The joint report provides policy suggestions for Congress, the Board of Governors of the Federal Reserve System, and the Federal Housing Authority on how to curb predatory lending.

HUD and Treasury created a task force to solicit information from industry and community representatives in five locations (Atlanta, Los Angeles, New York, Baltimore, and Chicago). The task force itself included representatives from consumer groups, industry trade associations representing lenders, brokers, and appraisers, local officials, and academics. The outreach effort provided substantial evidence through individual testimony that predatory lending does exist in the mortgage market and tends to be concentrated in the subprime market segment. The Board of Governors of the Federal Reserve System (Board) also found anecdotal evidence of predatory lending when holding a series of open meetings to hear individual testimony. In fact, the Board of Governors found that the testimony was widespread enough to indicate the need for increasing the coverage of HOEPA. Many of the

changes made to HOEPA and the concepts discussed in the Final Rule[4] were articulated in the HUD-Treasury report.

The HUD-Treasury report defines predatory lending as that involving deception or fraud and aggressive sales tactics, which takes advantage of the borrower's lack of understanding of basic rights and the terms of the mortgage. The report also concluded that predatory lending tends to occur more frequently in the refinancing of existing mortgages than in home purchase loans and more frequently in locations with low income and minority households.

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.

National 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 because they are more likely to have predatory features and require additional disclosures. 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.

There are two versions of 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.

[4] Federal Reserve System, 12 CFR Part 226, Regulation Z; Docket No. R-1090, Truth in Lending.

Original Triggers, Disclosures, and Restrictions

In the 1994 version of Regulation Z, 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 ten percentage points or more or (ii) if finance charges, including points and fees, were greater than eight percent of the loan amount or 400 dollars, whichever was smaller. The dollar amount was indexed to the consumer price index and rose to 480 dollars by 2002.

A creditor offering a HOEPA-covered loan was required to provide the consumer a shortened disclosure statement at least three days before the closing date. The creditor was also required to inform the consumer that they were not obligated to complete the transaction and that they could lose the home if they failed to make the mortgage payments.

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, 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.

2002 Changes in Triggers, Disclosures, and Restrictions

The 2002 amendments, which are still in effect today, adjusted the triggers, restricted some additional lending practices, adjusted the ability to pay requirements, and increased disclosure requirements. The APR trigger for first-lien loans was reduced to eight percentage points, while the trigger for second lien loans (subordinate loans) was left at ten percentage points. The fee trigger was expanded to include dollars paid at closing for optional insurance programs, such as credit life, accident, health, loss of income, and other debt protection programs. Regulations prohibited loans with call provisions and loans where the creditor had not verified or documented the consumer's ability to pay the mortgage. Therefore, no-documentation loans that met these triggers were expressly prohibited. However, HOEPA still covers only refinance and second mortgages, not for-purchase mortgages, lines of credit, or other open-end credit.

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 (2005) provide a detailed description of each law in Appendix A.[5]

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 eight percent of total loan amount to five percent for loans under $20,000. For loans $20,000 or larger, the same eight 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.

[5] 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 the all 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).

While most states followed the North Carolina example by expanding the coverage and restrictions associated with HOEPA, there is substantial variation in the laws. For example, Georgia passed a law that became effective in October 2002 (amended in March 2003) that also includes open-end credit but sets slightly different APR trigger levels to define high-cost loans and covered loans. The points and fees triggers then differ depending on whether the loan is categorized as high-cost or simply covered. Prepayment penalties are also prohibited during the first 12 months of the loan if they exceed two percent of the loan value or during the second 12 months if they exceed one percent. Therefore, Georgia prepayment safeguards are weaker than North Carolina's.

In an attempt to quantify the differences in the local laws an index is created. 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 beyond those required by HOEPA. Table 3 summarizes the construction of the law index. The full index is the sum of all the assigned points as defined in Table 3, while the coverage and restrictions indexes are the sum of points assigned in each subcategory.

