Lending Competition and Non-Traditional Mortgages*

Arthur Acolin
University of Washington
acolin@uw.edu

Xudong An
Federal Reserve Bank of Philadelphia
xudong.an@phil.frb.org

Susan M. Wachter
University of Pennsylvania
wachter@wharton.upenn.edu

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Abstract

We provide new perspectives on the rampant growth of non-traditional mortgages (NTMs) prior to the Great Recession by showing that local lending competition contributed significantly to the early growth of NTMs while growth of and non-bank lending. We also find that state level anti-predatory lending laws were more (less) effective in restraining the origination of NTMs in markets with higher (lower)levels of lending concentration and therefore lower (higher) competitive pressure.

Lending Competition and Non-Traditional Mortgages

Arthur Acolin, Xudong An and Susan M. Wachter

1. Introduction

Non-traditional mortgages (NTMs) such as option ARMs and low documentation loans became rampant during the housing boom prior to the Great Recession (Bernanke, 2007). It is well understood that demand side factors such as use of NTMs to lift borrowing constraints contributed to their expansion (see, e.g., Dell'Ariccia, Igan and Laeven, 2012; Cocco, 2013). In addition, the existing literature has pointed to supply-side factors such as lenders' ability to pass risk onto the securitization and re-securitization markets (see, e.g., Keys, et al, 2010; Cordell, et al, 2010) and their perception of low risk in these products in a rising house price environment (Demyanyk and Van Hemert, 2011; Calem and Nakamura, 2016). In this paper, we take a new perspective to study how the local mortgage market structure, particularly lending competition and the rise of non-bank lending, contributed to the rise of NTMs and how legislative interventions such as the anti-predatory lending laws worked in markets with different levels of lending competition.

Thakor (2011) describes a conceptual model in which innovations in the financial market are more likely to occur where competition in the standard loan market drives down lending profit margins, which provides incentives for existing banks to offer innovative loan products that provide positive profits. Banking deregulation mostly happened in the late 1990s led to increased competition among commercial banks (Rice and Strahan, 2010). Meanwhile, non-bank lending institutions such as mortgage companies expanded substantially. It is thus natural to hypothesize that lending competition had incentivized certain mortgage lenders to seek new opportunities – NTMs usually carrying high spreads and fees being one of them.

In a recent paper, Buchak et al. (2017) argue that the less regulatory scrutiny faced by non-bank lenders, (together with technology advantage of those lenders, especially FinTech firms), account for about 90 percent of the growth in shadow banking during 2007 to 2015. The regulatory framework has also been put forth as an explanation for NTM growth during the 2000s (Engels and McCoy 2016). Engels and McCoy (2016) show how the implementation of federal preemption rules in the 1990s and early 2000s affected lenders regulated by the Office of Thrift Supervision (OTS) and the Office of the Comptroller of the Currency (OCC) created incentives for lenders to choose the regulators and laws most favorable to them. Non-bank lenders could have had more

flexibility in taking extra risk, which in conjunction with their access to funding through the PLS channel could have led to risky NTM lending.

In addition, the traditional product mortgage market could have been crowded and dominated by the large lenders. Moreover, on a local level, large lenders with many local branch offices may have dominated markets and these entrenched lenders would make it more difficult for new firms to enter the market with new products (Aguirregabiria, Clark and Wang 2017). Therefore, local market competition could both lower the barriers for smaller and non-bank lenders to enter and may increase the incentives for existing banks to offer new products, such as NTMs, as well.

In our analysis, we mainly use the standard Herfindahl-Hirschman Index (HHI) as a measure of local lending concentration (competition). A simple plot shows that, in aggregate at the national level, lending concentration generally declined during 2001-2006, and during the same period, NTM lending grew exponentially (Figure 1).

It is worth noting that these supply-side factors could have been intertwined with demand-side factors. For example, when house prices grew fast affordability became an issue and thus many borrowers needed affordable loan products. Lenders could have found it a good business model to offer NTMs to address the affordability issue and at the same time earn high spreads and fees from borrowers who were in need of those products. Therefore, it is difficult to distinguish different factors by studying aggregate data. In this paper, we assemble loan-level data and utilize cross sectional variations in local lending market structure to test the supply-side effect.

Our loan-level data comes from McDash Analytics and HMDA. We use McDash-HMDA merged loan level origination data covering NTM and traditional mortgages. Meanwhile, we compile measures of lending competition and growth of non-bank lending at the MSA- and county-level based purely on the HMDA data. To study the impact of anti-predatory lending laws, we use state mini-HOEPA programs data. The McDash data also contains loan performance history, which allows us to examine ex post default risk of NTM vs. non-NTM loans as well as NTMs originated within different market/legal context.

Our analysis of NTM originations at the loan-level shows that, during 2001-2006, in metropolitan statistical areas (MSAs) with high (low) lending competition (concentration) it is more likely that the loans originated are NTMs rather than traditional mortgages, *ceteris paribus*. A one standard deviation increase in the concentration index (from 0.030 to 0.045) is associated with an 8 percent

reduction in the likelihood of a loan being an NTM as opposed to a traditional prime loan, compared to one standard deviation increase in the zip code HPA associated with a 5 percent increase in the likelihood of a loan being an NTM, and one standard deviation increase in local price to income ratio associated with a 15 percent higher likelihood of loan being an NTM. Considering that much of the growth in real estate development and mortgage lending during the housing boom happened at urban fringes, we go beyond MSAs and re-estimate our NTM originations model, and our results hold.

Of course, mortgage market concentration at the local level is not randomly assigned, so it is difficult to ascribe causality to these results. To address endogeneity concerns, we follow Scharfstein and Sunderam (2016) to use bank mergers as an instrument for mortgage market concentration. Mergers decrease the competition of mortgage lending. In a selective sample of counties where the counties themselves were not the key driver of the merger, we find that low (high) lending competition is associated with low (high) likelihood of NTM origination, consistent with our baseline results.

Prior to the mortgage market crisis, geography like MSA and county was not a pricing factor in the secondary mortgage market. Variations in mortgage spread across different geographies mainly reflect local lending competition. Therefore, we use average mortgage spread of the traditional prime 30-year fixed-rate mortgages (FRMs) in each MSA as an alternative measure of lending competition. We find that in areas where mortgage spread is thin NTM origination is more likely. This result is again consistent with our prior results, and provides some direct evidence on profit-driven innovations in lending.

Lending competition can arise from two channels: competition among existing lenders and competition from new entrants. A salient feature of the mortgage market during our study period is the growth of non-depository lending institutions. To better understand the role of non-bank lending in NTM originations, we conduct year-by-year analysis and include non-bank lending in our model. To orthogonalize the effect of non-bank lending and competition among existing large banks (Countrywide being an exception), we create an HHI-like index for the largest five lenders in each county and then include this index and the market share of non-bank lending in our model. Our results reveal interesting market dynamics: during 2001-2003, competition among large existing lenders was a main driver of NTM lending; however, during 2004-2006, the growth of

non-bank lending was a powerful force of NTM expansion.

In 2003-2004, as NTMs burgeoned, predatory lending (Bond, Musto, and Yilmaz, 2009) policy concerns arose around the NTM and subprime businesses and states imposed anti-predatory lending laws to control their expansion. Findings in the existing literature are mixed regarding the effects of anti-predatory lending laws (see, e.g., Ho and Pennington-Cross, 2006; Elliehausen, Staten and Steinbuks, 2006; Bostic et al. 2008). We contemplate that these inconclusive results are due to the fact that existing studies are not able to distinguish the effects of APLs on credit supply from their effects on credit demand since they do not use loan level data with controls for demand at the borrower level.

To test for the impact of APLs on the contraction in NTM supply, we pool different years of data together and utilize both the cross sectional and time series variations in APLs. We find the establishment of an APL is associated with a lower likelihood that a loan is originated as an NTM. More interestingly, we find that in counties where there is more lending concentration and therefore less competitive pressures, the effect of APL is stronger. Finally, we estimate a default model and find that while NTMs are generally riskier than the traditional prime 30-year fixed-rate mortgages, the establishment of APLs mitigates this risk – states with new APLs have lower default risk in their NTMs. These results suggest that APLs were effective in limiting the supply of NTMs, especially the riskier ones.

