The Impact of Air Quality on Mortgage Loans

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Abstract

This paper estimates the impacts of the Clean Air Act Amendment's division of counties into PM-2.5 pollutant-specific nonattainment and attainment categories on mortgage loan types. Empirical results reveal that nonattainment counties usually have more mortgage loans for non-primary residences. These loans often pay higher interest rates and have lower delinquency rates. Our results hold after conducting a series of robustness checks. We identify housing price appreciation and rental price inelasticity after the nonattainment designation as the underlying mechanisms. The effect is more pronounced in counties with more serious nonattainment levels and with stronger perception of climate risk beliefs. Collectively our results suggest that environmental policies affect the loan types for primary or non-primary residences in the mortgage markets.

JEL Classification: G21, Q53, R21

Keywords: Air Pollution; Mortgage Loans, Primary and non-primary Residences

1. Introduction

The evidence of the internalization of climate risk in housing markets continues to expand (as seen in studies by Barrage and Furst, 2019; Baldauf, Garlappi, and Yannelis, 2020; Giglio, Kelly, and Stroebel, 2020; Gibson and Mullins, 2023). Air pollution is a major climate risk, with Muller, Mendelsohn, and Nordhaus (2011) estimating its damages across U.S. industries and identifying coal-fired electric generation as the largest contributor, where damages frequently exceed value added. Air quality significantly influences housing decisions because it directly impacts health, quality of life, and property values. Potential homeowners often prioritize areas with cleaner air to avoid respiratory and cardiovascular health risks, especially for families with children or elderly members who are more vulnerable to pollution-related illnesses (Bayer, Keohane, and Timmins, 2009; Hanna and Oliva, 2015; Di et al., 2017; Isen, Rossin-Slater, and Walker, 2017; Miller, Molitor, and Zou, 2021; Childs et al. 2022). Despite this, there has been limited research on the influence of air quality on mortgage loans. In an effort to address this deficiency, we aim to investigate the effect of local air pollution regulations on the mortgage loan market in the United States.

We are focusing on the impact of air quality on the mortgage loan types. Specifically, we distinguish counties' air quality based on their classification under the National Ambient Air Quality Standards (NAAQS), a key element of the 1990 Clean Air Act Amendments (CAAA), which represents a major federal intervention in air quality. The NAAQS set maximum allowable ambient concentrations of local air pollutants by the United States Environmental Protection Agency (USEPA). If a county's pollution level exceeds the NAAQS, it is classified as a nonattainment area. This requires polluting firms within the local jurisdiction to incur significant costs to reduce emissions, leading to substantial environmental benefits overall but potentially distorting income distribution (Jha, Matthews, and Muller, 2019). Since PM-2.5 concentration is a key measure of air quality (Van Donkelaar et al., 2021), we use the nonattainment designation following the 2006 PM-2.5 NAAQS in our study.

Since houses are tied to specific locations, variations in environmental policy stringency can affect the home loan market at the community level. Air quality is a critical determinant of long-term property value, as homes in polluted areas may experience slower appreciation or even depreciation compared to those in cleaner environments (Sager and G. Singer, 2024). For primary residence buyers, the choice of location is often driven by considerations of daily living conditions, and poor air quality can detract from a neighborhood's appeal. Conversely, non-primary residence buyers, such as investors or vacation home purchasers, may be less sensitive to air pollution if the property aligns with their financial or recreational goals. For example, Lang (2015) finds that owner-occupied units capitalize air quality changes immediately but rent price response lags. Lopez and Tzur-Ilan (2024) document that rental prices are less responsive to air pollution than home prices. Ultimately, the perceived and actual risks associated with air pollution play a pivotal role in shaping housing preferences and investment decisions.

We hypothesize that a nonattainment designation following 2006 PM-2.5 NAAQS affects mortgage loan types for primary and non-primary residences in two ways. Firstly, previous research has shown that air quality improvement can lead to increased housing prices. Chay and Greenstone (2005) demonstrated that housing values in counties with nonattainment designation increased after improvements in air quality from the CAAA. This, in turn, affects the mortgage loan market. We expect to see more loans for non-primary residences in counties with nonattainment designation, since primary residence owners care more about air quality while non-primary residence investors focus on returns (Jordà et al., 2019). Air pollution represents a negative local dis-amenity affecting the location choices of households that value access to clean air (Bento et al., 2015; Roback, 1982; Rosen, 1974), which may deter primary residence investors in areas with low air quality. Secondly, non-primary residence investors are less affected by air quality because rental properties tend to have a lower sensitivity to changes in air quality compared to owner-occupied homes (Lopez and Tzur-Ilan, 2024). Renters often prioritize factors like affordability, location, and accessibility over environmental conditions, making rental demand less responsive to fluctuations in air quality. If the non-primary residence is used for vacation purposes, investors are less sensitive to air quality compared to primary homeowners who live in the property year-round.

Exploring a sample of mortgage loans in a six-year window from 2006 to 2012, we find that the nonattainment designation of a county following the 2006 PM-2.5 NAAQS in general increase mortgage loans for non-primary residences. In terms of economic magnitude, there is about 2.1% increase in the number of mortgage loans for non-primary residence purposes after the nonattainment designation. In addition, loans for non-primary residences are associated with higher interest rates and lower delinquency rates. The findings highlight the impact of poor air quality in deterring primary residence investors in affected areas.

The documented relationship between mortgage loan types and local environmental policies could be subject to endogeneity concerns. More specifically, the nonattainment and attainment counties might be fundamentally different, which may confound the results. In addition, some unobservable (omitted) variables could affect both the local housing market and environmental issues. To address these endogeneity concerns, we employ a propensity score matching approach to examine the impact of nonattainment designation on mortgage loan types for primary and non-primary residences. We also conduct placebo tests with 1,000 repetitions by randomly assigning the nonattainment counties. In addition, we conduct the analysis in a sample of border counties. The baseline results are still held.

We identify housing price appreciation after the nonattainment designation and the inelasticity of rental prices to air quality as the underlying economic mechanisms for the documented primary results. A nonattainment designation requires the area to take measures to improve air quality. As air quality improves, housing prices appreciate, leading to higher returns on real estate investments (Chay and Greenstone, 2005). Consequently, this increased housing prices could positively increase housing investment returns, potentially explaining the increase of mortgage loans for non-primary residences. In addition, rental prices increase in small units and do not fluctuate much in large units following the nonattainment designations. Our results suggest that cash flow on non-primary properties with rental purposes increases or does not change after the nonattainment designation, consistent with the argument that renters are less concerned about air quality than primary residents.

In the cross-sectional heterogeneity tests, we document that the impact on mortgage loan types is more pronounced in counties with stronger perceptions of climate risk beliefs. Moreover, our findings indicate that redesignation from nonattainment to attainment status has continuously increased mortgage loans for non-primary residences, suggesting that redesignation does not change the original impact of nonattainment designation.

This paper will first contribute to the burgeoning literature on the impact of environmental policy on mortgage loan markets. Some previous studies focus on the impacts of climate change on financial or housing markets (e.g., Giglio, Kelly and Stroebel, 2020; Gibson and Mullins, 2023). Others provide evidence on the relation between environmental policy and economic activities (Greenstone, 2002; Chay and Greenstone, 2005). To the best of our knowledge, this study will provide the first empirical evidence of how environmental regulations affect residential mortgage loan types.

Second, we document that housing price appreciation and inelastic rental prices following the nonattainment designations serve as the underlying economic mechanisms for the baseline results. Previous literature (e.g., Chay and Greenstone, 2005) has documented the housing price increase after nonattainment designations while no findings on the rental price movement after the nonattainment designations. Our studies fill the gap by examining both the housing and rental prices in an area after its designation to nonattainment following the air quality standards.

