Competition in Local Mortgage Markets*

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ABSTRACT

We identify local lending shocks for competing mortgage providers by uncovering discontinuities in mortgage acceptance models. Shocks to standard measures of the concentration of its competitors do not explain a bank's future lending patterns. Instead it is the expansion of a bank's most aggressive competitor that leads to reduced lending, particularly at the very local level. A stronger shock to this competitor also leads a bank to charge higher interest rates, which are partially explained by the observable worsening of its borrower pool. Competition also has a negative effect on unobservable risk; it leads to worse mortgage performance.

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The competitiveness of banking markets is important both for its direct impact on the quantity and pricing of financing made available to borrowers and for the potential spillover effects of lending terms on broad sectors of the economy. As a result, banking competition has been the subject of sustained interest both in academic and policy circles.[1] One of the main focuses of previous work has been to assess market concentration measures in markets defined at the Metropolitan Statistical Area (MSA) level or larger. In this paper, we study mortgage market competition at the micro level of census tracts. We show that the local neighborhood is a critical locus of competitive interactions and that standard concentration measures do not capture central aspects of this competition. We propose instead a new measure of competition based on the actions of a bank's most aggressive competitor and show that the activities of this competitor have a sizeable impact on a bank's origination volume, loan pricing and mortgage performance.

Our approach is to employ plausibly exogenous bank-specific variation in the attractiveness of U.S. mortgage applications to generate local lending shocks, and we find that these shocks have an effect on a bank's future lending in the neighborhood. We view the local lending shocks of competing banks as generating exogenous variation in the competitive environment. We have three main findings. First, shocks to common measures of concentration such as the lending of the three largest local banks or the Herfindahl-Hirschman Index (HHI) do not explain future lending patterns. We find instead that it is the competitor subject to the largest lending shock (i.e., the most aggressive competitor) that

[1]See Berger, Demsetz and Strahan (1999) and Degryse and Ongena (2008) for literature reviews and `https://www.federalreserve.gov/bankinforeg/competitive-effects-mergers-acquisitions-faqs.htm` (accessed Feb. 27, 2017) and DOJ-FTC (2010) for regulatory guidelines.

has the most substantial negative effect on a bank's future originations. Second, competitors' lending shocks have an impact at the very local level: effects are greatest at the census tract, smaller at the zip code and not significant at the MSA. Third, somewhat unexpectedly, greater competitive shocks lead banks to increase the rates they charge locally. This is at least partially explained by the fact that greater competition leads banks to lend to worse quality borrowers. In fact, we find during our sample period that these rate increases were insufficient to compensate banks facing competitive shocks for the additional risk of their new borrowers; we show that greater competition led to dramatically worse performance for a bank's mortgages.

From a theoretical perspective, what should be the impact on a bank of a surge in its competitors' lending? A number of papers suggest that a firm will reduce its activity in the face of increased competition. Caminal and Vives (1996) argue that market share serves as a signal of quality to consumers. Increased lending by a competitor will therefore attract potential borrowers, reducing lending opportunities for other banks. Fudenberg and Tirole (1986) show that a firm may engage in aggressive actions to complicate a competitor's assessment of its own profitability, thereby encouraging the competitor's exit from the market. Milgrom and Roberts (1982) demonstrate that firms may undertake predatory actions to deter competitors. Applying these models to a banking setting suggests that increased lending by one bank will lead to reduced lending by its competitors. Our results provide support for these theories and identify the most aggressive local competitor as the key driver of the predicted negative effects.

Bank strategies are fundamentally endogenous, a fact that must be confronted in any study of bank competition. Our empirical design is centered on identifying shocks to the probability that a bank extends a mortgage to a given applicant. We begin by splitting into two sections the 251 million mortgage applications in the Home Mortgage Disclosure Act (HMDA) database between 2003 and 2014. Using one part, labeled the training sample, we use each applicant's debt-to-income (DTI) ratio — a standard input to mortgage approval models (e.g., Mian and Sufi 2009, Dell'Ariccia, Igan and Laeven 2012) — to estimate jumps in the average acceptance rate of mortgage applications across narrow DTI bins for each bank across different individual characteristics.

We then discard the training sample but apply its estimated acceptance rate jumps to the other half of the HMDA data (the test sample), by imputing them to applications in similarly defined DTI bins. We demean these jumps from those of other banks to generate a bank-specific estimate of the shock to the attractiveness of an application with a given DTI relative to other applications with very similar DTIs. Our first result is that applicants from the test sample with DTIs in narrow bins shown to have jumps in acceptance rates in the training sample are indeed discontinuously more likely to be offered a loan. We show that these loan attractiveness shocks are unrelated to a number of contemporaneous covariates across DTI bins, suggesting that favored applications are otherwise quite similar to unfavored applications. Further, we document that there is not a inordinate number of applications in the attractive bins, thus offering evidence that loan officers are not systematically manipulating them into the favored narrow bins.

We define local lending shocks by aggregating each bank's application attractiveness shocks jointly at the census tract and application amount decile level, and consider their impact on the future (next year) lending of the bank. To be sure, as described above, exogenously attractive applications are more likely to be offered a loan, but how does the aggregate shock influence the bank's expansion next year in that local market? We find a positive and statistically strong effect of current year shocks on next year's number of local originations, controlling for bank, local market, and year fixed effects. The elasticity of future originations with respect to current originations is approximately 40%. We also find that current period shocks generate more future applications and a higher dollar volume of future originations. The magnitudes of the impacts on applications and originations are similar, suggesting that the main driver of increased future lending is greater borrower interest, rather than a change in bank local lending policy.

These local lending shocks are defined for each bank, which allows us to study the impact on a bank of shocks to its competitors. Do future originations for one bank come at the cost of future originations to its competitors? We show that a bank's future lending is unaffected by the total shocks of its competitors, the shocks of its three largest competitors or the shock to the local HHI. We do, however, find that the competitor with the largest current origination shock significantly hurts the focal bank's future lending. The elasticity of bank's future lending with respect to the largest current origination increase of its competitors is roughly -12%. This suggests that the most aggressive competitors in the banking market have a significant influence on a bank's expansion and should not be pooled with others when considering the competitive landscape. We further show the negative impact of the most aggressive tract-level competitor is more than twice that of the most aggressive zip code-level competitor. The most aggressive competitor at the MSA level has an insignificant impact on a bank's lending. In this sense, the relevant market for the competitive shocks we analyze is highly localized. This is consistent with work showing that competitive effects diminish considerably with distance for firms in a variety of industries (Davis 2006, Pinske, Slade and Brett 2002 and Seim 2006) including banking (Degryse and Ongena 2005).

What is the price response of a bank to increased competition? Somewhat surprisingly, we find that banks increase the rates they charge in the face of greater competition. We show that increased shocks to a bank's most aggressive competitor lead to changes in its pool of borrowers. Specifically, FICO scores of borrowers decline, which partially explains the increase in rates charged. It appears that competition leads banks to retreat to a risker subset of the overall market.

Do all these competition considerations matter for loan performance? We merge the HMDA loan-level data with information from BlackBox, Fannie Mae and Freddie Mac on loan performance to study whether the current origination shocks impact the future delinquency status of bank portfolios. We find that a bank's current origination shocks have no significant effects on future loans' probability of delinquency. However, we find that delinquency is strongly increasing in the origination shock of the most aggressive competitor of the focal bank. This suggests that banks underestimated the powerful negative effects of competition on the quality of their local borrowing pools. Competition appears to have increased both observable and unobservable risks.