The coverage category includes measures of loan purpose, APR 1st lien, APR higher liens, and points and fees. In general, if the law does not increase the coverage it is assigned zero points. Higher points are assigned if the coverage is broader. The highest point total for extending the loan purpose coverage is when the law covers all loans. The points assigned for extending the APR triggers is defined as the difference between the HOEPA trigger and the law's trigger. In addition, laws with no APR triggers are assigned the maximum observed difference plus one. The point and fees trigger points also follow a similar approach. Laws that extend HOEPA in any way are assigned one point, other laws are assigned the difference between the HOEPA percent points and fees trigger and the minimum trigger used in the law minus one. Laws with no points and fees triggers are assigned four points.

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 restriction or requirement 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.[6] The last two restrictions measure whether the law requires counseling before the loan is originated or restricts fully or partially mandatory arbitration clauses.

Table 4 reports the calculated full or law index, the coverage index, and the restrictions index for each law included in the appendix. 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 noisy. Therefore, there are laws that increase coverage without increasing restrictions (Nevada) and other states that extend restrictions more than coverage (Florida and Georgia, for example).

However, for empirical estimation scaled indexes are created. 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. For example, the 1st lien trigger goes from 0 to 3 and the higher lien trigger goes from 0 to 4. As a result the mean 1st lien subcomponent is 0.36 and the mean higher liens subcomponent is 0.71. As a result, the law index implicitly places greater importance on higher lien coverage than first liens. To rectify this implied weighted 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 mean equal 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 with standard deviation of 4.98. Zero also retains the appealing intuition as reflecting no increase in law

[6] The law in Cleveland was determined to be restrictive and was assigned four points despite not neatly falling into any of the categories.

strength beyond HOEPA. The law index varies from 17.16 to 1.47. The scaled and original law index is highly correlated (0.87).

In summary, the state and local laws tend to expand the coverage of HOEPA by either reducing the triggers and/or including home purchase and open-end credit. Prepayment penalties and/or balloon payments can also be limited in size or prohibited early in the life of a loan. The packing of credit life or other insurance premiums into the mortgage is also typically restricted or prohibited.

Table 3: 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	HOEPA equivalent =0, (HOEPA Trigger) –Trigger, and no trigger=max+1=3
APR Trigger Higher Liens	HOEPA equivalent =0, (HOEPA Trigger) –Trigger, and no trigger=max+1=4
Points and Fees Trigger	HOEPA equivalent =0, any extension=1, HOEPA%-min%-1, 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

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

Table 4: 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 5: 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

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 (2002) and Quercia, Stegman, and Davis (2003 and 2004) use tables of mortgage conditions before and after the North Carolina law becomes 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 (2002) 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 (2003) find no volume impact on purchases or for 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 (2004) 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 (2005) 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 better market coverage.

Harvey and Nigro (2003 and 2004) and Elliehausen and Staten (2004) go beyond univariate tables and estimate multivariate equations to identify the impact of the laws in North

Carolina, Chicago, and Philadelphia (since publication this law is no longer effective). On both Harvey and Nigro papers a proprietary version of HMDA along with the HUD subprime lender list is used as the data source 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 United States.

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. 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 decline in credit.

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.[7] Any loan application or origination associated with a lender on the list is identified as a subprime loan. All other

[7] 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 lender 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.

loans are treated as not-subprime or 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.[8] Therefore, only counties that border other states without a local predatory lending law are used for the treatment group. The control group only includes counties in neighboring states that border the treatment state and do not have a predatory lending law in effect during the observed time period (the year before and after the introduction of the law). This contrasts with other studies (Harvey and Nigro 2004; Elliehausen and Staten 2004) 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 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 6 describes the variables and data sources. Similar to Harvey and Nigro (2003 and 2004) 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.

[8] 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.

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 derived 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.

Both Harvey and Nigro (2003 and 2004) and Elliehausen and Staten (2004) 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 2004 and Pennnington-Cross 2002). Economic conditions are proxied by the county level 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, 2003), is not reported in the HMDA data and therefore cannot be included in this analysis.

Table 6: 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 (2205) provide a detailed description of each law in Appendix A (http://research.stlouisfed.org/wp/2005/2005-049.pdf). The detailed descriptions of the laws are too long to include in this paper and have been summarized by the law index discussed above.

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:

(1) $\Pr(Y = 1 \mid x) = \Phi(x'\beta)$

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:

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

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.[9] To provide context for the marginal effects, table 7 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 application. In fact, in some of the law samples, over 50 percent of subprime applications were rejected.