Third, we contribute to the existing literature on real estate investments by identifying how air quality environmental policies impact mortgage loan types for primary and non-primary residences. Prior studies document the impact of air quality on housing and rental prices (Smith and Huang, 1995; Chay and Greenstone, 2005; Wang and Lee, 2022; Lopez and Tzur-Ilan, 2024), inequality of housing prices in different neighborhoods (Sullivan, 2016; Zivin and Singer, 2023), worker productivity (Zivin and Neidell, 2012), and individual investor activity (Steffen and Pagel, 2024). We contribute to this stream of literature by documenting nonattainment designation attracts more mortgage loans for non-primary residences in the area.

The rest of the paper proceeds as follows. In section 2, we describe the data and how we assemble the sample from various databases. In section 3, we present the empirical methodology and empirical results including baseline results, robustness tests, channel effects, and cross-sectional results. We conclude in Section 4.

2. Data and Descriptive Statistics

2.1. The Data

2.1.1. The Clean Air Act Amendment

The identification strategy uses a quasi-natural experiment that relies on a key regulatory component of the CAAA, which is the yearly designation of counties into attainment or non-attainment status with respect to the National Ambient Air Quality Standards (NAAQS) for pollutants. The CAAA requires the USEPA to establish NAAQS for six common pollutants: particulate matter ($PM_{2.5}$), ozone (O_3), carbon monoxide, sulfur dioxide, nitrogen dioxide, and lead (EPA, 2010). Our study focuses on PM-2.5 since it results in the largest damage among the pollutants (Muller, Mendelsohn, and Nordhaus, 2011). Through the NAAQS, the federal USEPA sets maximum allowable concentrations of PM-2.5 pollution. Counties with pollution levels above the NAAQS threshold are deemed to be noncompliant (i.e., nonattainment), while those with pollution levels below the threshold are considered compliant (i.e., attainment). We focus on the 2006 standard for PM-2.5, which is implemented in the year 2009. Thus, our sample period is from 2006 to 2012, which includes three years before and three years after the implementation of the standard. The time frame provides a balanced pre- and post-implementation window to assess the impact of air quality changes.

We obtain the attainment status data from the Environmental Protection Agency (EPA), which publishes annual county-level nonattainment and maintenance area information, including revoked counties, for all pollutant standards in its Green Book. The 2006 NAAQS for PM-2.5 set two thresholds: a 24-hour standard of 35 micrograms per cubic meter ($\mu g/m^3$) and an annual standard of 15 $\mu g/m^3$. All of the areas designated nonattainment for the 2006

PM-2.5 standard violated the 24-Hour standard.[1] We plot the nonattainment areas in Figure 1, which shows nonattainment and attainment counties. In our following regressions, a county is regarded as nonattainment as long as it has areas designated as nonattainment by the 2006 PM-2.5 NAAQS.

— Insert Figure 1 about here —

2.1.2. The HMDA Dataset

We get the mortgage loan data from the Home Mortgage Disclosure Act (HMDA) Database, which includes detailed information on mortgage loan applications at the individual loan level. The database provides comprehensive records, including loan amount, applicant income, demographic characteristics of applicants (race, ethnicity, sex), loan purposes, the decision on loan approval or denial, and many others.

In processing the HMDA data, we exclude applications that were withdrawn or closed due to incompleteness. We focus exclusively on conventional loans, which are not guaranteed by government programs such as the Federal Housing Administration (FHA), Veterans Administration (VA), or the Farm Service Agency (FSA)/Rural Housing Service (RHS). Additionally, loans for purposes other than home purchases, that is loans for refinancing or home improvement, are removed. We further restrict the sample to single-family home loans, excluding other property types. We also exclude loans from areas with state FIPS codes exceeding 56.

Among the HMDA variables, we can observe whether a mortgage is applied for an owner-occupied primary residence or a non-owner-occupied property. In our setting, loans for

[1]The standard is listed on this website: https://www.epa.gov/green-book/green-book-pm-25-2006-area-information. The 24-hour PM-2.5 concentration is determined by the 98th percentile of average concentration over three years, and the annual PM-2.5 concentration is calculated as the annual mean over three years.

non-owner-occupied properties are treated as non-primary residences. The binary variable *Invest* serves as a key dependent variable in our analysis, taking a value of 1 for non-primary residence properties and 0 for primary residences. We match the HMDA data with the 2006 PM-2.5 NAAQS EPA County level nonattainment data. The final dataset spans from 2006 to 2012. It comprises 16,618,043 loan-level observations.

2.1.3. Merging with Fannie Mae/Freddie Mac Data

To examine whether investors' decisions are influenced by interest rates, we incorporate an additional dataset by merging the Home Mortgage Disclosure Act (HMDA) data with loan-level information from the Federal National Mortgage Association (Fannie Mae, FNM) and the Federal Home Loan Mortgage Corporation (Freddie Mac, FND). These two government-sponsored enterprises (GSEs) are crucial players in the U.S. housing finance system, primarily purchasing mortgages from lenders such as banks and credit unions rather than directly originating or providing loan services themselves. A key feature of their operations is the application of Loan-Level Price Adjustments (LLPAs), which are risk-based fees reflecting the credit risk associated with individual mortgage loans.

The Fannie Mae and Freddie Mac datasets provide detailed origination and loan performance data, which allow us to observe the delinquency status of borrowers. This data also contains granular information not available in the HMDA dataset, such as origination interest rates, loan-to-income (LTI) ratios, debt-to-income (DTI) ratios, and applicants' credit scores.

We first conducted a fuzzy match between loans in the HMDA and FNM/FND datasets based on some common characteristics: year, bank institution identifier, metropolitan statistical areas (MSA), three-digit zips code, loan amount, loan purpose, occupancy, and whether the loan has co-applicant. Institutional identifiers in HMDA are uniquely represented by a combination of respondent ID and agency code, whereas FNM/FND use bank names as identifiers. To bridge this discrepancy, we utilized the Avery file[2] to link the institutions and ultimately assigned a unique RSSD ID, provided by the Federal Reserve (FRB), to each institution as our main institution identifier. After the initial fuzzy matching on institutions, we manually reviewed the matches to ensure accuracy. In addition, HMDA uses a five-digit county FIPS code, while FNM/FND employs a three-digit location code. We used the MABLE/Geocorr crosswalk from the Missouri Census Data Center to reconcile these differences. For ZIP codes spanning multiple counties, we matched them to the county with the highest population, following the methodology outlined by Dou and Roh (2024).

We refine the merged dataset by applying several filters following Li (2023). Loans with a credit score below 620 were excluded, as were those with a loan-to-value (LTV) ratio greater than 95 or less than 30. Additionally, loans with interest rates outside the range of 2.75% to 8% were removed, along with loans for amounts less than $40,000. We also excluded loans with terms that did not conform with the standard 360-month duration. After applying these filters, the final dataset comprises 737,430 observations, with 285,869 loans from FNM and 451,561 loans from FND.

2.1.4. Other Variables

We get the bank characteristics from the Federal Deposit Insurance Corporation's (FDIC) Research Information System (RIS). The RIS is a data warehouse that consolidates bank institutional information from various sources on a quarterly basis. We use data from the Financial Time Series (FTS) database, which offers detailed insights into banks' financial

[2] Avery file source: https://sites.google.com/site/neilbhutta/data

performance. We use financial data in December as the measure for the bank's annual financial performance. We construct the following bank characteristics: *bank size*, *capital ratio*, *deposit ratio*, *liquidity ratio*, and *income diversity*. The detailed definition is listed in Appendix 1.

