Competing for Deal Flow in Mortgage Markets*

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ABSTRACT

We analyze competitive dynamics in the mortgage market. Using discontinuities in mortgage acceptance models to generate shocks to a bank's current local lending, we show that future applicants are attracted to growing lenders. Local mortgage markets resemble tournaments: a bank's originations are reduced by the lending of its quickest-growing competitors, not that of its overall competitors nor of its largest competitors. Moreover, future lending activity is convex in current originations. Tougher competition leads a bank to charge higher interest rates, partially due to the increased risk of its loans, and results in 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] In this paper, we show that across local mortgage markets in the U.S. lenders engage in tournament-like competition for applicant deal flow. We begin by showing that plausibly exogenous increases in a lender's current period originations in a local area lead to increased applications and lending in the following year. Applicants are attracted to growing lenders. We then analyze the competitive dynamics of mortgage markets and show that only the quickest-growing lenders in a market have an impact on others. This feature of the market is consistent with a tournament model in which the fastest growing lenders receive disproportionate applicant attention. In support of this interpretation, we show that future lending is convex in current year originations. We also find, somewhat unexpectedly, that increased lending by their quickest-growing competitor leads banks to increase the interest rates they charge locally. Together these findings have implications for the strategies of banks striving for market share and for investors, regulators and depositors seeking to understand the evolution of banking markets and to assess which lenders are most vulnerable.

Two central ideas from the theoretical literature motivate our analysis. The first is the argument that market share serves as a signal of quality to consumers (Caminal and Vives (1996)). Increased lending by a bank will therefore attract other potential borrowers.

[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.

A similar concept arises in network models of social learning (e.g., Young (2009)): as more local borrowers engage with a given lender, others in the same area become more likely to adopt the same practice and approach the bank. This reasoning also suggests that increased lending by a lender's competitors will reduce its future opportunities. The second theory is that firms compete in tournaments in which the actions of market leaders are particularly important.[2] Under this analysis, it is the lenders with the most positive signals (increases in mortgage originations, in our setting) who will have the greatest effect on market outcomes. We apply these two theories to the mortgage market and find that both are highly effective in describing how it operates.

Assessing bank strategies is challenging, as these strategies are fundamentally endogenous. Our empirical design is centered on identifying shocks to the probability that a bank extends a mortgage to a given applicant. We analyze the 251 million mortgage applications in the Home Mortgage Disclosure Act (HMDA) database between 2003 and 2014. We use half of the data, which we label the training sample, to estimate each bank's mortgage approval model (each year) as a function of applicants' debt-to-income (DTI) ratios. DTI ratios are a typical input to bank acceptance models (e.g., Mian and Sufi 2009, Dell'Ariccia, Igan and Laeven 2012), and it is standard for different banks to use varying DTI cutoffs in assessing applications (Temkin, Levy and Levine 1999, Listokin et al. 2001 and Rose 2011), with loans above the cutoffs significantly less likely to be approved. We use the data from the training sample to identify these bank-specific cutoffs for each lender's

[2] The mutual fund tournament literature explores this idea in an examination of fund flows (Chevalier and Ellison (1997), Sirri and Tufano (1998), Huang, Wei, and Yan (2007) and Barber, Huang and Odean (2016)).

national loan approval model.

Our empirical strategy contrasts different applications received by a given bank in various areas. Applications just above a bank's national DTI threshold are deemed to be relatively unattractive, and applications just below a cutoff should be relatively attractive. If a bank happens to receive many relatively attractive applications in one local area and many relatively unattractive applications in a second area, then we should expect to observe a local lending surge in the first region but not in the second.

We test this hypothesis by discarding the training sample and examining the second half of the data, labeled the test sample. Our first result is that applicants from the test sample with DTIs in narrow bins shown to be relatively attractive for a given bank in the training sample are indeed discontinuously more likely to be offered a loan. We describe these discontinuities as loan attractiveness shocks and show that they are unrelated to a number of contemporaneous covariates across narrow 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 (or applicants) 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 the current year's lending supply shocks on next year's local applicant flow, controlling for bank, local market, and year fixed effects. The elasticity of future applications with respect to current originations is approximately 37%. We also find that current period shocks generate more future originations and a higher dollar volume of future originations. This is clear evidence in favor of the Caminal and Vives (1996) theory that increased market share attracts future consumers. 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 applicant flow and lending are both unaffected by the total shocks of its competitors, the shocks of its three largest competitors or the shock to the local Herfindahl-Hirschman Index (HHI). We do find, however, that the quickest-growing competitor (i.e., the competitor with the largest current origination shock) significantly hurts the focal bank's future applications and originations. The elasticity of a bank's future applications with respect to the largest current origination increase of its competitors is roughly -19%. The fact that only the quickest-growing competitor's lending matters, not that of all competitors nor that of the largest, indicates that the mortgage market has features of a tournament. The mutual fund tournament model of Huang, Wei, and Yan (2007) describes a setting in which informationconstrained investors are only willing to pay a cost to learn more about the funds with the highest signals, so the sensitivity of future flows to the current signal is greatest for those funds with the best signals. We find that a similar dynamic applies in the mortgage market: increased current originations (higher signals) lead to more future lending particularly for those lenders that are already making many loans.

We show that the relevant market for the competitive shocks we analyze is highly localized; the negative impact of the quickest-growing tract-level competitor is more than twice that of the quickest-growing zip code-level competitor. 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). Our spatial findings suggest that lenders are competing in local tournaments.