Table 8 reports the marginal impact of a local predatory lending law becoming effective for each state. Consistent with prior literature, the 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

[9] Detailed results are available upon request.

is replicated in only one-half of the laws examined. In the 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 9 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 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 borrower income, originations and applications are more likely in locations with relatively lower incomes and more likely to be rejected when applications come from locations with relatively lower incomes. Lastly, as anticipated, applicants requesting larger loans relative to their income are more likely to be rejected on their applications

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 application, origination, and rejection probabilities.

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.

Table 7: 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 8: 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*

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

Table 9: Summary of Control Variable Coefficient Estimates

	Coefficient				T-stats
Variable	Min	Max	Mean	Std. Dev.	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

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 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 10 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 the stronger laws may be associated with larger declines in the flow of credit, while simultaneously being associated with lower rejection rates.

Table 10: 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. 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 California law sample as the excluded group. The impact of the average law can then be interpreted directly from the *Ineffect* variable.[10]

[10] At this time North Carolina is not included in the estimation, but will be added once we have collected the necessary information from the 1998 HMDA data release.

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 either Republicans or Democrats may be more or less likely to respond to predatory lending concerns through legislation. Table 11 provides a description of the variables used to identify whether the state where the property is located will enact a local predatory lending law.

Tables 12a and 12b provide descriptive statistics of the variables by outcome. The application sample includes over 540,000 prime and subprime loan applications, the origination sample includes over 370,000 prime and subprime originations and the rejection sample includes over 81,000 subprime applications which are either accepted or rejected.[11]

Table 12 provides summary statistics. For example, just over 20 percent of the applications were subprime, while only 9.6 percent of the originations were subprime. Consistent with the relative magnitude of applications and originations the rejection rate is very high for our sample of subprime loans at 42.4 percent. The states in the sample are best described as urban, majority white, and predominately democratic 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 include rejects and accepts 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

[11] The rejection sample excludes loans whose application was withdrawn by applicant or whose file was closed for incompleteness. For estimation purpose we only include a 10 percent random sample of each law in the pool dataset. Re-estimation using 25 percent and 50 percent random samples indicates that results are robust across sample sizes.

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 sample and Texas is the smallest. In addition, the number of loans either before or after a law becomes effective varies by location and just over 40 percent of the sample has a law in effect.

Table 11: 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 (2205) provide a detailed description of each law in Appendix A (http://research.stlouisfed.org/wp/2005/2005-049.pdf). The detailed descriptions of the laws are too long to include in this paper and have been summarized by the law index discussed above.

Table 12a: Descriptive Statistics – Dependent and Control Variables

	Application sample		Origination sample		Rejection sample	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Application	0.203	0.402	---	---	---	---
Origination	---	---	0.096	0.295	---	---
Rejection	---	---	---	---	0.424	0.494
Mktshare	9.8%	2.7%	9.6%	2.6%	10.4%	2.6%
Urban	82.9%	11.9%	83.0%	11.7%	83.8%	11.9%
Nonwhite	26.6%	11.2%	26.6%	11.0%	27.5%	11.6%
Politics	2.460	1.823	2.494	1.844	2.330	1.714
Income (thousands $)	82.9	111.3	88.9	110.5	65.8	67.3
Loan2inc	2.075	4.111	2.059	2.088	2.085	2.618
Relinc	1.108	0.323	1.135	0.328	1.019	0.289
Minority	24.7%	24.3%	23.7%	23.3%	30.6%	27.6%
Vacant	8.2%	6.6%	7.9%	6.7%	8.9%	5.8%
Population	1.9%	2.0%	1.9%	2.0%	2.1%	2.0%
Unemployment	4.7%	2.3%	4.6%	2.3%	5.0%	2.3%