We get the county-level economic variables from the Bureau of Economic Analysis (BEA) and the Federal Housing Finance Agency (FHFA). The variables include both economic, population, and housing index at the county level in our sample period.

2.2. Summary Statistics

The final mortgage loan sample consists of 16,618,043 loans over the sample period of 2006 to 2012. Panel A of Table 1 presents the descriptive statistics of the loan-specific variables. The sample average mortgage loan amount and average income is $211,000 and $121,000, respectively. The average loan-to-income ratio is 2.179. After merging the HMDA data with FNM/FND, our sample average originating interest rate is 5.474%. An average applicant has a credit score about 749 and loan-to-value ratio at 78.7%.

Panel B presents the statistics of the bank characteristics. The average bank size in our sample is $291 million. The mean of capital ratio, deposit ratio, liquidity ratio is about 0.104, 0.818, and 0.064, respectively. *Income diversity* is noninterest income divided by the total of noninterest income and interest income, which is 0.118 in our sample.

— Insert Table 1 about here —

3. Research Design and Empirical Results

3.1. Model Specification

We examine whether the nonattainment designation would affect mortgage investment loans in that county within a difference-in-difference (DiD) framework. We use a county's designation of nonattainment following the 2006 PM-2.5 NAAQS, which is implemented in

2009. Our sample period is from 2006 to 2012, so that we can investigate three years before and three years after the implementation year. A county is "treated" in a given year if it is designated as nonattainment. The regression takes the following format:

$$Y_{i,t} = \alpha_i + \beta_1 NA_{i,t} + Control_{i,t} + \varepsilon_{i,t} \qquad (1)$$

where $Y_{i,t}$ is the variable *Invest*, which is a dummy variable equal to in one if the mortgage loan application purpose is for non-primary residence and zero otherwise. $NA_{i,t}$ is an indicator that is equal to one if a county is out of attainment with the relevant 2006 PM-2.5 NAAQS in year *t*. We include the county, bank, and year fixed effects, and cluster the standard error at the county level. We also include control variables relating to county characteristics such as population, income per capita, and housing values, and control variables relating to bank characteristics, such as size, capital ratio, deposit ratio, liquidity ratio, and income diversity. The dependent variables are dummy variables, and we use a linear probability model to incorporate our fixed effects to avoid the incidental parameters problem of nonlinear models such as logic and probit (Neyman and Scott, 1948; Lancaster, 2000).

In addition, we examine the interest rates and delinquency rates on mortgage investment loans for nonattainment counties. This analysis aims to uncover potential disparities or patterns in loan terms and borrower behavior that may be linked to the air quality regulatory changes in these counties. By focusing on these financial metrics, we can gain insights into how mortgage investment loans are structured and how they perform in areas that do not meet the 2006 PM-2.5 NAAQS, potentially shedding light on the broader financial implications for borrowers and lenders in these regions. The regression takes the following format:

$$Y_{i,t} = \alpha_i + \beta_1 NA_{i,t} \times Invest_{i,t} + \beta_2 NA_{i,t} + \beta_3 Invest_{i,t} + Control_{i,t} + \varepsilon_{i,t} \qquad (2)$$

where $Y_{i,t}$ is the outcome variable, which is either the interest rates at loan origination or the 30- (60- or 90-) day loan delinquency rates. We include the county, bank, and year fixed effects, and cluster the standard error at the county level. We also include control variables relating to county characteristics such as population, income per capita, and housing values, and control variables relating to bank characteristics, such as size, capital ratio, deposit ratio, liquidity ratio, and income diversity.

3.2. Baseline Results

We estimate model (1) and present our baseline results in Table 2. Column (1) – (4) display the regression results on *Invest* using different fixed effects. Using the whole sample with county, bank, and year fixed effects and all the control variables, the coefficient on *NA* is positive and significant, suggesting that nonattainment of PM-2.5 NAAQS is positively associated with the mortgage loans for non-primary residences. In terms of economic magnitude, there is a 2.1% increase in the percentage of mortgage loans for non-primary residences after the county is designated as nonattainment by 2006 PM-2.5 NAAQS. The results of increased mortgage investment loan are consistent with previous studies (e.g., Chay and Greenstone, 2005) that document that housing values in counties with nonattainment designation increased after improvements in air quality from the Clean Air Act.

The regression results show that females are less likely to apply for mortgage loans for non-primary residences in counties with poor air quality, suggesting that females have a higher level of air pollution awareness than males. The negatively significant coefficients on HPI show that counties with low housing values usually attract more investors after they are designated as nonattainment areas following the 2006 PM-2.5 NAAQS. Moreover, mortgage investment loans are typically concentrated in counties with higher populations and greater per capita income following their nonattainment designation. The coefficients on deposit ratio are both positively significant at the 1% level in columns (3) and (4), implying that mortgage loans for non-primary residences usually originated in banks with higher deposit ratios. The positively significant coefficients on capital ratio confirms that notion that banks with higher capital ratio originate more mortgage loans for non-primary residences.

– Insert Table 2 about here –

We also plot the coefficients on *NA* based on the regressions with *Invest* as the dependent variable using an event window of [-3, 3] for three years before and after the nonattainment designation year. We include the loan, county, and bank-level control variables. The regressions are conducted separately for each year and include state and bank fixed effects. Standard errors are clustered at the county level. The graph shows that the mortgage investment loans increase after the nonattainment designation, which is consistent with our primary findings in Table 2. Before the nonattainment designation, there was no significant trend.

– Insert Figure 2 about here –

Next, we examine the interest rates and delinquency rates in the merged HMDA and GSE sample. The regression includes loan, bank, and county-level control variables, along with fixed effects for year, bank, and county. We cluster the standard errors at the county level. The regression results are presented in Table 3. In column (1), the interaction term of *NA* × *Invest* is significantly positive at 1% level, suggesting a 7.7% increase in the interest rates for mortgage loans for non-primary residences originated in nonattainment counties. The results suggest that investors bear a higher borrowing cost in their mortgage loans for non-primary residences.

In column (2) to (4), we run the regressions on the delinquency rates over multiple days with the same loan, county, and bank control variables. We include county, bank, and year fixed effects and cluster the standard errors at the county level. The coefficients on the interaction term of *NA* × *Invest* are negatively significant across all the models, suggesting that the default risk of the mortgage loans for non-primary residences decreases in nonattainment counties.

– Insert Table 3 about here –

3.3. Robustness Tests

To ensure the validity and reliability of the baseline results, we conducted several robustness tests including propensity matching analysis and placebo tests to address potential biases, omitted variable concerns, or measurement errors. Our baseline results hold in the robustness tests.

3.3.1. Propensity Score Matching

We first employ a propensity score matching approach to address the concern that the fundamental differences between nonattainment and attainment counties might confound our results. Specifically, we match loans from nonattainment counties with loans attainment counties based on the logarithmic values of borrower-specific variables including applicant income and loan amount. The matching is based on a one-to-one nearest-neighbor kernel matching with replacement. The propensity scores are obtained by running a logit regression on whether a county has ever been designated as a nonattainment area under the 2006 PM-2.5 NAAQS with the borrower-specific loan amount and applicant income. *Ever_NA* is a dummy variable that equals 1 if the county was ever designated as a nonattainment area at any time between 2009 and 2012 under the 2006 PM2.5 NAAQS, and 0 otherwise. Then we re-estimate model (1) to examine how the nonattainment designation affects the mortgage loans for non-primary residences using the matched sample.

The result of our selection model is presented in Panel A of Table 4. Column (1) shows the results for the unmatched sample. We can see that the borrower-specific control variables are significant in the regression. Column (2) displays the results for the matched sample. We find that none of the borrower-specific control variables is significant, which suggests that our matching procedure removes most of the differences between the treatment and control groups.

