Lender Expectations and Real Estate Dynamics*

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Abstract

I create a new Metropolitan Statistical Area (MSA) level database to test the role of lender expectations about housing prices and borrower incomes on the dynamics of housing markets. As lender expectations are difficult to measure directly, I employ a new proxy–banks' local branching decisions–to capture them. I find that banks opening new branches in an MSA also lower their denial rates on mortgage applications associated with properties in that MSA. Moreover, further analysis of this result shows that the banks reacting to positive changes in home prices or borrower incomes by more rapidly expanding their branch network also approve more mortgage applications.

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1 Introduction

One often-cited cause of the recent U.S. financial crisis is that mortgage lending standards in the pre-crisis years were too lax.[1] Most of the literature so far has focused on the role securitization played in lowering lending standards. For example, Keys et al. (2010) find that loans just above a credit score cutoff, making them easier to securitize, default 20% more often than loans with similar risk characteristics just below the cutoff. There is also a new literature that studies the role played by optimistic lender expectations.[2] Foote et al. (2012), for example, argue that overly optimistic beliefs about house prices were a main feature of pre-crisis lending decisions. Understanding both of these channels is important in order to prevent future crises.

This paper contributes along the expectations dimension by testing the role of lender expectations about housing prices and borrower incomes on the dynamics of housing markets. I employ a Metropolitan Statistical Area (MSA) level data set that includes individual mortgage loan application data from the Home Mortgage Disclosure Act (HMDA) and bank branching data from the FDIC Summary of Deposits Survey to test whether a proxy for lender expectations can explain changes in lenders' mortgage denial rates in the 2005-2011 period. A key component of this study is to test whether overly optimistic lender expectations can be observed in the data and whether this optimism led to overzealous mortgage lending.

As lender expectations are difficult to measure directly, I employ a new proxy to capture them. The proxy I study is the change in the number of lender branch locations. Because new branch locations are costly to open and operate, only lenders that expect favorable future lending conditions in an area will choose to open them. Similarly, lenders expecting a deterioration in future lending conditions in an area will choose to close branches. Hence, banks' branching decisions are likely a good indicator of banks' expectations.

[1] See, for example, Dell'Ariccia et al. (2012), Demyanyk and Van Hemert (2011), Favilukis et al. (2012), Keys et al. (2010 and 2012), or Maddaloni and Peydro (2011).

[2] See, for example, Brueckner et al. (2012), Cheng et al. (2013), Foote et al. (2012) and Goetzmann et al. (2012).

I use my data set to test whether bank branching decisions are a reliable predictor of banks' lending standards. Specifically, I examine whether banks opening new branches in an MSA exhibit lower mortgage denial rates on properties located within that same MSA. Because the timing of the branching data runs from July 1-June 30 and the timing of the denial rate data runs during the calendar year, I am able to partially rule out reverse-causality. New branches take time to build, so branches completed within the January 1-June 30 time frame would likely reflect expectations formed within the prior calendar year. It is thus unlikely that what I'm capturing in my analysis is that lower denial rates increase borrower demand and generate a need for new branches.

A novel feature of my data set is that I am able to exploit the heterogeneity in lenders' expectations within the same MSA by comparing the lending behavior of banks that opened new branches to those that did not. I am also able to estimate separately the response functions of individual lenders' branching and mortgage denial rate decisions to the same sequence of changes in MSA conditions. By comparing these separate response functions, I am able to study whether banks that are overly optimistic also engage in overzealous mortgage lending.

My results show that lenders that invest in new branches in a particular MSA significantly lower their denial rates on mortgage loans for properties within that same MSA. When I break my sample by banks' asset sizes, I find that this relationship is more pronounced for mid-size banks with assets between $2 billion and $10 billion. These results suggest that bank branching decisions may be a reliable proxy for bank expectations.

When I examine separately lenders' branching and mortgage denial decisions, I find that lenders responding to positive movements in house prices and borrower incomes by increasing (decreasing) the number of branch locations in an MSA more than average also lower (raise) their mortgage denial rates by more than average. This result suggests that banks that are more optimistic on average lower their lending standards by more than average, supporting the hypothesis that optimistic expectations may be a driver of lower lending standards.

To explore the robustness of my results, I redo my analysis by lien priority, focusing on the pre-crisis period. Loans secured by first liens are inherently less risky, as the lender is first in line to capture the underlying value of the mortgage property should the loan default. Second liens and loans not secured by a lien, on the other hand, carry more risk. One would expect that lender expectations would play a large role in the approval/denial decision of second liens and unsecured loans. However, I find that my expectations proxy does a better job explaining the behavior of lenders' first lien approval/denial decisions.

There is an existing literature that addresses the relationship between expectations about housing prices and lending standards. Gete and Tiernan (2014) finds using a quantitative model that under imperfect information about the persistence of house price growth, lenders who observe a sequence of positive house price shocks will rationally expect future price growth and lower their lending standards in response. Brueckner et al. (2012) and Goetzmann et al. (2012) provide empirical evidence that lenders extrapolated pre-crisis housing price trends to make subprime lending decisions. Mian and Sufi (2009), however, finds that increased mortgage credit in areas with high levels of subprime lending was driven largely by credit supply factors rather than by housing price expectations.

My study is also related to Cheng et al. (2013), Cortes (2012), and Dell'Arricia et al. (2008). Cheng et al. (2013) provides evidence that overly optimistic lender expectations may have negatively influenced lending standards. The paper compares the performance of the personal home transactions of mid-level managers in securitized finance with those of uninformed control groups and finds that the transactions of securitization agents performed worse. The authors conclude that this result signals distorted beliefs of agents in the mortgage market during the pre-crisis period. My study, in contrast, employs branching decisions as a new proxy to determine whether optimistic beliefs were present in the housing market. Cortes (2012) examines the behavior of local lenders, i.e. lenders who operate branches in the same county in which they engage in mortgage lending, in the presence of home price shocks and finds that local lenders have better information about home-price fundamentals than non-local lenders.