Our study contributes to the literature that tries to understand the rise of risky lending prior to the Great Recession (see, e.g., Calem, Gillen and Wachter, 2004; Mayer and Pence, 2008; Mian and Sufi 2009; Keys et al., 2010; LaCour-Little and Yang; Demyanyk and Van Hemert, 2011; Dell'Ariccia, Igan and Laeven, 2012; Agarwal, et al., 2014; Brueckner, Calem and Nakamura, 2012; 2016; Amromin et al., 2015). We provide new perspectives on the rampant growth of NTMs by showing that local lending competition and its resulting profit incentives and lower entry barriers contributed significantly to the early growth of NTMs through existing bank lenders while growth of non-bank lending played an important role in expanding NTMs in a later stage.

Our study is related to the broader literature on competition and innovation. Competition can help spur product innovation (Aghion, et al. 2005). However, in non-repeat and complex transactions, such as prevail in the mortgage market, borrower decisions may not be well informed. During the early stage of NTM market development, in markets with strong competition lenders may have

been particularly likely to exploit profit opportunities through the offering of complex and products which had the potential to decrease welfare (Bond, Musto, and Yilmaz, 2009).

Finally, our paper contributes to the literature on predatory lending and legislative interventions (see, e.g., Engel and McCoy, 2002; Barr, 2005; Ho and Pennington-Cross, 2006; Elliehausen, Staten and Steinbuks, 2006; Bostic et al. 2008, 2012; Bond, Musto, and Yilmaz, 2009; Agarwal et al., 2013). Prior studies mostly focused on subprime mortgages while our focus in this paper is on NTMs. However, we similarly show aggressive supply of risky products with strong profit incentives. In addition, we provide new evidence that the anti-predatory lending laws might have been effective in restraining the supply of those products, which has not been made clear by the existing literature. This is consistent with findings from Di Maggio, Kermani and Korgaonkar (2016) who find that national banks increased their origination of mortgages with prepayment penalties by comparison with national banks in states without predatory-lending laws following the OCC's federal preemption from state APL in 2004.

The remainder of the paper is organized as follows: in Section 2, we describe the data; in Section 3, we discuss our analysis of lending competition and NTM originations; in section 4, we present our findings on anti-predatory lending laws and NTM; concluding remarks are in a final section.

2. Data

2.1. Data sources

Our main sources of data include the McDash Analytics servicing database, the Home Mortgage Disclosure Act (HMDA) data, and the McDash-HMDA merge.

The McDash dataset contains records of individual mortgage loans serviced by the large servicers in the US. It contains detailed information on origination as well as on monthly loan performance. The loan and borrower information at origination includes loan amount, interest rate type (fixed-rate versus adjustable-rate), amortization type and term, interest only (IO) term, option ARM indicator, loan-to-value ratio (LTV), maturity term, documentation type (full, low, no or reduced), borrowers credit score (FICO), debt-to-income ratio (DTI), loan purpose (e.g., home purchase vs. refinance), occupancy status (e.g., owner occupied versus investment); property type (e.g., single-family house vs. condominium), property location (state, county, MSA, and zip code), and so forth.

The dynamic file of the McDash data identify the current status of the loan in each month subsequent to loan origination, therefore we can identify delinquency and default.

The detailed loan characteristics in the McDash data allow us to accurately classify loans into NTMs and non-NTMs, which we will define shortly. In addition, the McDash-HMDA merge provides additional borrower demographic information such as race and ethnicity, which are important demand-side variables for mortgage loans.

However, since the McDash data does not cover the entire mortgage market[1], we need HMDA data itself to learn about the mortgage market structure. The HMDA was enacted by US Congress in 1975 to provide public loan-level loan application data that could be used to determine whether financial institutions are serving the housing needs of the community as well as practicing discriminatory lending. HMDA covers most of the US mortgage market, therefore it is an ideal source to calculate lender shares in each year in each MSA or county. Given the existence of subsidiaries of many lenders, we make a major effort to identify distinct lenders to calculate market share. A standard Herfindahl-Hirschman Index (HHI) is calculated based on lender market share as one of our competition measures.

The HMDA data contains loan information such as loan amount (in thousands), loan purpose, and property occupancy status, borrower demographic information such as race, ethnicity and gender, and borrower income, etc. The merge between the McDash and HMDA data is based on loan amount, origination date, location of the property and other loan characteristics that are common in both datasets.[2]

In addition to the McDash and HMDA data, we use a legal index for each state based on the existence of mini-HOEPA programs as a measure of the strength of state anti-predatory lending law (APL). The index is adapted from Ho and Pennington-Cross (2006a) by Bostic et al. (2008) and used by other studies for similar purposes. We also obtain from the Census Bureau 2000 census tract-level information such as population, age group composition, homeownership rate and percentage of college graduate. From the American Community Survey (ACS), we extract annual MSA/county median house price, rent and income information and construct price-to-rent ratio

[1] Coverage of the data varies from year to year but on average they cover about 70 percent of the market during our study period.

[2] However due to the lack of a unique mortgage identifier, the merge is not perfect and a number of observations from both datasets are dropped.

and price-to-income ratio. House price index (HPI) at the zip code-level is obtained from FHFA.[3] Finally, we calculate county-level credit card delinquency rate based on New York Fed Consumer Credit Panel (CCP) information.

The competition (concentration) index and other variables such as the legal index, HPI, Census and ACS variables, credit card delinquency rate are merged to the loan-level data based on geography (state, county, MSA, and zip code) and origination/performance date.

3.2. Sample and variable construction

Similar to Acolin et al. (2017), we define NTM as a mortgage loan with at least one of the following characteristics: 1) has an interest-only (IO) or negative amortization period; 2) is an option ARM; 4) has balloon payment; 4) has a maturity term over 30-year; 5) has low or no documentation. Each of these loan features relieve borrowers from income constraints to some extent, and they differ substantially from the features of the traditional "American Mortgage" (Green and Wachter, 2002), which are usually fixed rate, 30-year, fully amortizing loan with full (income, asset and employment) verification (full documentation). We do not include higher than 97% LTV loans as Acolin et al. (2017) do as those loans usually involve another type of player, mortgage insurance companies. Note that we make a distinction between NTM and subprime mortgage similar to Acolin et al. (2017) and only focus on NTMs in this paper.

NTMs were less than one percent of all mortgage loans prior to 2001 and post-2007 (see, Acolin et al., 2017). Further, the year of 2007 is a special year when the crisis started and the whole mortgage market landscape started to change. Therefore, we select 2001-2006 as our study period. We limit our tests to home purchase loan originations.

Based on the aforementioned NTM definition, Table 1 provides a summary of the number and share of NTMs we identify in each year as well as the number and share of NTMs that carry each of the five NTM features. The number of NTMs we identify in our data was less than 25,000 in 2001. This increased to over 500,000 in 2005. The share of NTMs increased from 18% in 2001 to 48% in 2005. Note that the share of NTMs in our sample during the early years such as 2001-2003 is significantly higher than that in Acolin et al. (2017). This is likely due to the fact that Fannie Mae and Freddie Mac loans, which are mostly non-NTM loans, are under-represented in the

[3] We also used CoreLogic HPI with similar results, available from the authors upon request.

McDash data in the early years.

As shown in the table, in the early years such as 2001-2003, most of the NTMs are option ARMs or low/no documentation loan, but in later years such as 2004-2006, the NTMs are more diversified. Further, many of the NTMs have more than one NTM features.

In Table 2, we compare the average loan characteristics such as FICO, LTV and DTI of NTMs and non-NTMs in our sample by year of origination.[4] NTMs have significantly lower average FICO score than non-NTMs in all the years, consistent with NTMs being extended to more marginal (subprime) borrowers. Overtime, the average FICO score and LTV of both NTMs and non-NTMs (at origination) are relatively stable but the average DTI increased significantly in later years, consistent with lending standard relaxation shown in the existing literature.[5]

As we just discussed, we use the HMDA data to infer the mortgage market structure. We do it at the MSA and county-level. We first clean lender names, and then identify the share of loans originated by each lender in each year and each MSA/county. Doing so allows us to calculate a Herfindahl-Hirchman Index (HHI) of lender shares. A higher (lower) HHI indicates higher (lower) concentration and lower (higher) competition. Since the HMDA data also provides lender type, we also use it to calculate share of loans originated by non-depository lending institutions (non-bank lending) in each year and each MSA/county.

In Figure 2, we plot the concentration index of the major MSAs. There are significant variations across MSAs, e.g., mortgage lending is much more concentrated in Detroit than in Dallas and the concentration in Miami is higher than that in Chicago. Lending concentration also changes significantly over time, e.g., most of the MSAs plotted had increased (decreased) competition (concentration) during 2001-2005, and in 2006 concentration tickled up in certain areas given that house price had turned the corner in 2006 and that we started to see failure of some lenders. In Figure 2, we also provide maps of lending concentration for all MSAs in the U.S. for the years of 2001 and 2005. Consistent with the trend we see from the top 10 MSAs, we see lending

[4] We do not include interest rate in the comparison on these products because of the limit in comparing rates on products with varying levels of fees, teaser rates and different reset periods. Nonetheless interest rates on these products do not appear to be a major factor in their take-up (Davidson et al. 2016).

