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# Racial differences in mortgage denials over the housing cycle: Evidence from U.S. metropolitan areas

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ABSTRACT

The cyclical movement of housing prices likely affects the supply of and demand for credit for home purchases, but little is known about how this process might influence differential access to credit between minority and non-minority borrowers. This paper uses data reported through the Home Mortgage Disclosure Act (HMDA) over the period 1990–2013 to estimate the relationship between annual metropolitan area-level house price inflation and the extent to which Black borrowers are denied relative to 'comparable' White borrowers on their loan applications. The results indicate that, on average, Black borrowers are denied more frequently than White borrowers, but this difference in denial rates decreases significantly as house prices rise more rapidly. Such results demonstrate the importance of considering local housing market conditions when using HMDA data to assess lender compliance with fair lending laws.



## 1. Introduction

Discrimination in mortgage lending has been the subject of a large academic literature and continues to be a primary focus of government agencies responsible for enforcing the nation's fair lending laws. The overarching goal of this work is straightforward: determining whether individuals have been treated differently with respect to their access to credit based upon some 'prohibited' characteristic, such as age, race, or gender.

One aspect of the mortgage lending process that studies of discrimination have largely overlooked, however, is the natural variation in loan activity over the course of the housing cycle (i.e., the cyclical movements in the rate of house price inflation). A large literature, of course, has established the presence of a general credit cycle, in which the supply of loanable funds changes as the economy moves between periods of growth, when lending increases, and decline, when it contracts. The volume of mortgage lending shows a similar tendency to fluctuate as conditions in the housing market change.[2]

Although fluctuations in credit may have a number of underlying causes, it is likely that they are at least partly the product of changes in lending standards. That is, in response to a slowing economy, lenders tighten their underwriting criteria, which, holding loan demand and the distribution of borrower risk profiles fixed, results in fewer loans extended in equilibrium. As the economy expands, in turn, standards fall, leading to an increase in loan activity. Evidence drawn from surveys of bank officers indicates that

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[2] Avery et al. (2010) provide summaries of mortgage activity over time.

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the criteria underlying commercial and industrial loans tend to vary systematically over the business cycle.[3] A large literature suggests there is a similar phenomenon among mortgage lenders with respect to changes in both aggregate measures of default risk as well as the state of the housing market.[4]

Systematic changes in the criteria with which lenders evaluate mortgage applications, however, may influence the differential lending outcomes that government regulators measure in the process of monitoring the mortgage industry for potential violations of fair lending laws. Consider, for example, differences between loan applicants who belong to a minority racial group and those who do not. A housing boom may sharply increase the supply of mortgage credit as lenders ease their underwriting standards. Because racial and ethnic minorities tend to have lower average measures of borrower quality, such as credit scores, than White borrowers, minority denial rates may fall more than non-minority rates during a period of rapidly rising house prices. In this case, periods of strong house price appreciation may be associated with less apparent discrimination.[5]

Of course, the opposite outcome is also plausible. Housing booms may draw greater fractions of borrowers with especially weak credit histories – i.e., those that do not meet even extremely generous underwriting standards – into the market, as the demand for housing rises. If this happens to a larger degree among minorities than White borrowers, minority denial rates may rise relative to White approval rates, even though lending standards have been relaxed.

This paper explores whether measured differentials between White and Black borrowers show any variation over the housing cycle. To this end, we use annual data reported through the Home Mortgage Disclosure Act (HMDA) covering the period 1990–2013 to estimate how racial disparities in denial rates vary with the state of the housing market in which a lender is located.

The analysis is based upon the estimation of a simple screening model, similar to what government agencies that enforce fair lending laws might estimate in the process of identifying mortgage lenders for further scrutiny, to determine the difference in the probability of denial between Black and White borrowers. Because we carry out this estimation separately for each lender in each metropolitan area in every year, this process generates a set of metropolitan area-specific time series of Black–White differentials for each HMDA reporter institution.

The results indicate that increases in house price inflation are indeed significantly associated with Black–White differentials in loan denials. As the rate of inflation within a metropolitan area increases, the gap between Blacks and Whites shrinks, suggesting that, in times (or places) in which real estate is booming, mortgage lending appears to be more equal across individuals of these two racial groups than in times (or places) in which real estate is declining. A 10 percentage point increase in the rate of house price inflation, for example, tends to be accompanied by a 0.5 to 1 percentage point decrease in the gap between the Black denial rate and the White denial rate, on average. These magnitudes amount to approximately 5–10% of the overall mean Black–White denial differential in the data.

This somewhat modest average association, interestingly, masks a much larger (negative) association among the top half of the distribution of denial differentials. In particular, the estimated magnitude is approximately twice as large as this 'average effect' at the 75th percentile of the denial differential distribution. As demonstrated below, this feature induces substantial variation over the housing cycle in the fraction of lenders that are likely to be deemed worthy of further investigation by government regulators (i.e., those that exhibit especially large differentials).

A follow-up exercise that examines the geographic distribution of lending activity (applications, originations, and denials), offers similar conclusions. As a metropolitan area's rate of house price inflation increases, the fraction of denials within that metro area associated with properties in majority Black Census tracts decreases among locally situated lenders. Assuming that mortgage applications coming from majority Black neighborhoods are largely filed by Black applicants, this result merely suggests that Black denial rates fall relative to White denial rates. Yet, it also indicates that an additional gauge of fair lending compliance – redlining (i.e., the systematic avoidance of lending to certain neighborhoods) – also appears to be countercyclical, at least when measured by neighborhood denial shares.

We believe these findings raise an important consideration for agencies engaged in fair lending enforcement, as well as mortgage lenders that attempt to monitor their own fair lending compliance. The (apparent) systematic variation of underwriting standards with local house price inflation implies that perceived inequality in lending outcomes between races also varies over the housing cycle. This may naturally lead to greater enforcement activity by regulatory agencies, as well as the perception of a greater need for underwriting modification by lenders that self-monitor, during downturns in the real estate market.

The question is whether fluctuations in lending differentials over the housing cycle truly involve changes in discriminatory behavior, or whether they are merely the product of changing (but fair) lending standards interacted with the distribution of applicant risk by race. If the former explanation holds, agencies and lenders may wish to focus their fair lending analysis on areas or time periods in which housing markets are weak. If the latter holds, agencies and lenders should consider explicitly taking into account the state of the local housing market when gauging compliance with the nation's fair lending laws rather than employing standards that are constant over time. Both cases argue for the consideration of local house price inflation in the study of differential mortgage lending outcomes.

The remainder of the paper proceeds as follows. The next section describes how the present analysis relates to the extant literature. Section 3 then describes the data, empirical methods, and results. Section 4 discusses some of

[3] See, for example, Schreft and Owens (1991), Asea and Blomberg (1998), Lown et al. (2000), and Lown and Morgan (2006).

[4] See, for example, Duca and Rosenthal (1991), Ambrose et al. (2002), and Dell'Ariccia et al. (2008).

[5] Note, this assumes that the estimation of discrimination does not fully account for applicant risk, which is typical of the initial stages of fair lending enforcement.

the implications for fair lending enforcement and policy. The final section concludes.

## 2. Relevant literature

This paper bridges two literature studies. The first explores how lending standards vary over the course of an economic cycle, commonly the business cycle. The second examines discriminatory lending.

A long-standing result in the business cycle literature is the procyclical movement of credit. The strong correlation between measures of aggregate economic activity and the flow of bank loans of various types (e.g., commercial and industrial, real estate, consumer) has been a stylized fact in business cycle research for decades (e.g., Berger and Udell, 2004; Bernanke and Lown, 1991).

The fact that bank lending expands as the macroeconomy grows, and drops off as it contracts, may reflect a variety of underlying mechanisms. During times of rising economic activity, most obviously, the demand for loans may grow, leading to higher equilibrium quantities of credit extended. Alternatively, the availability of capital may vary systematically with the business cycle, say as the Federal Reserve influences the money supply or general level of interest rates. Some have even argued that periodic changes in regulation, such as increasing stringency or laxity in bank examinations, may generate a credit cycle, which then contributes to changes in aggregate economic growth (Bernanke and Lown, 1991; Peek and Rosengren, 1995).

One of the more straightforward explanations for the linkage between the business cycle and the supply of credit, however, involves the systematic variation of lending standards with fluctuations in economic activity. Quite simply, boom periods may be associated with the easing of underwriting criteria as banks become willing to accept greater levels of risk on the loans they make. For a given distribution of borrower risks, this produces an increase in the stock of loans made. During economic slowdowns, then, we see just the opposite: standards become more stringent, and lending drops off.[6]

A number of studies have found evidence supporting this idea within the context of commercial and industrial lending. Schreft and Owens (1991), Lown et al. (2000), and Lown and Morgan (2006), for example, use data from the Federal Reserve's Senior Loan Officer Survey to document the countercyclicality of lending standards for this type of credit. Asea and Blomberg (1998) find a similar result in data from the Federal Reserve's Survey of Terms of Bank Lending.

There is also an extensive literature that explores changes in mortgage lending standards, both with respect to the business cycle and the housing cycle. Duca and Rosenthal (1991), for instance, examine the share of mortgage loans backed by the Federal Housing Administration (FHA) – a product that typically attracts riskier borrowers – as compared to conventional mortgage credit. They find that, as macro measures of default risk increase, FHA-backed lending rises relative to conventional credit.

Ambrose et al. (2002) extend this analysis, finding that several measures of local economic activity influence FHA-backed mortgage lending relative to conventional lending at the metropolitan area level. Their results are consistent with the idea that lending standards governing conventional mortgage loans tighten as the state of a local housing market deteriorates, but loosen as it improves.

More recently, a number of papers have explored the rise of subprime lending in the United States during the early 2000s (e.g., Chomsisengphet and Pennington-Cross, 2006; Demyanyk and Van Hemert, 2011; Mian and Sufi, 2009), which coincided with a massive increase in real estate values. Because the very nature of subprime lending involves less stringent underwriting criteria, this evidence is suggestive of a link between laxity in mortgage lending and a boom in housing.