Next, we run the baseline regression using the propensity score matched sample and present the results in Panel B of Table 4. The coefficient on *NA* remains positive and significant at the 1% level, which is consistent with our baseline results that mortgage investment loans increase after a county is designated as nonattainment area. Overall, our matching analysis shows that our primary findings are not likely driven by the fundamental differences between the nonattainment and attainment counties.

— Insert Table 4 about here —

3.3.2. Placebo Tests

Another concern is that the documented increase in mortgage investment loans might be the result of omitted variables that may coincide with the nonattainment designation. If so, we would observe the co-movement of mortgage investment loans and the nonattainment designation regardless of the exact timing of the designation. To address this concern, we conduct placebo (falsification) tests.

We randomly assign the nonattainment counties in 2009 and run the baseline regression model of Equation (1) 1000 times. We plot the distribution of the falsified coefficients in Figure 3 following the definition of *Pseudo_NA*. The distribution of falsified estimates concentrates around zero, while the true estimate 0.021 (red line) falls out of the distribution. Overall, the placebo tests rule out the possibility that our results are driven by omitted variables.

— Insert Figure 2 about here —

3.3.3. Border Analysis

To address unobservable factors in counties that might influence the impact of nonattainment air quality on housing investment, we conduct the border analysis. This method leverages the geographic and regulatory differences between areas on either side of a border where one side does not meet the air quality standards (nonattainment) and the other is not. By focusing on these adjacent regions, we can control many confounding factors, such as economic conditions, cultural preferences, or geographic features, which are likely to be similar across the border. This helps isolate the effect of air quality regulations on housing investment. Moreover, border analysis minimizes biases that could arise from broader regional or national trends, allowing for a more accurate assessment of how stricter air quality standards influence housing market behavior, including changes in property values, construction activity, and investment patterns.

We re-estimate our baseline regressions in a sample of counties on the state borders and present the results in Table 5. The results are qualitatively similar to the baseline results in Table 2. The coefficients on the *NA* continue to be positive and significant in both model specifications, suggesting that our primary results are not due to unobservable factors, confirming that nonattainment designation significantly increase the mortgage loans for non-primary residences.

— Insert Table 5 about here —

3.3.4. Alternative Measures

We now use the ratio of non-primary residents' applications to total applications and ratio of non-primary residents' loan amounts to total loan amounts at the county level to examine the impact of nonattainment air quality on mortgage loan types. To prevent fundamental differences between nonattainment and attainment counties from confounding our results, we conducted the analysis using a propensity-matched sample. Specifically, we match nonattainment counties under the 2006 PM-2.5 NAAQS with income per capita, population, and housing price based on a one-to-one nearest-neighbor kernel matching with replacement. The propensity scores are obtained by running a logit regression on the county characteristics. Then we estimate the following model to examine how the nonattainment designation affects the ratio of mortgage loans for non-primary residences using the matched sample.

$$Y_{i,t} = \alpha_i + \beta_1 NA_{i,t} + Control_{i,t} + \varepsilon_{i,t} \quad (3)$$

where $Y_{i,t}$ is the variable *Applicant ratio* or *Loan ratio*, which measures the ratio of the mortgage loan applications or loan amounts for non-primary residence. $NA_{i,t}$ is an indicator that is equal to one if a county is out of attainment with the relevant 2006 PM-2.5 NAAQS in year *t*. We include the county and year fixed effects, and cluster the standard error at the county level.

The result of our alternative measures for mortgage loans of non-primary residences are presented in Table 6. Column (1) shows the results for the ratio of loan applicants for non-primary residences. We find the coefficient on *NA* is significantly positive at the 1% level, suggesting that the nonattainment designation increases the ratio of non-primary residence loans in that county. Column (2) displays the results for the ratio of loan amount for non-primary residences. We find a similar result as column (1), which suggests that the loan amount for non-primary residences also significantly increases after a county is designated as nonattainment following the 2006 PM 2.5 NAAQS. Overall, our analysis with the two alternative measures shows that our primary findings are robust.

— Insert Table 6 about here —

4. Mechanism Analysis

We identify housing price appreciation following the nonattainment designation and the insensitivity of rental prices to air quality as key economic mechanisms underlying the documented primary results.

4.1. Housing Price Growth

A nonattainment designation obligates an area to implement measures aimed at improving air quality. Over time, these measures lead to better air quality, which in turn drives up housing prices. This appreciation reflects a higher perceived value of properties in areas with improved environmental conditions, as well as increased demand for homes in these regions (Chay and Greenstone, 2005). The rise in housing prices as a result of enhanced air quality translates into higher potential returns on real estate investments. These elevated returns create stronger incentives for property investment, particularly in non-primary residences, where investors aim to capitalize on the upward trend in property values. As housing becomes more desirable and valuable in nonattainment areas, this dynamic may help explain the observed increase in mortgage loans for non-primary residences.

We examine the nonattainment designation on housing price increase at the county level in our sample period and present the regression results in Table 7. The dependent variable is *HPI Growth*, the logarithmic growth of the Housing Price Index (HPI). The key independent variable is *NA*. The county control variables are *Inc_per_capita* and *Population*. We also include county and year fixed effects in the regressions. Standard errors are clustered at the county level. The coefficients on *NA* are positively significant in both models, consistent with the findings in Chay and Greenstone (2005). Our results suggest that higher housing price increase is one factor that attracts more mortgage loans for non-primary residences in nonattainment designated areas.

— Insert Table 7 about here —

4.2. Rental Growth

Furthermore, we examine how the nonattainment designation affects rental growth in different sizes of properties in Table 8. We collect the rental prices for properties with 0, 1, 2, 3, and 4 bedrooms in each county from the Office of Policy Development and Research (PD&R). The dependent variables are *RentalGrowth0(1,2, 3, 4)*, the logarithmic growth of county-level median rental estimates for properties with 0, 1, 2, 3, or 4 bedrooms. The key independent variable is *NA*. The county control variables are *Inc_per_capita, Population*, and *HPI*. We also include county and year fixed effects. Standard errors are clustered at the county level. The coefficients on *NA* are positively significant in columns (1)-(3), but not significant in columns (4) and (5). Our results suggest that rental increases in smaller units and does not change substantially in large units after the nonattainment designation in these counties.

The insensitivity of rental prices to these changes further reinforces the appeal of homeownership as a profitable investment, consistent with the argument that renters are less concerned about air quality than primary residents (Lopez and Tzur-Ilan, 2024). While rental prices for smaller units, such as those with 0, 1, or 2 bedrooms, tend to show noticeable increases, the rental prices for larger units, such as those with 3 or 4 bedrooms, remain largely unaffected. This divergence reflects a nuanced response in the rental market following the nonattainment designation under the PM-2.5 NAAQS. In contrast, the lack of significant rental price changes for larger units indicates a degree of insensitivity in this segment of the market. This insensitivity could be attributed to the distinct profile of renters seeking larger properties, who may be less influenced by air quality improvements or who already factor other considerations, such as space requirements, into their decisions. The increase or insensitivity of rental prices in nonattainment areas is another factor for the increase in mortgage loans for non-primary residences.