The author finds that in general, the share of local lending in a market fell as home prices grew rapidly. I only consider local lending in my analysis, but still find evidence of overly optimistic behavior by local lenders due to changes in prices and borrower incomes. Dell'Arricia et al. (2008) studies the determinants of denial rates at the MSA level and find that denial rates from 2001-2006 fell as home prices, population and average income rose. They find that credit boom conditions and market structure also mattered. My analysis addresses some of the same denial rate determinants, but approaches the question at the bank-MSA level.

The remainder of the paper is organized as follows. Section 2 discusses the conceptual framework of the exercise. Section 3 presents the data. Section 4 describes the empirical methodology. Section 5 discusses the empirical results. Section 6 offers a robustness check. Section 7 concludes.

2 Conceptual Framework

Before proceeding to the empirical exercise, I present here a conceptual framework that allows for rational overoptimism in lender expectations and illustrates the resulting impact on lending standards. Consider a model with banks and real estate investors. Investors are heterogeneous and must borrow from banks in order to invest in real estate projects. Banks and investors randomly meet, and banks form expectations about their investor's project return to decide whether or not to lend.

2.1 Investors and Lending Standards

In every period t there is a continuum of mass one of real estate investors. The return of an investor's project is affected by the exogenous process for real estate price growth $\left(\frac{p_t^h}{p_{t-1}^h}\right)$

and the investor's idiosyncratic ability to generate income (ω), according to

$$y(\omega, \frac{p_t^h}{p_{t-1}^h}, L_t) = \frac{p_t^h}{p_{t-1}^h}\omega^\alpha L_t \tag{1}$$

where L_t is the size of the loan the investor receives from the bank. Investors purchase $\frac{L_t}{p_{t-1}^h}$ units of real estate at the start of the period, then they sell those units at the end of the period, receiving as proceeds those units times the current real estate price $\left(p_t^h\right)$. The term ω^α captures the idiosyncratic characteristics of the investor. Heterogeneity among investors implies that for the same level of price growth $\left(\frac{p_t^h}{p_{t-1}^h}\right)$ and investment (L_t), some investors' projects are more profitable than others.

Investors' type ω is distributed following a Pareto distribution with support $[M, \infty)$ and distribution function $G(\omega) = 1 - \left(\frac{M}{\omega}\right)^\mu$, where $\mu > 0$ is the shape parameter. As μ increases, the dispersion of ω decreases and is increasingly concentrated towards the lower bound M. The Pareto assumption fits quite well firm-level data about the size and productivity distribution of firms (Ghironi and Melitz 2005) as well as households' wealth distribution.

Banks can implement lending standards to weed out bad investors. I denote by $\pi_t \in [0, \infty)$ the bank's lending standards. A bank with lending standards π_t denies credit to any investor with $\omega < M + \pi_t$ where M is the lower bound of the distribution of ω. Figure 1 plots the distribution of ω. Only developers to the right of $M + \pi_t$ receive credit. As π_t increases, lending standards are higher and the bank is more selective when lending because the bank has increased the minimum cutoff to give credit. This implies that higher lending standards are associated with higher credit denial rates.

Insert Figure 1 here

To ensure that all investors apply for credit, even if they have $\omega < M + \pi_t$, I assume that investors do not have any initial capital, cannot save and do not know or cannot signal their type. Moreover, to ensure that investors seek the maximum financing, I assume that a fraction

$\kappa \geq 0$ of the project's income is for the investor and cannot be seized by the banks.

To focus on the quantity of credit instead of on the price of credit, I assume that banks receive the remaining fraction $(1-\kappa)$ of the project's revenue. Several authors have previously used the simplification of banks as equity holders.[3] It is a reduced form approach to how the surplus from a lending relationship is split between the lender and the borrower. Thus, a bank would receive payments $(1-\kappa)y(\omega, \frac{p_t^h}{p_{t-1}^h}, L_t)$ from a borrower of type ω who received a loan of size L_t.

2.2 Imperfect Information about Real Estate Prices

Banks' lending standards will change with their expectations about real estate price growth. Real estate price growth $\left(\frac{p_t^h}{p_{t-1}^h}\right)$ is exogenous and stochastic. It is unknown at the time of decision-making in period t, but is observed at the end of the period. To introduce imperfect information about the persistence of real estate price growth, I assume that $\left(\frac{p_t^h}{p_{t-1}^h}\right)$ is the sum of two unobservable parts, both with permanent effects, but one part is persistent while the other is not:

$$\frac{p_t^h}{p_{t-1}^h} = \exp\left(z_t + \eta_t\right) \tag{2}$$

where z_t is the persistent part that follows a two state Markov chain. That is, prices can have high or low growth $z_t = \left\{z^L, z^H\right\}$, with $z^L < z^H$, and transition matrix

$$P = \begin{bmatrix} P_{LL} & P_{LH} \\ P_{HL} & P_{HH} \end{bmatrix}$$

The non-persistent part η_t is an *i.i.d.* Normal shock with mean $\frac{-\sigma_\eta^2}{2}$ and variance σ_η^2. This assumption for the mean of η_t ensures that, conditional on z_t, $\frac{p_t^h}{p_{t-1}^h}$ follows a lognormal distribution whose conditional mean is $\exp\left(z_t\right)$. I will refer to the η_t shock as a noise shock because

[3] See, for example, Gertler and Karadi (2011).

it prevents banks from perfectly observing z_t and it is a shock to which banks should not react because it is *i.i.d.*

Banks must make period t decisions before price growth is known, so they form expectations about it from their past observations (we denote by Θ_{t-1} the information set known at the start of the t period). They do so by forecasting the unobservable state of the persistent part, z_t, from past observations of $\frac{p_t^h}{p_{t-1}^h}$ using a Bayesian filter. I denote by $p_{t-1} \equiv \Pr(z_t = z^H|\Theta_{t-1})$ the belief or prior of z_t being in the high state in period t.[4]