[5] We do not have data that allow us to measure CLTV at origination but in the aggregate CLTV is observed to have increased substantially in this period through so-called "piggy back" loans, i.e., second liens (Levitin and Wachter 2016).

concentration (competition) declined (increased) significantly over time.

Turning back to Table 1, we compare the share of NTMs in high and low lending concentration areas. We sort county-year by HHI and define the top (bottom) quartile as high (low) concentration area.[6] We see that in more competitive (low concentration) markets, the share of NTM lending is significantly higher: 40% vs. 31%.

3. Local Lending Competition and NTM Origination

Much of the existing literature ascribes the expansion of NTMs in the boom period of 2001-2006 to demand side factors, associated with the overcoming of credit constraints: in the face of rising prices, borrowers face income and/or wealth constraints – they do not have sufficient income to meet the DTI requirement or enough savings to meet the down payment requirement. NTMs such as IO loans and option ARMs help relax those constraints and thus the origination of more NTMs might just reflect the growing demand for those products in response to affordability challenges. Evidence on the role of borrowing constraints on the spread of NTMs (and subprime lending) abounds (Calem, Gillen and Wachter, 2004; Dynan and Kohn 2007; Bostic et al. 2008; Barakova, Calem and Wachter 2014).

Market variation in origination of NTMs could also reflect perceptions of declining risks of those products in a rising house price environment (see, e.g. Demyanyk and Van Hemert, 2011; Brueckner, Calem and Nakamura, 2016). In fact, an increase in price expectations is likely to increase both borrowers' (with investment motives) demand and supply of lending into these markets.[7] Coleman, LaCour-Little and Vandell (2008) provide some evidence that the increase in housing prices itself as a cause of the expansion of NTMs. In addition, with securitization lenders were able to offload risk and pass it onto the securitization market, so they could have engaged in riskier lending (Mian and Sufi, 2009; Key et al., 2010).

[6] The HHI is 0.044 and 0.024 at the 75th and 25th percentile, respectively, showing that the mortgage market is generally very competitive. In the banking industry, markets HHI above .16 are usually considered to be concentrated, those with HHI below .08 to be un-concentrated, with those in-between moderately concentrated (De Jonghe and Vander Vennet 2007).

[7] See Levitin and Wachter (2011) for a discussion of the growth of NTM over time. The question of whether shifts in supply exceeded shifts in demand for these products in the boom years across the US in the aggregate is addressed there with support for the latter.

Thakor (2011) provides an additional interesting perspective. He describes a model in which innovations in the lending market are more likely to occur where competition in the traditional lending space drives down profit margins, which provides incentives for banks to offer innovative loan products that usually come with higher spreads and fees.

The mortgage market in general has historically been competitive (Figure 1). There are usually a large number of lenders in each MSA/county, who are a mix of commercial (large, regional, and community) banks, credit unions, mortgage companies, etc., and they compete with each other. Competition intensified as banking deregulation happened in the late 1990s and early 2000s (Rice and Strahan, 2010). Meanwhile, non-bank lending institutions such as mortgage companies had aggressive expansions. In fact, from 2001 to 2003, the average mortgage spread decreased from 205 bps to 88 bps, while during the same period, the average LTV and FICO remained stable while DTI even increased.[8]

Therefore, it is thus natural to hypothesize that lending competition had incentivized certain mortgage lenders to seek new opportunities – NTMs usually carrying high spreads and fees being one of them.

To test this hypothesis, we follow the mortgage choice literature to run Probit models for NTM vs. non-NTM originations (see, e.g., Calem, Gillen and Wachter, 2004; Nichols, Pennington-Cross and Yezer, 2005; LaCour-Little and Yang, 2010). Certainly, we have to control for the demand-side factors as well as the supply-side factors already identified in the existing literature.

The Probit model takes the following form:

$$Pr_{i,j} = \Phi\left(\alpha + \gamma C_j + X_{i,j}\beta\right), i = 1, \dots, N; j = 1, \dots, M. \qquad (1)$$

Here $Pr_{i,j}$ is the probability of loan i originated in MSA/county j being an NTM. $\Phi(\cdot)$ is the normal CDF, C_j is our measure of lending competition (concentration) in MSA/county j and is our focus variable, and $X_{i,j}$ is a vector of control variables. The control variables include loan and borrower characteristics such as log income, FICO, DTI, LTV, borrower race and ethnicity, property occupancy status, etc. They also include MSA/county median price-to-rent ratio, zip code house price appreciation (HPA) in the past 12 months, and other zip code characteristics such as

[8] Our calculation based on McDash data.

percentage of African American and percentage of college graduates. The loan and borrower characteristics control for demand side factors, HAP accounts for expectations, price-to-income for affordability, and percentage of college graduate for informed borrowers. We also include vintage- and state-fixed effects.

Summary statistics are provided in Appendix Table 1. We report our model results in Table 3. In Model 1, we exclude non-MSAs and focus on lending in MSAs. Signs of the control variable coefficients for demand variables largely conform to findings in the existing literature or economic intuition. For example, NTMs are more likely to be extended to African American and other minority borrowers, *ceteris paribus*, which is consistent with findings in Dell'Ariccia, Igan and Laeven (2012) and Acolin et al. (2017).[9] In addition, loans originated in areas with a higher share of minority borrowers (black or Hispanic) are more likely to be NTM, controlling for other factors, including individual level characteristics, which is consistent with targeting (Agarwal, et al., 2013, Calem, Gillen and Wachter, 2004). In terms of local market characteristics, NTMs are more likely to be originated in areas with a higher housing price to income, consistent with the affordability demand side mechanism (Demyanyk and Van Hemert, 2011; Brueckner, Calem and Nakamura, 2016). In line with the expectations theory, HPA over the last year is positively associated with NTM. Interestingly, borrowers with lower FICO score are more likely to take NTMs than non-NTMs, everything else equal. This result is contrary to the finding in Amromin et al. (2011).

Turning to our focus variables, the MSA lending concentration index is negative and significant in the model, meaning that stronger lending competition in the metro market is associated with a higher likelihood that a loan is originated as an NTM instead of a traditional prime 30-year FRM. These results are consistent with our hypothesis that competition drove lenders to "fly to opportunities".[10]

The results are economically significant, with a one standard deviation increase in the concentration index (from 0.030 to 0.045) associated with an 8 percent reduction in the likelihood of a loan being an NTM as opposed to a traditional prime loan. As a comparison, one standard

[9] However, Acolin et al. (2017) find that homeownership impact associated with NTM use is not larger for minority, perhaps due to steering (Courchane, Surette and Zorn 2004).

[10] In a different specification, we replace current year concentration index by lagged-concentration index as historical concentration is unlikely to be related to contemporary demand for credit. We find the coefficient of the lagged concentration index is negative and significant.

deviation increase in the zip code HPA is associated with a 5 percent increase in the likelihood of a loan being an NTM, and a 20 points increase of FICO (from 680 to 700) is associated with 11 percent decrease in of a loan being an NTM. The estimated effect of competition is smaller than the effect of affordability, with a one standard deviation increase in local price to income ratio to be associated with a 15 percent higher likelihood of loan being an NTM.[11]

Considering that much of the growth in real estate development and mortgage lending during the housing boom happened at urban fringes, we go beyond MSAs and re-estimate our NTM originations model. Results are shown under model 2 in Table 3. They are consistent with model 1 results. The county lending concentration coefficient is negative and significant, meaning that stronger competition is associated with higher likelihood of NTM origination.

Of course, mortgage market concentration is not randomly assigned, so it is difficult to ascribe causality to these results. To address endogeneity concerns, we follow Scharfstein and Sunderam (2016) to use bank mergers data to construct instruments for exogenous shocks to lending competition at the county level. We adopt their measure by replacing the market share of the top 4 lenders by the HHI of market share (both measures of competition are highly correlated).[12] The basic idea here is that bank mergers would reduce competition in the lending market and it represents an exogenous shock if the mergers are not driven by local considerations. For that purpose, mergers considered are those in which the merged bank represents more than 10 percent of local county deposits, but deposits in the county represent less than 2 percent of the bank's overall deposits. For the selected sample of counties, model results using these instruments are in under model 3 in Table 3, and they are consistent with previous results that lending competition is a driver of NTM originations with the instrumented HHI significantly negatively associated with the origination of NTM.