Table 12b: Descriptive Statistics – Identification Variables

	Application sample		Origination sample		Rejection sample	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Law	0.647	0.478	0.642	0.480	0.686	0.464
Postlaw	0.631	0.483	0.652	0.476	0.608	0.488
Ineffect	0.412	0.492	0.422	0.494	0.428	0.495
ca	0.231	0.421	0.221	0.415	0.302	0.459
ct	0.042	0.200	0.039	0.194	0.045	0.207
fl	0.043	0.203	0.041	0.198	0.039	0.194
ga	0.056	0.229	0.052	0.222	0.066	0.248
ma	0.200	0.400	0.211	0.408	0.156	0.363
md	0.311	0.463	0.338	0.473	0.234	0.423
oh	0.065	0.247	0.057	0.232	0.078	0.268
pa	0.041	0.199	0.032	0.176	0.065	0.246
tx	0.012	0.109	0.009	0.093	0.015	0.121
lawca	0.211	0.408	0.202	0.401	0.285	0.451
lawct	0.011	0.103	0.010	0.100	0.011	0.104
lawfl	0.031	0.172	0.029	0.167	0.028	0.166
lawga	0.026	0.159	0.025	0.157	0.029	0.167
lawma	0.145	0.352	0.158	0.364	0.103	0.304
lawmd	0.154	0.361	0.162	0.368	0.133	0.340
lawoh	0.038	0.192	0.033	0.179	0.051	0.221
lawpa	0.028	0.166	0.022	0.147	0.044	0.204
lawtx	0.002	0.041	0.001	0.036	0.002	0.040
postlawca	0.146	0.353	0.142	0.349	0.205	0.404
postlawct	0.027	0.163	0.027	0.162	0.027	0.162
postlawfl	0.026	0.158	0.025	0.157	0.023	0.149
postlawga	0.031	0.173	0.031	0.172	0.034	0.182
postlawma	0.138	0.345	0.152	0.359	0.092	0.290
postlawmd	0.199	0.399	0.220	0.414	0.145	0.352
postlawoh	0.034	0.182	0.031	0.174	0.040	0.197
postlawpa	0.022	0.148	0.018	0.133	0.032	0.176
postlawtx	0.007	0.084	0.006	0.075	0.008	0.090
Sample size	549,490		371,051		81,948	

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 (1998) 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 enacting law and the probability of subprime application/origination/rejection. The model specification is given by

(3a) $\pi_i^{*1} = X_i^1 \beta^1 + \varepsilon_i^1, \qquad \pi_i^1 = 1 \text{ if } \pi_i^{*1} > 0, 0 \text{ otherwise}$

(3b) $\pi_i^{*2} = X_i^2 \beta^2 + \pi_i^1 \gamma + \varepsilon_i^2 \qquad \pi_i^2 = 1 \text{ if } \pi_i^{*2} > 0, 0 \text{ otherwise}$

and

$$E\left[\varepsilon_i^1\right] = E\left[\varepsilon_i^2\right] = 0$$
(4) $$Var\left[\varepsilon_i^1\right] = Var\left[\varepsilon_i^2\right] = 1.$$
$$Cov\left[\varepsilon_i^1, \varepsilon_i^2\right] = \rho$$

Equation (3a) 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 (3b) 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 (1983) and Greene (2003) 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:

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

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

Marginal Effects with an Endogenous Variable on the Right Hand Side

As Greene (1996) 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. In this section we consider marginal effects for various types of variable in the model.

First, consider the treatment equation (3a). 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:

$$(6) \qquad P(\pi^1 = 1, \pi^2 = 1 \mid X^1, X^2) = \Phi_2(X^1\beta^1, X^2\beta^2 + \gamma, \rho)$$

Second, consider the outcome equation (3b). The conditional mean function is:

$$(7) \qquad \begin{aligned} &E[\pi^2 \mid X^1, X^2] = P(\pi^1 = 1)E[\pi^2 \mid \pi^1 = 1, X^1, X^2] + P(\pi^1 = 0)E[\pi^2 \mid \pi^1 = 0, X^1, X^2] \\ &= \Phi_2(X^1\beta^1, X^2\beta^2 + \gamma, \rho) + \Phi_2(-X^1\beta^1, X^2\beta^2, -\rho) \end{aligned}$$

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:

$$(8) \qquad \begin{aligned} &Meff = E[\pi^2 \mid X^1, X^2, q = 1] - E[\pi^2 \mid X^1, X^2, q = 0] \\ &= [\Phi_2(X^1\beta^1, X^2\beta^2 + \gamma, \rho) + \Phi_2(-X^1\beta^1, X^2\beta^2, -\rho)] \mid q = 1 \\ &- [\Phi_2(X^1\beta^1, X^2\beta^2 + \gamma, \rho) + \Phi_2(-X^1\beta^1, X^2\beta^2, -\rho)] \mid q = 0 \end{aligned}$$

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 (7).