Banks start period t with a prior p_{t-1} and base their period t decisions on this prior. Once $\frac{p_t^h}{p_{t-1}^h}$ is observed at the end of period t, agents compute their posterior beliefs about the state of the persistent component, $\Pr(z_t = z^i|\Theta_t)$, using the Bayesian filter

$$\Pr(z_t = z^i|\Theta_t) = \frac{f(\frac{p_t^h}{p_{t-1}^h}|z_t = z^i)\Pr(z_t = z^i|\Theta_{t-1})}{f(\frac{p_t^h}{p_{t-1}^h}|z_t = z^j)\Pr(z_t = z^j|\Theta_{t-1}) + f(\frac{p_t^h}{p_{t-1}^h}|z_t = z^i)\Pr(z_t = z^i|\Theta_{t-1})} \tag{3}$$

where the conditional density $f(\frac{p_t^h}{p_{t-1}^h}|z_t = z^i)$ is the normal probability density

$$f(\frac{p_t^h}{p_{t-1}^h}|z_t = z^i) = \frac{1}{\sigma_\eta\sqrt{2\pi}}\exp\left(-\frac{1}{2\sigma_\eta^2}\left(\frac{p_t^h}{p_{t-1}^h} - z^i + \frac{\sigma_\eta^2}{2}\right)^2\right) \tag{4}$$

Banks form next period's prior $p_t = \Pr(z_{t+1} = z^i|\Theta_t)$ by updating the posterior with the transition matrix P

$$p_t = \Pr(z_{t+1} = z^i|\Theta_t) = \Pr(z_t = z^i|\Theta_t)P_{ii} + \Pr(z_t = z^j|\Theta_t)P_{ji} \tag{5}$$

This is the prior used to make decisions in period $t+1$.

I will use the notation $E_{t-1}(.)$ to denote the expectation over $\frac{p_t^h}{p_{t-1}^h}$ conditional on the information known at the start of the period. That is, the conditional expectation of the proceeds

[4] Likewise, the prior of being in the low state is $(1 - p_{t-1})$.

from the real estate project conditional on information at the start of period t is:

$$E_{t-1}\left[y(\omega,\frac{p_t^h}{p_{t-1}^h},L_t)\right]=E_{t-1}\left[\frac{p_t^h}{p_{t-1}^h}\right]\omega^\alpha L_t=$$
$$=\left[p_{t-1}\left(\exp\left(z^H\right)\right)+\left(1-p_{t-1}\right)\left(\exp\left(z^L\right)\right)\right]\omega^\alpha L_t \tag{6}$$

2.3 Banks' Problem

In every period t there is a continuum of mass one of risk neutral banks. Banks can fund their loans with their own equity, K_t, or with deposits or borrowings, B_t, that cost R_t^B. Banks are subject to a capital requirement, $\gamma \geq 0$, such that

$$L_t \leq B_t + K_t \tag{7}$$
$$K_t \geq \gamma L_t \tag{8}$$

Each bank lives for one period, meets one borrower and maximizes shareholders' value over that period. Banks' decisions are taken before $\frac{p_t^h}{p_{t-1}^h}$ is known. Banks start period t with a prior, p_{t-1}, about $\frac{p_t^h}{p_{t-1}^h}$ inherited from the posterior of the previous cohort of bankers according to equation (5). Then banks decide their lending standards π_t and each bank meets with a borrower. If the bank meets with a borrower who does not satisfy its lending standards $(\omega < M + \pi_t)$, then it does not lend and sits on its capital.

If the bank meets with a borrower who satisfies the standards $(\omega \geq M + \pi_t)$ then it lends the amount L_t. At the end of the period $\frac{p_t^h}{p_{t-1}^h}$ is realized, the return from the project is observed, split between the bank and its borrower, and the borrower and the bank separate. With the proceeds received, the bank pays its debtholders. Any remaining proceeds then go to shareholders.

For a given K_t and p_{t-1} the bank chooses lending standards to maximize expected shareholders' value at the end of the period. The banks take expectations over both ω (because the bank does not know which type of borrower it will meet) and $\frac{p_t^h}{p_{t-1}^h}$. That is, the bank solves:

$$\max_{\{\pi_t,\, L_t\}_0^\infty} \int_M^{M+\pi_t} K_t dG(\omega) + E_{t-1}\left(\int_{M+\pi_t}^{\infty}\left((1-\kappa)y(\omega, \frac{p_t^h}{p_{t-1}^h}, L_t) - R_t^B B_t\right) dG(\omega)\right) \tag{9}$$

$s.t.$ (7) and (8)

where $[M, M+\pi_t]$ is the region where the banks are not lending.

Given banks' linear utility, if the borrower is considered worthy of receiving credit, the bank will always try to give her the maximum credit possible. Thus, equations (7) and (8) would hold with equality. The first-order condition that determines optimal bank lending standards is:

$$0 = \frac{1}{R_t^E}\mu M^\mu (M+\pi_t)^{-\mu-1}\left[K_t - (1-\kappa)E_{t-1}\left(\frac{p_t^h}{p_{t-1}^h}\right)(M+\pi_t)^\alpha L_t + R_t^B B_t\right] \tag{10}$$

which implies

$$K_t = (1-\kappa)E_{t-1}\left(\frac{p_t^h}{p_{t-1}^h}\right)(M+\pi_t)^\alpha L_t - R_t^B B_t$$

Hence, as expectations about real estate price growth rise, banks' optimal lending standards fall in response.

2.4 Rational Overoptimism

Due to imperfect information about the persistence of real estate price growth in this framework, banks can form expectations that are rationally overoptimistic. Ideally, banks would only consider the persistent component of real estate price growth (z_t) when forming their expectations. With imperfect information, however, it is possible that a positive transitory noise shock (η_t) can be interpreted as a positive change in the persistent component.

A bank that expects real estate price growth to be high will rationally lower its lending standards and lend to investors with lower idiosyncratic characteristics than it would have before. However, if the bank's expectation was formed after observing a positive shock to the transitory noise component, then those lower lending standards may imply end-of-period losses for the bank. This would represent an instance of a rational but optimism-driven relaxation in lending standards.

Taking this model to the data, since I cannot observe banks' expectations directly, I infer them from bank behavior. Specifically, I employ bank branching decisions as a proxy for bank expectations. Banks that are enthusiastic about future lending opportunities in a particular area will open a new branch to draw in and meet with more potential customers. A significant negative relationship between bank branch openings and bank lending standards would demonstrate that bank branching decisions can be used as a reliable proxy for bank expectations. Furthermore, if banks opening more branches than average also have lending standards or denial rates that are lower than average, I provide evidence of an optimism-driven relaxation in lending standards.