Prior to the mortgage market crisis, geography like MSA and county was not a pricing factor in the secondary mortgage market.[13] Variations in mortgage spread across different geographies mainly reflect local lending competition. Therefore, we use average mortgage spread of the

[11] Calculated based on the standard deviations of our sample variables and the model coefficients.
[12] As a robustness check, we also reproduce these results using the share of mortgage issued by top 4 lenders as the measure of concentration. The results using that measure are largely similar to those using the HHI. These results are available from the authors on request.
[13] During the crisis, for example, Fannie Mae and Freddie Mac started to charge adverse market G-fee premium.

traditional prime 30-year fixed-rate mortgages (FRMs) in each county as an alternative measure of lending competition. We find that in areas where mortgage spread is thin NTM origination is more likely (Model 4 in Table 3). This result is again consistent with our prior results. More importantly, this result provides some direct evidence that NTM origination is associated with lenders' profit in the traditional loan product market – the lower the profit in the prime mortgage market, the more likely the lender would seek opportunity in the alternative mortgage market.

Note that judged by the McKelvey and Zavoina's R-Squared, all four models fit the data reasonably well. About 22-24 percent of the variations in NTM origination are explained by these models.

So far, we have pooled six years of data together in running our models. Next, we want to run the models year-by-year. On the one hand, it will tell us whether our results hold based on purely cross sectional data. On the other hand, it will help us understand the market dynamics over time. Results are presented in Table 4. For the sake of space, we only list the focus variable estimates in the table. All control variables are the same as in Table 3 except for the vintage-fixed effects and results of the control variables are available upon request.

Panel A of Table 4 shows results with MSA-level HHI for loans in MSAs. From 2001 to 2002, lending concentration coefficient is shown to be negative and significant, consistent with the pooled sample results. In 2003, the coefficient is marginally significant even though the sign remains negative. In 2004-2006, the sign of the coefficient remains negative but the coefficient becomes insignificant. These results are quite interesting. Note that during the housing boom, as house price grew rapidly, real estate development in many places expanded onto the urban fringe, which on the one hand was due to land unavailability in the cities in supply-constrained areas like California but on the other hand helped mitigate affordability issues. We think the insignificant results of MSA HHI in the NTM model could be due to that reason.

For further investigation, we next re-run the year-by-year analysis with county HHI. Now urban fringes are included in our analysis. Results in Panel B of Table 4 show that in each and every year during 2001-2006, lending concentration is negatively and significantly associated with NTM origination. This supports our earlier finding of more NTM origination in high competition area, and also supports our argument that much of the lending, and particularly NTM growth, was in urban fringes.

In addition to the potential role for the level of lending competition, another market structure

element that may have contributed to the rise of NTMs in specific locations is the growth of non-depository lending institutions (non-bank lenders) relying on off-balance sheet funding (Keys et al. 2012). Non-depository lending institutions usually face less regulatory scrutiny. In a recent paper, Buchak et al. (2017) argue that the less regulatory scrutiny faced by non-bank lenders, together with technology advantage of those lenders (especially FinTech firms), account for about 90 percent of the growth in shadow banking during 2007 to 2015. It is possible that these lenders, facing lower levels of regulation, were able to grow due to the conjunction of access to funding through the PLS channel and their ability to take additional risk by originating NTMs.

In the period of our study, 2001 through 2006, NTM mortgages grew from being niche market products supplied by a selected number of lenders to market wide dominance. During this process, non-bank lenders played an important role. For example, Countrywide was the first to offer option ARMs (the "pick-a-pay" mortgage) designed for borrowers with currently low income but an expected growing income trajectory. Another non-bank lender, Ameriquest, was famous for its low-documentation mortgage loans.

Therefore, we want to identify the impact of non-bank lending on the growth of NTM. On the one hand, the growth and new entrance of non-bank lenders apparently contributed to increased competition and is reflected in our lending concentration HHI. We do notice that most of the non-bank lenders were relatively small lenders with the exception of Countrywide. However, we would like to identify the impact of existing (entrenched) competition on entry of non-banks and of the offering of NTMs. Therefore, what we do is to revise our HHI and compute an HHI-like measure of lending concentration (competition) among the largest five lenders, and then include such a measure and the share of non-bank lending in our model at the same time. We use this treatment to separate lending competition among existing big lenders and the growth/entrance of non-bank lenders.

Panel C of Table 4 presents our results. Interestingly, we see that during 2001-2002, the top 5 lenders HHI coefficient is negative and significant while the market share of non-bank lending is insignificant. This tends to suggest that during the early years, the growth of NTM was mainly driven by the competition among existing large lenders, along with other demand-side and supply-side factors. In the year of 2003, the share of non-bank lending becomes marginally significant, and during 2004-2006 it becomes a significant factor as shown by the positive and significant

coefficients. This is consistent with what we observe in the mortgage market during those years: many non-bank mortgage companies jumped into the mortgage origination during 2004-2006 and many of them had a focus on NTM originations.

In that later period, the top 5 lenders HHI coefficient changed from negative to positive around 2004 and remains positive and significant during 2005-2006. A possible explanation is that with extensive mergers and acquisitions during mid-2000s the mortgage market structure further evolved and in some oligopolistic markets a handful of big lenders compete with differentiated NTM products. What supports this interpretation is that in Table 1 we show that NTMs became more diversified during 2004-2006.

In Appendix Table 2, we look at the interaction between county level HHI in the previous year and the share of mortgage originated by non-bank lenders. This specification does not attempt to orthogonalize local competition from the share of non-bank lenders.[14] It shows that loans had higher (lower) likelihood to be NTMs in areas with a higher (lower) share of non-bank lenders when the local concentration was lower (higher). This is consistent with non-bank lenders being more likely to originate NTMs in areas with more competitive pressure as well.

Overall, lending competition and declining profits in the traditional prime mortgage lending during the early 2000s incentivized the big lenders to innovate and offer the NTMs, which carry higher spreads and fees, however, this growth was relatively limited. Later such opportunities were grasped by others and many lenders, especially non-bank lenders jumped onto the NTM business and fueled the major expansion of NTM lending.

4. Anti-predatory Lending Laws, Competition and NTMs

A great concern of the NTM and subprime mortgage businesses is predatory lending, in which lenders take advantage of uninformed borrowers and impose unfair and abusive loan terms or steer borrowers to certain adverse loan products (Bond, Musto and Yilmaz 2009; Agarwal, et al. 2014; 2016).

Congress had enacted the Home Ownership and Equity Protection Act (HOEPA) in 1994 as part of the Truth in Lending Act (TILA) to limit abusive lending practices, particularly loans with

[14] Non-bank lenders are included in the calculation of the HHI and there is substantial collinearity between HHI and non-bank share.

excessive interest rates or fees (Ho and Pennington-Cross 2006). However, the impact of HOEPA was limited due to loopholes (Ho and Pennington-Cross 2006a; Bostic et al. 2008). In the early 2000s, policy makers began to have concerns about the potential for NTM and subprime mortgages business to involve predatory lending. In response, particularly where NTM growth was high, some states adopted anti-predatory laws (APLs)[15] to limit this growth by prohibiting loans with specific potentially predatory features (White et al. 2011). In addition, some state APLs required lenders to establish borrower ability to repay (White et al. 2011).

The empirical question of the efficacy of these legal measures is not settled. Some studies find lower mortgage interest rates associated with APLs (see, e.g., Ho and Pennington-Cross, 2006a), but there is no evidence in the literature of APLs leading to a market-wide decline in subprime/NTM originations (see, e.g., Ho and Pennington-Cross, 2006a; Elliehausen, Staten and Steinbuks, 2006; Bostic et al. 2008). The literature suggests that lack of enforcement of the APLs and market response by suppliers substituting away from specific prohibited features of loans to other features (which similarly overcome lending constraints) as reasons for this.[16]

Estimating the impact of APLs on subprime and NTM originations is difficult. A challenge to identifying the impact of APLs on lenders' predatory lending behavior is that we cannot easily separate the APLs' impact on credit supply from that on credit demand. Market wide data using states or counties within states, for example, as units of analysis (which is typical for these studies) conflates demand and supply. This might contribute to mixed findings in the existing literature regarding the effects of those laws (see, e.g., Ho and Pennington-Cross, 2006a, 2006b; Elliehausen, Staten and Steinbuks, 2006; Bostic et al., 2008). This is because a major explanatory factor in APL adoption is a high rate of growth in NTMs and the demand factors associated with this. By looking at loan level origination data, we partially address the issue present in the existing literature by specifying demand characteristics at the borrower level (borrower credit and sociodemographic characteristics as well as local housing price appreciation). By pooling data across years of origination and identifying whether an APL is in effect or not while including MSA- and year-

[15] State APLs were more stringent than the federal HOEPA in covering a broader range of practices and adopting lower trigger points for interest rates and fees.