Most studies of banking competition have focused on either broad market regulatory constraints (e.g., Jayaratne and Strahan 1996 and Barth, Caprio and Levine 2004) or bank-specific evaluations of competitive behavior (e.g., Schaeck, Cihak and Wolfe 2009 and Bikker, Shaffer and Spierdijk 2012). Our emphasis is on the role of micro banking markets and the identities of the key competitive players, who may well differ from one local market to another, even within larger markets such as MSAs. The same bank can play very different competitive roles in varying local areas. The local competitive actions of lenders along dimensions such as advertising (Gurun, Matvos and Seru 2016), information acquisition (Stroebel 2016), and their potential exertion of market power (Scharfstein and Sunderam 2016) have attracted recent attention. Our results provide a general large-sample examination of how mortgage lenders compete following origination shocks at the local level of census tracts-loan decile markets. Our findings describing how competitive effects are selectively rivalrous, highly sensitive to spatial considerations, and influential for loan terms, borrower pool composition and mortgage performance expand the current understanding of financial institutions' strategic interactions.

I Data

The data in this paper consist primarily of residential mortgage loan applications reported to the Federal Financial Institutions Examination Council under the Home Mortgage Disclosure Act (HMDA) for the years 2003 through 2014. The HMDA requires that all financial institutions ("lenders") subject to the regulation[2] report into the Loan Application Registrar information about all applications for a residential mortgage loan

[2]Institutions subject to the HMDA are those that have a branch or office within a defined Metropolitan Statistics Area.

that it receives within a particular calendar year. The data covers about 80 percent of all residential mortgage loans nationwide (e.g., Bhutta, Popper, and Ringo 2015).

There are 219,612,982 application observations in the full data set. We split into the training and test samples all applications with a DTI less than five[3], leaving 104,933,664 and 104,944,092 in each sample respectively. Observations are dropped from the test sample if the corresponding DTI bin in the training sample is an empty set. Our final test sample then consists of 103,068,422 loan applications. All of the following statistics, unless otherwise noted, are in regards to this population.

As described in Table I, the data include detailed demographic and geographic characteristics as well as the borrower's income and the requested loan amount (each rounded to the nearest thousand). The DTI reported is the ratio of the requested loan amount to the income of the prospective borrower. Demographic information primarily consists of race and ethnicity. General loan type characteristics are also reported, including whether or not the loan will be occupied by the borrower, whether it is a conventional loan (any loan other than FHA, VA, FSA, or RHS loans), the property type, and whether the loan was for the purchase of a home or to refinance. We also observe whether or not the loan application was accepted by the lender and whether or not it was ultimately originated.

The HMDA data set includes a geographic indicator at the census tract level. We associate a corresponding zip code by utilizing the United States Postal Service Zip Code Crosswalk files from the U.S. Department of Housing and Urban Development. These files

[3]Our empirical method requires that DTIs lie in a fairly dense range, so we exclude outlier DTIs from the analysis

provide the percentage of residential addresses for a census tract that lay within a particular zip code. We assign the zip code that is most prevalent within a census tract as the zip code for that loan application.

Our data contain 12,557 unique lenders (87,252 lender-years) and 87,424 census tracts[4] (807,952 tract-years). Local markets are likely different for loans of different sizes. We calculate requested loan amount deciles across the entire data set and define a local market of applications to be the set of all applicants in a given year that are located in the same census tract and belong to the same requested loan size decile. Tracts are then divided into 821,768 markets (6,594,937 market-years), providing a total of 38,526,152 lender-market (65,375,784 lender-market-year) observations.

Additionally we append performance data (observed for the life of the loan within a securitization, through December 2015) and a broader set of borrower characteristics to a subset of loans using loan-level data provided from BlackBox Logic for a subset of 13,061,184 originated loans (6,234,543 in the test sample), from the Fannie Mae Single-Family Loan Performance Data for a subset of 14,982,509 originated loans (7,075,341 in the test sample) and from the Freddie Mac Single Family Loan-Level Dataset for a subset of 13,287,303 originated loans (6,313,509 in the test sample). Summary Statistics for performance outcomes in the test sample are presented in Table I.

[4]This is 13,290 more census tracts than were defined in the 2010 census because our sample crosses census regimes. Census tract boundaries were redefined after the 2010 census and some tract designations were eliminated while others were created.

II Empirical Specification

The focus of this study is to assess the effectiveness of various bank strategies in the mortgage market. Strategies, however, are deeply endogenous and may be influenced by a variety of unobserved factors. Our empirical specification therefore aims to identify plausibly exogenous shocks to bank lending activity in local markets. From a general perspective, we begin by estimating bank origination models. Using these models, we identify certain mortgage applications as relatively attractive to a given bank, while other applications are less attractive. We view the frequency of relatively attractive applications as a shock to a bank's lending activity in that market. We use our measure of relatively attractive applications as an instrument for the bank's local lending volume this period, and trace its impact on future lending.

A Estimating Bank Acceptance Models Using the Training Sample

The first step in our analysis is to assign each application, with equal probability, to either the training or test samples. The training sample is used to estimate bank acceptance models while the test sample is set aside for later analysis. The key variable in our estimated acceptance models is the applicant's debt-to-income ratio (DTI). The DTI is standard input to bank decision models (Dell'Ariccia, Igan and Laeven 2012). We do not observe loan interest rates (or the rate for which the applicant applied) so we calculate the DTI as the ratio of the loan amount requested to the applicant's income. We group applications into bins of DTI of width 0.1, and we define separate bins for each bank b every year t for each defined set of applicant characteristics c. We center the bin boundaries at the DTI sample mean $\hat{\mu} = 2.12$. Formally, we define DTI bin i for bank b in year t for applicants with characteristics c as

$$bin_{i,b,t,c} = \big\{ applications : applicant\, applied\, to\, bank\, b\, in\, year\, t, \tag{1}$$

$$has\, characteristics\, c\, and\, has\, DTI \in \big[0.1 * i + \hat{\mu}, 0.1 * (i + 1) + \hat{\mu}\big)\big\},$$

where the set of characteristics c is a 2-tuple describing the applicant's ethnicity (white or non-white) and owner-occupancy status and i may take positive, zero or negative values as the bins range over the full set of sample DTIs.

We then calculate an average acceptance rate $ar(bin_{i,b,t,c})$ for each bin. Underlying our approach is the idea that banks have origination models that depend on applicant DTIs and that may differ across the range of applicant characteristics. By calculating acceptance rates for each bin using the training sample, we are recovering an estimate of each bank's acceptance model.

B Uncovering Discontinuities in Estimated Acceptance Rates

The training sample thus supplies us with an estimated acceptance rate for every observation that is a function of the observation's bin. We now discard the training sample but use the model we estimated from it to assign to each observation k in the test sample an estimated acceptance rate that depends on its bin.

We are interested in identifying applications that are relatively attractive to specific banks. In particular, we seek applications that are substantially more likely to be accepted by a bank than other, quite similar, applications. Our analysis therefore contrasts the estimated average acceptance rates of neighboring bins. For example, if one bin has a much higher estimated acceptance rate than its neighbor with a higher DTI, then applications in the first bin are apparently much more attractive to a bank than those in the second. This could arise from the use of a DTI cutoff in the bank's acceptance model.[5] We make use of the estimated bank acceptance models to identify these acceptance ratio jumps. We define comparison bins that straddle two bins and contrast the estimated average acceptance rates across the two bins that are straddled. Formally, we define comparison bin i for bank b in year t for applicants with characteristics c as

$$compbin_{i,b,t,c} = \Big\{applications : applicant\ applied\ to\ bank\ b\ in\ year\ t, \tag{2}$$

[5] For a recent application, see Consumer Financial Protection Bureau (2016). Agarwal et al. (2015) study the use of credit score cutoffs.

$$has\ characteristics\ c\ and\ has\ DTI \in \big[0.1 * i + \hat{\mu} + 0.05, 0.1 * (i+1) + \hat{\mu} + 0.05\big)\big\}.$$

Comparison bin $compbin_{i,b,t,c}$ thus straddles half of $bin_{i,b,t,c}$ and half of $bin_{i+1,b,t,c}$. Every observation j in the test sample is a member of a bin denoted by $bin(j)$ and a comparison bin denoted by $compbin(j)$. We estimate the regression

$$ar(bin(j)) = \alpha_{compbin(j)} + u_j, \tag{3}$$

where $ar(bin(j))$ is the average acceptance rate of $bin(j)$, $\alpha_{compbin(j)}$ is a fixed effect for all the elements of $compbin(j)$ and u_j is an error term. The residuals $\hat{u}_j$ from regression (3) provide information about the differences in estimated acceptance rates between observation j's bin and the neighboring bin that is included in the comparison bin. Observations with a positive residual are in relatively high estimated acceptance ratio bins: they appear to be attractive to the bank. Observations with a negative residual are in apparently less attractive bins.