3 Data

My principal data sets are publicly available and include U.S. home mortgage application data from the Home Mortgage Disclosure Act and bank branch data from the FDIC Summary of Deposits Survey. My control variables include banking variables from the "Consolidated Reports of Condition and Income" (Call Reports) collected by U.S. bank regulatory authorities, MSA-level demographic and economic data from the Bureau of Economic Analysis and MSA-level home price data from Freddie Mac.

3.1 Home Mortgage Disclosure Act (HMDA) Data

The Home Mortgage Disclosure Act was enacted in 1975, and requires mortgage lending institutions to report data on mortgage loan applications to gauge compliance with fair lending laws and to guide public investment in housing. The data coverage includes mortgage applications received by depository institutions and mortgage finance companies with branch offices in MSAs. The data do not cover mortgage applications received by small or primarily rural depository institutions.

HMDA data include characteristics about mortgage loan itself, information regarding whether the loan was approved or denied, borrower demographic and income characteristics, as well as information regarding the underlying property and its location. My sample starts in 2005 and runs through 2011. HMDA data cover approximately 95% of the total volume of home mortgage originations in the U.S. in this period.[5] Because my proxy for lender expectations is only available for banks and savings institutions, I restrict my analysis to the application data reported by these institutions. With this restriction, my data account for approximately 40% of the lending activity captured by HMDA. The remaining fraction of lending activity was reported by mortgage finance companies.

My primary interest in the HMDA data is computing denial rates by lender in a particular MSA in a particular year. To ensure that my comparison of denial rates across lenders is sensible, I restrict my analysis to applications for conventional home purchase loans where the underlying property is a one-to-four family home that will be owner-occupied. Furthermore, I examine only those applications with clear approval or denial decisions. That is, I include applications where the lender either originated the loan, denied the loan, or the loan was approved but not accepted.[6] After all restrictions, my data set includes approximately 12% of the lending activity captured by HMDA. I define the denial rate as the total number of applications denied by a lender in a particular MSA in a particular year divided by the total number of applications received by a lender in a particular MSA in a particular year.

$$denial\_rate_{ikt} = \frac{apps\_denied_{ikt}}{apps\_received_{ikt}} \tag{11}$$

[5] Dell'Ariccia et al. (2008) provide estimates of HMDA coverage rates by year.

[6] I exclude applications that were withdrawn by the applicant, application files that were closed due to incompleteness, loans that were purchased by the lender, or any preapproval requests.

where i represents the lender, k represents the MSA and t represents the year. I compute the change in the denial rate as the difference in the denial rate between years t and $t-1$:

$$\Delta denial\_rate_{ikt} = denial\_rate_{ikt} - denial\_rate_{ik,t-1} \tag{12}$$

In order to use the HMDA data alongside data from the Summary of Deposits Survey and Call Reports, I must link records in the HMDA data to each financial institution's unique RSSD number. To do this, the HMDA data include a unique identifier for each lender based upon the combination of the lender's agency code and HMDA respondent identification number.[7] Those institutions listed as filing with the Office of the Comptroller of the Currency report their charter number as their respondent identification number, those filing with the Federal Reserve System report their RSSD number, those filing with the FDIC report their certificate number and those filing with the Office of Thrift Supervision report their docket number. I match these numbers to the related fields in the Call Report in order to find each institution's RSSD number.

3.2 Summary of Deposits Survey Data

The Summary of Deposits Survey contains data on the location and deposits of branch offices for all FDIC-insured institutions as of June 30th of each year. To use bank branching decisions as a proxy for expectations, I first compute the total number of branch offices in an MSA for each lender in a given year. I then compute the percent change in the total number of branch offices for each lender in a given year, accounting for any mergers and acquisitions.

$$\%\Delta branches_{ikt} = \frac{branches_{ikt} - branches_{ik,t-1}}{branches_{ik,t-1}} \tag{13}$$

where i represents the lender, k represents the MSA and t represents the year.

[7] The agency code represents the regulatory agency with which the lender files.

3.3 Summary Statistics

In what follows, I define a bank or a lender as the regulatory top holder financial institution. That is, where possible I aggregate observations up to the bank holding company level. In addition, because I study year-on-year changes in some of my variables of interest, I also make adjustments for merger and acquisition activity using data available from the Federal Reserve Bank of Chicago. Table 1 contains summary information about variable definitions and data sources.

Insert Table 1 here

Table 2 reports summary statistics. In Table 2, the mean year-on-year change in the denial rate within my sample is around 0.02, reflecting that on average denial rates increased by 2%. The maximum and minimum values for the change in the denial rate reflect a year-on-year change from a 0% denial rate to a 100% denial rate and vice versa. In each of these cases, the bank received less than five loan applications per year and either denied or approved all of them. The mean percentage change in bank branches, after adjusting for mergers and acquisitions, is close to 15% in my sample. House prices fell on average across all MSAs by 2.34% from 2005-2011. The most rapid decline in house prices occurred in the Las Vegas, Nevada MSA during 2008 and the most rapid increase occurred in the Midland, Texas MSA during 2006. Per capita income rose on average across all MSAs by 2.85% from 2005-2011. The most rapid increase and decrease in income occurred in the New Orleans, Louisiana MSA in 2006 and in the Midland, Texas MSA in 2009, respectively. Lastly, population across all MSAs rose by close to 1% from 2005-2011. The most rapid decline in population occurred in New Orleans, Louisiana in 2006 following Hurricane Katrina. The most rapid increase in population occurred in Palm Coast, Florida during 2006.

Insert Table 2 here

4 Empirical Methodology

I first test the relationship between bank branching and denial rate decisions using a simple regression. My hypothesis is that lenders that increase the size of their branch network in a given MSA in a particular year will also lower their mortgage denial rate in that MSA in that year. That is, lenders that invest in opening branches do so because they expect more favorable lending conditions, which will then be reflected in lower mortgage denial rates. My simple regression takes the following form:

$$\Delta denial\_rate_{ikt} = \beta_1 + \beta_2 \% \Delta branches_{ikt} + \varepsilon_{ikt} \tag{14}$$

where $\Delta denial\_rate_{ikt}$ represents the difference in the denial rate between years t and $t-1$ for bank i in MSA k and $\%\Delta branches_{ikt}$ represents the percent change in the number of branches between years t and $t-1$ for bank i in MSA k. I run this regression for the full sample of banks as well as for different samples of banks categorized by size.