[16] Also, as hypothesized by Ho and Pennington-Cross (2007) and Bostic et al. (2008), the passage of APLs can actually reduce borrowers' fear of predatory lending behavior and thus induce more demand for NTM and subprime loans.

fixed effects in our empirical strategy, we directly test for the impact of APLs.

Following the logic we had in the prior section, we think an examination of the relationship between APLs and market structure provides an avenue for us to tease out the supply-side effect. Particularly, we try to explore whether there is any variation in the impact of APLs on NTM originations with respect to lending competition. We test this hypothesis with both origination and performance data.

The mortgage choice model is similar to that in equation (1), except that we now include an APL indicator and its interaction with the lending concentration index in the model. For states that never established an APL (mini-HOEPA), the value of the legal index is zero in all years, and for those that did establish an APL, the value of the index is zero before APL establishment and is one after APL establishment. We also include MSA- and vintage-fixed effects in our model. Figure 3 shows the implementation of APLs over time and across markets.

The Probit model results are in Table 5. The lending concentration HHI coefficient is negative and significant, as we saw before. The legal index has a negative and significant coefficient, meaning that with the establishment of APLs NTMs become less utilized. We also find that the interaction term between the concentration index and the legal index has a negative and significant coefficient, suggesting that APLs are more effective in curbing NTM supply in areas with more concentrated lending where the incentives to substitute higher margin products is higher.

In addition to NTM origination, we analyze the performance of the NTMs to see whether NTMs originated after the establishment of APLs are of better quality. The McDash data allow us to infer loan quality through post-origination loan performance.

Our analysis focuses on default, which is defined here as 90 plus day delinquency. For each loan, we track its performance within three years of its origination. If it entered 90-day delinquency during the three-year window, we counted it as a default. In Figure 5, we compare the default rate of NTMs and non-NTMs. Interestingly, the 2001 vintage of NTM and non-NTMs had the same default rate. But in later vintages, the default rate of NTMs is much higher. For example, the 2005 vintage of NTMs had a default rate that is four times higher than that of the same vintage non-NTMs. On average, the default rate of NTMs is about twice that of non-NTMs.

We then run a simple linear regression model. For loans defaulted within three years, the dependent

variable takes a value of one and otherwise a value of zero. We include both NTM and non-NTM loans in our model with the hope that the non-NTM loans would act as a benchmark and help control for unobserved time trend in mortgage default. We separate counties with high and low lending concentration, as we want to see how APL works in different market context. The model takes the following form:

$$y_{i,j,k} = \alpha + \gamma_1 NTM_{i,j,k} + \gamma_2 APL_k + \gamma_3 NTM_{i,j,k} APL_k + X_{i,j,k}\beta + \varepsilon_{i,j,k}, i = 1, \dots N; j = 1, 2; k = 1, \dots 50. \quad (2)$$

Here $y_{i,j,k}$ is an indicator of whether loan i in area j (high vs. low lending concentration county) and state k defaulted within three years of its origination, $NTM_{i,j,k}$ is a dummy variable for NTM, APL_k is the APL legal index, and $X_{i,j,k}$ is a vector of control variables. One of the critical control variables is house price appreciation (HPA) within three years of loan origination, or the default/prepayment date, whichever comes first (hereinafter termination date). The other critical control variable is credit card delinquency rate at termination date. Other control variables include loan and borrower characteristics such as LTV, FICO, DTI, borrower race and ethnicity, property occupancy status, and property type. We also include state- and vintage-fixed effects.

We report our default model results in Table 6. Column 1 is for high lending concentration counties that are defined as counties that are ranking in the top quartile in the lending concentration HHI, and column 2 is for low lending concentration counties that are in the bottom quartile in the lending concentration HHI. All the control variables have the expected signs in the model. For example, as shown in the table, HPI is negative and significant and credit card delinquency rate is positive and significant. Coefficients of other control variables are not reported here in the interest of brevity but they are highly consistent with findings in the existing literature (see, e.g., An, Deng and Gabriel, 2015).

We see that, *ceteris paribus*, NTMs have higher default risk than non-NTMs (positive and significant coefficient) in both groups of counties. Interestingly, loans originated in places with APL are more likely to default (positive and significant coefficient), which is likely due to the fact that APLs were more likely to be enacted in areas with strong predatory lending practice and thus higher likelihood of loan failure.

The interaction terms show interesting results for the role of local competition. For example, the

interaction between NTM and APL is negative and significant (coefficient of -0.237 in the high lending concentration group and -0.185 in the low lending concentration group), suggesting that APLs help lower default risk of NTM loans even though establishment of APL is associated with higher default risk overall (positive and significant coefficient of 0.128 and 0.117 for the two groups, respectively). Furthermore, as we see this default risk reduction is more effective in areas with high lending concentration. This variation in post-APL default risk reduction with respect to lending competition should reflect the impact of APLs on NTM credit supply. Post-APL, lenders were making better NTM loans, especially in areas with high (low) lending concentration (competition). This is consistent with Di Maggio, Kermani and Korgaonkar (2016) who find that local market structure, specifically the share of OCC-regulated lenders, had an impact on the origination of complex mortgages. In response to the OCC preemption rule they find that non-OCC regulated lenders increased their origination of complex mortgages the most in areas where OCC regulated mortgage had a larger market share and therefore exerted more competitive pressure.

5. Conclusion and Discussions

Non-traditional mortgages (NTMs) grew from niche market products to prevailing mortgage instruments during the housing boom in the early half of 2000s. One explanation of the rise of NTMs is the ability of these products to overcome borrower income and wealth constraints. Other explanations include lenders' perception of low risk of these products in a rising house price environment, and securitization and its resulting lender ability to pass risk onto the securitization markets induced lenders to load more risk in origination. In this paper, we offer evidence for a new supply-side factor in the growth in NTM originations: roles for mortgage market structure such as lending competition and growth/entry of non-bank lending in the expansion of NTMs.

We overcome the difficulty of distinguishing the supply-side factors from the demand-side factors by exploiting variations in NTM originations associated with variations in local lending competition in addition to controlling for a set of demand-side factors as well as house price expectations. We also use bank mergers as instruments to help identify the role of lending competition.

Using McDash and HMDA data, we find lending competition is a significant driver of NTM originations during early years, and over time as the products became widely accepted, after initial

introduction through the role of heightened competition, dominant national players bring the products to market. This is consistent with the idea that during the early years of NTM growth, in markets with strong competition, lenders are "flying to opportunities" to offer NTMs as profit margins in the more traditional and transparent loans are compressed by competition. Later during 2004-2006, non-bank lending played an important role to fuel the growth of NTMs.

We also test for the efficacy of APLs and find that state APLs appear to have been effective in limiting the supply of NTMs as well as leading to less risky NTMs being originated in those areas, as measured by lower default rate *ex post*. Further, the effect is stronger in areas with higher (lower) lending concentration (competition) raising questions about the effectiveness of regulation in areas with more market pressure.

NTMs represent a form of financial innovation in the mortgage market. Unlike innovations in other consumer product markets, this complex innovation could have gone beyond the comprehension of many borrowers. The purpose of consumer protection regulation was to regulate the supply of products whose use was not beneficial. We find that APLs may have been instrumental in decreasing take up of these products.

For future research, it is worthwhile to separate different types of NTM instruments such as IO loans, low doc loans and low down payment loans to understand how exactly each of these products work, to evaluate what the costs and benefits are and to prescribe effective policies to lower the costs and to maximize their benefits.