It is a standard characteristic of tournament markets that future outcomes are convex in the current period signal, as signal improvements matter most for the best performers. We show that the mortgage market displays this feature: future lending and applications are both convex in current origination shocks, and current origination shocks have a greater impact on future outcomes for lenders whose shock is in the top quartile locally.

The results described above focus on quantity effects. What is the price response of a bank to increased competition? We merge the HMDA loan-level data with interest rate and performance information from BlackBox, Fannie Mae and Freddie Mac. Somewhat surprisingly, we find that banks increase the rates they charge in the face of greater competition. This may be explained by the fact that when faced with increased shocks to its quickest-growing competitor, a bank originates mortgages with higher loan-to-value ratios. Competition leads banks to retreat to a risker subset of the overall market.

Do all these competition considerations matter for loan performance? 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 increasing in the origination shock of the quickest-growing 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.

From a methodological perspective, we make two points. First, our approach simultaneously identifying plausibly exogenous shocks to the financing supplied by both a lender and its competitors provides a new technique for analyzing banking competition and allows us to supply direct evidence on competitive dynamics in mortgage markets. Second, our method of analyzing shocks in the training sample and verifying their importance in the test sample enables us to avoid endogeneity issues that arise when the entire sample is used to both identify shocks and test their impact. Specifically, it is clear that assessing the effect of current local lending on future local lending simply by regressing the latter on the former is subject to the concern that both are influenced by unobserved variables. If one sample is used to both identify relatively attractive DTI bins and to test their impact on future lending, there is a possibility that a bin may be identified as relatively attractive simply because it contains a specific local loan that was approved. Regressing future lending on the relative attractiveness of current period loan applications would thus be quite similar to regressing future local lending on current local lending. In our approach, we separately identify relatively attractive DTI bins in the national training sample and then relate future lending only to the attributed relatively attractive loans from the test sample, where the attribution of attractiveness arises from test sample applications submitted across the country. We thus sidestep this endogenity problem, as we do not specifically condition on the approval of any current local applications.

Our emphasis is on the functioning of micro banking markets and the identities of the key competitive players, in contrast to most prior studies of banking competition that 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). 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 establish that the mortgage market is susceptible to competitive fragility. Specifically, our central findings are that current growth fuels future growth and that this effect is convex. This suggests that new lenders can quickly achieve substantial market presence and even dominance. As a result, lenders without a long-established history and, perhaps, without a mature system of loan risk evaluation can become the most important mortgage suppliers in the market. The consequences of this competitive upheaval can be very negative, as has become clear after the 2008 crisis.

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[3] report into the Loan Application Registrar information about all applications for a residential mortgage loan 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[4], 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

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

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

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 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[5] (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.

We define lenders by their federal tax identification numbers. This allows our lenders to be invariant to reorganizations of the HMDA reporting structure. Entire classes of mortgage lenders were moved between reporting agencies during the sample period and agencies often

[5]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.

reorganized respondent identification numbers between years. Additionally, the use of tax identification numbers mitigates the impact of merger activity within mortgage lenders as it allows for the separateness of pre-merged entities while maintaining at least some portion of an appropriate lending history across time for the post-merger entity.

Additionally we append interest rate and performance data (the latter is observed for the life of the loan within a securitization, through December 2015) and a broader set of borrower characteristics 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.

II Empirical Specification

The focus of this study is to assess the effectiveness and implications of bank expansion 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, the first step is to use half the data (the training sample) to estimate national bank origination models each year relating a loan's DTI to its probability of acceptance. Different banks use heterogenous DTI cutoffs in assessing applications (Temkin, Levy and

Levine 1999, Listokin et al. 2001 and Rose 2011); applications with DTIs above the cutoffs are substantially less likely to be approved.[6] In the second step, we use the training sample origination models to identify these bank-specific DTI cutoffs.[7] We discard the training sample, and use the estimated DTI cutoffs to attribute to each application in the test sample an estimated measure of its attractiveness to a given bank. We regard test sample applications in narrow bins just below DTI cutoffs to be relatively attractive, while those in bins just above cutoffs are relatively unattractive.

For the third step, we test whether relatively attractive test sample applications are indeed more likely to be originated. In the fourth step, we aggregate all the test sample applications in a local market. We view the frequency of relatively attractive local applications as a shock to a bank's lending activity in that market. Although DTI thresholds are determined endogenously, the arrival of applications from one market just above or just below the thresholds creates quasi-random variation in the number of mortgages granted locally by the bank. We thus 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.

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

[7] Porter and Yu (2015) discuss the issue of unknown regression discontinuity points.

A Estimating Bank Acceptance Models Using the Training Sample

We begin by assigning 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 $\hat{\mu} = 2.08$. 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.

The first step in our analysis is to calculate an average acceptance rate $ar(bin_{i,b,t,c})$ for each bin. That is, we use the training sample to estimate each bank's national acceptance model every year as a function of applicant DTIs (we allow the model to vary across some applicant characteristics).

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 would be indicative of a DTI cutoff in the bank's acceptance model. 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

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

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

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. An illustrative example of our approach for one lender is provided in Figure 1.

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.

D Local Lending Shocks in the Test Sample

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 Exogeneity of Shocks

B.1 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.2 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.

B.3 Why Discard the Training Sample?