To further analyze the relationships I observe from this simple regression, I explore the effect of different MSA-level factors on the banks' decisions about branching and mortgage decisions independently.[8] First, I examine the impact of changes in population, changes in per capita income, and changes in house prices on a bank's decision to open or close its branch locations in a given MSA.[9] In order to capture individual banks' reactions to these different MSA conditions, I also include an interaction term in my specification. The coefficient on this term will measure the sensitivity of individual banks to changes in either home prices or per

[8]I conduct analyses of the branching and denial decisions separately to avoid issues with multicollinearity.

[9]Hannan and Hanweck (2008) find that population and per capita income explain the number of bank branches present in a given MSA.

capita income in terms of branching decisions. My specification takes the following form:

$$\%\Delta branches_{ikt} = \begin{pmatrix} \alpha_i D_i + \beta_1 \%\Delta population_{k,t-1} + \\ +\beta_2 \%\Delta income_{k,t-1} + \\ +\beta_3 \%\Delta prices_{k,t-2} + \\ +\gamma_i \left(D_i * selected\_control \right) + \varepsilon_{ikt} \end{pmatrix} \tag{15}$$

where D_i is a dummy variable for bank i, $\%\Delta population_{k,t-1}$ is the lagged percent change in population in MSA k, $\%\Delta income_{k,t-1}$ is the lagged percent change in per capita income in MSA k, $\%\Delta prices_{k,t-2}$ is the lagged percent change in house prices in MSA k, and $selected\_control$ can be either $\%\Delta prices_{k,t-2}$ or $\%\Delta income_{k,t-1}$. I focus on lagged MSA controls because changes in branches are measured July 1 to June 30, while my controls are measured January 1 to December 31.

Second, I examine the impact of the same MSA controls on changes in banks' mortgage denial rates.[10] I again include an interaction term with two separate specifications:

$$\Delta denial\_rate_{ikt} = \begin{pmatrix} \lambda_i D_i + \psi_1 \%\Delta population_{k,t-1} + \\ +\psi_2 \%\Delta income_{k,t-1} + \\ +\psi_3 \%\Delta prices_{k,t-2} + \\ +\theta_i \left(D_i * selected\_control \right) + \varepsilon_{ikt} \end{pmatrix} \tag{16}$$

where the independent variables have the same meaning as in Equation (15) and $selected\_control$ can be either $\%\Delta prices_{k,t-2}$ or $\%\Delta income_{k,t-1}$. Again, the coefficient on the interaction term will measure the sensitivity of individual banks to changes in either home prices or per capita income in terms of changes in mortgage denial rates.

Because my interest is in measuring and examining the effects of expectations, I study whether banks that are more sensitive to changes in either home prices or per capita income

[10] Dell'Ariccia et al. (2008) find that population, average income and house price appreciation can explain mortgage denial rates in an MSA.

are opening (closing) branches while at the same time lowering (raising) their denial rate. This relationship would show up in a comparison of γ_i, my measure for the sensitivity of bank i's branching decisions to changes in MSA conditions, with θ_i, my measure for the sensitivity of bank i's denial rate modifications in response to changes in MSA conditions.

5 Results

The first specification of Equation (14) that I test includes all of the banks in my sample, and I find that the relationship between branching decisions and the mortgage denial rate is negative and significant, confirming my hypothesis that branching decisions may be a reliable proxy for bank expectations and a reliable predictor of banks' denial rates. When I restrict my sample to banks of certain sizes, I find varying degrees of significance. Table 3 reports these results.

Insert Table 3 here

Banks with assets between \$2 billion and \$10 billion, which account for approximately 13% of the number of banks in my sample, tend to lower mortgage denial rates in MSAs where they are increasing the number of branch locations. However, smaller banks and very large banks do not exhibit a significant relationship between branch openings and changes in mortgage denial rates.

One could claim that a significant negative relationship between the dependent and independent variables above arise due to reverse causality. That is, a bank lowering its denial rates would experience an increase in borrower demand and open more branches in response. However, the fact that branch openings data begin and end as of June 30, while the approval-denial decisions are measured in a calendar year mitigates this argument somewhat. For example, if Bank A opens a new branch in Miami in June 2005, that opening would be compared to mortgage denial decisions from January-December 2005. Because the decision to open that new branch likely occurred with some lead time prior to the branch coming online, it is likely that I am capturing the lender expectations channel as opposed to the borrower demand channel.

To further explore the significant negative relationship between the percentage change in the number of bank branches and the change in the denial rate, I run the regessions in Equations (15) and (16) for my whole sample of banks and the subsample of banks with assets between \$2 billion and \$10 billion. I want to compare γ_i, my measure for the sensitivity of bank i's branching decisions to changes in MSA conditions, with θ_i, my measure for the sensitivity of bank i's denial rate modifications in response to changes in MSA conditions.

In Figure 2, I produce a scatter plot of γ_i and θ_i for my full sample of banks. Support for the expectations channel is present if in Figure 2 we observe a negative relationship between the two coefficients. I interpret such a result as evidence that banks responding to higher house prices or per capita income by opening (closing) more branches are also responding by lowering (raising) their denial rates to a larger degree. Figure 2 indeed illustrates that the expectations channel with regards to changes in both house prices and per capita income appears to drive the negative relationship between changes in bank branches and changes in bank denial rates.

Insert Figure 2 here

Figure 3 plots the coefficients γ_i and θ_i for the subsample of banks with assets between \$2 billion and \$10 billion. Again we see a negative correlation between banks' sensitivity to changes in house prices and per capita income.