Indeed, a recent paper by Dell'Ariccia et al. (2008) finds that, between 2000 and 2006, a period of extensive growth in subprime mortgage lending in the United States, metropolitan areas with rapid house price inflation experienced lower mortgage denial rates than metro areas with slower house price growth. Although true of all lenders, this relationship was particularly pronounced among the subprime lenders in their data, suggesting that hot real estate markets were especially likely to see an expansion of relatively risky mortgage credit.

Because, on average, racial and ethnic minorities tend to be characterized by higher levels of risk (e.g., lower income and credit scores), fluctuations in lending standards may affect the differential rates at which they receive loans relative to non-minority (White) borrowers.[7] Typically, however, the literature on discriminatory lending does not consider this possibility. Instead, studies of discrimination tend to examine some group of lenders observed over only a short period of time, often just a year or two, and focus on the potential influence of various borrower characteristics on underwriting and pricing outcomes (e.g., Black et al., 1978; Blackburn and Vermilyea, 2006; Courchane, 2007; Courchane and Nickerson, 1997; Gabriel and Rosenthal, 1991; Ladd, 1998; Munnell et al., 1996).[8]

Overall, of course, the objective of these studies is to determine the extent to which race (or ethnicity) plays a role in the mortgage origination or pricing process.[9] The state of the housing market in which lenders operate rarely appears in the analysis. This paper seeks to evaluate whether fluctuations in local housing conditions have any influence on statistical measures that are designed to detect discrimination in mortgage lending.

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[6] See, for example, Stiglitz and Weiss (1981) for a formalization of this idea in an equilibrium framework.

[7] For evidence on the variation of credit scores with race, see Board of Governors of the Federal Reserve System (2007).

[8] There is also a long-standing literature that discusses the estimation techniques underlying measures of discrimination (e.g., Browne and Tootell, 1995; Dietrich, 2005; Horne, 1997; Rachlis and Yezer, 1993; Ross and Yinger, 1999; Yezer et al., 1994; Zhang, 2013).

[9] Fair lending investigations also attempt to identify whether the nature of any role of race is explicit or not, which determines if an alleged case of discrimination is pursued as disparate treatment or disparate impact. Distinguishing between these 'types' of discrimination is well beyond the scope of the screening exercise performed here.

## 3. Empirical analysis

### 3.1. Data

Data are drawn from 24 years of reporting through the Home Mortgage Disclosure Act (HMDA), 1990–2013. HMDA was enacted by Congress in 1975 to promote fair lending practices by mortgage lenders.[10] It requires most lenders in the country to report information about the mortgage applications they receive, the subsequent actions taken on those applications, and the applicants themselves. Government regulators routinely use these data to monitor differential lending outcomes between minority and non-minority borrowers. If an initial 'screening' of the HMDA data reveals a sufficiently large disparity, a follow-up investigation of the lender in question may be pursued.

Although HMDA data extend back to the mid-1970s, we only consider data since 1990 because that is the earliest year in which application-level records are reported. Prior to that year, the data are only available as aggregate summaries at the Census tract level.

The information contained in HMDA is relatively limited. Fields such as loan amount, applicant income, race, gender, whether the loan in question is conventional or government-backed, Census tract of the property, and the lender's action on the application (e.g., origination, denial, file closure) are available in all years. Since 2004, there has also been some pricing information included, but this information is only available for a subset of loans that carry sufficiently high annual percentage rates relative to a benchmark yield.[11] Other information, including lien status and the type of property in question, also became available after 2003.[12]

Not all lenders are required to report data under HMDA; only those exceeding a minimum size that also operate primarily in metropolitan areas. Nevertheless, HMDA's coverage of the mortgage market is extensive. Avery et al. (2008) report that, in 2007, HMDA covered roughly 8600 lenders and accounted for approximately 80% of all mortgage lending in the United States.[13]

To construct a set of geographic areas with consistent definitions over time, the HMDA loan and application observations are assigned to metropolitan areas using data on the state and county reported for each property. Metro area definitions are formally determined by the Office of Management and Budget, and reported by the Census Bureau. For the sake of matching the HMDA data with data on house prices (described below), definitions are taken from February, 2013 and applied to all 24 years of HMDA data.[14] The resulting sample includes lenders with operations in one or more of 398 metropolitan areas.[15]

As already noted, the data fields reported through HMDA have changed somewhat over time. In this paper, we focus on some of the core quantities that appear throughout the entire 1990–2013 period. These include whether a loan application was approved or denied; the loan amount; and the applicant's race, gender, and income. We constrain the sample to conventional loans (as opposed to those backed by government guarantees) for home purchase (rather than refinance or home improvement).

We augment these data with information about average house prices within each metropolitan area reported by the Federal Housing Finance Agency. The "All-Transactions Index" is reported quarterly and extends back as early as 1975 for some metropolitan areas.[16] We aggregate these quarterly figures into annual house price levels taking a simple average of the quarterly values, and calculate rates of inflation by taking annual growth rates.

We also use data from the Bureau of Economic Analysis on total employment and per capita income at the metropolitan area level.[17] These quantities are transformed into annual growth rates and matched to the remainder of the data to serve as measures of local economic activity, which may affect lending practices independently of the state of the local housing market.

### 3.2. Statistical methods

The estimation proceeds in two stages. In the first, we conduct a simple screening exercise similar to what lenders or government agencies might perform to assess compliance with fair lending laws.[18] In particular, we estimate the following:

$$d_{ilmt} = \alpha_{lmt} + \beta_{lmt} X_{ilmt} + \gamma_{lmt} \mathrm{BLACK}_{ilmt} + \epsilon_{ilmt} \tag{1}$$

where $d$ is an indicator for whether individual $i$'s application to lender $l$ located in metropolitan area $m$ in year $t$ was

[10] HMDA also provides information about the geographic location of mortgage lending, thereby allowing lenders and regulators to assess if capital is flowing to low- and moderate-income neighborhoods.

[11] Avery et al. (2010) describe the recent changes made to the reporting of loan pricing beginning with the 2009 data.

[12] See Avery et al. (2007) for a discussion of how HMDA reporting has changed over time.

[13] There have been periodic changes in the regulations governing whether institutions of a given size (by assets) are covered by HMDA. In spite of these changes, HMDA has consistently covered the vast majority of mortgage activity in the United States.

[14] Metropolitan areas refer to core-based statistical areas (CBSAs) and correspond either to a metropolitan statistical area or a metropolitan division. Micropolitan areas have been dropped. Because the FHFA reports house price data aggregated to the CBSA level, we were forced to adopt the geographic delineations used by the FHFA (i.e., those from February, 2013) for all other data sources. The county-level composition of each CBSA is available at https://www.whitehouse.gov/sites/default/files/omb/bulletins/2013/b-13-01.pdf (accessed May 21, 2015).

[15] The number of metro areas identified in the data varies from year to year. A total of 398 metro areas are identified (i.e., possess estimated coefficients – see below) in at least two years, making the estimation of metro area fixed effects possible.

[16] This index is a repeat-sales measure based upon both purchases and refinance appraisals. Without the latter, there would be too few observations to construct the time series consistently at the metro area level over time. See Nagaraja et al. (2014) for a discussion of various methodologies underlying house price indices, including the repeat-sales approach. The data were accessed at http://www.fhfa.gov on May 14, 2015.

[17] These data were taken from Table CA04, available at http://bea.gov/regional/index.htm (downloaded May 18, 2015).

[18] See, for example, Calem and Longhofer (2002) and Dietrich (2005) for descriptions of the statistical techniques used by the Office of the Comptroller of the Currency and Federal Reserve Board in their screening of HMDA data. The methods used here should not be interpreted as representative of the exact approach used by any lender or regulatory agency in its fair lending work.

denied ($d = 1$) or approved ($d = 0$).[19] The vector $X$ denotes a set of covariates describing the applicant, including a quadratic in each of log loan amount and log income, the ratio of loan amount to the applicant's income (intended to proxy for the debt-to-income ratio), a gender dummy, a dummy for whether a co-applicant is present (including a dummy for whether this information is missing), and an indicator for whether the property is intended to be owner-occupied. BLACK is an indicator equal to 1 if the applicant is Black, 0 otherwise.

Again, this regression is limited to conventional loans (i.e. non-government backed) for home purchase. Loans intended for refinancing or home improvement are dropped from the sample in an effort to maintain uniformity of loan purpose. In addition, the sample of loan applicants is confined to Whites and Blacks so that the estimated inter-racial differences are based only on these two groups.[20] Otherwise, the estimated association between being Black and the likelihood of denial would be based on the comparison of Blacks to all other races, including other minorities, which would produce a more muddled picture of any racial disparities in the lending process.

Notice that this regression is estimated separately for each lender in each metropolitan area in each year. Hence, the end result from this first-stage screening process is an annual time series of parameters specific to every lender-metro area pair.[21] Because doing so involves an enormous amount of estimation time, we estimate Eq. (1) as a linear probability model, rather than a more conventional (non-linear) model, such as a logit or probit.

Over the 24 years, there are more than 770000 lender-metro area pairs for which parameters must be estimated. Of these, roughly 305000 have sufficient numbers of observations to produce estimates of the parameter of principal interest, $\gamma$, which measures the additional likelihood with which a Black applicant is denied on a mortgage loan application, conditional on covariates, $X$, relative to a White applicant. Given the lack of relevant underwriting data (e.g., credit scores and loan-to-value ratios) among the regressors in Eq. (1), these parameters should *not* be interpreted as direct measures of discrimination (Avery et al., 2008). They merely reflect estimates of differential outcomes between White and Black applicants similar to what regulatory agencies might compute in the initial stages of their fair lending work.

With the complete set of estimated values for these parameters, $\hat{\gamma}$, we then estimate the following second-stage regression, which models how these terms vary geographically and over time:

$$\hat{\gamma}_{lmt} = \mu + \delta_m + \delta_t + \phi Z_{mt} + \psi \text{AGENCY}_{lmt} + \theta HPI_{mt} + \nu_{lmt} \quad (2)$$

Here, $\delta_m$ denotes a metropolitan-area fixed effect; $\delta_t$ is a year-specific effect[22]; $Z_{mt}$ includes metro area $m$'s growth in total employment and per capita income over the current year; $\text{AGENCY}_{lmt}$ represents a vector of dummies describing the federal agency to which the lender reports its mortgage data, which is intended to account for fundamental differences across the various types of mortgage lending institutions[23]; $\mu$ is a constant; and $\nu$ is a residual, which is treated as potentially heteroskedastic and correlated within metropolitan areas. The regressor of primary interest is the rate of house price inflation within metro area $m$ over the previous year, $HPI_{mt}$.