To identify *bank-specific* origination shocks, for each bank and set of characteristics we demean $\hat{u}_k$ by the corresponding shocks for the relevant DTI bin for all banks in the sample that year. We label these bank-specific shocks $\hat{v}_k$, and we use them as our primary measure of discontinuities in bank acceptance models. Industry-wide DTI cutoffs are thus not reflected in these shocks- they identify loans that are particularly attractive or unattractive to a given bank.

C Acceptance Rate Jumps and Mortgage Origination in the Test Sample

Does the estimated acceptance model from the training sample actually predict the origination of mortgages from the test sample applications? To answer this question, we regress for every observation k in the test sample

$$originate_k = \xi \hat{v}_k + \epsilon_k, \tag{4}$$

where ϵ_k is an error term. The $\hat{v}_k$ terms describe bank-specific origination shocks generated from jumps in estimated loan acceptance models. A positive and significant estimate of ξ indicates that the acceptance model estimated from the training sample does indeed predict jumps in originations in the test sample over small ranges of DTI.

We define market-bank shocks $\hat{v}_{M,b,t}$ to be the sum of all the $\hat{v}_k$ for applications in a given market M made to bank b in year t. We examine the impact of these shocks on total current originations by the bank in this market:

$$originations_{M,b,t} = \phi \hat{v}_{M,b,t} + \beta_M + \zeta_b + \delta_t + controls + \eta_{M,b,t} \tag{5}$$

where β_M is a market fixed effect, ζ_b is a bank fixed effect, δ_t is a year fixed effect and $\eta_{M,b,t}$ is an error term. We also consider the impact of the origination shocks on future market-bank characteristics in regressions of the form

$$future\,outcome_{M,b,t+1} = \psi \hat{v}_{M,b,t} + \beta_M + \zeta_b + \delta_t + controls + \theta_{M,b,t} \tag{6}$$

where future outcomes include application and origination volumes and loan performance measures in the following year and $\theta_{M,b,t}$ is an error term. A positive and significant estimate of ψ is evidence that plausibly exogenous shocks to a bank's local originations this year generate an increase in the bank's local originations in the following year. We typically cluster the standard errors in these regressions at the bank and market levels.

III Results

A Relatively Attractive Loans and Origination

As described in Section II, we use the training sample to estimate acceptance models and to identify loans that have DTIs that appear to make them attractive to a given bank. Our first test examines whether the loans in the test sample that are predicted to be attractive are actually accepted and originated by banks. We estimate equation (4) with mortgage acceptance by the bank as the dependent variable. The result is displayed in the first column of Table II. We find a coefficient on the bank-specific shock of 0.02 and a t-statistic of 19.78. This is clear evidence that the estimated acceptance model from the training sample does identify jumps in the bank's probability of granting a loan. Test sample applicants with

DTIs in narrow bins shown to be favored in the training sample are significantly more likely to be offered a loan.

Including DTI as a control has little impact on the estimated effect of the bank-specific shock, nor does including a third-degree polynomial in DTI, as shown in the second and third columns of Table II. The DTI bins and comparison bins are quite narrow, and the bank-specific shock is capturing discontinuities in acceptance rates for applications with very similar DTIs. As expected, we do find in the regression described in the second column that higher DTI loans are less likely to be accepted, but including this variable has very little impact on our the bank-specific shock coefficient estimate. In the fourth column of Table II, we show that our main result is also robust to the inclusion of bank and year fixed effects and to clustering at the bank level. Including third degree polynomials in the distance of an application's DTI from the closest bin boundary also has little effect, as shown in the fifth column of Table II.

The results in the sixth through tenth columns of Table II show that bank-specific jumps are highly effective in predicting loan origination, as well as loan acceptance. The estimated coefficient on the bank-specific shock is robust to including DTI, a third-degree polynomial in DTI, bank and year fixed effects and a third-degree polynomial in distance to the bin boundary.

B Covariate Balance

The results in Table II show that the estimated bank-specific acceptance rate jumps do identify applications that a particular bank is likely to originate. Do these loans differ in other ways from loans with similar DTIs that the bank is less likely to originate? The basic acceptance rate jumps are estimated from models that condition on ethnicity and owner-occupancy status so we expect little systematic variation between high and low jump applications across these variables. The bank-specific acceptance rate jumps, though, reflect an additional adjustment for jumps from other banks and might in theory weight more heavily on one of these characteristics. Do other characteristics such as loan type (conventional or non-conventional), property type (single or multi-family) and loan purpose (purchase or refinance) covary with the bank-specific shocks? To examine this question, we regress indicators for all these characteristics on the bank-specific acceptance rate jump and display the results in Table III. As shown in the first five columns of the table, there is no significant relationship between the bank-specific jumps and any of these characteristics. In the sixth column of Table III we show that there is also no systematic relationship between the bank-specific jumps and a loan's DTI: the bank-specific jumps identify loans that are attractive to a bank relative to other loans with quite comparable DTIs. The result displayed in the seventh column of Table III shows that the bank-specific shocks are not correlated with the jumbo status of the loan application.

B.1 Loan Officer DTI Manipulation

Might it be the case that the bank wants to make certain loans and therefore manipulates the income or loan amount to ensure origination? There is well-documented evidence of misrepresentation in retail mortgage applications (Jiang, Nelson and Vytlacil 2014, Garmaise 2015 and Griffin and Maturana 2016). It is important to note, however, that we are focusing on bank-specific jumps in the acceptance rate. Any industry-wide factors such as minimum DTIs for securitization have been removed. If the bank as an organization wanted to originate a specific loan in a given area, it could presumably choose to do so, making an exception to its own rules if that is what it desired. A more difficult question is whether particular loan officers may be manipulating the DTI to ensure origination of their loans. There is evidence for this practice as well (Keys et al. 2010). Are the loans with positive acceptance rate jumps chosen quasi-randomly or are they the specific loans manipulated by loan officers to boost origination volume?

We explore this issue by calculating application counts for each bin and comparison bin pair. For each pair, we also have a bank-specific acceptance rate jump. If loan officers are manipulating applications so that they enter the narrow DTI ranges that are relatively attractive, then we should expect to see more applications in those ranges and fewer in the less attractive ranges. We test this hypothesis by regressing the log of the number of applications on the bank-specific acceptance rate jump. Results are displayed in the eighth column of Table III. The t-statistic on the bank-specific acceptance rate jump is 1.10. In other words, there is no systematic evidence that loan officers are pushing applications into the most attractive bins. While this manipulation was likely present to some degree during the sample period, it does not appear to have been prevalent enough to affect our results.

C Local Origination Shocks and Future Lending Activity

We now analyze the impact of a bank's expansion of its current market presence on its future local lending activity in the same market. When we observe banks lending more in a given area this is often driven by strategic considerations and other unknown determinants. Any observed correlations over time in local lending could be due to medium-term bank decisions to concentrate on certain markets. It is difficult to assess the future causal impact on a bank of more lending today in a given region. We propose to use the presence of bank-specific relatively attractive applications as a plausibly exogenous shock to the bank's current local lending. Consider a bank that receives applications in two different areas. Suppose the average DTIs of applicants in both areas are quite similar, but that, due to chance, most of the applicants in the first area fall just short of the bank's institution-specific DTI cutoffs while most of the applicants in the second area have DTIs that slightly exceed these thresholds. It is likely that the bank will make relatively more loans in the first area, as the applications from that area will be regarded as relatively attractive in the bank's acceptance model. We argue that the first area receives a local origination shock. In essence, we are using the discontinuities in the bank's estimated acceptance model to generate an instrument for local bank lending strategy- we are identifying shocks to the amount of lending that banks do in different markets.