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

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

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 (2004), the full interaction effect is the double difference.

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

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.

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:

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

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

Results

We estimate the model specified in equations (3), (4), and (5) using maximum likelihood. Table 13 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. Table 13 contains four panels (a-d). To aid comparison across outcome 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 (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 legislatures with more republicans have tended to be more likely to have predatory lending laws. Inconsistent with expectation, locations with more subprime lending are associated with a lower probability of enacting a law. In addition, the results are consistent across the three samples associated with each outcome.

The results in panel (b) largely meet expectations that location, borrower, and mortgage information indicting economic stress is 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.

The results for originations are very similar to the application results. Again, in general, indicators of economic stress (borrower income, relative income, minority status, population growth, and unemployment rates) are associated with higher probabilities of originating a subprime loan. However, both higher vacancy rate and higher loan to value ratios are both negatively associated with subprime origination probabilities. These unexpected results, however, are consistent with the large variation in coefficient estimates found for these variables before the pooled data sample is used as shown in table 9.

The results for the rejection equations also show that in general more adverse economic conditions (borrower income, loan to income ratio, relative income, property vacancy, and unemployment) are 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 California so that coefficients should be interpreted as relative to the California law sample. However, there are no priors on the sign, magnitude, or statistical significance of these variables. The coefficients on law sample dummy variables (e.g., *ct, fl, ga*, etc.) are additive with the intercept, which represents the intercept for the California law sample. In addition, all the interactions of each state's law sample with the variables *Law* and *Postlaw* (e.g., *lawct*, *postlawct*, *lawfl*, *postlawfl*, etc.) are additive relative to the variables *Law* and *Postlaw*, which represents the California 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 (prelaw versus postlaw), 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 95 and 99 percent level in the application equation and rejection equation, respectively, and insignificantly different from zero for 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 10 percentage point (coefficient = 0.10) increase in the probability of applying for a subprime loan relative to the average application rate of 20.3 percent. The average impact of a local predatory lending law, using the variable *Ineffect*, is a reduction of 4.4 percentage points in the probability of being rejected (mean = 42.2 percent), an increase of 0.1 percentage points in applying (mean = 20.3 percent), and an increase of 1.5 percentage points in originating (mean = 9.6 percent) a

subprime loan.[12] 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 substantial reduction in the flow of credit found by the introduction of a law in North Carolina is not typical.

Results – Strength of the Law

While the average law may only have 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 a reduction in applications and originations. In addition, stronger laws may reduce rejections by deterring marginal applications or through increased screening by lenders to insure compliance with the predatory lending law.

To gauge the potential relevance of a law's strength we estimated two additional models. Model II adds the scaled law index as an explanatory variable in the outcome equation, and Model III adds the disaggregated law index along the dimensions of coverage and restrictions. The results (coefficient, standard error, and marginal effects) are reported in Table 14. [13]

In Model II, the coefficient estimates indicate that stronger laws are associated with lower probabilities of being rejected and applying for a subprime loan and are not statistically associated with the probability of originating a subprime loan. Again, the magnitude of the impact is small for both originating and applying. For example the marginal impact, measured by a one standard deviation increase in the index from the mean, is only 1.06 percentage points in the application equation and 0.58 percentage points in the origination equation. In contrast, the marginal impact is much larger for rejection (4.57 percentage points). This is highlighted in Figure 2 which plots the change in the probability of the outcome (apply, originate, and reject) relative to the strength of the law. Model II includes

[12] Note that the sign of the coefficient estimate on *Ineffect* is different from the sign of its marginal effect for the application equation. This is because of the double difference approach in calculating the full interaction effect. As noted by Norton, Wang and Ai (2004), because there are four additive terms, each of which can either be positive or negative, the interaction effect may have different signs for different values of covariates. Therefore, the sign of the coefficient does not necessarily indicate the sign of the interaction effect.

[13] To conserve space all the control variables are not reported, but are available on request.

the variable *Ineffect* to measure any fixed effect associated with the law, but its coefficient is insignificant in all specifications.