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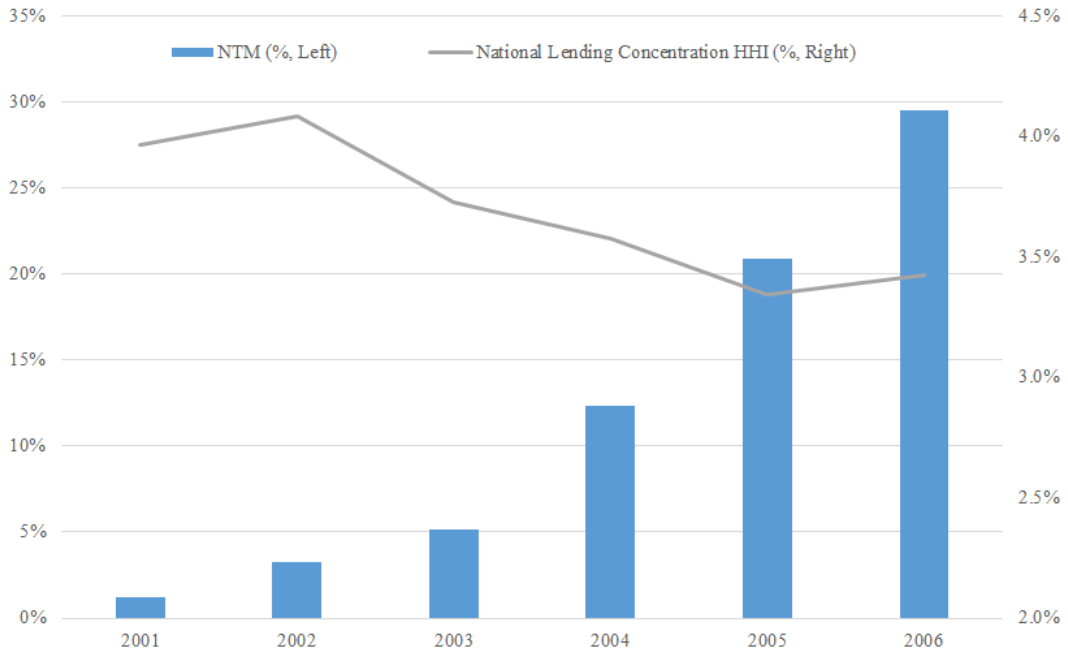

Figure 1 Share of NTMs Originated and Lending Concentration Herfindahl-Hirschman Index (HHI)

Note: the lending concentration HHI is the authors' calculation based on the HMDA data, and the share of NTMs is from Acolin et al. (2017) and is based on BlackBox data.

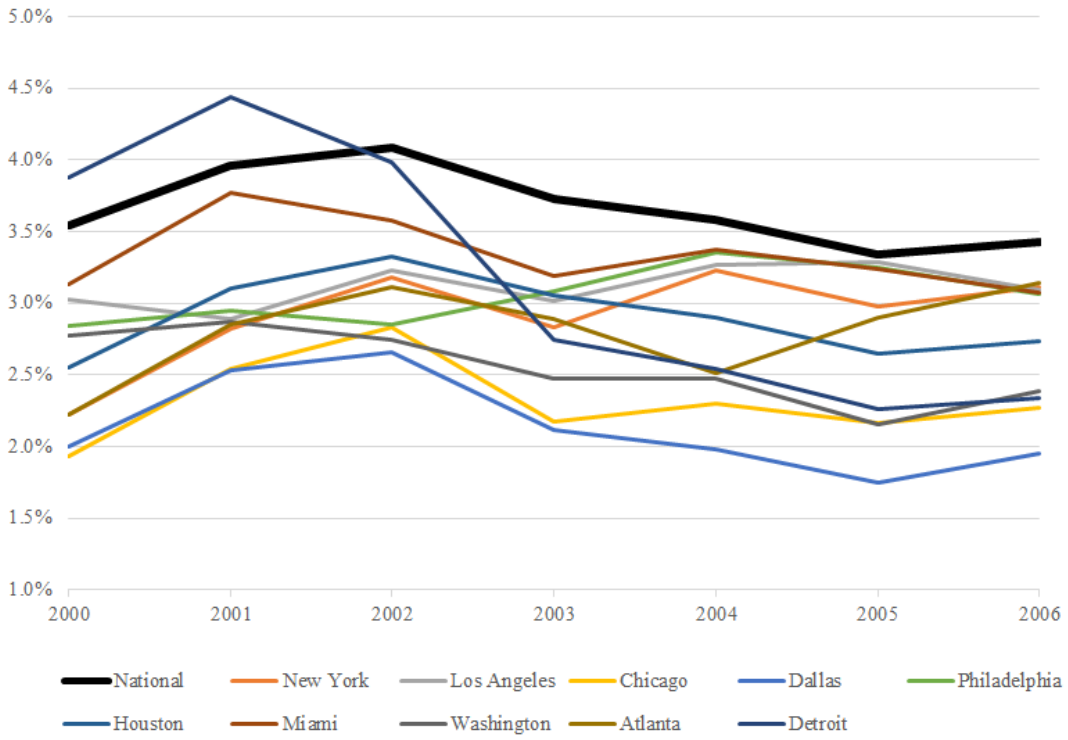

Figure 2 Lending Concentration HHI: National and Top 10 MSAs

Note: our own calculation based on the HMDA data.