In order to generate a measure of local origination shocks, we must define the local market. The HMDA data provide census tract locations for all applicants. Local markets depend on both the location of applicants and the loan size. As described in Section I, we define a local market of applications to be the set of all applicants in a given year that are located in the same census tract and belong to the same requested loan size decile. The local market for loans is defined in an analogous manner. We define the local origination shock by aggregating all the bank-specific acceptance rate jumps across the local market. As shown in Table II, these jumps do indeed predict origination at the loan level. We limit attention to banks that exist in the following year and consider whether shocks to current local lending increase future lending as well.

First we consider whether loan-level acceptance rate shocks aggregate. Do banks with higher local origination shocks experience more overall lending this year? We regress the log of one plus the current originations on the current local origination shock and the following set of controls: the log of one plus the number of local originations in the previous year, the log of one plus the current number of applications, bank fixed effects, market fixed effects and year fixed effects. We cluster the standard errors at both the bank and market levels. For market-level regressions like this one, the unit of observation is a bank-market-year. The result, displayed in the first column of Table IV, is that the coefficient on the local origination shock is 0.0163 and the t-statistic is 8.64. This is strong evidence of aggregation: markets with more positive shocks experience significantly more originations that year. This result also makes clear that banks do not adjust or correct for the presence of many relatively-attractive local applications by reducing originations to other applicants to maintain a fixed level of local originations.

To examine the impact of expanded market presence on future lending, we regress the log of one plus the number of local originations next year on the current local origination shock and the previously described controls. We cluster these regressions as well at both the bank and market levels. As detailed in the second column of Table IV, the coefficient on the local origination shock is 0.0065 and the t-statistic is 4.77. A shock to local originations in the current year has a follow-on effect in generating more originations in the next year as well.

In the third column of Table IV we report results from an instrumental variables regression of the log of one plus future originations on the log of one plus current originations, using the local origination shock as an instrument (the first stage from this regression is described in the first column of Table IV). The coefficient on instrumented log of one plus current originations is 0.398 and the t-statistic is 5.31. We use one plus the number of originations in the arguments of the log functions to include markets with zero originations, but this causes the estimated elasticity to depend on the number of current and future originations. As long as these are similar, however, the elasticity of future originations with respect to current originations is approximately 0.398, as described by the coefficient in column three. This gives a sense of the meaningful economic magnitude of the impact of current originations on future lending.

The current period origination shock also generates more applications in the following year (coefficient of 0.0061 and t-statistic of 4.28) and a higher total dollar volume of originations in a year (coefficient of 0.016 and t-statistic of 2.41), as shown in the fourth and fifth columns of Table IV. The coefficients on the origination shock are similar for both total originations and total applications, which suggests that the increased originations are driven by increased applications rather than by a systematic change in future bank local lending standards.

D Competition

What is the impact of a bank's increased lending on other banks in the local market? The most natural hypothesis is that the pool of potential applicants is relatively fixed, in which case increased future originations for one bank must come at the cost of future originations to its competitors. Alternatively, it is possible that more originations in the current year may actually expand the overall market (for example, by raising information levels or general awareness of mortgages) which may lead to a neutral impact or even a potentially positive spillover effect on other banks (Vives 2001). We examine this question by regressing a bank's future originations on its own current local origination shock, the sum of all the local origination shocks of its competitors and the standard controls. The result, described in the first column of Table V, is that the total current origination shock for all competitors has an insignificant effect (coefficient=0.0004 and t-statistic=0.56) on a bank's future originations. This somewhat surprising finding implies that banks may simply ignore the competitive effects of expanded market presence on the part of all their competitors taken as a whole.

It may be suggested that only the actions of a bank's three largest competitors will matter. We regress a bank's future originations on its current origination shock, the origination shock of its three competitors with the largest local market shares and the usual controls. We find an insignificant impact (coefficient=0.0002 and t-statistic=0.13) of the shock of the three largest competitors, as detailed in the second column of Table V. A bank's future originations are unaffected by the extent to which its largest local competitors expands their current lending. We also examine the impact of the origination shocks on the Herfindahl-Hirschman Index (HHI) of all local competitors and show, in the third column of Table V, that increases in the competitors' HHI generated by origination shocks have an insignificant impact on a bank future lending.

It seems unlikely that banks may completely disregard the origination strategies of their competitors. Neither the overall lending of its competitors, nor the lending of its largest competitors or the competitors' HHI appears to be important, but are there some competitors whose actions are strategically relevant? We define a bank's most aggressive competitor as the competitor with the largest current local origination shock. We regress a bank's future originations on its current origination shock, the origination shock of its most aggressive competitor and the standard controls, and we display the results in the fourth column of Table V. We find that the origination shock of the most aggressive competitor has a strong negative impact (coefficient=-0.0218 and t-statistic=-4.67) on the bank's future lending. Banks facing tough competitors do experience a significant reduction in future originations, as suggested by the theories of Caminal and Vives (1996), Fudenberg and Tirole (1986) and Milgrom and Roberts (1982).

These results highlight some interesting features of local banking market competition. Competitive analyses often focus on the market shares or overall quantities produced by a firm's competitors, but these do not appear to have much of an impact on a bank's future lending. It also common for competitive studies to focus on HHI measures of market concentration that are most sensitive to expansion by the largest market players, but we find that an increase in current lending by a firm's largest competitors does not have a significant effect, and nor does the HHI itself. It is instead the actions of a bank's most aggressive competitors that have the most deleterious effect. Essentially, what is most important for a bank are the dynamics of lending activity with a focus on the competitors that are most increasing their originations, rather than a static analysis of current market shares or largest competitors.

E Most Aggressive Competitor

To get a sense of the mechanism underlying the impact of the most aggressive competitor, we regress the log of one plus the largest increase in deal count for any competitor on the origination shock of the most aggressive competitor. The result, reported in the first column of Table VI, shows that the most aggressive origination shock does indeed have a positive and significant impact on the largest deal count increase experienced by any of the bank's competitors. This regression is restricted to the sample in which in the largest increase is at least zero so that the log is well-defined. In this restricted sample, the shock of the most aggressive competitor is again strongly negatively associated with a bank's future originations, as shown in the second column of Table VI. The causal impact of increased loans by the bank's most aggressive competitor is negative, as displayed in the instrumented regression displayed in third column of Table VI. The elasticity of a bank's future originations with respect to the largest increase in originations for its competitors is approximately -12% (t-statisic=-5.12).

It is not sufficient, however, to simply consider the degree to which competitors are increasing originations. In the fourth column of Table VI we detail the results from an endogenous, descriptive regression in which we regress a bank's future deal count on the largest deal count increase experienced by a competitor. We find a *positive* and significant result (coefficient=0.02 and t-statistic=9.04). On a naive interpretation this would seem to suggest that banks benefit when their competitors make more loans. This is likely driven, of course, by the fact that positive local shocks lead to more originations both for a bank and its competitors. The causal impact of increasing lending by a bank's most aggressive competitor, however, as demonstrated in the previous regressions, is clearly negative. When aggregating the origination shocks of the bank's two most aggressive local competitors, we find a similar very negative effect, as shown in the fifth column of Table VI.

How local are the negative competitive effects? We calculate the most aggressive competitor shock at both the zip and MSA-levels and contrast their impact with our main tract-level competitor shock. We regress a bank's future originations on its own tract-level origination shock, the tract-level shock of its most aggressive competitor, the zip-level shock of its most aggressive competitor, the MSA-level shock of its most aggressive competitor and the previous controls. (The zip and tract level competitors are defined at their respective geographies and may thus differ.) We find, as shown in the sixth column of Table VI that the coefficient on the tract-level competitor shock of -0.018 (t-statistic=-5.99) is significantly larger, at the 1% level, than the -0.007 coefficient (t-statistic=-2.66) on the zip-level competitor shock, which is in turn greater at the 10%-level than the -0.001 (t-statistic=-0.48) coefficient on the MSA-level competitor shock. We find that competition between mortgage lenders is a highly localized phenomenon.