6 Robustness

As a robustness check, I repeat my analysis by lien status for the pre-crisis period 2005-2007. Because mortgages based on subordinated and unsecured liens are inherently more risky, it is likely that the expectations channel would be even more apparent on these types of loans in the lead-up to the crisis. In the HMDA data, lien status is reported for loan applications and originations as either a first lien, a subordinate lien, or not secured by a lien. Tables 4 and 5 report the results of the simple regression for first lien and subordinate/unsecured liens respectively. The results in Table 4 are fairly similar to those in Table 3 and show that the change in denial rates of banks with assets less than \$900 million and banks with assets between \$2 billion and \$10 billion is negatively related to branch openings. All results in Table 5 are insignificant, suggesting that branching decisions may not be a reliable proxy for expectations about subordinate and unsecured lien lending prospects.

Figure 4 plots the coefficients of the interaction terms in the regressions of Equations (15) and (16) for the first lien sample. This plot resembles those of Figures 2 and 3.

7 Conclusion

I examine at the MSA level bank branching decisions as a proxy for lender expectations and test whether this proxy can explain changes in lenders' mortgage denial rates. I find a significant negative relationship between banks' branch openings and their mortgage denial rates and find that this relationship is more pronounced for banks with assets between \$2 billion and \$10 billion. When I break the sample by lien status, I find similar results relationship for first lien mortgage applications, but find no such relationship for second lien and unsecured applications. These results provide support for the use of bank branching decisions as a proxy for lender expectations.

Next, I compute the sensitivity of individual lenders' denial rate and branch opening decisions to changes in MSA level home prices and per capita income. Comparing the sensitivity of changes in the denial rate with changes in branch openings, I find evidence of an optimism-driven relaxation in lending standards. Optimistic lenders opening more branches than average in response to positive changes in home prices and borrower incomes also lower their mortgage denial rates by more than average. This evidence lends support to the effect of an expectations channel on lending standards.

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Tables

Table 1: Variables and Sources

Variable Name	Definition	Source
Data at the Bank-MSA-Year Level		
Δ Denial Rate	Annual difference in the ratio of denied applications to total applications in an MSA for a particular bank	HMDA
%Δ Bank Branches	Annual percentage change in the number of bank branches within an MSA for a particular bank	FDIC Summary of Deposits Survey
Data at the Bank-Year Level		
Bank Assets	Total bank assets	Call Report
Data at the MSA-Year Level		
%Δ housing prices	Annual percentage change in housing prices in the MSA	Freddie Mac
%Δ income	Annual percentage change in per capita income in the MSA	BEA
%Δ population	Annual percentage change in population in the MSA	BEA

Table 2: Summary Statistics

Variable Name	Obs.	Mean	Std. Dev.	Min	Max
Data at the Bank-MSA-Year Level					
Δ Denial Rate	4163	0.0193	0.1635	-1.0000	1.0000
%Δ Bank Branches	4163	14.80%	45.97%	-93.33%	966.67%
Data at the Bank-Year Level					
Bank Assets (in 000's)	2075	9,986,037	97,931,759	28,657	2,187,631,000
Data at the MSA-Year Level					
%Δ housing prices	1232	-2.34%	6.14%	-36.11%	25.65%
%Δ income	1232	2.85%	4.45%	-22.42%	33.11%
%Δ population	1232	1.02%	1.36%	-25.41%	9.52%

Table 3: Simple Regression Results, Full Sample

Dependent variable: $\Delta denial$ [illegible]	All bank[illegible]	Assets [illegible]	Assets $0.9B-$2B	Assets [illegible]	Assets [illegible]
$\%\Delta branches_{ikt}$	-0.012**	-0.014	0.025	-0.055***	-0.007
	(0.006)	0.010	0.017	0.019	0.007
Constant	0.021***	0.018***	0.013*	0.030***	0.023***
	(0.003)	0.005	0.008	0.008	0.003
Observations	4163	1713	438	550	1462
No. of Banks	962	617	162	129	54

Notes: Standard errors are in parentheses. * denotes significance at 10%, ** at 5%, and *** at 1%. The change in the denial rate is computed from HMDA and the percent change in bank branches is computed from the Summary of Deposits Survey. Results reported for years 2005-2011.

Table 4: Simple Regression Results, First Liens Only

		Assets	Assets	Assets	Assets
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
$\%\Delta branches_{ikt}$	-0.007	-0.038*	0.018	-0.036**	0.006
	(0.008)	(0.021)	(0.024)	(0.018)	(0.010)
Constant	0.016***	0.028**	0.012	0.012	0.017***
	(0.004)	(0.013)	(0.013)	(0.008)	(0.006)
Observations	1737	387	251	351	748
No. of Banks	633	314	156	127	52

Notes: Standard errors are in parentheses. * denotes significance at 10%, ** at 5%, and *** at 1%. The change in the denial rate is computed from HMDA and the percent change in bank branches is computed from the Summary of Deposits Survey. Results reported for first liens only during pre-crisis years 2005-2007.

Table 5: Simple Regression Results, Subordinate and Unsecured Liens Only

		Assets	Assets	Assets	Assets
Dependent variable: $\Delta denial\ rate_{it}$	All banks	< $0.9B	$0.9B-$2B	$2B-$10B	> $10B
$\%\Delta branches_{ikt}$	0.008	-0.014	0.037	-0.017	0.008
	(0.009)	(0.044)	(0.028)	(0.038)	(0.010)
Constant	0.004	0.017	-0.011	0.007	0.004
	(0.005)	(0.017)	(0.016)	(0.013)	(0.006)
Observations	1313	182	164	248	719
No. of Banks	413	157	111	107	47

Notes: Standard errors are in parentheses. * denotes significance at 10%, ** at 5%, and *** at 1%. The change in the denial rate is computed from HMDA and the percent change in bank branches is computed from the Summary of Deposits Survey. Results reported for subordinate and unsecured liens during pre-crisis years 2005-2007.