The strength of the law can also be measured along the dimensions of coverage and restrictions. The impact of restrictions should be unambiguous. Assuming appropriate substitutes cannot be found, more restrictions on allowable lending should lead to less lending. Therefore, originations should be lower for stronger laws and likely applications will be deterred due to the reduced availability of loan types. While it is less clear why rejections should be impacted it may be that lenders provide more prescreening of potential applications to insure compliance with the predatory lending law and hence reduce the number of applications with little chance of being accepted. If this conjecture is correct then loans in locations with stronger restrictions may lead to lower rejection probabilities. In Model III, the coefficients results indicate that laws with more restrictions are associated with reduced probabilities of applying, originating, and rejecting subprime loans. For example, a one standard deviation increase in the scaled restrictions index reduces the probability of applying by 4.89 percentage points, the probability of originating by 2.26 percentage points, and the probability of being rejected by 2.85 percentage points. Relative to the means the impact is largest for application probabilities (a 24 percent decrease).

The impact of increased coverage of a law, after controlling for restrictions, is largely an empirical question. Model III in Table 14 reports that laws with broader coverage tend to be associated with increased originations and applications and have no statistically significant impact on rejections. In fact, the coefficient estimates are very similar in magnitude, although opposite signs, to the impact of stronger restrictions. Again, the variable *Ineffect* is included to measure any fixed effect associated with the law, but is insignificant in all specifications.

Table 13: Bivariate Probit Results – Base Model

Panel (a): Treatment (Law) Equation

Variable	Coeff.	Std. Err.	Marg. Eff.	Unit
	Application Model			
Intercept	-15.701***	0.060	---	---
Mktshare	-2.242***	0.111	-0.0277	10%
Urban	20.384***	0.079	0.1296	10%
Nonwhite	1.781***	0.038	0.0214	10%
Politics	-0.392***	0.003	-0.0480	1
	Origination Model			
Intercept	-17.113***	0.078	---	---
Mktshare	-2.022***	0.142	-0.0114	10%
Urban	21.904***	0.103	0.0605	10%
Nonwhite	2.303***	0.049	0.0126	10%
Politics	-0.391***	0.004	-0.0219	1
	Rejection Model			
Intercept	-11.862***	0.130	---	---
Mktshare	-3.988***	0.276	-0.0673	10%
Urban	16.084***	0.173	0.1217	10%
Nonwhite	1.374***	0.089	0.0203	10%
Politics	-0.380***	0.006	-0.0640	1

Note: Marginal effects for treatment variables 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.

Table 13: Bivariate Probit Results – Base Model (continued)
Panel (b): Outcome Equation – Control Variables

Variable	Coeff.	Std. Err.	Marg. Eff.	Unit
		Application Model		
Intercept	-1.111***	0.034	---	---
Income	-0.162***	0.004	-0.0047	$10,000
Loan2inc	0.001***	0.000	0.0000	10%
Relinc	-0.424***	0.009	-0.0122	10%
Minority	0.426***	0.013	0.0127	10%
Vacant	-0.526***	0.130	-0.0150	10%
Population	-0.011***	0.002	-0.0032	1%
Unemployment	1.545***	0.269	0.0045	1%
Corr. Coeff. (ρ)	-0.312***	0.014	---	---
Log likelihood		-341,203		
		Origination Model		
Intercept	-1.549***	0.054	---	---
Income	-0.127***	0.007	-0.0021	$10,000
Loan2inc	-0.015***	0.002	-0.0003	10%
Relinc	-0.332***	0.013	-0.0055	10%
Minority	0.547***	0.020	0.0096	10%
Vacant	-0.983***	0.208	-0.0155	10%
Population	0.005**	0.002	0.0009	1%
Unemployment	1.154***	0.426	0.0020	1%
Corr. Coeff. (ρ)	-0.230***	0.021	---	---
Log likelihood		-168,907		
		Rejection Model		
Intercept	-0.131*	0.079	---	---
Income	-0.045***	0.008	-0.0018	$10,000
Loan2inc	0.022***	0.003	0.0009	10%
Relinc	-0.262***	0.020	-0.0104	10%
Minority	0.002	0.026	0.0001	10%
Vacant	1.312***	0.319	0.0523	10%
Population	-0.017***	0.004	-0.0069	1%
Unemployment	1.046*	0.636	0.0041	1%
Corr. Coeff. (ρ)	-0.130***	0.031	---	---
Log likelihood		-63,518		