The results in Section III.A make clear that the DTI cutoffs identified in the training sample do indeed provide useful predictions for which test sample loan applications will be approved. One may ask, however, what is the purpose in discarding the training sample? Why not make use of the full sample to estimate DTI cutoffs?

Our ultimate goal is to study the effects of a current period local lending surge on a bank's own future lending and on the future lending of its competitors. It is clear that regressing a bank's future lending on its current lending would not supply a clean estimate of the causal impact of the latter on the former, as both these variables may be influenced by unobserved factors. If the entire sample is used to estimate the DTI cutoffs, a similar problem arises. Consider a specific loan application that is approved in one local area. A full-sample estimate of the lender's DTI cutoffs would quite likely regard this application's narrow DTI bin as relatively attractive. After all, this application was approved. If we were to regress future local lending on the attractiveness of current applications, it would be quite similar to regressing local lending on current application approvals, with the same attendant endogeneity issue.

Under our approach of separately identifying the DTI cutoffs from the training sample and estimating the impact of current lending on future lending using the attractiveness of the test sample, this difficulty does not arise. The bank origination model generates estimates of DTI cutoffs using application approvals from the national training sample. These cutoffs are then applied to attribute the relative attractiveness of applications from the test sample. The actual approval of test sample applications plays no role in estimating the attractiveness of an application- we do not condition on test sample loan approval. We instead assess the attractiveness of a test sample application by considering the approval rates of loans from the training sample from across the country with which its shares a narrow DTI bin. In other words, we ask to what degree applications with very similar DTIs were approved nationally, in a manner that is specific to this bank. This is presumably unrelated to any unobserved local variable. Our subsequent analysis will consider the relationship between the concentration of these bank-specific attractive applications and future lending.

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 supply 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.

Caminal and Vives (1996) argue that consumers (potential mortgage applicants, in our setting) gauge the quality of a firm (i.e., lender) in part though an analysis of its volume of transactions. A lender who experiences a surge in originations is attracting many new customers, who apparently think highly of the lender. As a result, an increase in origination is a positive signal about a lender, and lenders who originate more loans should attract greater future customer flow. The lending shocks we study are exogenous, but that is not observable to potential applicants; they simply see an increase in lending by a bank and raise their assessment of the lender's quality.

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 applications 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 0.0165 and the t-statistic is 8.59. 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. We are identifying shocks to the supply of local mortgage financing by banks.

To examine the impact of expanded market presence on future applicant flow, we regress the log of one plus the number of local applications 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 0.0061 and the t-statistic is 4.28. A shock to local originations in the current year has a follow-on effect in generating more applications in the next year as well. This is consistent with the intuition from Caminal and Vives (1996) that increased lending this year leads to greater customer flow next year, as applicants view lenders who experience origination surges in a more positive light.

In the third column of Table IV we report results from an instrumental variables regression of the log of one plus future applications 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 0.37 and the t-statistic is 4.28. We use one plus the number of applications/originations in the arguments of the log functions to include markets with zero applications/originations, but this causes the estimated elasticity to depend on the number of current originations and future applications. As long as these are of similar magnitude, however, the elasticity of future applications with respect to current originations is approximately 0.37, 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 applicant flow.

The current period origination shock also generates more originations in the following year (coefficient of 0.0065 and t-statistic of 4.77) 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 future applications and future originations, which suggests that the increased originations are driven by increased applications (i.e., heightened applicant interest, as suggested by Caminal and Vives (1996)) 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. We examine this question by regressing a bank's future applications 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=0.0005 and t-statistic=0.64) on a bank's future applications. 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 applications on its current origination shock, the origination shock of its three competitors with the largest local market shares and the usual controls. We also include a fixed effect for the number of local competitors. We find an insignificant impact (coefficient=0.0009 and t-statistic=0.71) of the shock of the three largest competitors, as detailed in the second column of Table V. A bank's future applications 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. The analysis precedes in three steps. First, we calculate the HHI of all local competitors employing the count of current originations as the measure of market share. Second, using the origination shocks of each lender and the regression model for current deal count described in the first column of Table IV, we calculate the estimated deal count for each lender if the shocks did not occur. Third, we calculate the HHI of all local competitors using the estimated deal counts in the absence of shocks and subtract this from the actual HHI. This difference we describe as the HHI origination shock. We show, in the third column of Table V, that the HHI origination shock has an insignificant impact (coefficient=1.176 and t-statistic=1.33) on a bank's future applicant flow.

These results show that neither the overall lending of its competitors, nor the lending of its largest competitors nor the change in its competitors' HHI appears to be important to a lender, but are there some competitors whose actions are strategically relevant? It seems unlikely that banks may completely disregard the origination strategies of their competitors. The mutual fund tournament literature provides a useful insight. This research shows that fund inflows respond in a convex manner to the fund's previous year returns (Chevalier and Ellison (1997), Sirri and Tufano (1998), Huang, Wei, and Yan (2007) and Barber, Huang and Odean (2016), though see Spiegel and Zhang (2013) for a contrary view), which is consistent with the argument that funds are engaged in a tournament to attract investors' attention. Huang, Wei, and Yan (2007) provide a theoretical model that argues that investors must pay an information cost to investigate a fund for potential investment. To minimize these costs, investors limit their research to funds that had high returns last year, as these funds are the likeliest to be worthy of investment.