F Lender Risk Taking and Competition

How do lenders respond to increased competition? We analyze this question by regressing the interest charged on a mortgage on the previous origination shock of the lender, the previous origination shock of the most aggressive competitor and the standard HMDA application and market controls. We find, as described in the first column of Table VII, that a lender's own previous shock has an insignificant (t-statistic=0.26) effect on the rate charged, but the prior origination shock of the most aggressive competitor has a positive and significant impact (coefficient=0.0904 and t-statisic=6.61). That is, lenders charge higher rates in the presence of increased competition. This a surprising and counter-intuitive finding. To provide additional insight, we regress applicant FICO scores on the origination shocks of the lender and its most aggressive competitor and find, as displayed in the second column of Table VII, that the most aggressive competitor shock has a negative and significant impact (coefficient=-2.83 and t-statisic=-6.02). The lender's own shock has an insignificant impact. In the presence of greater competition, lenders are supplying mortgages to riskier borrowers. This partially explains the higher interest rates they charge, though, including FICO as a control still leaves a negative and significant (but much smaller in magnitude) coefficient on the most aggressive competitor shock, as shown in column three of Table VII. Lender LTV values are unaffected as the most aggressive competitor shock, but loan terms increase, as shown in the fourth and fifth columns of Table VII. An explanation consistent with these results is that greater competition leads lenders to provide mortgages to riskier borrowers- some of this risk is observable to us (in higher FICO scores) and other aspects are not, but the higher risk is reflected in higher rates. As before, changes in the HHI index appear uninformative about loan terms, as shown in columns six through ten of Table VII.

G Performance

In Table VIII we showed that competition leads lenders to lend to riskier borrowers at higher interest rates. What is the impact of competition on future loan delinquency? To address this question, we regress an indicator for whether a loan ever experiences a 60-day delinquency on the previous year local origination shock, HMDA controls, FICO, interest rate, LTV, loan term, bank fixed effects, market fixed effects and year fixed effects. We cluster standard errors at the market and bank levels. The result, displayed in the first column of Table VIII, is that the previous year local origination shock has an insignificant effect (coefficient=0.002 and t-statistic=1.04) on a loan's probability of delinquency.

We examine the impact of competition on performance by regressing the 60-day delinquency indicator on the bank's origination shock, the shock of its most aggressive competitor and the previously outlined controls. The result, shown in the second column of Table VIII, is that delinquency is strongly increasing (coefficient=0.038 and t-statistic=15.85) in the origination shock of the most aggressive competitor. When a bank's most aggressive competitor makes more loans, the performance of the bank's future loans degrades significantly. This result includes a control for interest rate, so it appears that competition has an even more negative impact on lenders than they expected during our sample period. The results in column three of Table VIII shows that this result holds in the specification in which we instrument for the deal increase of the largest competitor with the most aggressive competitor shock. As shown in the fourth column, the shock to HHI has no impact on delinquency. Results described in the fifth through eighth columns of Table VIII confirm the same pattern of results for an indicator for whether a loan ever defaults. The only exception is the unexpected result in the eighth column that a positive shock to HHI appears to be weakly associated with a decrease in delinquency.

Why does the increased lending of the most aggressive competitor have such a negative impact on the bank's loan performance? The results in Tables VI and Table VII show that in the face of strong competition, lenders supply fewer mortgages and focus their lending on a riskier segment of the market. During our sample period, lenders may have underestimated the changing unobservable risk characteristics of the pool of applicants who continue to seek them out when an aggressive competitor is expanding its lending. This suggests that the greatest competitive threat to a bank may be a silent danger: aggressively expanding competitors seize not just more potential applicants but especially those whose positive characteristics are hard to uncover.

IV Conclusion

In this paper we analyze the dynamics of competition in the U.S. mortgage market. We uncover discontinuities in the acceptance rates of applications with very similar debt-to-income ratios, which enables us to identify shocks to the attractiveness of applications for specific banks. We show that banks that receive many relatively attractive applications in a given local market do indeed lend more in that market. We provide evidence that lending more this year leads to more applications and originations in the following year. Banks are not affected by the total lending shock to their competitors, nor by the shock to their three largest competitors or to the local HHI, but the shock to a bank's most aggressive competitor does have strong negative consequences for originations. Greater lending shocks to a bank's most aggressive competitor lead it to charge higher interest rates; this is partly driven by the fact that competition leads to a weaker (lower FICO score) borrower pool for the bank. We further find that a bank's mortgage performance is harmed by competition; the higher rates it charges are insufficient to compensate for the unobservable risk of the borrowers it receives in the face of competition.

Our results show that in certain essential respects banking markets are highly local, with selectively important roles played by various competitors. More generally, our approach of seeking instruments for bank lending activity may be applied to a broader set of questions about competition and firm interactions in other settings.

References

Agarwal, Sumit, Souphala Chomsisengphet, Neale Mahoney, and Johannes Stroebel. 2015. Do Banks Pass Through Credit Expansions to Consumers Who Want to Borrow?. Working Paper 21567. National Bureau of Economic Research.

Bailey, Michael, Ruiqing Cao, Theresa Kuchler, and Johannes Stroebel. 2016. Social Networks and Housing Markets. Manuscript.

Barth, James, Gerard Caprio, Ross Levine. 2004. Bank regulation and supervision: What works best? *Journal of Financial Intermediation* 13: 205–248.

Berger, Allen, Rebecca Demsetz, and Philip Strahan. 1999. The Consolidation of the Financial Services Industry: Causes, Consequences, and Implications for the Future. *Journal of Banking and Finance* 23: 135–194.

Berger, Allen, Nathan Miller, Mitchell Petersen, Raghuram Rajan, and Jeremy Stein. 2005. Does Function Follow Organizational Form? Evidence From the Lending Practices of Large and Small Banks. *Journal of Financial Economics* 76: 237–269.

Bhutta, Neil, Jack Popper, and Daniel R. Ringo, 2015, The 2014 Home Mortgage Disclosure Act Data, Federal Reserve Bulletin, Vol. 101, No. 4.

Bikker, Jacob A., Sherrill Shaffer, and Laura Spierdijk. 2012. Assessing competition with the Panzar-Rosse model: The role of scale, costs, and equilibrium. *Review of Economics and*

Statistics 94: 1025–1044.

Caminal, Ramon and Xavier Vives. 1999. Why Market Shares Matter: An Information-Based Theory. *RAND Journal of Economics* 27: 221–239.

Christen, Markus and Ruskin Morgan. 2005. Keeping up with the Joneses: Analyzing the effect of income inequality on consumer borrowing. *Quantitative Marketing and Economics* 3: 145–173.

Consumer Financial Protection Bureau. 2016. What is a debt-to-income ratio? Why is the 43% debt-to-income ratio important? http://www.consumerfinance.gov/askcfpb/1791/what-debt-income-ratio-why-43-debt-income-ratio-important.html, accessed 21 October 2016.

Davis, Peter. 2006. Spatial competition in retail markets: movie theaters. *RAND Journal of Economics* 37: 964–982.

Degryse, Hans and Steven Ongena. 2005. Distance, lending relationships, and competition. *Journal of Finance* 60: 231–266.

Degryse, Hans and Steven Ongena. 2008. Competition and regulation in the banking sector: A review of the empirical evidence on the sources of bank rents. In Thakor, Anjan and Arnoud W. A. Boot (eds.), *Handbook of Financial Intermediation and Banking*, 483–554.

Dell'Ariccia, Giovanni, Deniz Igan, and Luc Laeven. 2012. Credit Booms and Lending Standards: Evidence from the Subprime Mortgage Market. *Journal of Money, Credit and*

Banking 44: 367–384.

Fudenberg, Drew and Jean Tirole. 1986. A "Signal-Jamming" Theory of Predation. *RAND Journal of Economics* 17: 366–376.