In this first, baseline exercise, we specify $HPI_{mt}$ as the contemporaneous rate of inflation. That is, the rate corresponding to a lender whose approve-reject policies are observed, say, in the year 2000 is that calculated between 1999 and 2000. However, because contemporaneous inflation may be endogenous with respect to differential lending outcomes, we also consider the use of lags in a follow-up exercise.

### 3.3. Results

To begin, consider a few summary results from the first-stage screening regressions. Because some lenders have relatively few applications in certain metropolitan areas, the estimated coefficients on race occasionally take on extremely large or small values. To eliminate the influence of these outliers, we trim the top and bottom 1% from the sample before performing the analysis.

On average, the estimated coefficients indicate that Black applicants are significantly more likely to be denied on a mortgage application than White applicants, conditional on some basic characteristics including income and loan amount. Based on the roughly 299000 lender-metropolitan area values of $\hat{\gamma}$ in the trimmed sample, the mean estimate is 0.098, suggesting that Black applicants are 9.8 percentage points more likely to be denied than comparable White applicants.[24] Still, only a modest majority, 60.4%, of these coefficients are positive, indicating that there is a fair amount of variation in the estimated differentials between Blacks and Whites in their (conditional) loan denial frequencies.

A summary of the estimated coefficients, $\hat{\gamma}$, appears in Table 1 for each of the 24 years in the sample time frame.

[19] A denial is based on each record's action code reported in HMDA. A denial is defined as an application that was either denied or for which a preapproval request was rejected (wherever this code is reported). Approvals are defined as originations or applications that were approved but not accepted by the applicant. For all other outcomes – application withdrawn, file closed for incompleteness, or loan purchase – the dependent variable is set to missing.

[20] Beginning with the 2004 HMDA data, applicants may be characterized as both White and Hispanic. Hence, for 2004–2013, we define White to be non-Hispanic White. Although one might be concerned that the change in race/ethnicity coding between 2003 and 2004 might create inconsistencies in the classification of applicants, the estimated denial differentials show no evidence of a structural break between these two years.

[21] Blackburn and Vermilyea (2006) stress the importance of lender-specific estimation in studies of discrimination. Because we are also fundamentally interested in whether lenders vary lending policies across geographic areas, we perform the estimation separately by metro area too.

[22] These are intended to capture aggregate national trends, including technological changes, in the mortgage industry, including automated underwriting, which grew rapidly after the mid-1990s (Gates et al., 2002; Straka, 2000).

[23] Because the federal regulatory structure changed in 2011 (i.e., the Office of Thrift Supervision was phased out, and the Consumer Financial Protection Bureau began operations), we actually include two sets of agency dummies: those for 2010 and earlier, and those for 2011 and later.

[24] This estimate is similar in magnitude to estimates from existing studies of mortgage denial. Munnell et al. (1996), for instance, estimate 7 to 8 percentage point differentials in both OLS and logit specifications.

**Table 1**
Summary statistics of estimated Black–White denial differentials, 1990–2013.

| | Mean | Standard deviation | 10th percentile | 90th percentile | Observations | Average house price inflation |
|---|---|---|---|---|---|---|
| 1990 | 0.139 | 0.346 | −0.183 | 0.625 | 5711 | 0.034 |
| 1991 | 0.142 | 0.339 | −0.183 | 0.587 | 5836 | 0.018 |
| 1992 | 0.134 | 0.335 | −0.180 | 0.586 | 7025 | 0.026 |
| 1993 | 0.114 | 0.323 | −0.190 | 0.519 | 8837 | 0.022 |
| 1994 | 0.107 | 0.317 | −0.181 | 0.491 | 10739 | 0.021 |
| 1995 | 0.102 | 0.316 | −0.186 | 0.473 | 11073 | 0.029 |
| 1996 | 0.111 | 0.317 | −0.178 | 0.493 | 12694 | 0.034 |
| 1997 | 0.107 | 0.313 | −0.187 | 0.478 | 13698 | 0.033 |
| 1998 | 0.095 | 0.311 | −0.191 | 0.465 | 14904 | 0.050 |
| 1999 | 0.099 | 0.318 | −0.202 | 0.477 | 16151 | 0.046 |
| 2000 | 0.098 | 0.321 | −0.197 | 0.473 | 16515 | 0.061 |
| 2001 | 0.085 | 0.313 | −0.201 | 0.463 | 14783 | 0.074 |
| 2002 | 0.086 | 0.311 | −0.191 | 0.464 | 14069 | 0.065 |
| 2003 | 0.081 | 0.308 | −0.198 | 0.441 | 16267 | 0.065 |
| 2004 | 0.079 | 0.310 | −0.203 | 0.444 | 20199 | 0.101 |
| 2005 | 0.076 | 0.311 | −0.205 | 0.434 | 22787 | 0.124 |
| 2006 | 0.087 | 0.324 | −0.212 | 0.466 | 22091 | 0.077 |
| 2007 | 0.101 | 0.324 | −0.206 | 0.487 | 17542 | 0.011 |
| 2008 | 0.121 | 0.343 | −0.213 | 0.564 | 10311 | −0.050 |
| 2009 | 0.116 | 0.368 | −0.240 | 0.626 | 6938 | −0.056 |
| 2010 | 0.110 | 0.358 | −0.241 | 0.602 | 6967 | −0.039 |
| 2011 | 0.102 | 0.353 | −0.229 | 0.565 | 7029 | −0.037 |
| 2012 | 0.100 | 0.348 | −0.220 | 0.569 | 7827 | −0.002 |
| 2013 | 0.089 | 0.331 | −0.212 | 0.504 | 9343 | 0.042 |

Note: Statistics summarizing estimated coefficients on Black indicator from denial regression (1). Average house price inflation is calculated as the average of house price inflation taken over the corresponding lender-metropolitan area-year observations.

For the sake of comparison, we have also provided an average value of house price inflation, calculated by averaging the metropolitan area-specific changes in the FHFA index across all lender-metro area observations. Hence, the reported average inflation measures are weighted averages of the metro area values, where the weights are the number of lenders for which the Black–White differential, $\gamma$, could be estimated. Interestingly, there is an apparent inverse relationship between the mean Black–White differential and the average rate of house price inflation throughout the time series. This finding can be seen more clearly in Fig. 1, which plots the mean estimated differential against average house price inflation, by year.

Results from the second-stage regression, in which these estimated Black–White differentials are regressed on time effects, metro area effects, reporting agency dummies, and rates of growth in metropolitan area-level employment, per capita income, and house prices are reported in the first column of estimates in Table 2. They clearly indicate that higher rates of house price appreciation are associated with significantly smaller Black–White differentials. The estimated coefficient (standard error) on house price appreciation in Eq. (2), −0.045 (0.014), suggests that a 10 percentage point increase in the rate of inflation tends to be accompanied by a 0.45 percentage point decrease in the gap between the Black and White denial rates.[25]

Because the dependent variable in (2) is estimated for a set of lenders that differ considerably in size, it is likely that the specified error, $\nu$, is heteroskedastic.[26] Although we estimate heteroskedasticity-consistent standard errors, we also estimate (2) by generalized least squares (GLS), where the observations are weighted by the number of applications used to estimate the dependent variable, $\hat{\gamma}$, in the first-stage regression. This procedure assumes that values of $\hat{\gamma}$

**Table 2**
Regression estimates – Black–White differential and housing inflation.

| | (1) OLS | (2) GLS | (3) OLS | (4) GLS |
|---|---|---|---|---|
| HPI | −0.045* | −0.066* | −0.055* | −0.062* |
| | (0.014) | (0.010) | (0.014) | (0.010) |
| Per capita income growth | −0.017 | 0.028 | −0.025 | 0.023 |
| | (0.043) | (0.031) | (0.042) | (0.030) |
| Employment growth | −0.067 | −0.013 | −0.024 | 0.001 |
| | (0.054) | (0.043) | (0.052) | (0.040) |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Metro area fixed effects | Yes | Yes | Yes | Yes |
| Reporting agency fixed effects | Yes | Yes | Yes | Yes |
| Lender fixed effects | No | No | Yes | Yes |

Note: Coefficient estimates from Eq. (2). Robust standard errors, clustered within metro areas, are reported in parentheses. An asterisk (*) denotes significance at convential levels ($p < 0.10$). GLS estimates are produced by weighting the regression by the number of records used in the first-stage regression to estimate the dependent variable: the Black–White denial differential.

[25] The standard deviation of the metro area house price inflation distribution across all 24 years is 0.057. Within individual years, the standard deviation ranges from 0.017 (for 1998) to 0.081 (for 2005).

[26] Over all 24 years, the number of applications per lender-metro area-year observation in the HMDA data used to estimate (1) ranges from 3 to 80070. The mean is 177.9. Clearly, not all parameters in (1) could be estimated for those lenders with fewer than 11 observations (about 1% of the sample), but each lender included in the estimation of (2) produced an estimate of $\gamma$.