Table 13: 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	0.866***	0.030	0.738***	0.047	0.190***	0.071
Postlaw	0.116***	0.014	0.184***	0.022	-0.302***	0.032
Ineffect	-0.027**	0.011	0.007	0.018	-0.117***	0.026
ct	0.729***	0.034	0.596***	0.054	0.048	0.077
fl	0.668***	0.043	0.514***	0.070	0.110	0.103
ga	0.904***	0.035	0.646***	0.056	0.411***	0.081
ma	0.834***	0.031	0.762***	0.048	0.026	0.071
md	0.378***	0.030	0.243***	0.047	0.115*	0.068
oh	0.608***	0.032	0.405***	0.051	0.340***	0.073
pa	0.786***	0.036	0.823***	0.057	0.019	0.076
tx	0.861***	0.042	0.872***	0.070	0.221**	0.092
lawct	-0.583***	0.035	-0.564***	0.055	0.109	0.080
lawfl	-0.802***	0.043	-0.699***	0.069	0.110	0.101
lawga	-0.314***	0.041	-0.278***	0.067	0.065	0.084
lawma	-0.736***	0.031	-0.703***	0.048	-0.162**	0.071
lawmd	-0.429***	0.030	-0.497***	0.046	0.141**	0.068
lawoh	-0.255***	0.035	-0.217***	0.058	-0.090	0.078
lawpa	-0.251***	0.042	-0.255***	0.069	0.024	0.089
lawtx	-0.878***	0.071	-0.617***	0.115	-0.006	0.162
postlawct	-0.265***	0.026	-0.229***	0.040	0.002	0.061
postlawfl	-0.021	0.025	-0.215***	0.042	0.469***	0.058
postlawga	-0.218***	0.025	-0.214***	0.041	0.084	0.055
postlawma	-0.342***	0.016	-0.401***	0.025	0.181***	0.039
postlawmd	-0.162***	0.014	-0.163***	0.021	0.102***	0.032
postlawoh	-0.146***	0.020	-0.186***	0.033	0.311***	0.044
postlawpa	-0.160***	0.022	-0.537***	0.036	0.567***	0.045
postlawtx	-0.199***	0.045	-0.486***	0.077	0.264***	0.096

Table 13: Bivariate Probit Results – Base Model (end)