Garmaise, Mark J. 2015. Borrower misreporting and loan performance. *Journal of Finance* 70: 449–484.

Georgarakos, Dimitris, Michael Haliassos and Giacomo Pasini. 2014. Household debt and social interactions. *Review of Financial Studies* 27: 1404–1433.

Goolsbee, Austan and Peter Klenow. 2002. Evidence on Learning and Network Externalities in the Diffusion of Home Computers. *Journal of Law and Economics* 45: 317–344.

Griffin, John M., and Gonzalo Maturana. 2016. Who facilitated misreporting in securitized loans? *Review of Financial Studies* 29.2: 384–419.

Gurun, Umit, Gregor Matvos and Amit Seru. 2016. Advertising Expensive Mortgages. *Journal of Finance* 71: 2731–2416.

Holmes, Thomas and John Stevens. 2004. Spatial distribution of economic activities in North America. In J. Vernon Henderson and Jacques-Francois Thisse (eds.) *Handbook of Regional and Urban Economics*, 2797–2843.

Jayaratne, Jith and Philip Strahan. 1996. The Finance-Growth Nexus: Evidence from Bank Branch Deregulation. *Quarterly Journal of Economics* 111: 639–670.

Jiang, Wei, Ashlyn Aiko Nelson, and Edward Vytlacil. 2014. Liar's loan? Effects of origination channel and information falsification on mortgage delinquency. *Review of Economics and Statistics* 96.1 : 1–18.

Keys, Benjamin, Tanmoy Mukherjee, Amit Seru, and Vikrant Vig. 2010. Did Securitization Lead to Lax Screening? Evidence from Subprime Loans. *Quarterly Journal of Economics* 125: 307–362.

Mian, Atif and Amir Sufi. 2009. The consequences of mortgage credit expansion: Evidence from the 2007 mortgage default crisis. *Quarterly Journal of Economics* 124: 1449–1496.

Milgrom, Paul and John Roberts. 1982. Predation, reputation, and entry deterrence. *Journal of Economic Theory* 27: 280–312.

Petersen, Mitchell and Raghuram Rajan. 1995. The Effect of Credit Market Competition on Lending Relationships. *Quarterly Journal of Economics* 110: 407–443.

Pinkse, Joris, Margaret E. Slade, and Craig Brett. 2002. Spatial price competition: a semiparametric approach. *Econometrica* 70: 1111–1153.

Risselada, Hans, Peter Verhoef, and Tammo Bijmolt. 2014. Dynamic Effects of Social Influence and Direct Marketing on the Adoption of High-Technology Products. *Journal of Marketing* 78: 52–68.

Santikian, Lori. 2014. The ties that bind: Bank relationships and small business lending.

Journal of Financial Intermediation. *Journal of Financial Intermediation* 23: 177–213.

Schaeck, Klaus, Martin Cihak and Simon Wolfe. 2009. Are competitive banking systems more stable? *Journal of Money, Credit and Banking* 41: 711–734.

Scharstein, David and Adi Sunderam. 2016. Market Power in Mortgage Lending and the Transmission of Monetary Policy. Manuscript.

Seim, Katja. 2006. An empirical model of firm entry with endogenous producttype choices. *RAND Journal of Economics* 37: 619–640.

Stroebel, Johannes. 2016. Asymmetric Information About Collateral Values, *Journal of Finance* 71: 1071–1111.

U.S. Department of Justice and Federal Trade Commission. 2010. Horizontal merger guidelines.

Vives, Xavier. 2001. Competition in the changing world of banking, *Oxford Review of Economic Policy* 17: 535–547.

Table I

Summary Statistics

For the first two panels below, observations are at the loan application level. Summary Statistics for all of these items are related to the 103,068,422 applications in the test sample. For the third panel below, observations are at the level indicated. Lender Specific Origination Shock ($\hat{v}_k$) is our primary measure of discontinuities in lender acceptance models. Debt-To-Income is the ratio of the requested loan amount to the applicant's income. Income ('000s) is the applicant's gross annual income in thousands of dollars. Loan Amount ('000s) is the amount, in thousands of dollars, requested for the loan. Loan Accepted is an indicator of whether or not the loan request was approved. Loan Originated is an indicator of whether or not the loan was ultimately originated (and is a subset of Loan Accepted). White is an indicator of whether or not the applicant disclosed their race as white. Owner Occupied is an indicator as to whether or not the proposed loan is intended to be occupied by the applicant. Conventional is an indicator for any loan other than FHA, VA, FSA, or RHS loans. Single Family is an indicator for whether the property type is a one to four family (other than manufactured housing) structure. Purchase is an indicator as to whether the loans is intended for the purchase of a new home (as opposed to for refinancing or home improvement). Market Level Lender Specific Origination Shock ($\hat{v}_{M,b,t}$) is the sum at the market level of all Lender Specific Origination Shocks ($\hat{v}_k$). Deals in Lender-Market-Year is the number of loans a lender originated in a market for the year. Applications in Lender-Market-Year is the number of applications a lender received in a market for the year. Volume ('000s) in Lender-Market-Year is, in thousands of dollars, the total loan amount a lender originated in a market for the year. Lender Count in Market-Year is the count of unique lenders that received a loan application in a market for the year. Lender Deal Share in Market-Year is the number of loans originated by an individual lender divided by the total loans originated by all lenders in a market for the year. For the final panel, the Delinquency and Default Rates are calculated for the loans in the relevant subsamples of the test sample for which performance data was matched. Delinquent is an indicator of whether or not the loan ever went 60 days or more delinquent at any point in the observed performance of the loan. Default is an indicator of whether or not the loan ever entered Foreclosure, became a Real Estate Owned property, or was liquidated (in a manner other than a borrower payoff in full) at any point in the observed performance of the loan. Observed performance of the loan begins at the first month the loan was placed into a securitization and ends at the earlier of loan liquidation, borrower payoff in full, or December 2015.

	Mean	Median	St Dev	10^{th}%	90^{th}%
Lender Specific Origination Shock ($\hat{v}_k$)	0.00	0.00	0.05	-0.03	0.03
Debt-To-Income	2.08	2.02	1.19	0.50	3.76
Income ('000s)	99.09	72.00	149.95	33.00	172.00
Loan Amount ('000s)	175.15	135.00	172.57	35.00	350.00
Loan Accepted	0.64				
Loan Originated	0.57				
White	0.63				
Owner Occupied	0.91				
Conventional	0.90				
Single Family	0.97				
Purchase	0.34				
Market Level Lender Specific Origination Shock ($\hat{v}_{M,b,t}$)	0.00	0.00	0.06	-0.03	0.03
Deals in Lender-Market-Year	1.48	1.00	2.59	0.00	3.00
Applications in Lender-Market-Year	2.60	1.00	3.70	1.00	5.00
Volume ('000s) in Lender-Market-Year	280.52	112.00	1,006.95	0.00	600.00
Lender Count in Market-Year	9.36	6.00	9.41	1.00	21.00
Lender Deal Share in Market-Year	0.10	0.04	0.17	0.00	0.25

	Full Sample	BBx	FNMA	FHLMC
Delinquency Rate	0.17	0.40	0.07	0.07
Default Rate	0.12	0.33	0.02	0.03