In our setting, we showed in Table IV that high local originations this year lead a lender to receive more applications and make more loans in the following year. This suggests that increased local lending volume is viewed by mortgage applicants as a positive signal. Applying the reasoning of Huang, Wei, and Yan (2007) to the mortgage market, we should expect applicants to be most interested in paying information costs to investigate lenders who experienced large lending surges in the previous year; these are the lenders that are likeliest to be of high quality. An increase in current year originations will not have much impact on the future applicant flow of a lender that is not experiencing a surge, for even with this increase the lender's apparent quality will be too low to attract the attention of applicants. An increase in current originations will, however, have a meaningful effect on future applicant flow for a lender that is already making a large number of loans, for its current level of lending activity places it in the region in which applicants are considering investigating it further, and higher current lending will make this lender even more attractive. If this tournament-like description of the competition of local lenders for applicant attention is correct, then the lenders with the biggest impact on the market will be those who increased their originations most quickly this year, rather than the largest lenders.

We test this hypothesis by examining the impact of the lending of a bank's quickest-growing competitor, which we define to be the competitor with the largest current local origination shock. We regress a bank's future applications on its current origination shock, the origination shock of its quickest-growing 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 quickest-growing competitor has a strong negative impact (coefficient=-0.0149 and t-statistic=-5.37) on the bank's future lending. The most important competitors for a bank are those who are growing most quickly, consistent with the intuition of Huang, Wei, and Yan (2007). In columns five through eight of Table V we display results showing a similar pattern for future originations: a bank's future originations are unaffected by the total origination shock of its competitors, the shocks to its three largest competitors or the HHI origination of its competitors, but future originations decrease strongly in the origination shock of a bank's quickest-growing competitor.

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 applications or 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 quickest-growing competitors that have the most deleterious effects. Essentially, what is most important for a bank are the dynamics of local competitive tournaments, in which the lenders who are most quickly increasing their originations play the central roles.

E Quickest-Growing Competitor

To get a sense of the mechanism underlying the impact of the quickest-growing competitor, we regress the log of one plus the largest increase in deal count for any competitor on the origination shock of the quickest-growing competitor. The result, reported in the first column of Table VI, shows that the quickest-growing competitor 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 quickest-growing competitor is again strongly negatively associated with a bank's future applications, as shown in the second column of Table VI. The causal impact of increased loans by the bank's quickest-growing competitor is negative, as displayed in the instrumented regression displayed in third column of Table VI. The elasticity of a bank's future applications with respect to the largest increase in originations for its competitors is approximately -19% (t-statisic=-6.38).

We also find that the elasticity of a bank's future originations with respect to the largest increase in originations for its competitors is negative and significant (coefficient=-0.17 and t-statistic=-5.99), as shown in the fourth column of Table VI. These results describe the effects of exogenous increases in originations by the quickest-growing competitor. In the fifth column of Table VI, by contrast, 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=0.03 and t-statistic=9.68). 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 quickest-growing competitor, however, as demonstrated in the previous regressions, is clearly negative. When aggregating the origination shocks of the bank's two quickest-growing local competitors, we find a similar very negative causal effect, as shown in the sixth column of Table VI.

How local are the negative competitive effects? We calculate the quickest-growing competitor shock at the zip code-level and contrast its 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 quickest-growing competitor, the zip-level shock of its quickest-growing 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 seventh column of Table VI that the coefficient on the tract-level competitor shock of -0.017 (t-statistic=-7.55) is significantly larger, at the 1% level, than the -0.006 coefficient (t-statistic=-3.39) on the zip-level competitor shock. We find that competition between mortgage lenders is a highly localized phenomenon. The tournaments for applicant deal flow are occurring largely at the census-tract level.

F Convexity

The results in Tables V and VI show that the competitiveness of the local lending market is mainly determined by the actions of the quickest-growing lenders; other lenders appear not to have much impact. This is consistent with a tournament style of competition. The mutual fund tournament literature has also emphasized that in this form of competition the payoff from sending a better signal is convex. When firms are far behind in the tournament, an increase in their signal will not attract much additional interest from consumers. For firms that are leading the tournament, by contrast, an improved signal will influence additional prospective customers to pay information costs to investigate their products (Huang, Wei, and Yan (2007)). In our setting, increased current period originations is the positive signal. This suggests the prediction that a bank's future lending will be convex in its current period origination shock.

We test this hypothesis by regressing a bank's future applications on its current origination shock, the square of its current origination shock and the standard controls. As shown in the results displayed in the first column of Table VII, the coefficient on both origination shock and the squared origination shock are positive and significant (with t-statistics of 4.35 and 3.86, respectively). This demonstrates that a lender's future applications are increasing and convex in its current origination shock. This result holds true for future originations as well, as shown in the second column of Table VII. These results provide strong evidence consistent with the tournament hypothesis. Lenders are competing for applicant attention and those experiencing the largest surge in current deals receive disproportionate future customer flows.

We further explore the differential effects of increased current lending for banks with varying positions in the local tournament by regressing a bank's future applications on its current origination shock, an indicator for lenders with origination shocks in the top quartile of their local market, the interaction between these two variables and the standard controls. Do increases in current originations matter more for top quartile lenders? In the third and fourth columns of Table VII we show that they do. The interaction between the top quartile indicator and the current origination shock has a positive and significant effect on both future applications (t-statistic=2.02) and originations (t-statistic=2.66). Overall, there is robust evidence that a bank's current originations have a convex impact on future deal flow and that increases in current lending matter more for those who are already lending more than their competitors. These results emphasizing the crucial roles played by the local market leaders are precisely what tournament theories predict.