Panel (d): Outcome Equation – Marginal Effect for Identification Variables

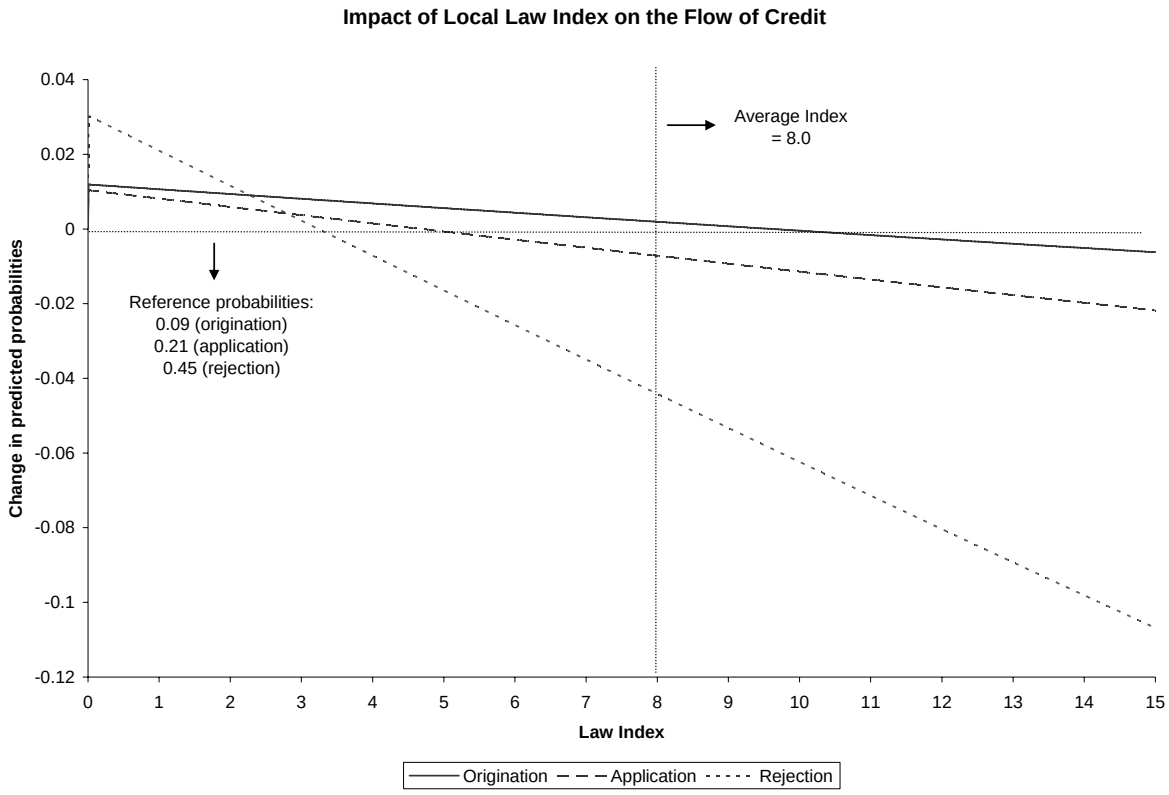
Variable	Application	Origination	Rejection
Law	0.100	0.056	-0.012
Postlaw	0.033	0.030	-0.119
Ineffect	0.001	0.015	-0.044
ct	0.260	0.139	0.019
fl	0.236	0.115	0.044
ga	0.328	0.153	0.164
ma	0.284	0.168	0.010
md	0.116	0.043	0.046
oh	0.210	0.085	0.136
pa	0.283	0.213	0.007
tx	0.316	0.234	0.088
lawct	-0.181	-0.098	0.043
lawfl	-0.249	-0.119	0.044
lawga	-0.079	-0.031	0.025
lawma	-0.233	-0.132	-0.064
lawmd	-0.116	-0.075	0.056
lawoh	-0.058	-0.022	-0.036
lawpa	-0.055	-0.020	0.010
lawtx	-0.289	-0.127	-0.003
postlawct	-0.091	-0.042	0.000
postlawfl	0.005	-0.037	0.185
postlawga	-0.073	-0.037	0.036
postlawma	-0.118	-0.085	0.071
postlawmd	-0.047	-0.024	0.039
postlawoh	-0.044	-0.030	0.122
postlawpa	-0.050	-0.131	0.224
postlawtx	-0.067	-0.123	0.105

Table 14: 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					
Ineffect	0.035	0.029	0.0208	-0.044	0.029	-0.0177
Law index	-0.007**	0.003	-0.0106	---	---	---
Coverage index	---	---	---	0.069***	0.007	0.0774
Restriction index	---	---	---	-0.063***	0.006	-0.0489
	Origination Results					
Ineffect	0.068	0.049	0.0268	0.002	0.050	0.0015
Law index	-0.007	0.005	-0.0058	---	---	---
Coverage index	---	---	---	0.055***	0.011	0.0363
Restriction index	---	---	---	-0.052***	0.009	-0.0226
	Rejection Results					
Ineffect	0.076	0.064	0.0304	0.070	0.066	0.0283
Law index	-0.024***	0.007	-0.0457	---	---	---
Coverage index	---	---	---	-0.020	0.016	-0.0282
Restriction index	---	---	---	-0.025**	0.012	-0.0285

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 5.

Figure 2:



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 five 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.

This paper provides a summary of 28 state and local predatory lending laws that were passed and in effect by the end of 2004. Beyond this summary, we extend the current literature in a number of ways: (i) the impact of predatory lending laws in many other states in addition to North Carolina is examined, (ii) the data design compares loans, and loan applications, that are geographically close instead of whole states and regions, (iii) the estimation strategy treats the outcome (application, origination, or rejection) as jointly determined with the probability the loan is in a state that passes and enacts a predatory lending law, and (iv) the impact of the strength of the law in terms of coverage of the market and strength of the restrictions is examined.

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 24 percent for the typical law. The reduction in rejections may reflect less aggressive in 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 have little impact. The strength of 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 contrast, laws with broad coverage are associated with an increase in the flow of credit. Therefore, the design of the law can have economically important impacts on 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.

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