Table II

Instrument Tests

This table reports results related to tests of the validity of our methodology for identifying discontinuities in lender acceptance models. An indicator for loan application acceptance (columns 1-5) or loan originated (columns 6-10) within the test sample are regressed on our Lender Specific Origination Shock ($\hat{v}_k$) calculated from the training sample. The regressions also include as controls the Debt-To-Income Ration of the application (columns 2-4 and 7-9) as well as a third-degree polynomial in DTI (columns 3-4 and 8-9). Lender and Year Fixed Effects are included (columns 4-5 and 9-10). A measure of DTI proximity to the nearest bin boundary is included (columns 5 and 10). Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Application Accepted					Loan Originated				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Lender Specific	0.0200***	0.0200***	0.0200***	0.0218***	0.0219***	0.0172***	0.0172***	0.0172***	0.0188***	0.0189***
Origination Shock ($\hat{v}_k$)	(19.78)	(19.79)	(19.79)	(8.83)	(8.75)	(16.41)	(16.42)	(16.41)	(8.83)	(8.74)
DTI		-0.00479***	0.0946***	0.0720***			-0.000887***	0.117***	0.0858***	
		(-118.77)	(245.89)	(2.59)			(-21.44)	(296.08)	(3.18)	
DTI^2			-0.0315***	-0.0251**				-0.0376***	-0.0295***	
			(-173.00)	(-2.54)				(-202.10)	(-3.13)	
DTI^3			0.00241***	0.00211**				0.00295***	0.00259***	
			(97.13)	(2.00)				(116.45)	(2.61)	
Distance From					-0.150***					-0.155***
Bin Boundary					(-11.44)					(-12.10)
Squared Distance From					0.286***					0.294***
Bin Boundary					(2.64)					(2.63)
Cubed Distance From					136.7***					141.7***
Bin Boundary					(17.85)					(19.71)
Lender FE				Yes	Yes				Yes	Yes
Year FE				Yes	Yes				Yes	Yes
Lender Clustered SE				Yes	Yes				Yes	Yes
N	103,068,422	103,068,422	103,068,422	103,068,164	103,068,164	103,068,422	103,068,422	103,068,422	103,068,164	103,068,164
adj. R^2	0.000	0.000	0.002	0.199	0.198	0.000	0.000	0.003	0.190	0.189

Table III

Covariate Balance

This table reports results demonstrating that characteristics observed in the data do not vary systematically with our lender-specific acceptance rate jumps. Indicators for all available characteristics are regressed on our Lender Specific Origination Shock ($\hat{v}_k$) (columns 1-7). Column 8 tests the quasi-random nature of loans with positive acceptance rate jumps, distinguishing them from loans that may have been specifically manipulated by loan officers to boost origination volume, by regressing the log of one plus the application counts on the lender-specific acceptance rate jump. Reported t-statistics in parentheses are heteroskedasticity-robust. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	White	Owner Occ	Conventional	Single Fam	Purchase	DTI	jumbo	log(1+Applications)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lender Specific	-8.70e-11	1.01e-10	0.000841	0.000112	0.000481	0.0000549	-0.000144	0.00279
Origination Shock ($\hat{v}_k$)	(-0.00)	(0.00)	(1.25)	(0.16)	(0.45)	(0.02)	(-0.28)	(1.10)
N	103,068,422	103,068,422	103,068,422	103,068,422	103,068,422	103,068,422	103,068,422	5,967,599
adj. R^2	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	0.000	-0.000

Table IV

Impact of Shock on Future Activity

This table reports regressions demonstrating that a lender's current expansion of its market presence increases its future local lending activity in the same market. Column 1 regresses a lender's current year originations in a market for the year on our instrument, the Market Level Lender Specific Origination Shock, representing the first stage in our instrumental variable approach. Column 2 regresses a lender's originations one year in the future in a market on our same instrument, representing the reduced form representation in our instrumental variable approach. Column 3 reports a 2SLS coefficient of future originations on current originations (instrumented with the Market Level Lender Specific Origination Shock). Columns 4 and 5 report reduced form results (similar to Column 2) for application count and origination loan amount volume respectively. The regressions also include as controls the previous period's origination count (columns 1-3), the current period's application count (columns 1-4), the previous period's application count (column 4) and the previous period's originated dollar volume (column 5). Lender, Market, and Year fixed effects are also included. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	log(1+Curr Deal Count)	log(1+Fut Deal Count)		log(1+Fut App Count)	log(1+Fut Vol Total)
	(1)	(2)	(3)	(4)	(5)
Market Level Lender Specific	0.0163***	0.00651***		0.00612***	0.0157**
Origination Shock ($\hat{v}_{M,b,t}$)	(8.64)	(4.77)		(4.28)	(2.41)
log(1+Curr Deal Count)			0.398***		
(Instrumented with $\hat{v}_{M,b,t}$)			(5.31)		
log(1+Prev Deal Count)	Yes	Yes	Yes		
log(1+Curr App Count)	Yes	Yes	Yes	Yes	
log(1+Prev App Count)				Yes	
log(1+Prev Vol Total)					Yes
Lender FE	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Lender Clustered SE	Yes	Yes	Yes	Yes	Yes
Market Clustered SE	Yes	Yes	Yes	Yes	Yes
N	56,017,529	56,017,529	56,017,529	56,017,529	56,017,529
adj. R^2	0.662	0.402	0.389	0.434	0.276

Table V

Comparing Measures of Competition

This table reports comparative results related to the interaction between a lender's lending activity and that of it's competitors for various measures of the level of competition within a market. The number of loans originated by a lender in a market for the following year (columns 1-4) and the number of applications received by a lender in a market for the following year (columns 5-8) is regressed on that lender's market level origination shock and a set of covariates of interest. The covariates of interest include the sum of all the origination shocks of a lender's competitors in a market for that year (columns 1 and 5), the shock of the largest three (by origination volume in a market for that year) competitors in a market for that year (columns 2 and 6), the shock to the Herfindahl-Hirschman Index of a particular market for that year (columns 3 and 7), and the largest shock of a competitor in a market for that year (columns 4 and 8). The regressions also include as controls the count of competitors in a market for that year (columns 2-4 and 6-8), the previous period's origination count (columns 1-4), the current period's application count (columns 1-8), and the previous period's application count (columns 5-8). Lender, Market, and Year fixed effects are also included. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	log(1+Fut Deal Count)				log(1+Fut App Count)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market Level Lender Specific	0.00656***	0.00645***	0.00646***	0.00563***	0.00619***	0.0062***	0.00587***	0.0050***
Origination Shock ($\hat{v}_{M,b,t}$	(4.77)	(4.62)	(4.78)	(3.96)	(4.27)	(4.13)	(4.01)	(3.42)
Total Competitor	0.000404				0.00053			
Origination Shock	(0.56)				(0.62)			
Largest Three Competitors		0.000161				0.00114		
Origination Shock		(0.13)				(0.80)		
Herfindahl-Hirschman Index			0.000317				-0.00228	
Origination Shock			(0.19)				(-0.84)	
Most Aggressive Competitor				-0.0218***				-0.0270***
Origination Shock				(-4.67)				(-6.74)
Number of Competitors		-0.000100	-0.0000604	-0.0000164		0.00111***	0.0012***	0.00127***
		(-0.50)	(-0.29)	(-0.08)		(4.48)	(4.89)	(5.12)
log(1+Prev Deal Count)	Yes	Yes	Yes	Yes				
log(1+Curr App Count)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
log(1+Prev App Count)					Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	56,017,529	53,047,248	55,316,530	55,404,549	56,017,529	53,047,248	55,316,530	55,404,549
adj. R^2	0.402	0.403	0.401	0.402	0.434	0.434	0.434	0.434