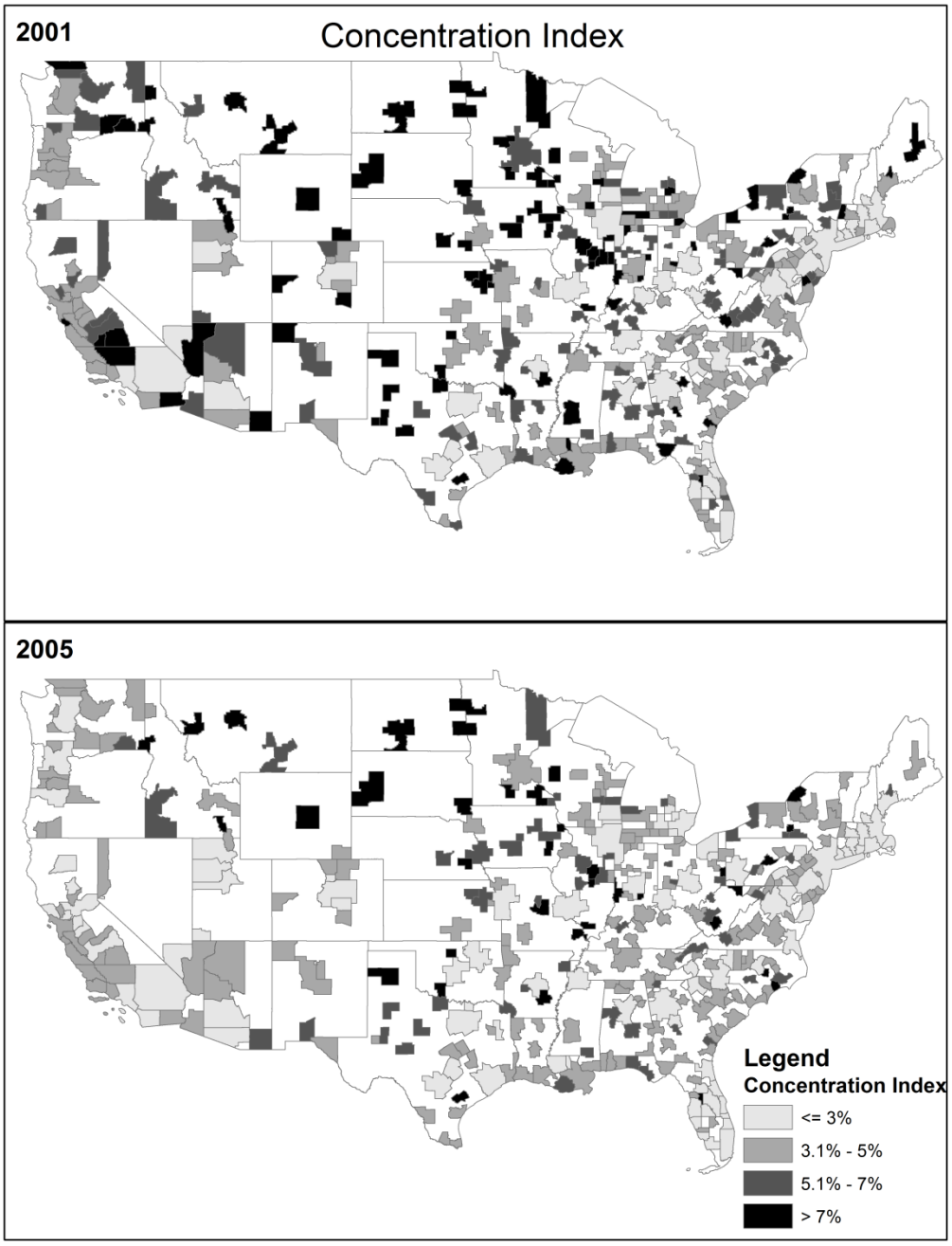

Figure 3 Lending Concentration HHI 2001 and 2005 Comparison

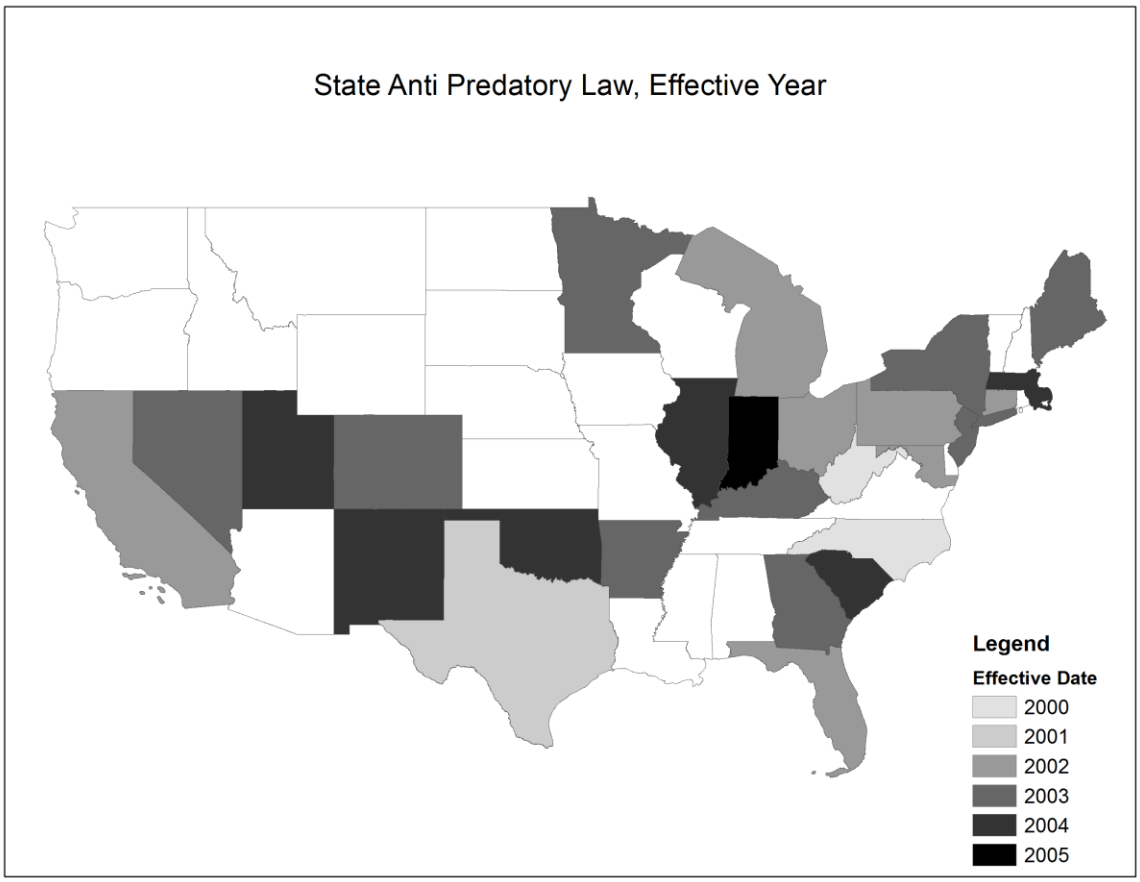

Figure 4 State Anti-Predatory Law Effective Year

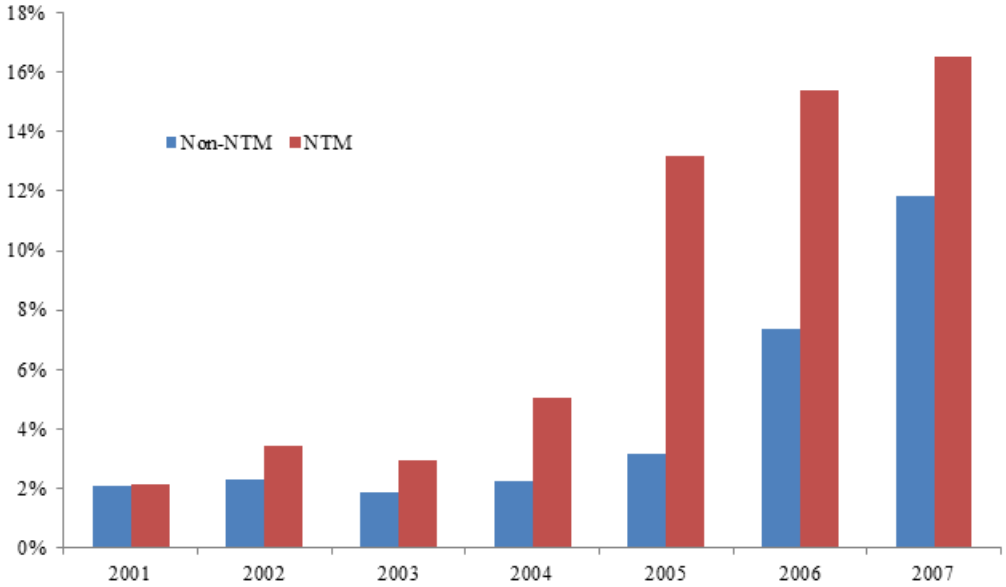

Figure 5 Default Rate of NTMs and non-NTMs

Table 1 Number and Share of NTMs in our Sample and their Features

Number and share of loans	Pooled	By year					
	2001-2006	2001	2002	2003	2004	2005	2006
All loans	4,175,652	124,250	302,143	702,560	963,217	1,087,229	996,253
# NTM	1,524,373	22,569	60,074	144,588	322,650	526,261	448,231
% NTM	*37%*	*18%*	*20%*	*21%*	*33%*	*48%*	*45%*
% NTM in high lending concentration area	31%	15%	16%	18%	27%	41%	39%
% NTM in low concentration area	40%	22%	23%	23%	35%	51%	47%
# IO or Negative Amortization	506,301	469	5,147	20,851	113,705	185,031	181,098
% IO or Negative Amortization	*12%*	*0%*	*2%*	*3%*	*12%*	*17%*	*18%*
# option ARM	482,534	4,889	18,029	46,431	119,809	187,218	106,158
% option ARM	*12%*	*4%*	*6%*	*7%*	*12%*	*17%*	*11%*
# with balloon payment	10,322	256	681	2,373	2,982	1,664	2,366
% with balloon payment	*0%*	*0%*	*0%*	*0%*	*0%*	*0%*	*0%*
# over 30-year term	71,127	274	452	742	2,453	25,249	41,957
% over 30-year term	*2%*	*0%*	*0%*	*0%*	*0%*	*2%*	*4%*
# low/no doc	729,417	16,771	36,098	76,973	104,118	253,105	242,352
% low/no doc	*17%*	*13%*	*12%*	*11%*	*11%*	*23%*	*24%*

Note: This is based on the McDash Servicing Analytics data. NTM is a loan with any of the listed features in the table, i.e., interest only (IO), option ARM, with balloon payment, over 30-year term, and low or no documentation of income and/or asset. The McDash data has a lower representation of the Fannie Mae and Freddie Mac loans (which are mostly non-NTMs) in early years, so the share of NTMs we see in this table in the early years is higher than that is shown in Figure 1 based on Acolin et al. (2017). Lending concentration is measured by the Herfindahl-Hirschman Index (HHI) of lenders' share of the market. High lending concentration area is the top quartile based on the HHI and low lending concentration area is the bottom quartile.