G Lender Risk Taking and Competition

How do lenders respond to increased competition? Tables V and VI show that greater current period lending by the quickest-growing competitor leads to reduced future lending by the other local banks. What is the price impact of increased lending by the quickest-growing competitor? 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 quickest-growing competitor and the standard HMDA application and market controls. We find, as described in the first column of Table VIII, that a lender's own previous shock has an insignificant (t-statistic=-0.01) effect on the rate charged, but the prior origination shock of the quickest-growing competitor has a positive and significant impact (coefficient=0.02 and t-statisic=2.55). 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 quickest-growing competitor and find, as displayed in the second column of Table VIII, that the quickest-growing competitor shock has an insignificant impact (coefficient=-0.07 and t-statisic=-0.26). The lender's own shock also has an insignificant impact. Lender LTV values increase with the quickest-growing competitor shock, but loan terms are unaffected, as shown in the fourth and fifth columns of Table VIII. An explanation consistent with these results is that greater competition from its quickest-growing competitor leads a lender to provide riskier mortgages-some of this risk is observable to us (in higher LTV values) and other aspects may not be, but the higher risk is reflected in higher rates. Lenders with little growth in origination activity who fall behind in the tournament competition for applicant attention, appear to receive both fewer and riskier future applications. As before, changes in the HHI index appear uninformative about loan terms, as shown in columns six through ten of Table VIII.

H Performance

In Table VIII we showed that tougher competition leads lenders to lend to make riskier loans 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 IX, is that the previous year local origination shock has an insignificant effect (coefficient=0.002 and t-statistic=1.12) 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 quickest-growing competitor and the previously outlined controls other than loan characteristics. The result, shown in the second column of Table IX, is that delinquency is increasing (coefficient=0.003 and t-statistic=2.03) in the origination shock of the quickest-growing competitor. When a bank's quickest-growing competitor makes more loans, the performance of the bank's future loans degrades significantly. When including controls for interest rate and other loan characteristics, the result continues to hold at the 10%-level, as shown in the third column of Table IX, so it appears that competition has an even more negative impact on lenders than they expected during our sample period. The result in column four of Table IX shows that this finding holds at the 10%-level as well in the specification in which we instrument for the largest deal increase of a competitor with the quickest-growing competitor shock. As shown in the fifth column, the shock to HHI has no impact on delinquency. Results described in the sixth through tenth columns of Table IX confirm the same pattern of results (with slightly stronger statistical significance) for loan default.

Why does the increased lending of the quickest-growing competitor have a negative impact on the bank's loan performance? The results in Tables VI and Table VIII show that in the face of strong competition, lenders supply fewer mortgages and make riskier loans. During our sample period, lenders whose loan growth was weak and who did not win their local competition tournaments may have underestimated the changing unobservable risk characteristics of the pool of applicants they subsequently faced. This suggests that the greatest competitive threat to a bank may be a silent danger: quickly 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. Using discontinuities in the acceptance rates of applications with very similar debt-to-income ratios, we provide evidence that a plausibly exogenous shock to a bank's local lending this year leads to more applications and originations in the following year. Applicants are attracted to growing lenders. We show that local mortgage markets resembles tournaments in which the lending of a bank's quickest-growing competitors has the strongest negative impact on its future lending; neither the overall lending of all competitors, nor the lending of the largest competitors has much effect. We confirm the disproportionate influence of the quickest-growing lenders by showing that future applications and originations are convex in the current period shock to lending. Greater lending shocks to a bank's quickest-growing competitor lead it to charge higher interest rates; this may be partly driven by the fact that competition leads lenders to make riskier (higher LTV) loans. We further find that a bank's mortgage performance is harmed by intense competition; the higher rates it charges are insufficient to compensate for the unobservable risk of the borrowers it receives in the face of greater lending by its quickest-growing competitor.

The tournament-like features we describe are reminiscent of the common intuition that it is important for firms to play a dominant role in the markets in which they compete. We provide evidence for a dynamic variation on this static argument: we show that it is the quickest-growing, rather than the largest, lenders who are the toughest competitors. Our results also show that in certain essential respects banking markets are highly local. More generally, our approach of exploiting bank-specific shocks to analyze mortgage market dynamics may be applied to a broader set of questions about competition and firm interactions in other settings.