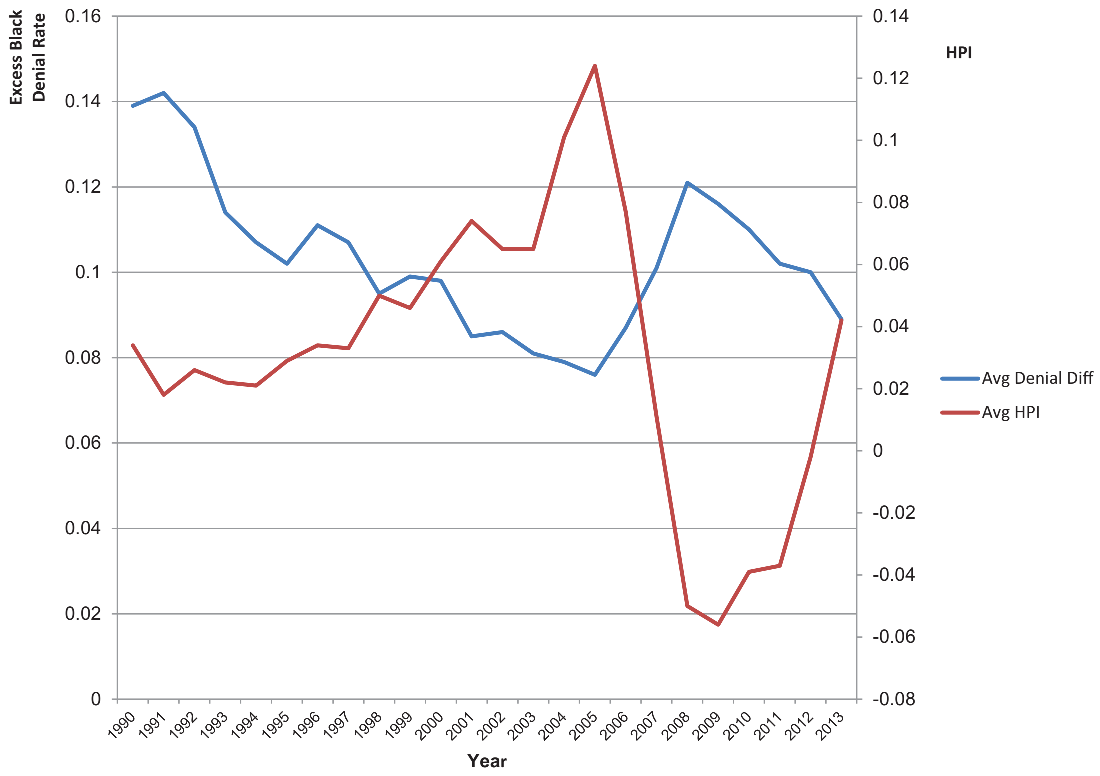


**Fig. 1.** Denial differentials and house price inflation.

estimated from larger numbers of observations have lower variances than those estimated from fewer observations, and thus are weighted more heavily in the estimation. Weighting the regression in this way also likely provides a more representative estimate of the underlying application-level relationship between housing inflation and the relative likelihood a Black applicant is denied when compared to a White applicant.[27] The resulting house price inflation coefficient estimate (standard error), which is reported in the second column in Table 2, has a similar, but somewhat larger, magnitude than the OLS estimate: −0.066 (0.01).

We also estimate (2) using lender-specific fixed effects, thus focusing on within-lender variation over time (and for some lenders, variation across metro areas within a year). Doing so adds 13577 parameters to the estimation, but changes the results only slightly. Those results appear in the final two columns of Table 2. The coefficient (standard error) on house price inflation is −0.055 (0.014) in the unweighted regression, −0.062 (0.01) in the weighted regression.

Although these estimates may seem small, they actually imply some potentially large effects on regulatory efforts over time. Table 3 summarizes the fraction of lender-metro area observations in each year for which the estimated denial differential satisfies two criteria: (i) it differs statistically from zero at conventional levels ($p$-value $< 0.1$), and (ii) its magnitude exceeds one of four cutoff values (5 percentage points, 10 percentage points, 15 percentage points, and 20 percentage points). These values represent four hypothetical thresholds beyond which the screening estimates might be thought to warrant further investigation.[28]

Consistent with the summary statistics reported in Table 1, there is a discernible association between average inflation, reported in the last column of Table 3, and the share of lender-metro area observations with differentials exceeding each of these thresholds. For example, compare the year 2005, where metro area HPI averaged 12%, with 2008, where it averaged −5%. The fraction of statistically significant Black–White differentials exceeding each threshold is noticeably larger in 2008, ranging from 3 to 5 percentage points higher. With several thousand lenders, these differences could very well translate into hundreds of additional lenders meeting a cutoff for further analysis.

To investigate this relationship more precisely, we regress a set of indicators describing whether a lender-metro area differential in a given year is statistically significant *and* exceeds each of these thresholds against all of the regressors above in Eq. (2), including contemporaneous house price inflation.[29] The estimates indicate that, while house price inflation is not significantly related to the share of differentials exceeding 5 percentage points (coefficient = −0.044,

[27] See, for example, sections 3.1.2 and 3.4.1 of Angrist and Pischke (2009).

[28] Calem and Longhofer (2002), for instance, suggest that, in the first-stage screening work at the Federal Reserve, differentials less than 5 percentage points are not generally considered worthy of further investigation.

[29] These regressions are also estimated as linear probability models weighted by the number of observations used to estimate the denial differences in the first stage.

**Table 3**
Selected thresholds for Black–White denial differentials, 1990–2013.

| | 5 percentage points | 10 percentage points | 15 percentage points | 20 percentage points | Average house price inflation |
|---|---|---|---|---|---|
| 1990 | 0.231 | 0.226 | 0.216 | 0.201 | 0.034 |
| 1991 | 0.236 | 0.232 | 0.221 | 0.206 | 0.018 |
| 1992 | 0.240 | 0.234 | 0.221 | 0.202 | 0.026 |
| 1993 | 0.207 | 0.200 | 0.186 | 0.170 | 0.022 |
| 1994 | 0.205 | 0.196 | 0.177 | 0.158 | 0.021 |
| 1995 | 0.214 | 0.201 | 0.180 | 0.156 | 0.029 |
| 1996 | 0.228 | 0.217 | 0.194 | 0.167 | 0.034 |
| 1997 | 0.226 | 0.214 | 0.190 | 0.165 | 0.033 |
| 1998 | 0.211 | 0.197 | 0.175 | 0.153 | 0.050 |
| 1999 | 0.216 | 0.203 | 0.179 | 0.156 | 0.046 |
| 2000 | 0.212 | 0.201 | 0.179 | 0.157 | 0.061 |
| 2001 | 0.184 | 0.172 | 0.157 | 0.140 | 0.074 |
| 2002 | 0.179 | 0.165 | 0.148 | 0.132 | 0.065 |
| 2003 | 0.181 | 0.165 | 0.147 | 0.131 | 0.065 |
| 2004 | 0.178 | 0.161 | 0.141 | 0.124 | 0.101 |
| 2005 | 0.197 | 0.177 | 0.154 | 0.136 | 0.124 |
| 2006 | 0.217 | 0.197 | 0.172 | 0.150 | 0.077 |
| 2007 | 0.227 | 0.214 | 0.190 | 0.166 | 0.011 |
| 2008 | 0.225 | 0.219 | 0.205 | 0.187 | −0.050 |
| 2009 | 0.196 | 0.192 | 0.185 | 0.173 | −0.056 |
| 2010 | 0.179 | 0.176 | 0.169 | 0.159 | −0.039 |
| 2011 | 0.173 | 0.170 | 0.163 | 0.153 | −0.037 |
| 2012 | 0.179 | 0.175 | 0.166 | 0.156 | −0.002 |
| 2013 | 0.159 | 0.155 | 0.144 | 0.134 | 0.042 |

Note: Table reports fractions of lender-metro area observations in each year for which the Black–White denial differential exceeds the given thresholds and differs significantly from zero at conventional levels ($p < 0.1$). Average house price inflation is calculated as the average rate of house price inflation taken over the corresponding lender-metropolitan area-year observations.

s.e. = 0.064), it strongly (and negatively) correlates with the shares exceeding 10, 15, and 20 percentage points. Those estimates (standard errors) are, respectively, −0.29 (0.08), −0.22 (0.05), and −0.18 (0.03), suggesting that a 10 percentage point rise in the rate of house price inflation tends to be accompanied by a 1.8 to 2.9 percentage point decrease in the fraction of lender-metro area observations meeting the threshold. Again, with several thousand lenders under consideration, this suggests that, for a given threshold by which first-stage screens are evaluated, periods of stagnating house prices may be associated with considerably more lenders to investigate than periods of rapid house price appreciation.

These results also suggest that the (negative) responsiveness of the Black–White differential is more pronounced at the top end of the distribution of denial differentials than at the bottom. This feature is further implied by a comparison of the 90th percentile of the distribution (which varies considerably over time) to the 10th (which does not), reported in Table 1. This feature of the data can be seen in Fig. 2.

A more formal analysis of Eq. (2) by quantile regression – weighted by numbers of applications from the first stage – yields the same conclusion. The estimated coefficients (standard errors) on house price inflation are −0.015 (0.013), −0.048 (0.014), and −0.12 (0.02) for the 25th, 50th, and 75th percentiles of the distribution of Black–White differentials. These findings help to explain why we observe such significant variation over the housing cycle in the fraction of lenders with differentials above certain thresholds in spite of the relatively modest estimated (average) association between those differentials and the rate of house price inflation.

### 3.4. Endogeneity of house price inflation

The estimation above does not address the possible endogeneity of house price inflation with respect to the dependent variable. It is, however, plausible that inflation may be directly affected by differential lending outcomes.

For example, positive shocks to the supply of credit may lead to a smaller Black–White denial difference as more applicants are approved for loans. The increase in the number of individuals receiving mortgage loans, in turn, may serve to boost real estate prices. This would imply that house price inflation in Eq. (2) is negatively correlated with the error, $\nu$, leading to a negative bias in standard least squares estimates. The estimates reported above, then, may be more negative than the true causal effect of house price inflation on denial rate differentials.[30]

We attempt to handle this issue in two ways. First, rather than using the contemporaneous rate of house price inflation within a lender's metropolitan area, we use the value lagged one year. Thus, when examining racial differences in the rate of mortgage denial observed in the year 2000, we use the rate of house price appreciation between 1998 and 1999 rather than 1999 and 2000. Presumably, the volume of loans made in 2000 (which may be associated with the Black–White differential in approvals) would not influence the local rate of inflation registered between 1998 and 1999. Hence, one can

[30] Glaeser et al. (2010) find little evidence that low interest rates and 'permissive' lending policies drove the recent housing boom (i.e. between 1996 and 2006). Nevertheless, it is worthwhile examining the possibility of endogenous house price inflation in this somewhat different context.