— Insert Table 8 about here —

5. Heterogeneity Analysis

5.1. Different Climate Risk Beliefs

In this section, we explore how the impact of air quality on mortgage investment loans differs by climate risk beliefs. We collect the public perceptions of global warming from the 2014 survey data provided by the Yale Climate Opinion Maps. The data has been used in Howe, et al. (2015) and Marlon, et al. (2022). We use two variables to capture the climate risk beliefs at the county level: *FutureGen* and *Worried*. *FutureGen* represents the estimated percentage of individuals who believe global warming will harm future generations to a moderate or great extent in each county, and *Worried* measures the estimated percentage of individuals who are somewhat or very worried about global warming in each county. We then divide the sample into three tertiles based on the 2014 values of these two variables, respectively. Counties in the first tertile are categorized as having a lower perception of climate risk since only a smaller proportion of the population is concerned about its impacts on future generations or worried about global warming.

We run the baseline regressions in the top and bottom tertiles and present the results in Table 9. The dependent variable is *Invest*. The key independent variable is the interaction term of *NA* × *FutureGen* or *NA* × *Worried*. Columns (1) and (3) present regression results for counties in the 1st tertile (lowest) of climate risk beliefs, and columns (2) and (4) show results for counties in the 3rd (highest) tertile of climate risk beliefs. The dependent variable is *Invest*. The key independent variable is *NA*. We include the loan, county, and bank control variables, and bank, year, and county fixed effects in the regressions. The standard errors are clustered at the county level.

Our results show that the impact of air quality or mortgage loans for non-primary residences is more pronounced in those counties with higher climate risk beliefs. The coefficients on the interaction terms are positively significant at the 1% in both columns (2) and (4) while they are negatively significant in columns (1) and (3). The findings align with the intuitive expectation that primary residence owners are more concerned about air quality than non-primary residence owners. In counties where beliefs about climate risk are high, there may be fewer mortgage loans for primary residences once the areas are designated as nonattainment following air pollution standard, as residents in these areas are likely to consider air quality a significant factor when purchasing homes. Non-primary residence owners may prioritize investment opportunities or other factors over environmental conditions, leading to a greater concentration of such properties in areas with lower air quality.

— Insert Table 9 about here —

5.2. Further Analysis

In this section, we analyze how the redesignation of nonattainment counties to maintenance status impacts mortgage investment loans, focusing on a sample of counties that were classified as nonattainment under the 2006 PM2.5 National Ambient Air Quality Standards (NAAQS). The analysis covers the period from 2009 to 2022, enabling us to monitor the timing and impact of redesignations over an extended timeframe. The reasoning behind this test lies in understanding whether changes in air quality compliance influence investment behavior in the real estate market. Nonattainment status signifies areas where air pollution levels exceed federal standards, which could discourage mortgage financing on primary residences, due to concerns about health risks. Conversely, a shift to maintenance status, indicating improved air quality and compliance, may mitigate these concerns. We extend the sample period to 2022 so that we can observe the long-term effects of redesignation. We run the regressions in Equation (2) with the dependent variable *Invest*. *Redesignated* is the key independent variable, which is a dummy variable that equals 1 for counties after being redesignated from nonattainment to maintenance status and 0 for counties that remain in nonattainment status. We control loan, bank, and county characteristics and cluster the standard errors at the county level.

We present the regression results in Table 10. The coefficients on *Redesignated* are positively significant in all the four models, suggesting that a county's redesignation from nonattainment to attainment areas significantly increases the mortgage loans for non-primary residences. The redesignation from nonattainment to maintenance status does not appear to alter investors' intentions to invest in non-primary residences within these areas. This suggests that the decision to finance non-primary residences, such as rental properties or vacation homes, is less influenced by air quality improvements or regulatory status changes compared to primary residences. Investors in non-primary residences may prioritize factors such as market demand, potential rental income, or property appreciation over environmental considerations. As a result, the transition to maintenance status, which signals better air quality and compliance with federal standards, does not significantly impact their investment strategies in these regions.

— Insert Table 10 about here —

6. Conclusions

Over the last decade, air pollution has emerged as a significant climate risk with far-reaching consequences. It adversely impacts public health by increasing respiratory and cardiovascular diseases, reduces productivity due to illness, and disrupts housing markets with poor air quality, among other socio-economic effects. We leverage plausibly exogenous variation in nonattainment designation by 2006 PM-2.5 NAAQS to whether the effects of nonattainment on mortgage loan types. We find that nonattainment designation leads to a significant increase in the mortgage loans for non-primary residences. The results suggest that differences in tolerance to air pollution between investors for primary and non-primary residence is driving a differential response between the two groups. In particular, the housing price increase and rental price inelasticity are the main mechanisms of our findings.

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Figure 1. Distribution of nonattainment counties following 2006 PM-2.5 NAAQS
This figure shows the distribution of PM-2.5 nonattainment areas following the 2006 standard, which is obtained from: https://www3.epa.gov/airquality/greenbook/mappm25_2006.html.

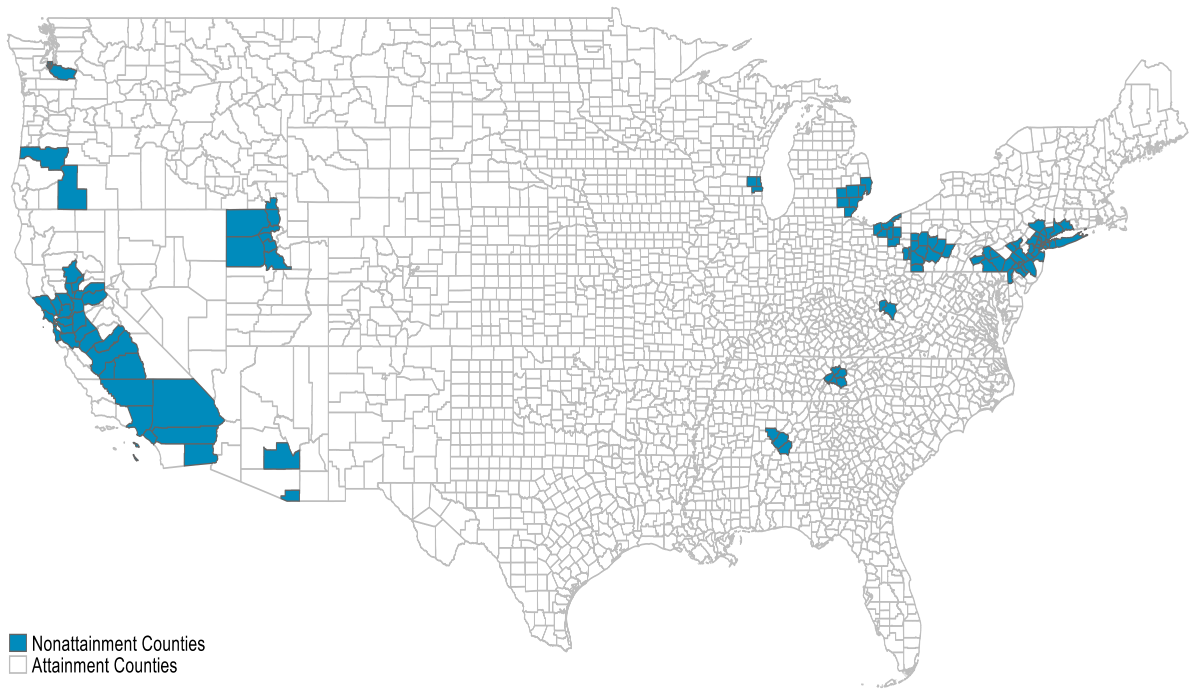

Figure 2. Parallel trend analysis

The figure shows the parallel trends before and after the event year. We plot the regression coefficients of *NA* in the regression model where *Invest* is the main dependent variable and *NA* is the main independent variable. We include loan, county, and bank-level control variables. The regressions are conducted separately for each year and include state and bank fixed effects. Standard errors are clustered at the county level.