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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 1-6) or loan originated (columns 7-12) 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 2-3, 5, 8-9 and 11) as well as a third-degree polynomial in DTI (columns 3, 5, 9, and 11). Bin Fixed Effects are included (columns 4 and 10). Lender and Year Fixed Effects are included (columns 5-6 and 11-12). A measure of DTI proximity to the nearest bin boundary is included (columns 6 and 12). 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)	(11)	(12)
Lender Specific Origination Shock ($\hat{v}_k$)	0.0200***	0.0200***	0.0200***	0.0200***	0.0218***	0.0219***	0.0172***	0.0172***	0.0172***	0.0172***	0.0188***	0.0189***
	(19.78)	(19.79)	(19.79)	(19.78)	(8.83)	(8.75)	(16.41)	(16.42)	(16.41)	(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 Bin Boundary						-0.150***						-0.155***
						(-11.44)						(-12.10)
Squared Distance From Bin Boundary						0.286***						0.294***
						(2.64)						(2.63)
Cubed Distance From Bin Boundary						136.7***						141.7***
						(17.85)						(19.71)
Lender FE					Yes	Yes					Yes	Yes
Year FE					Yes	Yes					Yes	Yes
Bin FE				Yes						Yes		
Lender Clustered SE					Yes	Yes					Yes	Yes
N	103,068,422	103,068,422	103,068,422	103,068,422	103,068,164	103,068,164	103,068,422	103,068,422	103,068,422	103,068,422	103,068,164	103,068,164
adj. R^2	0.000	0.000	0.002	0.003	0.199	0.198	0.000	0.000	0.003	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	-1.15e-10	1.18e-10	0.000841	0.000112	0.000481	0.0000549	-0.000144	0.00279
Origination Shock ($\hat{v}_k$)	(-0.00)	(0.00)	(1.25)	(0.30)	(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 applications received one year in the future in a market on our same instrument, representing the reduced form representation of our instrumental variable approach. Column 3 reports a 2SLS coefficient of future applications 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 future origination count and loan amount volume respectively. The regressions also include as controls the previous period's origination count (column 4), the current period's application count (columns 1-4), the previous period's application count (columns 1-3) 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 App Count)		log(1+Fut Deal Count)	log(1+Fut Vol Total)
	(1)	(2)	(3)	(4)	(5)
Market Level Lender Specific	0.0165***	0.00612***		0.00651***	0.0157**
Origination Shock ($\hat{v}_{M,b,t}$)	(8.59)	(4.28)		(4.77)	(2.41)
log(1+Curr Deal Count)			0.370		
(Instrumented with $\hat{v}_{M,b,t}$)			(4.28)		
log(1+Prev Deal Count)				Yes	
log(1+Curr App Count)	Yes	Yes	Yes	Yes	
log(1+Prev App Count)	Yes	Yes	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	0.659	0.434	0.418	0.402	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 applications received by a lender in a market for the following year (columns 1-4) and the number of loans originated 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, the previous period's origination count (columns 5-8), the current period's application count (columns 1-8), and the previous period's application count (columns 1-4). 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 App Count)				log(1+Fut Deal Count)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market Level Lender Specific	0.00619***	0.00619***	0.00531***	0.00544***	0.00657***	0.00645***	0.00620***	0.00589***
Origination Shock ($\hat{v}_{M,b,t}$)	(4.27)	(4.12)	(3.22)	(3.73)	(4.77)	(4.62)	(3.95)	(4.20)
Total Competitor	0.000531				0.000443			
Origination Shock	(0.64)				(0.63)			
Largest Three Competitors		0.000946				0.000140		
Origination Shock		(0.71)				(0.12)		
Herfindahl-Hirschman Index			1.176				0.436	
Origination Shock			(1.33)				(0.59)	
Quickest-Growing Competitor				-0.0149***				-0.0147***
Origination Shock				(-5.37)				(-5.26)
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				
Competitor Count FE	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	56,017,529	53,047,248	37,777,357	55,404,549	56,017,529	53,047,248	37,777,357	55,404,549
adj. R^2	0.434	0.434	0.460	0.434	0.402	0.404	0.405	0.402

Table VI
Competition Impact of Quickest-Growing Competitor

This table reports results detailing the competitive impact the quickest-growing 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 the number of applications received by a lender in a market for the following year 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 repeats the 2SLS specification, with the number of loans originated by a lender in a market for the subsequent year as the dependent variable. Column 5 reports the results of the naive OLS version of column 4. Column 6 is similar to column 2, but instead uses the sum of the two largest competitor shocks within the market. Column 7 regresses a lender's originations one year in the future in a market on the largest shock received by a competitor at two different geographic-market levels. The F-Statistic 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 1-6 at the tract-market level, column 7 at the zip-market level), the previous period's origination count (columns 4-7), the current period's application count (columns 1-7), and the previous period's application count (columns 1-3). 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 App Count)		log(1+Fut Deal Count)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market Level Lender Specific Origination Shock ($\hat{v}_{M,b,t}$)	0.00459***	0.00516***	0.00603***	0.00659***	0.00644***	0.00566***	0.00553***
	(4.51)	(3.40)	(3.98)	(4.55)	(4.50)	(3.99)	(3.77)
Quickest-Growing Competitor Origination Shock	0.0991***	-0.0187***					-0.0168***
	(26.97)	(-6.69)					(-7.55)
log(1+Largest Competitor Deal Increase)					0.0272***		
					(9.68)		
log(1+Largest Competitor Deal Increase) (Instrumented with Quickest-Growing Competitor Origination Shock)			-0.189***	-0.172***			
			(-6.38)	(-5.99)			
Two Quickest-Growing Competitors Origination Shocks						-0.0147***	
						(-5.30)	
Quickest-Growing Zip-Market Competitor Origination Shock							-0.00642***
							(-3.39)
log(1+Prev Deal Count)				Yes	Yes	Yes	Yes
log(1+Curr App Count)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
log(1+Prev App Count)	Yes	Yes	Yes				
Tract Competitor Count FE	Yes	Yes	Yes	Yes	Yes	Yes	
Zip Competitor Count FE							Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	48,020,874	48,020,874	48,020,874	48,020,874	48,020,874	54,386,746	49,208,873
adj. R^2	0.660	0.436	0.422	0.391	0.407	0.403	0.405
Tract=Zip Comp Shock F:							14.58
p-value							0.0001