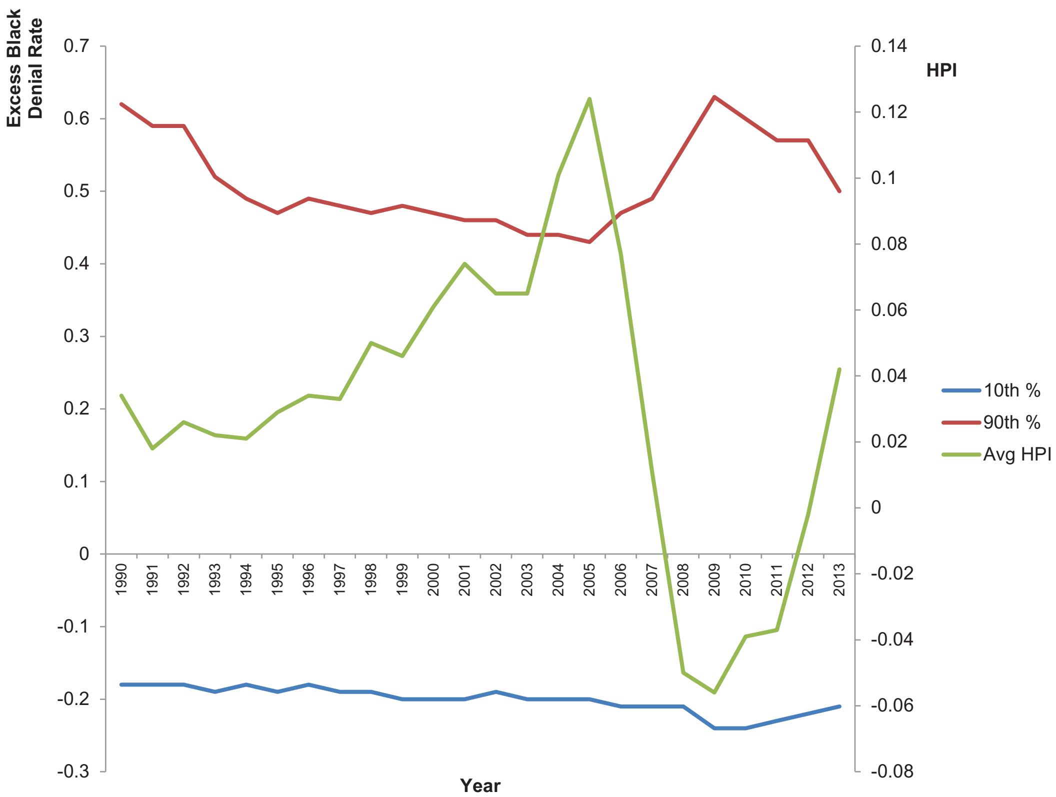


**Fig. 2.** Denial differential percentiles and house price inflation.

at least reasonably argue that this lagged value of inflation is not endogenous with respect to the dependent variable.

The estimates appear in the first four columns of Table 4. In general, the substitution of lagged for contemporaneous inflation only changes the coefficients slightly. In the unweighted regression, the coefficient (standard error) on lagged house price inflation is −0.028 (0.015) without lender fixed effects and −0.038 (0.016) with them. When the number of records is used to weight each observation, the resulting coefficient (standard error) is somewhat larger: −0.042 (0.011) without lender fixed effects, −0.039 (0.011) with them. Although somewhat smaller in magnitude than what is reported above using contemporaneous inflation (again, −0.045 to −0.055 (OLS) and −0.062 to −0.066 (GLS)), each is statistically significant.

The second approach to handling endogenous contemporaneous inflation follows this first strategy. We estimate (2) by instrumental variables (IV), where we use inflation lagged one year to instrument for contemporaneous house price inflation. As just described, lagged inflation is plausibly exogenous with respect to current racial differences in denial rates. It also turns out to be highly relevant. The F statistic from the first-stage regression of inflation on its lag (and all other regressors in (2)) is 225656 ($p$-value $< 0.01$) when observations are not weighted by the number of records; 211004 ($p$-value $< 0.01$) when they are.

Importantly, lagged inflation also appears to satisfy the exclusion restriction: that is, it is not simply a relevant regressor that has been wrongly omitted from Eq. (2). To see this, consider the results from two regressions: (i) Eq. (2) in which lagged inflation has been added to the list of regressors (including contemporaneous inflation) and (ii) Eq. (2) in which lagged inflation is included but contemporaneous inflation has been dropped (as in the first exercise discussed above).

As just reported, the second regression clearly shows that lagged inflation is significantly associated with the Black–White differential. Yet, when contemporaneous inflation is added to (2) along with lagged inflation, the coefficient on lagged inflation drops in magnitude and becomes statistically insignificant: −0.003 (standard error = 0.013) in the weighted version, −0.001 (standard error = 0.021) in the unweighted version. These results suggest that, while lagged inflation is correlated with current Black–White denial differences, that correlation seems to operate through each variable's association with contemporaneous inflation. Once we condition on contemporaneous inflation, lagged inflation offers little explanatory power, and thus may be reasonably omitted from (2). Collectively, these results suggest that lagged inflation is a plausible instrument for contemporaneous inflation.

IV estimates appear in the final four columns of Table 4. Although we surmise that any bias in the results reported above is negative, the instrumental variables estimates are virtually identical to the OLS and GLS results reported above. In the unweighted regression, the IV coefficient on contemporaneous inflation is −0.045 (0.024) without lender fixed effects, −0.061 (0.025) with them. With weights, the

**Table 4**
Regression estimates – Black–White differential and housing inflation using lagged HPI.

| | Lagged HPI as proxy | | | | Lagged HPI as instrument | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) OLS | (2) GLS | (3) OLS | (4) GLS | (5) Unweighted | (6) Weighted | (7) Unweighted | (8) Weighted |
| HPI | | | | | −0.045* | −0.068* | −0.061* | −0.064* |
| | | | | | (0.024) | (0.017) | (0.025) | (0.017) |
| Lagged HPI | −0.028* | −0.042* | −0.038* | −0.039* | | | | |
| | (0.015) | (0.011) | (0.016) | (0.011) | | | | |
| Per capita income growth | −0.029 | 0.008 | −0.038 | 0.006 | −0.016 | 0.030 | −0.021 | 0.025 |
| | (0.044) | (0.032) | (0.042) | (0.031) | (0.043) | (0.030) | (0.042) | (0.029) |
| Employment growth | −0.100* | −0.077* | −0.063 | −0.059 | −0.066 | −0.011 | −0.016 | 0.002 |
| | (0.053) | (0.042) | (0.051) | (0.039) | (0.056) | (0.045) | (0.055) | (0.044) |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Metro area fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Reporting agency fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Lender fixed effects | No | No | Yes | Yes | No | No | Yes | Yes |

Note: Coefficient estimates from Eq. (2). Robust standard errors, clustered within metro areas, are reported in parentheses. An asterisk (*) denotes significance at convential levels ($p < 0.10$). GLS estimates are produced by weighting the regression by the number of records used in the first-stage regression to estimate the dependent variable: the Black–White denial differential. In the IV estimation, lagged inflation instruments for contemporaneous inflation.

coefficient (standard error) is −0.068 (0.017) without lender fixed effects, −0.064 (0.017) with them. All differ statistically from zero. Accounting for endogenous house price inflation, we conclude, has little effect on the conclusions drawn above.

### 3.5. *Robustness: accounting for subprime lending*

Because the time frame we examine contains an enormous run-up in house prices followed by a massive collapse between 2000 and 2008 that many have tied to the growth and decline of subprime mortgage lending in the United States, it is possible that the relationship we estimate between Black–White denial differentials and house price inflation is also a product of the rise and fall of subprime lending. In this section, we consider two robustness tests that seek to address this possibility.

First, we split the sample into two time periods: 1990 to 1999 and 2000 to 2013. Evidence largely suggests that the subprime mortgage lending began to increase significantly around 2001 or 2002 (Chomsisengphet and Pennington-Cross, 2006; Mian and Sufi, 2009), and had collapsed by 2008 or 2009. These two regimes, then, are intended to capture the mortgage market prior to and during the subprime boom and bust.

Results appear in Table 5. What is particularly striking about them is that the estimated relationship between house price inflation and the Black–White denial difference is actually stronger in the pre-2000 period than after 2000. While the post-2000 regime produces coefficients on HPI ranging between −0.043 and −0.058, we see coefficients falling between −0.098 and −0.158 in the 1990–1999 period. All are statistically significant at conventional levels.

Second, we use a list of subprime lenders compiled by the Department of Housing and Urban Development (HUD) for the years 1993 to 2005 to estimate two additional versions of Eq. (2).[31] In the first, we drop all lenders from HMDA that HUD identifies as a subprime lender. In the second, we retain all lenders, but allow the coefficient on house price inflation to differ by lender type: subprime vs. non-subprime. In both cases, we restrict the estimation to include data only from the 1993–2005 period.

For the sake of brevity, we summarize only the GLS results without lender fixed effects. Dropping subprime lenders produces a coefficient on HPI of −0.073 (s.e. = 0.015). Allowing different lender types generates an HPI coefficient of −0.044 (s.e. = 0.015) for non-subprime lenders and −0.12 (s.e. = 0.024) for subprime lenders. While this latter result seems to suggest that high-risk mortgage lenders may be somewhat more responsive to changes in local housing conditions, our basic result still holds for lenders who do not specialize in subprime products. The results established above, therefore, do not appear to be simply a product of the subprime boom and collapse of the 2000s.

### 3.6. *Alternative measures of the housing cycle*

Although we have focused on the association between inter-racial denial differentials and contemporaneous (annual) house price inflation, other aspects of a metropolitan area's housing cycle may influence the extent to which Black and White mortgage applicants are denied on a loan. Here, we consider several additional specifications of Eq. (2) in order to delve deeper into how a lender's underwriting may be related to the local market housing cycle.