Figures

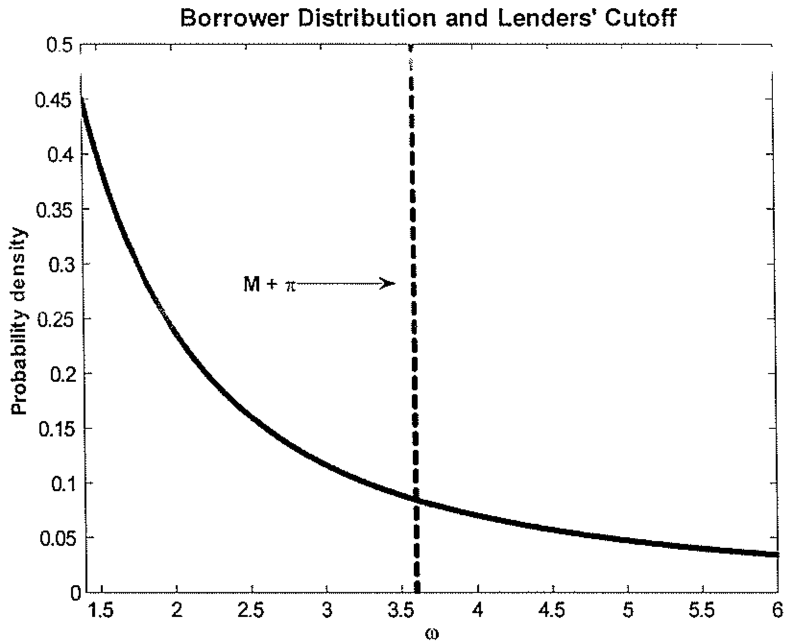

Figure 1: Distribution of borrowers' idiosyncratic income. Borrowers to the right of the approval cutoff receive loans, borrowers to the left do not. The approval cutoff, or lending standard, changes with the bank's expectation about real estate price growth.

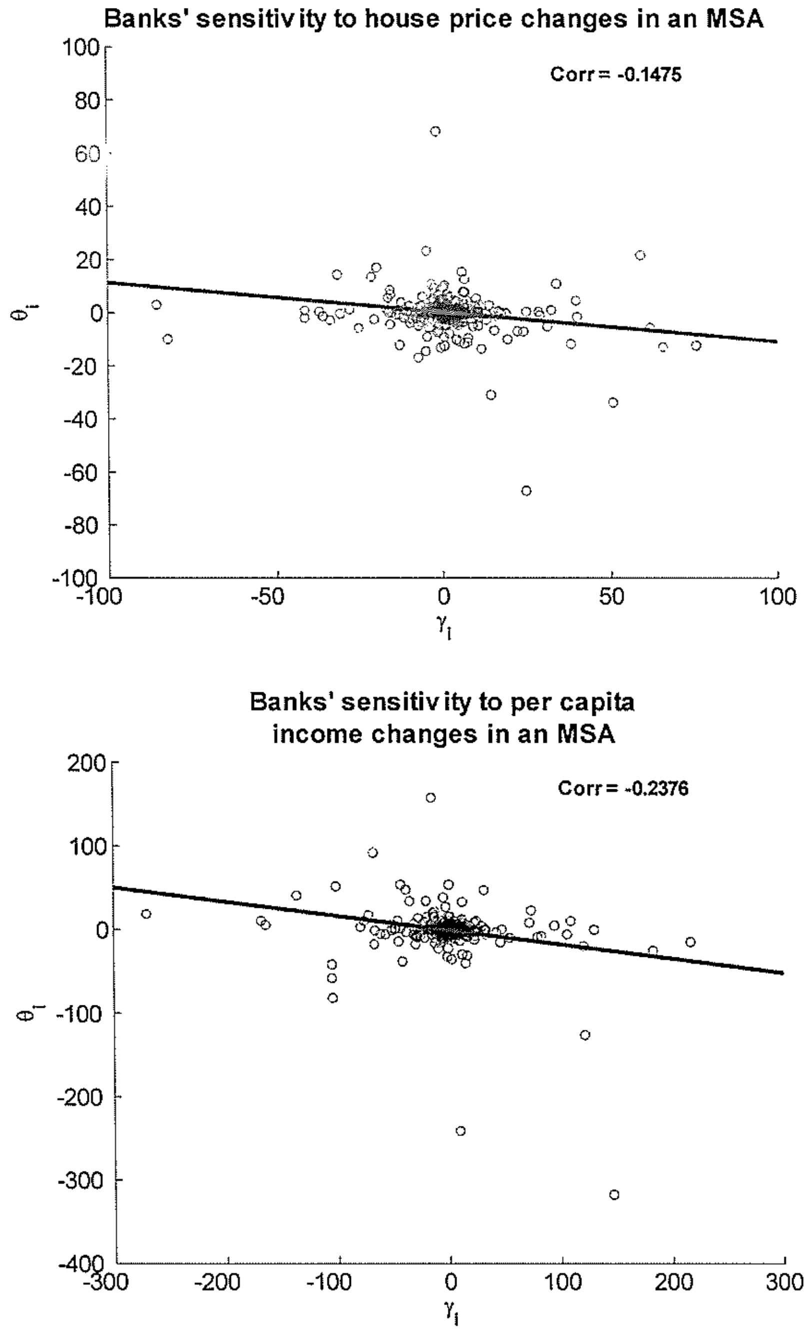

Figure 2: Sensitivity of individual banks' branch openings (γ_i) and denial rates (θ_i) in response to changes in MSA conditions from 2005-2011. Data are shown for all banks.