Table 2 Characteristics of NTMs and non-NTMs

NTM Characteristics	Pooled	By-year					
	2001-2006	2001	2002	2003	2004	2005	2006
FICO at Origination	704	692	705	711	701	704	705
Debt to Income at Origination	33	29	30	31	34	34	35
Income at Origination ($ 000)	88	71	116	104	115	123	128
Loan to Value at Origination	79	85	81	80	79	79	79
White	61%	63%	63%	66%	61%	58%	57%
Black	7%	11%	7%	6%	6%	7%	8%
Hispanic	14%	13%	9%	10%	13%	16%	17%
Asian	6%	3%	5%	6%	6%	7%	8%
Other Races	14%	14%	20%	17%	20%	19%	18%
Prime Conventional Characteristics							
	2001-2006	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**
FICO at Origination	728	749	749	748	748	752	752
Debt to Income at Origination	33	30	31	32	31	33	34
Income at Origination ($ 000)	70	76	104	90	100	108	114
Loan to Value at Origination	80	75	76	76	75	74	74
White	70%	60%	67%	70%	71%	72%	71%
Black	5%	3%	3%	3%	3%	4%	4%
Asian	4%	2%	3%	4%	4%	5%	5%
Hispanic	8%	5%	6%	6%	7%	7%	8%
Other Races	15%	32%	24%	21%	19%	17%	18%

Table 3 NTM Probit Model Estimates

	Model 1	Model 2	Model 3	Model 4
MSA HHI of lending concentration	-0.083***			
	(0.031)			
County HHI of lending concentration		-0.053***		
		(0.010)		
County HHI instrumented by M&A			-0.143***	
			(0.027)	
County avg. 30-year FRM mortgage spread				-0.176***
				(0.053)
Borrower credit score	-0.006***	-0.006***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
Debt-to-income ratio	-0.005***	-0.005***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
Loan-to-value ratio	-0.001	-0.001**	-0.001	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
African American borrower	0.086***	0.093***	0.102***	0.102***
	(0.016)	(0.010)	(0.016)	(0.011)
Hispanic borrower	0.112***	0.113***	0.132***	0.118***
	(0.021)	(0.010)	(0.012)	(0.010)
Asian borrower	0.065*	0.076***	0.051*	0.071***
	(0.035)	(0.023)	(0.028)	(0.023)
Other non-white borrower	-0.026**	-0.026***	-0.015*	-0.025***
	(0.010)	(0.006)	(0.008)	(0.007)
Owner-occupied property	-0.204***	-0.205***	-0.201***	-0.204***
	(0.014)	(0.008)	(0.012)	(0.008)
Zip code % of African American	0.136***	0.125***	0.184***	0.161***
	(0.036)	(0.032)	(0.033)	(0.034)
Zip code % of Hispanic	0.218**	0.196***	0.249**	0.235***
	(0.089)	(0.064)	(0.097)	(0.065)
Zip code % of college graduates	0.601***	0.563***	0.577***	0.541***
	(0.069)	(0.050)	(0.061)	(0.051)
County/MSA price-to-income ratio	0.111***	0.117***	0.100***	0.113***
	(0.014)	(0.012)	(0.015)	(0.013)
Zip code HPA, lag	0.006***	0.007***	0.006***	0.007***
	(0.002)	(0.001)	(0.002)	(0.001)
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
N	2,544,649	3,361,010	1,715,350	3,049,719
LogL	-1,557,616	-2,073,937	-1,039,849	-1,882,792
AIC	3,115,332	4,148,012	2,079,827	3,765,722
McKelvey and Zavoina's R-Squared	0.23	0.22	0.24	0.22

Table 4 By-Year NTM Probit Model Estimates

Panel A	2001	2002	2003	2004	2005	2006
MSA HHI of lending concentration	-0.084**	-0.104***	-0.072*	-0.073	-0.043	-0.056
	(0.038)	(0.033)	(0.039)	(0.045)	(0.055)	(0.052)
Control variables	Same as in Table 3					
N	70,554	174,206	415,086	539,540	698,215	647,048
LogL	-44,425	-110,410	-266,608	-338,536	-414,813	-407,439
AIC	88,880	220,850	533,246	677,102	829,655	814,909
McKelvey and Zavoina's R-Squared	0.18	0.12	0.11	0.19	0.21	0.17

Panel B	2001	2002	2003	2004	2005	2006
County HHI of lending concentration	-0.071***	-0.045***	-0.026*	-0.061***	-0.073***	-0.082***
	(0.014)	(0.013)	(0.014)	(0.016)	(0.015)	(0.016)
Control variables	Same as in Table 3					
N	96,064	234,403	544,375	708,247	919,150	858,814
LogL	-59,852	-148,239	-349,975	-442,482	-552,487	-544,505
AIC	119,733	296,507	699,981	884,993	1105,003	1089,039
McKelvey and Zavoina's R-Squared	0.20	0.12	0.11	0.20	0.22	0.17

Panel C	2001	2002	2003	2004	2005	2006
Top 5 lenders HHI	-0.083***	-0.080***	-0.065***	0.004	0.043***	0.027*
	(0.018)	(0.014)	(0.015)	(0.013)	(0.012)	(0.014)
Market share of non-bank lending	0.052	0.024	0.032*	0.143***	0.142***	0.137***
	(0.043)	(0.022)	(0.018)	(0.017)	(0.016)	(0.020)
Control variables	Same as in Table 3					
N	96,063	234,399	544,366	708,236	919,137	858,804
LogL	-59,735	-147,805	-349,020	-439,657	-549,206	-542,053
AIC	119,501	295,642	698,072	879,347	1,098,443	1,084,138
McKelvey and Zavoina's R-Squared	0.20	0.12	0.11	0.21	0.23	0.17

Table 5 Impact of Predatory Lending Law on NTM Origination

	Model 1	Model 2
County HHI of lending concentration	-0.053***	-0.047***
	(0.001)	(0.051)
Anti-predatory lending law (APL)	-0.027***	-0.026***
	(0.003)	(0.005)
County HHI × APL		-0.024***
		(0.093)
Control variables	Same as in Table 3	
N	3,361,010	3,361,010
LogL	-2,073,898	-2,073,841
AIC	4,147,938	4,147,826
McKelvey and Zavoina's R-Squared	0.22	0.22

Table 6 Impacts of Predatory Lending Law on Default

	High lending concentration counties	Low lending concentration counties
Non-traditional mortgage (NTM)	0.245***	0.459***
	(0.014)	(0.016)
Anti-predatory lending law (APL)	0.128***	0.117*
	(0.025)	(0.063)
NTM × APL	-0.237***	-0.185***
	(0.023)	(0.071)
Zip code-level HPA	-1.530***	-1.634***
	(0.119)	(0.049)
County-level credit card 60-day delinquency rate	0.019*	0.060***
	(0.011)	(0.023)
Loan characteristics	Yes	Yes
Borrower characteristics	Yes	Yes
Vintage FE	Yes	Yes
State FE	Yes	Yes
N	803,225	829,548
LogL	-134,526	-207,423
AIC	269,188	414,945
McKelvey and Zavoina's R-Squared	0.34	0.46

Appendix Table 1 Sample Descriptive Statistics

	2001-2006 Pooled		By-year Mean					
	Mean	**STD**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**
MSA HHI of lending concentration	3.3%	0.01	3.7%	3.8%	3.4%	3.3%	3.1%	3.2%
County HHI of lending concentration	4.0%	0.02	4.7%	4.8%	4.2%	3.9%	3.7%	3.8%
FICO at Origination	712	63.94	700	708	716	712	713	712
Debt to Income at Origination	33	13.70	31	31	32	33	34	35
Loan to Value at Origination	80	14.81	83	82	81	79	78	79
Black	6%	0.24	8%	7%	6%	5%	7%	8%
Hispanic	11%	0.31	9%	8%	9%	10%	12%	13%
Asian	6%	0.23	3%	4%	6%	6%	7%	6%
Other Races	15%	0.36	21%	17%	13%	21%	12%	12%
Owner-occupied as a Principal Dwelling	86%	0.35	92%	90%	89%	86%	84%	87%
Percent Black, ZIP 2000	9%	0.15	11%	10%	9%	9%	9%	10%
Percent Hispanic, ZIP 2000	9%	0.13	9%	8%	9%	9%	9%	9%
Median Value/Median Household Income	10.80	0.16	10.73	10.77	10.82	10.81	10.80	10.79
Percent Annual HPA, ZIP over previous year	12.7	1.29	6.8	5.9	5.4	11.0	14.8	8.5
County-level credit card delinquency rate	3.2	8.16	3.7	3.8	3.9	3.3	2.7	2.8

Appendix Table 2 By-Year NTM Probit Model Estimates of Interaction between Concentration on Non-Bank Lending

	2001	2002	2003	2004	2005	2006
County HHI of lending concentration	-0.076**	-0.062**	-0.035	-0.036*	-0.028	-0.037*
	(0.031)	(0.028)	(0.025)	(0.021)	(0.020)	(0.020)
Market share of non-bank lending	0.062**	0.050**	0.062***	0.138***	0.130***	0.121***
	(0.024)	(0.019)	(0.018)	(0.018)	(0.017)	(0.020)
County HHI*Market share of non-bank lending	-0.020	-0.022	-0.026**	-0.025**	-0.028**	-0.031**
	(0.016)	(0.015)	(0.013)	(0.010)	(0.012)	(0.012)
Control variables	Same as in Table 3					
N	96,063	234,399	544,366	708,237	919,139	858,806
LogL	-59839	-148085	-349453	-439508	-549353	-541966
AIC	119712	296205	698940	879049	1098740	1083966
McKelvey and Zavoina's R-Squared	0.20	0.12	0.11	0.21	0.23	0.17