Table VII

Convexity

This table reports results detailing the convexity of the payoff received from sending a better signal. Columns 1 and 2 regress a lender's applications received one year in the future in a market and a lender's current year originations in a market for the year, respectively, on its current origination shock and the square of its current origination shock. Columns 3 and 4 regress a lender's applications received one year in the future in a market and a lender's current year originations in a market for the year, respectively, on its current origination shock, an indicator for lenders with origination shocks in the top quartile of their local market, and the interaction between these two variables. The regressions also include as controls the previous period's origination count (columns 2 and 4), the current period's application count (columns 1-4), the previous period's application count (columns 1 and 3). 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 App Count) (1)	log(1+Fut Deal Count) (2)	log(1+Fut App Count) (3)	log(1+Fut Deal Count) (4)
Market Level Lender Specific	0.00622***	0.00672***	-0.00747	-0.0357
Origination Shock ($\hat{v}_{M,b,t}$)	(4.35)	(4.94)	(-0.51)	(-1.45)
Squared Market Level Lender	0.0581***	0.120***		
Specific Origination Shock	(3.86)	(4.43)		
Top Quartile of Market Level			-0.00244	-0.00269*
Lender Specific Origination Shock			(-1.56)	(-1.65)
Market Level Lender Shock * Top Quartile			0.0457**	0.105***
			(2.02)	(2.66)
log(1+Prev Deal Count)		Yes		Yes
log(1+Curr App Count)	Yes	Yes	Yes	Yes
log(1+Prev App Count)	Yes		Yes	
Lender FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Lender Clustered SE	Yes	Yes	Yes	Yes
Market Clustered SE	Yes	Yes	Yes	Yes
N	56,017,529	56,017,529	56,017,529	56,017,529
adj. R^2	0.434	0.402	0.434	0.402

Table VIII

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 and 5 investigate the impact on the Original Interest Rate of a loan. Columns 2 and 6 look at the change in the FICO composition, while columns 3 and 7 as well as 4 and 8 look at the LTV and Amortization Terms at origination, respectively. Columns 1-4 measure increased competition through the Quickest-Growing Competitor Origination Shock, while columns 5-8 utilize the shock to the market Herfindahl-Hirschman Index. Applicant/Loan Characteristic Controls include indicators for White, Owner Occupied, Conventional, Single Family, and Purchase. Tract-Market Competitor Count, 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	LTV	Term	Int Rate	FICO	LTV	Term
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Previous Market Level Lender Specific	-0.0000576	-0.00912	0.109	-0.263	0.00186	0.0760	0.102	-0.362
Origination Shock ($\hat{v}_{M,b,t-1}$)	(-0.01)	(-0.03)	(1.12)	(-0.71)	(0.23)	(0.21)	(1.03)	(-0.95)
Previous Quickest-Growing Competitor	0.0187**	-0.0683	0.250**	0.234				
Origination Shock	(2.55)	(-0.26)	(2.16)	(0.85)				
Previous Herfindahl-Hirschman Index					5.120	272.5	-11.73	134.3
Origination Shock					(1.49)	(1.39)	(-0.22)	(0.63)
Applicant/Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competitor Count FE	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	7,423,376	7,060,182	7,510,336	7,405,496	6,760,202	6,446,421	6,837,189	6,746,798
adj. R^2	0.568	0.351	0.347	0.174	0.565	0.341	0.343	0.175