First, we add two lags of annual house price inflation to capture a longer history of recent changes in house values. While the most recent year might be important for lender decisions, there may also be an important effect associated with recent house price dynamics, even conditional on the most recent year. This would differentiate between, say, a lender observing a current growth rate of 3% following a 2% decline in each of the previous two years from a lender observing the same current growth rate of 3% following a 2% increase in each of the previous two years.

Second, we calculate the number of consecutive years of either growth or decline in house prices for each lender's

[31] We found this information at http://www.huduser.org/portal/datasets/manu.html (accessed June 11, 2015).

**Table 5**
Regression estimates – Black–White differential and housing inflation (1990–1999 and 2000–2013).

| | 1990–1999 | | | | 2000–2013 | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) OLS | (2) GLS | (3) OLS | (4) GLS | (5) OLS | (6) GLS | (7) OLS | (8) GLS |
| HPI | −0.108* | −0.158* | −0.098* | −0.125* | −0.043* | −0.044* | −0.058* | −0.049* |
| | (0.048) | (0.034) | (0.048) | (0.036) | (0.017) | (0.013) | (0.017) | (0.013) |
| Per capita income growth | 0.146* | 0.155* | 0.086 | 0.144* | −0.029 | 0.007 | −0.042 | −0.001 |
| | (0.082) | (0.075) | (0.084) | (0.075) | (0.047) | (0.026) | (0.047) | (0.025) |
| Employment growth | −0.198* | 0.002 | −0.151 | 0.031 | 0.005 | −0.040 | 0.051 | −0.014 |
| | (0.102) | (0.075) | (0.102) | (0.082) | (0.073) | (0.048) | (0.071) | (0.046) |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Metro area fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Reporting agency fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Lender fixed effects | No | No | Yes | Yes | No | No | Yes | Yes |

Note: Coefficient estimates from Eq. (2). Robust standard errors, clustered within metro areas, are reported in parentheses. An asterisk (*) denotes significance at convential levels ($p < 0.10$). GLS estimates are produced by weighting the regression by the number of records used in the first-stage regression to estimate the dependent variable: the Black–White denial differential.

metropolitan area.[32] For example, if a metro area in 1990 has experienced positive HPI in each year since (and including) 1987, this variable would take on a value of 4. 'Turning points' (i.e. years in which negative growth first becomes positive or positive growth first becomes negative) would take on a value of 1. This measure would help to differentiate between, for example, a metro area with a current 3% growth rate as part of a 10 year expansion from one with a current 3% growth rate in its first year of positive growth following a downturn. Because periods of growth and decline should have different effects on lending standards, we allow this variable – 'phase length' – to differ depending on whether it represents a period of positive or negative HPI.[33]

Third, we compute the total growth in house prices associated with each metropolitan area's housing phase: i.e., the cumulative growth (positive or negative) in house prices since the last turning point. This measure allows us to distinguish between two metro areas with the same current annual rate of house price appreciation and length of the current phase, but in which one has grown, for instance, 10 percent since the last turning point while the other has grown only 5%.

Results are reported in Table 6. The first column reports coefficients from the inclusion of contemporaneous HPI and its first two lags only; the second, the coefficients from the inclusion of two phase length variables (i.e., positive and negative growth) only; the third, the coefficient from the inclusion of cumulative phase growth only; and the fourth, coefficients from the inclusion of all six variables. In an effort to reduce the effects of measurement error, we drop from each regression that includes either phase length or cumulative phase growth any observations in which the current cycle is left-censored (i.e., when a turning point is not observed prior to the beginning of the current phase).[34]

The coefficient estimates reveal three primary findings. First, with respect to phase length, longer sustained periods of growth in house prices tend to be associated with smaller Black–White denial differentials, while longer sustained periods of decline tend to correspond to larger Black–White differentials. This is consistent with the idea that lenders take the length of a housing expansion or contraction into account when deciding upon lending standards, even conditional on current rates of HPI. Second, there is some evidence that greater cumulative growth during a housing cycle phase is associated with smaller differences in Black and White denial rates. However, this result disappears once we simultaneously condition on each of the other housing cycle measures. Third, current HPI is strongly associated with mean Black–White denial differences, but the first and second lags of HPI are not. In fact, across all four of the house price growth measures we consider, contemporaneous annual inflation is the only one that consistently varies negatively (and significantly) with measured Black–White denial differentials.

### 3.7. Differences by type of lender

A wide variety of institutions are engaged in mortgage lending, including banks, thrift institutions, credit unions, and non-depositories. Given the differences in how these institutions are structured and the regulatory requirements they face, it is possible that there are important differences in how their racial differentials in mortgage origination and denial vary over time.

For example, commercial banks face greater supervisory oversight from federal regulators, such as the Office of the Comptroller of the Currency (OCC) and Federal Reserve Board (FRB), than do independent non-depository mortgage companies, which, over the time frame covered in this paper, reported HMDA data to the Department of Housing and Urban Development (HUD). This additional layer of regulation may

[32] The fact that the FHFA house price index extends back to the 1970s for many metropolitan areas makes this exercise feasible.

[33] In practice, this means that phase length is captured with two regressors: one capturing the number of years of positive growth, the other capturing the number of years of negative growth. When one of these applies to a lender-metro area-year observation, the other is set to zero. While we could have specified one as the negative of the other, we did not want to impose 'symmetry' across expansions and contractions.

[34] Keeping observations with left-censored phases actually produces similar regression estimates to those reported in the table.

**Table 6**
Alternative measures of the housing cycle.

| | (1) HPI with lags | (2) Phase length | (3) Phase growth | (4) All measures |
|---|---|---|---|---|
| HPI | −0.068* | | | −0.073* |
| | (0.013) | | | (0.013) |
| Lag 1 HPI | 0.007 | | | −0.029 |
| | (0.018) | | | (0.019) |
| Lag 2 HPI | −0.011 | | | −0.030 |
| | (0.018) | | | (0.019) |
| Phase length positive | | −0.0005* | | −0.002* |
| | | (0.0001) | | (0.0003) |
| Phase length negative | | 0.003* | | 0.002* |
| | | (0.001) | | (0.001) |
| Phase growth | | | −0.009* | 0.028* |
| | | | (0.002) | (0.006) |

Note: Dependent variable is Black-White denial differential. Regressions include all variables from Eq. (2) except lender fixed effects. Robust standard errors, clustered within metro areas, are reported in parentheses. An asterisk (*) denotes significance at conventional levels ($p < 0.10$). All regressions are weighted by the number of records used in the first-stage regression to estimate the dependent variable: the Black–White denial difference.

influence the lending practices of banks and thrift institutions relative to those of non-depositories.

We begin with a simple regression of the estimated Black–White denial differentials against a set of six indicators representing the federal agencies to which each lender reports HMDA data. For this exercise, we limit our data to the 1990–2010 time frame to maintain a consistent regulatory framework.[35] The resulting coefficients (standard errors), which represent average differentials for each agency, turn out to be roughly similar to one another: 0.095 (0.002) for the OCC, 0.094 (0.002) for the FRB, 0.1 (0.003) for the Federal Deposit Insurance Corporation (FDIC), 0.095 (0.002) for the Office of Thrift Supervision (OTS), 0.128 (0.005) for the National Credit Union Administration (NCUA), and 0.074 (0.001) for HUD.[36] Nevertheless, a joint test rejects the equality of these means at 1% significance (F statistic = 58.78; $p$-value < 0.01).[37]

In this section, we extend the analysis to account for potential differences in the coefficients on house price inflation in addition to these fixed effects. We do so by interacting each of the agency dummies with house price inflation. To keep the model relatively parsimonious, we maintain a constant set of time and metro area effects for all types of lenders.

Results are reported in Table 7 for three estimation strategies: GLS using contemporaneous inflation (i.e., the baseline specification), GLS using lagged inflation, and IV using lagged inflation to instrument for contemporaneous inflation. In all cases, we use the number of observations used to estimate the dependent variable in the first-stage to weight the regressions.

The estimates reveal significant variation in the responsiveness of denial differentials across lender types. Looking across the three sets of coefficients, it is evident that banks reporting to the FDIC (state-chartered banks that are not members of the Federal Reserve system) are the most responsive with respect to house price inflation. The FDIC's estimates range from −0.12 to −0.16, and all are statistically significant.

Credit unions reporting to the NCUA and thrift institutions falling under the jurisdication of the OTS also produce sizable, significant negative associations with HPI: the NCUA coefficients range between −0.09 and −0.12; the OTS coefficients fall between −0.072 and −0.11. The OCC (nationally chartered banks) produces somewhat smaller estimates (−0.059 to −0.091), but all are statistically different from zero.

**Table 7**
Regression estimates – Black–White differential and housing inflation, by agency (1990–2010).

| | (1) GLS contemporaneous | (2) GLS lagged | (3) Weighted IV |
|---|---|---|---|
| OCC | −0.075* | −0.059* | −0.091* |
| | (0.014) | (0.014) | (0.016) |
| FRB | −0.022 | 0.075* | 0.081* |
| | (0.022) | (0.025) | (0.022) |
| FDIC | −0.140* | −0.118* | −0.158* |
| | (0.023) | (0.025) | (0.028) |
| OTS | −0.072* | −0.075* | −0.114* |
| | (0.016) | (0.018) | (0.019) |
| NCUA | −0.090* | −0.091* | −0.125* |
| | (0.045) | (0.043) | (0.052) |
| HUD | −0.059* | −0.037* | −0.061* |
| | (0.013) | (0.014) | (0.015) |
| Test statistic | 4.1 | 9.9 | 80.4 |
| $p$-value | 0.001 | 0.000 | 0.000 |

Note: Coefficients on house prices are interacted with agency dummies from estimation of Eq. (2). Robust standard errors, clustered within metro areas, are reported in parentheses. An asterisk (*) denotes significance at conventional levels ($p < 0.10$). The test statistic (F statistic for GLS, $\chi^2$ statistic for IV) and $p$-value are reported for test of equality of all six coefficients. All regressions are weighted by the number of records used in the first-stage regression to estimate the dependent variable: the Black–White denial difference. In the IV estimation, lagged inflation instruments for contemporaneous inflation.

[35] Beginning in 2011, the Office of Thrift Supervision (OTS) was phased out as a regulatory agency, while the Consumer Financial Protection Bureau (CFPB) was newly established.