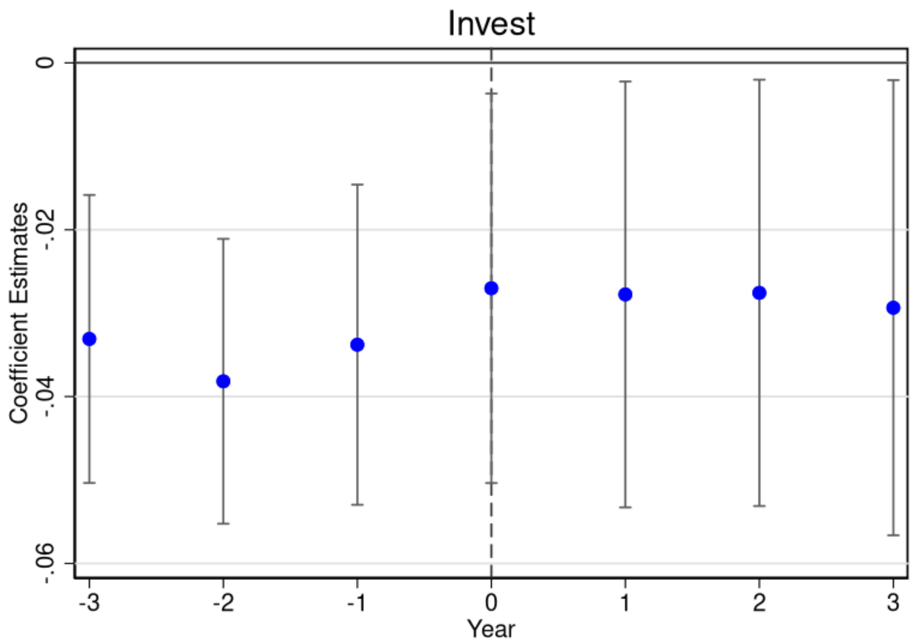

Figure 3. Placebo tests

The figure shows the kernel density of the coefficients from the placebo tests. We randomly assign the nonattainment counties in 2009 and run the baseline regression model of Equation (1) 1000 times.

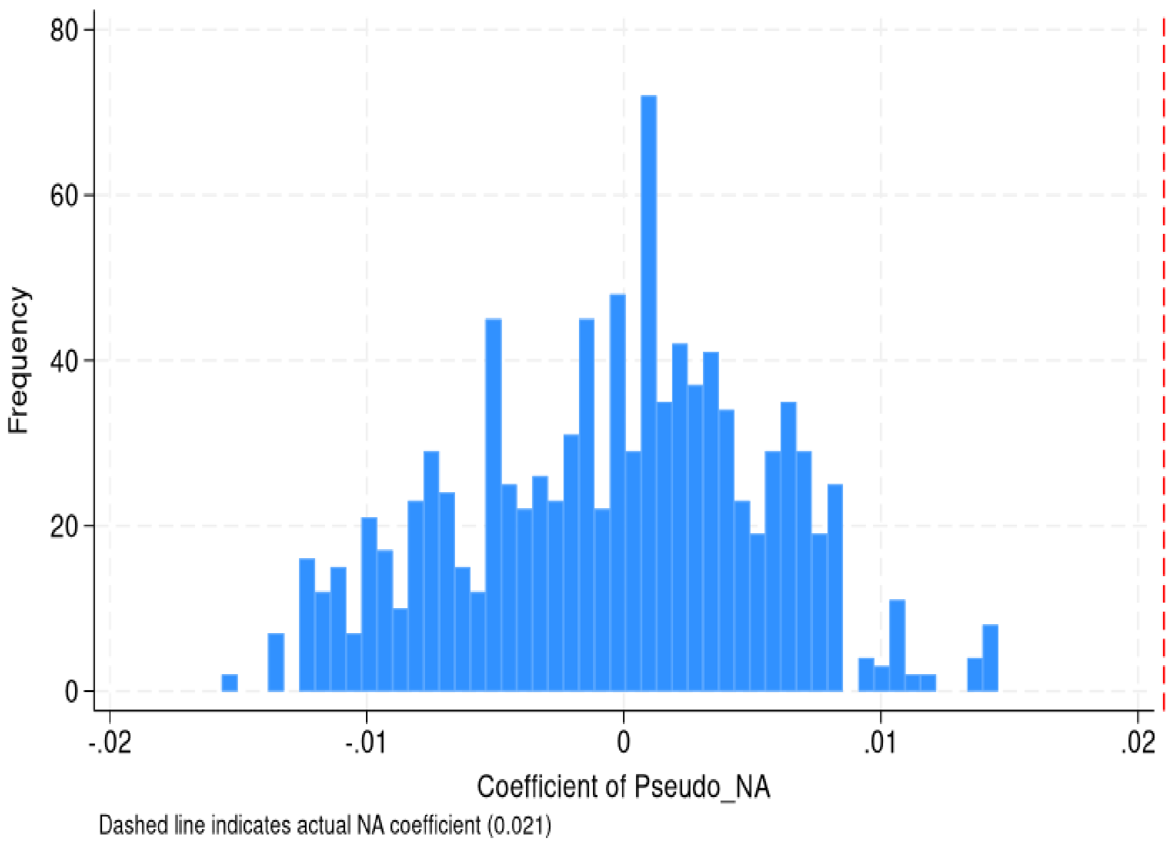

Table 1. Summary statistics

This table presents summary statistics for the main sample from 2006 to 2012. Continuous variables in the dataset are winsorized at the 1st and 99th percentiles by county and year to address outliers. Panel A lists loan-level variables, while Panel B includes bank-level institutional variables.

Panel A					
Loan variables	N	Mean	Std. dev.	P25	P75
LTI	16,618,043	2.179	1.326	1.127	3.014
Income (‘000s)	16,618,043	121	186	53	134
Amount (‘000s)	16,618,043	211	217	90	270
Interest Rate (%)	737,430	5.474	0.963	4.750	6.250
Credit score	737,430	6.619	0.063	6.578	6.669
LTV	737,430	0.787	0.118	0.750	0.830
DTI	737,430	0.352	0.111	0.270	0.430
Panel B					
Bank variables	N	Mean	Std. dev.	P25	P75
Bank size (million$)	30,992	2,643	40,994	121	541
Capital ratio	30,981	0.104	0.036	0.085	0.116
Deposit ratio	30,992	0.818	0.083	0.781	0.876
Liquidity ratio	30,981	0.064	0.064	0.024	0.081
Income diversity	30,970	0.118	0.158	0.058	0.158