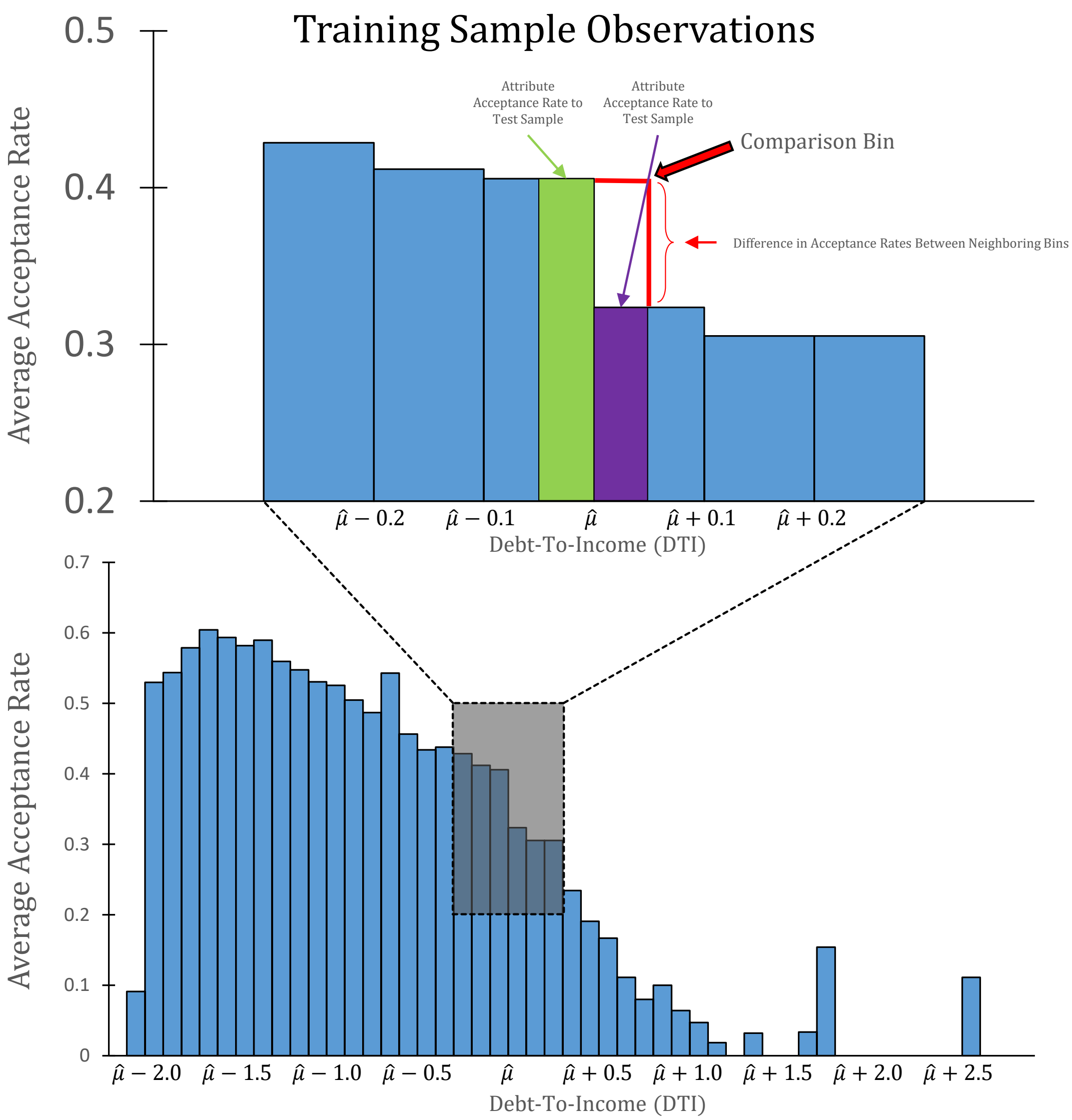
Table IX

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 Quickest-Growing Competitor Origination Shock in the year preceding the loan application. The performance outcomes investigated are Delinquent (columns 1-5) and Default (columns 6-10). 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 6 include only the Lender Specific Origination Shock. Columns 2, 3, 7 and 8 include the Quickest-Growing Competitor Origination Shock in addition to the Lender Specific one, representing the reduced form representation in our instrumental variable approach. Columns 4 and 9 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 5 and 10 compare to columns 3 and 8 respectively, instead utilizing the shock to the Herfindahl-Hirschman Index. Controls for FICO, Interest Rate, LTV and Amortization Term at origination are also included (in all columns except 2 and 7). 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)	(9)	(10)
Previous Market Level Lender Specific	0.00220	0.00288	0.00302	0.00281	0.00226	0.00100	0.00186	0.00133	0.00110	0.000632
Origination Shock ($\hat{v}_{M,b,t-1}$)	(1.12)	(1.38)	(1.55)	(1.46)	(1.13)	(0.66)	(1.06)	(0.85)	(0.71)	(0.41)
Previous Quickest-Growing Competitor		0.00336**	0.00290*				0.00343**	0.00324**		
Origination Shock		(2.03)	(1.80)				(2.15)	(2.16)		
log(1+Previous Largest Competitor Deal Increase) Instrumented with Previous Quickest-Growing Competitor Origination Shock				0.0278*					0.0310**	
				(1.84)					(2.22)	
Previous Herfindahl-Hirschman Index					1.165					0.467
Origination Shock					(1.28)					(0.66)
FICO	-0.00131***		-0.00133***	-0.00133***	-0.00131***	-0.000750***		-0.000775***	-0.000774***	-0.000747***
	(-19.89)		(-17.11)	(-17.09)	(-19.04)	(-11.60)		(-10.11)	(-10.09)	(-11.12)
Int Rate	0.00957***		0.0100***	0.0101***	0.00851**	0.0132***		0.0137***	0.0138***	0.0119***
	(3.02)		(3.26)	(3.29)	(2.56)	(3.97)		(4.23)	(4.26)	(3.41)
LTV	0.00168***		0.00175***	0.00174***	0.00171***	0.00134***		0.00140***	0.00139***	0.00136***
	(9.99)		(9.06)	(9.04)	(9.61)	(8.32)		(7.62)	(7.60)	(7.98)
Term	0.000220***		0.000198***	0.000198***	0.000215***	0.000155***		0.000134***	0.000134***	0.000151***
	(5.53)		(5.52)	(5.52)	(5.36)	(3.88)		(3.69)	(3.69)	(3.77)
Applicant/Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Competitor Count FE	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	6,823,231	6,517,056	6,040,782	6,040,782	6,229,038	6,823,231	6,517,056	6,040,782	6,040,782	6,229,038
adj. R^2	0.320	0.306	0.348	0.347	0.320	0.296	0.294	0.318	0.317	0.296

Figure 1. Example of Estimated Lender Origination Model



This graph displays the estimated origination model of the lender 21st Mortgage Corporation for white owner-occupied applicants in 2011. Data from the training sample is used to estimate the average acceptance rate as a function of applicant DTI. The upper portion of the figure highlights the differences in acceptance rates for two neighboring DTI bins sharing a comparison bin. The average acceptance rates depicted for each DTI bin are attributed to the test sample in order to estimate the acceptance ratio jumps and generate lender-specific shocks for applicants with varying DTIs.