[36] The regression is weighted by the number of observations used in the estimation of each differential.

[37] This result justifies the inclusion of agency dummies throughout the estimation of Eq. (2).

Among the least responsive to movements in house price inflation are the non-depositories that report to HUD, which produce coefficients ranging from −0.037 to −0.06 (all of which are significant), and the banks reporting to the Federal Reserve Board (FRB), which show no evidence of a significantly negative association between HPI and mean Black−White denial differentials.[38] In fact, the two sets of results using lagged inflation suggest that denial differentials among FRB lenders may grow larger as house price inflation rises. Interestingly, these are the only estimates that suggest that the GLS estimates using contemporaneous inflation might be biased downward.

The reason for these differences across lender types is not clear. One hypothetical explanation for the large magnitudes of the OCC, FDIC, and OTS estimates, relative to those of the institutions that report to HUD, involves the Community Reinvestment Act (CRA), which requires banks and thrifts to meet the lending needs of the communities in which they are located.[39] In practice, compliance with the CRA requires lenders to make sufficiently many loans in low-to-moderate income neighborhoods, which often possess sizable minority populations. Lenders that are affected by this requirement report to the OCC, FDIC, OTS, and FRB, the first three of which generate some of the largest estimates. While FRB lenders clearly do not follow the same pattern, the institutions that report to the OCC, FDIC, and OTS may approve greater proportions of Black applicants relative to White applicants during housing booms in an attempt to demonstrate their compliance with the CRA.

This possibility suggests that, among these types of lenders especially, there should be a geographic component to racial lending differentials over the housing cycle, namely that minority neighborhoods should see a rise in activity as local (average) housing conditions improve. This issue is considered in the next section.

### *3.8. Evidence on redlining*

To follow up on the observed inter-agency differences in the results, as well as to explore an additional test of whether racial differences in lending vary significantly with the housing cycle, we now consider whether the geographic distribution of mortgage activity across minority and non-minority neighborhoods shows any significant pattern as house prices fluctuate. Mortgage industry regulators routinely examine these patterns as a test for redlining – i.e., the systematic avoidance of minority neighborhoods – which also constitutes a violation of fair lending laws. Given the evidence above that Black–White differences in denial rates on mortgage applications fall during housing booms, one might expect to find that minority neighborhoods are more likely to receive housing credit in periods of rapidly rising house prices. Of course, this result would not necessarily follow if the increase in the rate at which Black borrowers are approved for mortgage loans tends to be associated with properties in predominantly White residential areas (or, at least, neighborhoods that are not majority Black).

Here, we calculate for each lender in each year, the share of its applications, originations, and denials in a given metropolitan area that come from Census tracts in which the majority of residents are Black.[40] Originations and denials are identified from the HMDA codes for a lender's action taken. Applications are calculated by summing all HMDA records – including originations, denials, and other outcomes (e.g., file closures and withdrawals) – except loans reported as having been purchased from another institution.

While redlining is often measured purely by application or origination activity (e.g. Holmes and Horvitz, 1994), some studies have looked at denial rates instead (e.g. Tootell, 1996). For the sake of completeness, we consider all three. In addition, although redlining is commonly evaluated by examining raw counts of lending activity in different neighborhoods, analyzing shares of activity should also provide a reasonable estimate of the extent to which minority neighborhoods receive differential treatment by lenders.[41]

On average, each of the three shares tends to be small. Across all lender-metro area-year observations over the years 1990 to 2010, the average share of a lender's applications associated with a majority-Black Census tract is only 3.8%. Minority neighborhood shares of originations and denials are similarly low: 3.2% and 6.1%, respectively. The fact that the origination fraction is somewhat smaller, while the denial fraction somewhat larger, than the overall application fraction is consistent with the result that, on average, Black applicants are approved less frequently than White applicants.[42]

To determine how they vary over the housing cycle, we perform a regression similar to the one above describing lender-specific Black–White denial differentials:

$$s_{lmt} = \mu + \delta_m + \delta_t + \phi Z_{mt} + \psi \text{AGENCY}_{lmt} + \theta HPI_{mt} + \nu_{lmt} \tag{3}$$

where $s$ denotes one of the three shares (applications, originations, denials) for lender $l$ in metropolitan area $m$ in year $t$ accounted for by majority-minority Census tracts; the $\delta$ terms are metro area- and year-specific fixed effects; $Z_{mt}$ represents contemporaneous employment and per capita income growth; AGENCY is the lender's HMDA reporting agency; and $HPI$ is the local rate of house price inflation. Because contemporaneous and lagged inflation produce similar results, we only report estimates using contemporaneous inflation.

The findings (which we summarize here) indicate that, as house price inflation rises, the share of a lender's

[38] The Federal Reserve also oversees non-bank mortgage lenders that are subsidiaries of bank holding companies.

[39] Congress passed the CRA in 1977.

[40] The classification of Census tracts as majority Black is based upon data from the 1990 U.S. Census for years 1990 to 2002 and the 2000 Census for years 2003 to 2010. The 1990 Census produces a substantially better match with the 2000–2002 HMDA data than the 2000 Census. We also found that the 2000 Census produces a substantially better match with the 2010 HMDA data than the 2010 Census. Note, we refer to all non-majority Black Census tracts as "non-minority" tracts, even though it is possible that some may have substantial fractions of residents belonging to other minority groups.

[41] Indeed, as noted by Courchane and Skanderson (2012), redlining allegations in recent cases settled by the U.S. Department of Justice involve "failing to make available or to market mortgage loans equally in all parts of a bank's CRA assessment areas." p. 6.

[42] We also performed this analysis defining minority Census tracts as those in which Black residents account for at least 25% of the population. Doing so produced qualitatively similar results.

denials associated with majority Black neighborhoods falls significantly. The estimate (standard error) is −0.063 (0.03), indicating that the share of metropolitan area-wide denials coming from majority Black neighborhoods falls by 0.63 percentage points as house price inflation rises by 10 percentage points.[43] When we consider applications, we see a somewhat smaller result: −0.054 (0.03). The fraction of a lender's originations in minority tracts also tends to decline as house price inflation increases, but tends to do so to an even lesser extent: the coefficient (standard error) is −0.048 (0.025).

Together, these results reveal an interesting pattern. During housing booms, the number of applications coming from *non-minority* neighborhoods rises relative to those coming from majority Black neighborhoods. Yet, while the share of denials coming from majority Black neighborhoods also falls, it does so more than proportionately when compared to applications, suggesting that the denial rate for applications coming from Black tracts declines relative to that for applications from non-Black tracts. The less-than-proportionate decline of the share of originations coming from majority Black neighborhoods as HPI rises suggests a similar result: the frequency with which applications from Black neighborhoods become originated loans rises relative to that for applications from non-Black neighborhoods. Assuming that mortgage applications from majority Black Census tracts come primarily from Black applicants, these results mimic those above describing average Black–White denial differences.

Are there differences across types of mortgage lenders? Recall, denial differentials show greater variation over the housing cycle among banks and thrifts reporting to the FDIC, OTS, and (to a lesser degree) OCC – all of which must comply with the Community Reinvestment Act – than non-bank HUD reporters, which do not. Table 8 reports regression coefficients on interactions of the six reporting-agency dummies with contemporaneous house price inflation from Eq. (3). Three columns of results are listed, one for each dependent variable (i.e., shares of each lender's applications, originations, and denials).

Across all six agencies, lenders show a strikingly similar pattern with respect to the change in the share of applications relative to those of denials and originations. In particular, each of the point estimates indicates that the fraction of a lender's applications coming from majority Black Census tracts declines as HPI rises, albeit not always significantly, but does so to a lesser extent than the fraction of denials. At the same time, the share of originations from minority tracts decreases to a lesser degree than the share of applications (and actually increases, although not significantly, for FDIC lenders) for each type of institution. This implies that, relative to applications coming from non-Black neighborhoods, denial rates tend to fall, while origination rates tend to rise, for applications coming from majority Black Census tracts in response to rising HPI.

Furthermore, the differences between the application-share and denial-share coefficients for lenders reporting to the OCC, FRB, FDIC, and OTS are all somewhat larger than the difference estimated for the non-depository lenders

**Table 8**
Regression estimates – Shares of mortgage activity in minority neighborhoods and housing inflation, by agency (1990–2010).

| | (1) Applications | (2) Originations | (3) Denials |
|---|---|---|---|
| OCC | −0.076* | −0.074* | −0.089* |
| | (0.025) | (0.022) | (0.030) |
| FRB | −0.052* | −0.048* | −0.070* |
| | (0.027) | (0.023) | (0.035) |
| FDIC | −0.003 | 0.004 | −0.013 |
| | (0.033) | (0.031) | (0.036) |
| OTS | −0.049* | −0.044* | −0.056* |
| | (0.027) | (0.027) | (0.033) |
| NCUA | −0.092* | −0.080* | −0.114* |
| | (0.024) | (0.022) | (0.029) |
| HUD | −0.047 | −0.039 | −0.051 |
| | (0.036) | (0.033) | (0.038) |
| F statistic | 6.8 | 5.2 | 2.7 |
| *p*-value | 0.000 | 0.000 | 0.019 |

Note: Coefficients on house prices are interacted with agency dummies from estimation of Eq. (3). Dependent variables are shares of a lender's metro area applications, originations, and denials from majority Black Census tracts. Robust standard errors, clustered within metro areas, are reported in parentheses. An asterisk (*) denotes significance at conventional levels ($p < 0.10$). The F statistic and $p$-value are reported for test of equality of all six coefficients. All regressions are weighted by the total number of applications received by the lender in a year.

reporting to HUD. Based on the point estimates, a 10 percentage point rise in HPI is associated with a decrease in the majority-Black-tract denial share of 0.7 to 1.8 percentage points *in excess* of the decrease in the majority-Black-tract total application share for lenders reporting to the OCC, FRB, FDIC, and OTS. For HUD, the same increase in house price inflation corresponds to denial shares decreasing only 0.4 percentage points beyond the dropoff in application shares. In response to a housing boom, then, we tend to observe denial rates for applications coming from majority Black Census tracts decrease to a greater extent among lenders facing CRA compliance exams than among HUD lenders.