Table VI

Competition Impact of Most Aggressive Competitor

This table reports results detailing the competitive impact the most aggressive competitor has on a market. Column 1 regresses the largest increase in originations for any one competitor within a market and year over the prior year on the largest shock of a competitor in a market for that year (our instrument for this table) and the Market Level Lender Specific Origination Shock, representing the first stage in our instrumental variable approach. Column 2 regresses a lender's originations one year in the future in a market on our same instrument, representing the reduced form representation in our instrumental variable approach. Column 3 reports a 2SLS coefficient of the largest increase in originations for any one competitor within a market and year over the prior year (instrumented with the largest shock of a competitor in a market for that year). Column 4 reports the results of the naive OLS version of column 3. Column 5 is similar to column 2, but instead uses the sum of the two largest competitor shocks within the market. Column 5 regresses a lender's originations one year in the future in a market on the largest shock received by a competitor at three difference geographic-market levels. F-Statistics for the difference in these coefficients are also reported. The regressions also include as controls the count of competitors in a market for that year (columns 1-5 at the tract-market level, column 6 at the MSA-market level), the previous period's origination count (columns 1-6), the current period's application count (columns 1-6). Lender, Market, and Year fixed effects are also included. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	log(1+Largest Competitor Deal Increase)			log(1+Fut Deal Count)		
	(1)	(2)	(3)	(4)	(5)	(6)
Market Level Lender Specific Origination Shock ($\hat{v}_{M,b,t}$)	0.00827***	0.00553***	0.00655***	0.00643***	0.00529***	0.00545***
	(7.85)	(3.76)	(4.55)	(4.50)	(3.65)	(3.64)
Most Aggressive Competitor Origination Shock	0.189***	-0.0232***				-0.0183***
	(36.99)	(-5.32)				(-5.99)
log(1+Largest Competitor Deal Increase)				0.0247***		
				(9.04)		
log(1+Largest Competitor Deal Increase) (Instrumented with Most Aggressive Competitor Origination Shock)			-0.123***			
			(-5.12)			
Two Most Aggressive Competitors Origination Shocks					-0.0222***	
					(-4.89)	
Most Aggressive Zip-Market Competitor Origination Shock						-0.00749***
						(-2.66)
Most Aggressive MSA-Market Competitor Origination Shock						-0.00113
						(-0.48)
Number of Competitors	0.0214***	0.00011	0.0027***	-0.00048*	0.000009	
	(109.96)	(0.44)	(4.05)	(-1.80)	(0.04)	
Number of Competitors in MSA						0.0000670
						(1.50)
log(1+Prev Deal Count)	Yes	Yes	Yes	Yes	Yes	Yes
log(1+Curr App Count)	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Market Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
N	48,020,874	48,020,874	48,020,874	48,020,874	54,386,746	49,205,577
adj. R^2	0.649	0.406	0.397	0.406	0.403	0.405
Tract=Zip Comp Shock F:						14.38
p-value						0.00
Zip=MSA Comp Shock F:						2.71
p-value						0.10
Tract=MSA Comp Shock F:						22.40
p-value						0.00

Table VII

Portfolio Risk Taking in Response to Competition

This table reports results investigating the impact increased competition has on the portfolio of loans originated by lenders. Columns 1, 3, 6, and 8 investigate the impact on the Original Interest Rate of a loan (columns 3 and 8 conditional on the FICO score). Columns 2 and 7 look at the change in the FICO composition, while columns 4 and 9 as well as 5 and 10 look at the LTV and Amortization Terms at origination (conditional on FICO), respectively. Columns 1-4 measure increased competition through the Most Aggressive Competitor Origination Shock, while columns 5-10 utilize the shock to the market Herfindahl-Hirschman Index. Applicant/Loan Characteristic Controls include indicators for White, Owner Occupied, Conventional, Single Family, and Purchase. Lender, Market, and Year fixed effects are also included. Reported t-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Int Rate	FICO	Int Rate	LTV	Term	Int Rate	FICO	Int Rate	LTV	Term
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Previous Market Level Lender Specific	0.00211	-0.114	-0.000882	0.132	-0.129	-0.000623	-0.121	-0.00279	0.143	-0.170
Origination Shock ($\hat{v}_{M,b,t-1}$)	(0.26)	(-0.31)	(-0.12)	(1.39)	(-0.34)	(-0.08)	(-0.33)	(-0.38)	(1.50)	(-0.43)
Previous Most Aggressive Competitor	0.0904***	-2.827***	0.0457***	0.164	2.912***					
Origination Shock	(6.61)	(-6.02)	(5.00)	(1.13)	(6.92)					
Previous Herfindahl-Hirschman Index						-0.0177	-1.257	-0.0228	0.365	0.547
Origination Shock						(-0.68)	(-1.06)	(-0.98)	(0.73)	(0.29)
FICO			-0.00626***	-0.0446***	-0.0858***			-0.00625***	-0.0446***	-0.0858***
			(-14.15)	(-57.84)	(-26.48)			(-14.15)	(-57.86)	(-26.47)
Applicant/Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,423,376	7,060,182	6,951,899	7,032,015	6,928,985	7,428,451	7,065,359	6,957,094	7,037,192	6,934,196
adj. R^2	0.567	0.350	0.616	0.369	0.179	0.567	0.350	0.616	0.369	0.179

Table VIII

Portfolio Performance in Response to Competition

This table reports the results from regressions of ex-post performance outcomes on the Market Level Bank Specific Origination Shock and the Most Aggressive Competitor Origination Shock in the year preceding the loan application. The performance outcomes investigated are Delinquent (columns 1-4) and Default (columns 5-8). Delinquent is an indicator of whether or not the loan ever went 60 days or more delinquent at any point in the observed performance of the loan. Default is an indicator of whether or not the loan ever entered Foreclosure, became a Real Estate Owned property, or was liquidated (in a manner other than a borrower payoff in full) at any point in the observed performance of the loan. Observed performance of the loan begins at the first month the loan was placed into a securitization and ends at the earlier of loan liquidation, borrower payoff in full, or December 2015. Columns 1 and 5 include only the Lender Specific Origination Shock. Columns 2 and 6 include the Most Aggressive Competitor Origination Shock in addition to the Lender Specific one, representing the reduced form representation in our instrumental variable approach. Columns 3 and 7 report 2SLS coefficients of the largest increase in originations for any one competitor within a market and year over the prior year (instrumented with the largest shock of a competitor in a market for that year). Columns 4 and 8 compare to columns 2 and 6 respectively, instead utilizing the shock to the Herfindahl-Hirschman Index. Controls for FICO, Interest Rate, LTV and Amortization Term at origination are also included. Applicant/Loan Characteristic Controls include indicators for White, Owner Occupied, Conventional, Single Family, and Purchase. Lender, Market, and Year fixed effects are also included. Reported *t*-statistics in parentheses are heteroskedasticity-robust and clustered at the level indicated. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Delinquent				Default			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Previous Market Level Lender Specific Origination Shock ($\hat{v}_{M,b,t-1}$)	0.00205	0.00387**	0.00223	0.00170	0.000786	0.00198	0.000516	0.000298
	(1.04)	(1.97)	(1.17)	(0.85)	(0.52)	(1.27)	(0.33)	(0.19)
Previous Most Aggressive Competitor Origination Shock		0.0384***				0.0343***		
		(15.85)				(13.90)		
log(1+Previous Largest Competitor Deal Increase) Instrumented with Previous Most Aggressive Competitor Origination Shock			0.0852***				0.0759***	
			(17.82)				(15.96)	
Previous Herfindahl-Hirschman Index Origination Shock				-0.00767				-0.0103*
				(-1.31)				(-1.90)
FICO	-0.00132***	-0.00134***	-0.00133***	-0.00132***	-0.000755***	-0.000781***	-0.000773***	-0.000755***
	(-20.26)	(-17.39)	(-17.14)	(-20.27)	(-11.81)	(-10.27)	(-10.12)	(-11.82)
Int Rate	0.00948***	0.00991***	0.0101***	0.00946***	0.0130***	0.0135***	0.0137***	0.0130***
	(3.00)	(3.24)	(3.30)	(2.99)	(3.94)	(4.21)	(4.26)	(3.94)
LTV	0.00168***	0.00174***	0.00174***	0.00168***	0.00134***	0.00139***	0.00139***	0.00134***
	(9.90)	(9.02)	(8.99)	(9.91)	(8.24)	(7.57)	(7.54)	(8.25)
Term	0.000227***	0.000201***	0.000199***	0.000227***	0.000161***	0.000137***	0.000135***	0.000161***
	(5.58)	(5.59)	(5.54)	(5.59)	(3.95)	(3.76)	(3.72)	(3.95)
Applicant/Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,823,231	6,040,782	6,040,782	6,816,588	6,823,231	6,040,782	6,040,782	6,816,588
adj. R^2	0.317	0.345	0.339	0.317	0.292	0.315	0.309	0.292