Table 2. The impact of air quality on mortgage investment loans

This table shows the impact of nonattainment county designation on mortgage investment loans. The dependent variable is *Invest*, which is a dummy variable equal to one if the mortgage loan application purpose is for non-primary residence and zero otherwise. *NA* is an indicator equal to one if a county is designated as a non-attainment county according to the 2006 PM-2.5 NAAQS. The regression includes loan, bank, and county-level control variables, along with fixed effects for year, bank, and county. Loan control variables are *LTI*, *Amount*, *Income*, *Female*, *Hispanic*, *Black*, *Asian*, *Native*; bank control variables are *bank size*, *capital ratio*, *deposit ratio*, *liquidity ratio*, and *income diversity*; county control variables are *Inc_per_capita*, *Population*, and *HPI*. Variable definitions are listed in Appendix 1. Standard errors are clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
NA	0.042***	0.019**	0.045***	0.021***
	(3.10)	(2.48)	(3.25)	(2.86)
Income	0.204***	0.208***	0.202***	0.206***
	(51.92)	(53.73)	(51.37)	(64.10)
Amount	-0.119***	-0.119***	-0.118***	-0.119***
	(-35.78)	(-34.63)	(-35.76)	(-40.61)
LTI	-0.001	0.000	-0.001	0.000
	(-0.42)	(0.20)	(-0.60)	(0.18)
Female	-0.011***	-0.010***	-0.011***	-0.008***
	(-11.42)	(-10.76)	(-10.77)	(-9.09)
Hispanic	-0.004	0.003	-0.004	0.002
	(-0.67)	(0.52)	(-0.71)	(0.38)
Asian	0.039***	0.038***	0.040***	0.038***
	(8.60)	(8.46)	(8.78)	(8.54)
Native	0.001	0.003	0.001	0.005
	(0.27)	(0.76)	(0.29)	(1.30)
Black	0.040***	0.041***	0.040***	0.043***
	(7.99)	(8.55)	(7.94)	(10.21)
Inc_per_capita		0.155***		0.136***
		(4.59)		(4.25)
Population		0.163**		0.175***
		(2.54)		(2.84)
HPI		-0.267***		-0.282***
		(-13.70)		(-14.72)
Capital ratio			0.065**	0.247***
			(2.41)	(8.67)
Bank size			-0.003***	0.007***
			(-12.45)	(4.07)
Deposit ratio			0.067***	0.038***
			(11.58)	(7.51)
Liquidity ratio			-0.026**	0.059***
			(-2.06)	(5.59)
Income diversity			0.003	0.012***
			(0.58)	(2.90)

Loan Control	Y	Y	Y	Y
Bank Control			Y	Y
County Control		Y		Y
Year FE	Y	Y	Y	Y
Bank FE				Y
County FE	Y	Y	Y	Y
Obs. #	16,595,954	16,595,860	16,499,318	16,499,140
Adj. R-squared	0.191	0.194	0.191	0.216

Table 3. The impact of air quality on interest rates and delinquency rates

The table examines the impact of non-attainment designation on interest rates and delinquency rates in the merged HMDA and GSE sample. The regression includes loan, bank, and county-level control variables, along with fixed effects for year, bank, and county. Loan control variables are *LTI*, *Amount*, *Income*, *Female*, *Hispanic*, *Black*, *Asian*, *Native*; bank control variables are *bank size*, *capital ratio*, *deposit ratio*, *liquidity ratio*, and *income diversity*; county control variables are *Inc_per_capita*, *Population*, and *HPI*. Variable definitions are listed in Appendix 1. Standard errors are clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(2)	(2)	(3)	(4)
Dep. Variable	*Interest Rate*	*Dlq_30days*	*Dlq_60days*	*Dlq_90days*
NA × *Invest*	0.077***	-0.020***	-0.008**	-0.007**
	(4.59)	(-4.16)	(-2.29)	(-2.17)
NA	0.018**	-0.007	-0.007	-0.006
	(2.48)	(-1.56)	(-1.49)	(-1.54)
Invest	0.247***	0.027***	0.011***	0.010***
	(42.62)	(13.05)	(6.34)	(5.95)
Loan Control	Y	Y	Y	Y
County Control	Y	Y	Y	Y
Bank Control	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Obs. #	737,413	737,413	737,413	737,413
Adj. R-squared	0.868	0.109	0.111	0.107

Table 4. Propensity Score Matching

This table presents the results using propensity score matching (PSM) approach. We match loans from attainment counties with loans from non-attainment counties based on loan amount and applicants' income. The matching process is conducted on a one-to-one basis with replacement to maintain comparability between the treatment and control groups. Panel A evaluates the quality of the matching process by running the logistic regression of *Ever_NA*. Column (1) presents regression results for the unmatched sample, while column (2) reports results for the matched sample. The analysis includes year and county fixed effects. The standard errors are clustered at the county level. Panel B shows the results of baseline regressions using PSM sample. The dependent variable is *Invest*, which is a dummy variable equal to one if the mortgage loan application purpose is for non-primary residence and zero otherwise. *NA* is an indicator equal to one if a county is designated as a non-attainment county according to the 2006 PM2.5 NAAQS. The regression includes loan, bank, and county-level control variables, along with fixed effects for year, bank, and county. Loan control variables are *LTI*, *Amount*, *Income*, *Female*, *Hispanic*, *Black*, *Asian*, *Native*; bank control variables are *bank size*, *capital ratio*, *deposit ratio*, *liquidity ratio*, and *income diversity*; county control variables are *Inc_per_capita*, *Population*, and *HPI*. Variable definitions are listed in Appendix 1. Standard errors are clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Comparison before and after matching

	(1)	(2)
Dep. Variable	*Ever_NA*	*Ever_NA*
Amount	0.085**	-0.034
	(2.20)	(-0.73)
Income		
	0.536***	(0.02)
	(6.69)	(-0.32)
Year FE	Y	Y
County FE	Y	Y
Obs. #	16,618,043	13,880,856
Adj. R-squared	0.049	0.007

Panel B. Baseline regressions in the PSM sample

	(1)	(2)	(3)	(4)
NA	0.056***	0.038***	0.057***	0.038***
	(4.20)	(6.34)	(4.29)	(6.63)
Loan Controls	Y	Y	Y	Y
Bank Controls			Y	Y
County Controls		Y		Y
Year FE	Y	Y	Y	Y
Bank FE				Y
County FE	Y	Y	Y	Y
Obs. #	13,862,544	13,862,479	13,783,549	13,783,371
Adj. R-squared	0.167	0.174	0.168	0.192

Table 5. Border analysis

This table analyzes the effects of nonattainment on mortgage investors decision, with a specific focus on border counties. Column (1) includes loan- and county-level controls with fixed effects, while Column (2) adds bank-level controls and fixed effects. Both columns are clustered at county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
NA	0.019*	0.022**
	(1.65)	(1.98)
Loan Controls	Y	Y
Bank Controls		Y
County Controls	Y	Y
Year FE	Y	Y
Bank FE		Y
County FE	Y	Y
observations	5,783,338	5,748,388
Adj. R-squared	0.214	0.235

Table 6. Alternative Measures

This table shows the impact of nonattainment county designation on the ratio of mortgage loan applicants (amounts) for non-primary residences. The dependent variable is *Applicant ratio* or *Loan ratio*, which is the ratio of loan applicants (amounts) for non-primary residences in total applicants (loans). *NA* is an indicator equal to one if a county is designated as a non-attainment county according to the 2006 PM-2.5 NAAQS. The regression includes county-level control variables (*Inc_per_capita*, *Population*, and *HPI*), along with fixed effects for year and county. Variable definitions are listed in Appendix 1. Standard errors are clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Dep. Variable	*Applicant ratio*	*Loan ratio*
NA	0.028***	0.028***
	(4.04)	(4.29)
County Control	Y	Y
Year FE	Y	Y
County FE	Y	Y
Obs. #	1,283	1,283
Adj. R-squared	0.893	0.898

Table 7. Mechanism Analysis: Housing Price Growth

This table explores the impact of air quality on housing price growth. *HPI Growth* represents the logarithmic growth of the Housing Price Index. The key independent variable is *NA*. The county control variables are *Inc_per_capita* and *Population*. Variable definitions are listed in Appendix 1. We also include county and year fixed effects in the regressions. Standard errors are clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Dep. Variable	*HPI Growth*	*HPI Growth*
NA	0.009**	0.014***
	(2.43)	(3.85)
County Control		Y
Year FE	Y	Y
County FE	Y	Y
Obs. #	18,841	18,841
Adj. R-squared	0.465	0.476