At the same time, it is important to stress that none of these differences are statistically significant. Moreover, we see a similar pattern when we consider the lending activity of credit unions, which are not covered by the CRA. In fact, of the six agencies considered, NCUA lenders produce the largest difference between the application-share and denial-share coefficients, indicating that majority-Black-tract denial shares decrease by 2.2 percentage points beyond the decrease in total application shares, on average, in response to a 10 percentage point rise in HPI. Overall, then, we interpret these findings as showing only limited evidence to support the hypothesis that institutions facing CRA-compliance evaluation from regulators are particularly likely to expand their lending to minority neighborhoods during run-ups in housing markets.

There is one final observation worth noting with respect to the analysis of redlining in fair lending investigations. When defined by shares of *denials* associated with properties in minority Census tracts, alleged redlining appears to become less pronounced during upturns in a metropolitan area's housing market. Increasingly, denials seem to come from non-minority neighborhoods during periods of rapid real estate appreciation. Hence, just as with the results on

[43] Because the primary focus of the analysis is on house price inflation, the remainder of the output from Eq. (3) has been suppressed.

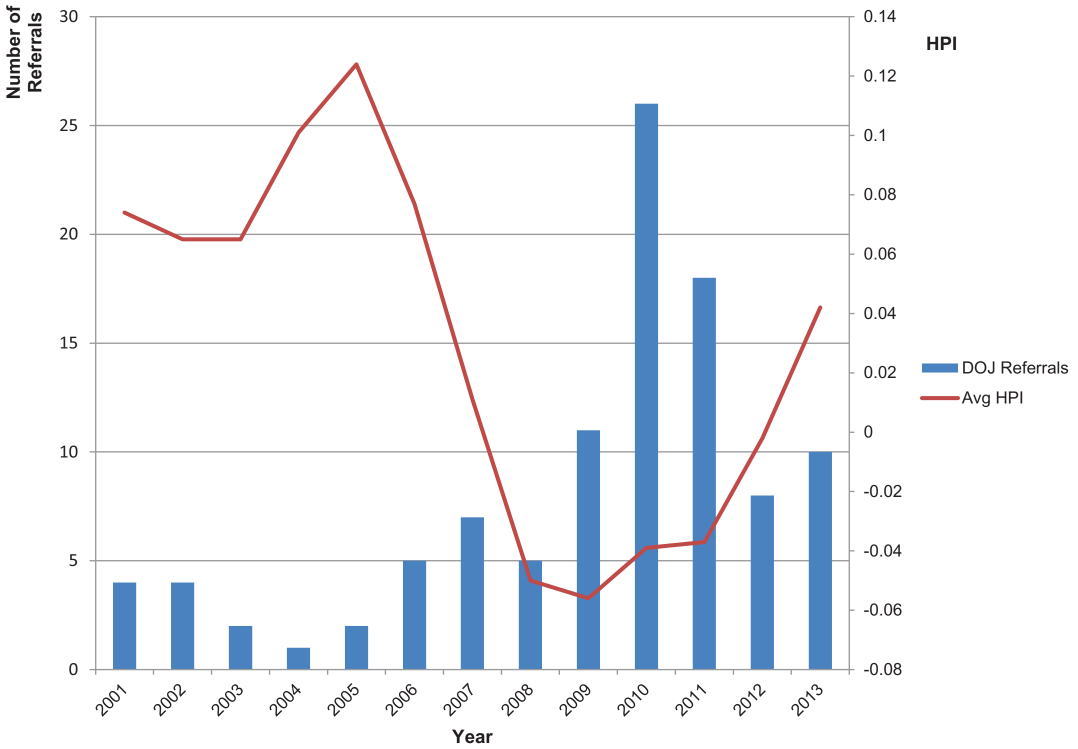


**Fig. 3.** DOJ Referrals and house price inflation.

individual rates of loan denial, evidence of fair lending violations associated with redlining may appear to diminish as real estate markets boom.

If defined by shares of *applications* tied to minority Census tracts, however, evidence of redlining may become stronger as house price inflation increases within a metropolitan area. Because non-minority neighborhoods appear to have larger swings in both their mortgage-application and denial activity as house prices fluctuate, it may be particularly important to keep the state of a local housing market in mind when evaluating the geographic distribution of mortgage activity.

## 4. Policy considerations

The data clearly indicate that the state of a local housing market can significantly influence the perceived differential between Black and White outcomes in the mortgage application process. Does this imply that enforcement activity follows suit, rising during downturns in the housing market and dropping off as house prices boom?

At the federal level, anecdotal evidence is certainly suggestive of such a pattern. By law, five of the federal mortgage-industry regulators (the OCC, FDIC, FRB, OTS, and NCUA) are required to refer matters in which a lender is suspected of having engaged in "a pattern or practice of discouraging or denying applications" in violation of the Equal Credit Opportunity Act (ECOA) to the Attorney General of the United States.[44] The Department of Housing and Urban Development faces a similar requirement under the Fair Housing Act (FHA). Each year, the Civil Rights Division at the U.S. Department of Justice (DOJ) submits a summary of these referrals to the U.S. Congress. While referrals may pertain to potentially discriminatory practices in both mortgage *and* non-mortgage lending, it is likely that mortgage lending accounts for a sizable proportion of this activity.

The summary submitted in April of 2015 indicated that, over the course of the last housing cycle – the run-up through 2005–2006, followed by the sharp decline and subsequent recovery thereafter – the number of referrals concerning alleged violations of ECOA based on race or national origin changed dramatically.[45] In particular, over the years 2003, 2004, and 2005, DOJ received a total of 5 referrals: 2 in 2003, 1 in 2004, 2 in 2005. As house price inflation began to fall, however, the number of referrals for alleged discriminatory lending practices rose significantly (5 in 2006, 7 in 2007, 5 in 2008, 11 in 2009, 26 in 2010, 18 in 2011) before dropping off as house prices began to grow again. This apparent negative association between HPI and federal referral activity is borne out statistically – the contemporaneous correlation between the two series over the 2001–2013 time frame is $-0.69$ ($p$-value $< 0.01$) – and can be seen in Fig. 3.

[44] See Regulation B, 12 CFR Section 202.16. The Federal Trade Commission and, since its creation, the Consumer Financial Protection Bureau are also subject to this requirement. The OTS existed as a separate federal agency over much of the sample time frame, but was merged with the OCC in 2011.

[45] *The Attorney General's 2014 Annual Report to Congress Pursuant to the Equal Credit Opportunity Act Amendments of 1976*, submitted by Acting Assistant Attorney General Vanita Gupta, April, 2015. It was accessed at http://www.justice.gov/crt/publications on August 4, 2015.

Although formal referrals to DOJ are based upon a more comprehensive review of lending practices than the HMDA screens considered here, results from simple screens may still be broadly indicative of what is found upon further review.[46] In particular, even if the screening estimates systematically over- (or under-) predict the denial differences between minorities and non-minorities, the mere fact that there are more 'potential' violations during times of slow house price appreciation suggests that there may also be greater numbers of referrals after more careful scrutiny.

The question that naturally arises, then, is whether these observed changes in enforcement are warranted. If fluctuations in racial or ethnic differentials in mortgage lending with respect to the housing cycle are indicative of changes in discriminatory behavior, then increased scrutiny of lenders during real estate downturns is certainly justified. Indeed, in that case, it is probably worthwhile paying additional attention to lenders located in areas (or operating in time periods) in which housing markets are stagnating. The state of the housing market may very well provide an informative signal of the frequency of fair lending violations.

On the other hand, if the systematic movement of racial lending differentials is a product of changing (but fair) lending standards, possibly combined with shifts in the relative distributions of riskiness among minority and non-minority applicants, then this variation in enforcement activity may not be justified. In this instance, housing booms would not involve less discrimination, and housing busts would not involve more. Incorporating information about the state of the local housing market, then, might help properly interpret any estimated racial differences in lending.

For example, benchmark differentials used to guide fair lending investigations (e.g., 5 or 10 percentage points) could be adjusted based on the local rate of house price inflation. Alternatively, investigations could compare denial rate differentials across similar types of lenders within the same metro area. Given that house price movements should shift lending practices similarly among certain types of lenders, judgments about which differentials merit further scrutiny could be based upon relative, rather than absolute, magnitudes. Either practice may serve to smooth regulatory efforts over time, curtailing the number of investigations during periods of stagnating house prices while increasing oversight during housing booms.

## 5. Conclusion

The state of the nation's housing market undoubtedly influences the practices of mortgage lenders. Judgments about acceptable levels of risk and expected rates of return on housing-related assets surely vary as house prices fluctuate. This variation may then translate into changes in the outcomes experienced by minority borrowers relative to non-minorities.

This paper examines how some simple measures of fair lending compliance, based upon the examination of data reported through the Home Mortgage Disclosure Act, vary with metropolitan area-level house price appreciation. The results suggest that, during housing booms, differences in the conditional denial rates between Whites and Blacks become smaller. Booms are also associated with decreases in the fraction of a lender's denials in a metro area coming from majority Black Census tracts, on average.

Given the extremely limited nature of the data reported through HMDA, however, there remain a number of unresolved issues. In particular, we are unable to account for direct measures of borrower risk such as an applicant's credit history, the loan-to-value ratio associated with an application, or the ratio of an applicant's debt payments to his or her income in the estimation of denial probabilities. It would be worthwhile to consider these quantities in the analysis if more detailed data were available.

More extensive data would also allow the analysis to look more carefully at the types of loans being made over the housing cycle. Do the types of loans (e.g., adjustable versus fixed rate) vary with fluctuations in housing market conditions? What types of loan products might have contributed to the decline of inter-racial differences observed during the most recent housing boom, and what happened to the distributions of products when prices collapsed? Answers to these questions would likely help to enhance our understanding of differential lending outcomes.

[46] Referrals in a given year also frequently pertain to lending activity from *previous* years. Nevertheless, because the 2003–2011 time frame involves generally falling house price inflation and generally rising referral activity, the data are still consistent with increased regulatory efforts as real estate markets cool.

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