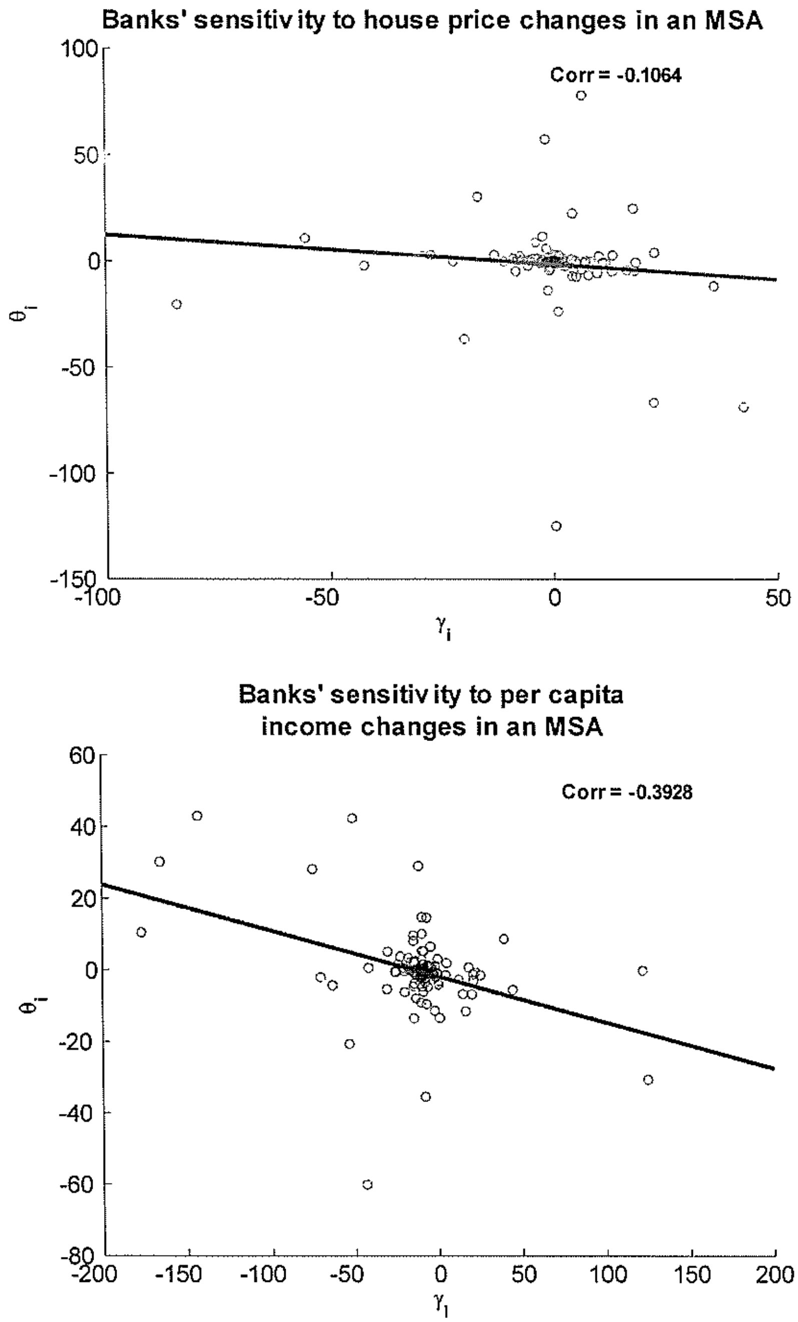

Figure 3: Sensitivity of individual banks' branch openings (γ_i) and denial rates (θ_i) in response to changes in MSA conditions from 2005-2011. Data are shown for banks with assets between \$2 billion and \$10 billion.

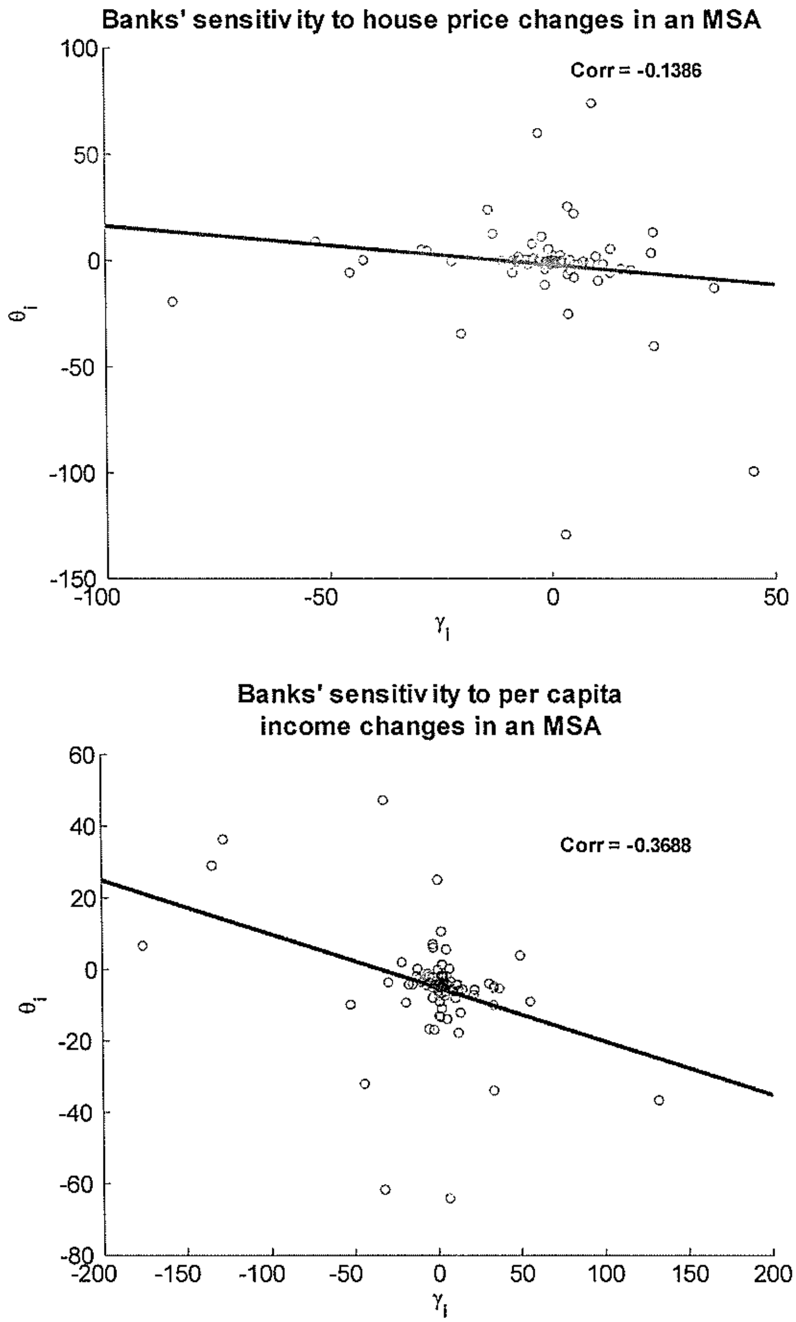

Figure 4: Sensitivity of individual banks' branch openings (γ_i) and denial rates (θ_i) on first lien loan applications in response to changes in MSA conditions in pre-crisis years 2005-2007. Data are shown for banks with assets between $2 billion and $10 billion.