Table 8. Mechanism Analysis: Rental Growth

This table explores the impact of air quality on rental price growth. *RentalGrowth0*, *RentalGrowth1*, *RentalGrowth2*, *RentalGrowth3*, *RentalGrowth4* refer to the logarithmic growth of county-level median rental estimates for 0, 1, 2, 3, and 4 bedrooms respectively. The dependent variable is *Invest*. The key independent variable is *NA*. We control the county control variables: *Inc_per_capita*, *Population*, and *HPI*. Variable definitions are listed in Appendix 1. We also include county and year fixed effects in the regressions. Standard errors are clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	*RentalGrowth0*	*RentalGrowth1*	*RentalGrowth2*	*RentalGrowth3*	*RentalGrowth4*
NA	0.005*	0.006**	0.006**	0.004	0.005
	(1.69)	(2.22)	(1.99)	(1.31)	(1.59)
County Control	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y
Obs. #	18,892	18,892	18,892	18,892	18,892
Adj. R-squared	0.237	0.245	0.247	0.261	0.253

Table 9. The impact of air quality on mortgage investment loans with different climate risk beliefs

This table explores how the impact of air quality on mortgage investment loans differs by climate risk beliefs at the county level. The dependent variable is *Invest*. The key independent variable is the interaction term of *NA* × *FutureGen* or *NA* × *Worried*. Columns (1) and (3) present regression results for counties in the 1st tertile (lowest) of *FutureGen* and *Worried*, and columns (2) and (4) show results for counties in the 3rd (highest) tertile of these variables. *FutureGen* is the percentage of population who believe global warming will harm future generations a moderate amount or a great deal. *Worried* is Percentage of population who are somewhat/very worried about global warming in each county. The dependent variable is *Invest*. The key independent variable is *NA*. Loan control variables are *LTI*, *Amount*, *Income*, *Female*, *Hispanic*, *Black*, *Asian*, *Native*; bank control variables are *bank size*, *capital ratio*, *deposit ratio*, *liquidity ratio*, and *income diversity*; county control variables are *Inc_per_capita*, *Population*, and *HPI*. Variable definitions are listed in Appendix 1. We also include fixed effects in different models. Standard errors are clustered at the county level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	1st	3rd	1st	3rd
	(1)	(2)	(3)	(4)
NA × *FutureGen*	-0.023*	0.027***		
	(-1.70)	(3.48)		
NA × *Worried*			-0.032***	0.030***
			(-3.38)	(3.92)
Loan Control	Y	Y	Y	Y
Bank Control	Y	Y	Y	Y
County Control	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Obs. #	3,916,116	12,582,532	3,596,883	12,901,821
Adj. R-squared	0.237	0.211	0.239	0.211

Table 10. Further analysis

This table examines the effect of redesignating nonattainment counties to maintenance status on mortgage investment loans in a sample of counties which were designated as nonattainment under the 2006 PM2.5 NAAQS. The regressions include controls for loans, banks, and counties, with fixed effects for year, bank, and county for the period from 2009 to 2022. The dependent variable is *Invest*. *Redesignated is* a dummy variable that equals 1 for counties after being redesignated from nonattainment to maintenance status and 0 for counties that remain in nonattainment status. Loan control variables are *LTI*, *Amount*, *Income*, *Female*, *Hispanic*, *Black*, *Asian*, *Native*; bank control variables are *bank size*, *capital ratio*, *deposit ratio*, *liquidity ratio*, and *income diversity*; county control variables are *Inc_per_capita*, *Population*, and *HPI*. Variable definitions are listed in Appendix 1. Standard errors are clustered at the county level.*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Redesignated	0.051***	0.018**	0.052***	0.018**
	(5.33)	(2.05)	(5.37)	(2.27)
Loan Control	Y	Y	Y	Y
Bank Control			Y	Y
County Control		Y		Y
Year FE	Y	Y	Y	Y
Bank FE				Y
County FE	Y	Y	Y	Y
Obs. #	3,889,323	3,867,623	3,889,241	3,867,111
Adj. R-squared	0.181	0.183	0.182	0.204

Appendix 1. Variable definitions

Variable Name	Definition	Source
Loan Variables		
Invest	A dummy variable that equals 1 if the loan application is for a non-primary residence and 0 otherwise.	HMDA
Amount	Log of loan amount.	HMDA
Income	Log of applicant income.	HMDA
LTI	Loan to income ratio, calculated by dividing the loan amount by the applicant's income.	HMDA
Female	A dummy variable that equals 1 if the primary applicant is female and 0 otherwise.	HMDA
Hispanic	A dummy variable that equals 1 if the primary applicant is Hispanic and 0 otherwise.	HMDA
Black	A dummy variable that equals 1 if the primary applicant is Black and 0 otherwise.	HMDA
Asian	A dummy variable that equals 1 if the primary applicant is Asian and 0 otherwise.	HMDA
Native	A dummy variable that equals 1 if the primary applicant is Native and 0 otherwise.	HMDA
Applicant ratio	The ratio of loan applicants for non-primary residences to total applicants in a county.	HMDA
Loan ratio	The ratio of loan amounts for non-primary residences to total loan amounts in a county.	HMDA
Interest Rate	Loan origination rate.	FNM/FND
Dlq_30days	A dummy variable that equals 1 if the applicant is delinquent for over 30 days, and 0 otherwise.	FNM/FND
Dlq_60days	A dummy variable that equals 1 if the applicant is delinquent for over 60 days, and 0 otherwise.	FNM/FND
Dlq_90days	A dummy variable that equals 1 if the applicant is delinquent for over 90 days, and 0 otherwise.	FNM/FND
LTV	Loan to value ratio.	FNM/FND
DTI	Debt to income ratio.	FNM/FND
Credit score	Log of applicant credit score.	FNM/FND
Bucket	Loan-level price adjustment (LLPA) grid of FNM/FND in 2018.	FNM/FND
Bank Variables		
Bank size	Log of total bank assets.	FDIC-RIS
Capital ratio	Bank total equity standardized by total bank assets.	FDIC-RIS
Deposit ratio	Bank total deposits standardized by total bank assets.	FDIC-RIS
Liquidity ratio	Bank total liquidity (noninterest-bearing cash & due + interest-bearing cash & due) standardized by total bank assets.	FDIC-RIS
Income diversity	Noninterest income divided by the total of noninterest income and interest income.	FDIC-RIS
County Variables		

NA	A dummy variable that equals 1 if the county is classified as a nonattainment area for the current year under the 2006 PM2.5 NAAQS, and 0 otherwise.	EPA
Ever_NA	A dummy variable that equals 1 if the county was ever designated as a nonattainment area at any time between 2009 and 2012 under the 2006 PM2.5 NAAQS, and 0 otherwise.	EPA
Redesignated	A dummy variable that equals 1 for counties after being redesignated from nonattainment to maintenance status and 0 for counties that remain in nonattainment status.	EPA
Inc_per_capita	Log of county level income per capita.	BEA
Population	Log of total county population.	BEA
HPI	Log of county level Housing Price Index.	FHFA
HPI Growth	Log growth of HPI index	FHFA
RentalGrowth0	Log growth of county level median rent estimates for rental properties with 0 bedroom.	PD&R
RentalGrowth1	Log growth of county level median rent estimates for rental properties with 1 bedroom.	PD&R
RentalGrowth2	Log growth of county level median rent estimates for rental properties with 2 bedrooms.	PD&R
RentalGrowth3	Log growth of county level median rent estimates for rental properties with 3 bedrooms.	PD&R
RentalGrowth4	Log growth of county level median rent estimates for rental properties with 4 bedrooms.	PD&R
FutureGen	Percentage of population who believe global warming will harm future generations a moderate amount or a great deal.	YCOM
Worried	Percentage of population who are somewhat/very worried about global warming in each county.	YCOM