The Value of School Social Climate Information: Evidence from Chicago Housing Transactions*

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Abstract

In this paper, I investigate how publicizing school social climate information is capitalized into the housing market and how it affects the sorting of homebuyers from different demographic backgrounds. Using a plausibly exogenous shock of school climate information in Chicago, I employ event studies and a difference-in-differences framework. I find that providing this information publicly leads to price increases for homes assigned to better climate ratings, and more advantaged families sort into these homes. The initial impacts dissipate over time as the information becomes less salient and the search costs increase. My work provides revealed preference evidence that households value school climate quality.

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1 Introduction

School social climate refers to the social, learning, and working conditions experienced by students, families, and teachers in schools. Educators and researchers argue that this school characteristic provides a measure of students' social wellbeing that is lacking from more traditional measures of school quality, such as test scores (Bryk et al., 2010; Darling-Hammond, 2004; Gagnon and Schneider, 2019; Jackson et al., 2020a; Thapa et al., 2013). Students' exposure to worse social and learning conditions, based on disruptive peers, has been linked to worse academic performance and labor market outcomes (Carrell et al., 2018; Carrell and Hoekstra, 2010). Furthermore, better social conditions may foster students' socioemotional development, which can, in turn, positively influence students' educational attainment and criminal involvement (Fricke et al., 2019; Jackson et al., 2020a,b; Loeb et al., 2018).

Due to the growing acknowledgement that school climate is likely to matter for student outcomes, many educational institutions have begun to standardize the measurement and reporting of their social climate. As of 2019, the federal government, 16 states, and various school districts across the US have invested millions of dollars to measure and improve school climate, and many are publishing these data for accountability or public transparency (Gagnon and Schneider, 2019; Gonzalez et al., 2020; Jordan and Hamilton, 2019; Kostyo et al., 2018; The Aspen Institute, 2021).

The increasing focus on measuring and promoting school climate can potentially have effects beyond internal school decision-making and improvement. Much prior research shows that local residents value school quality, which is capitalized into house prices (Bayer et al., 2007; Black, 1999). Studies using school test score performance information shocks show that this school characteristic can affect families' sorting patterns as well (Bergman et al., 2020; Figlio and Lucas, 2004). If families value school climate, then increased collection and distribution of school climate information could change families' school choice and residential sorting, similar to the impacts of school test score information. This can have implications for house prices, districts' tax bases, and neighborhood and school demographics, as well as for equity of access to quality schools. The extent to which school climate information affects these outcomes depends on how families value this dimension of school quality, and which families value it and/or are able to take advantage of the opportunities to access better-climate schools. Currently, little is known about the value families place on school climate and the resulting impacts of providing clear and consistent school climate information to the public.

In this paper, I provide the first causal evidence of how publicized school climate information is capitalized into the housing market and how it affects sorting of homebuyers from

different demographic backgrounds across neighborhoods. I leverage a plausibly-exogenous shock of new information that increased the salience of school climate quality across the Chicago Public Schools (CPS) district in fall of 2011. Prior to 2011, these biennial reports were privately provided to school administrators for internal use but were not released to the public (Levenstein, 2016). By only changing the salience of school climate quality but not other school characteristics, I isolate the parental preferences for school climate from preferences for other school characteristics.

The climate information in this study was based on surveys administered to students and teachers in the spring of 2011, which were then summarized into school climate reports. The climate reports provided information to consistently compare schools based on five dimensions of school climate: (1) supportive environments, (2) ambitious instruction, (3) parental involvement, (4) teacher collaboration, and (5) effective leadership. Each school in the district was assigned an overall composite school climate quality rating based on a five-point color-coded scale, as well as ratings for each individual school climate dimension.

I use parcel-level home transactions data to explore differences in house prices two years before and one year after the information campaign as a function of the newly released school climate information. The granularity of the data allows me to compare transactions across the district as well as transactions adjacent to school attendance boundary borders. Additionally, the high frequency of the data allows me to explore immediate and dynamic reactions in the housing market over time. Furthermore, I link the transactions data with home mortgage data that contain information on homebuyers' demographics. The breadth and depth of these two datasets combined allow me to investigate differential effects of school climate information on incoming homebuyers by socioeconomic and racial/ethnic background.

I first demonstrate that the publicly-released school climate ratings provided new insights about schools that would not have been easily observable by parents and homebuyers before the information shock. These ratings are only weakly correlated with school proficiency rates, poverty levels, and value-added measures. Additionally, they were difficult to predict based on these and other already public information. Furthermore, the ratings were not positively capitalized into house prices. Together, these findings suggest that when school climate information is not publicly available, parents cannot easily predict it, and even if they knew about it through other means, they were not paying for this school quality component. However, I find that lower-income, Black, and Hispanic homebuyers sorted into better climate school zones before the information shock.

Next, I study families' willingness to pay for homes zoned to better-climate schools after the information is publicly available. I focus on the initial public release of school climate

ratings in CPS in September 2011. I leverage the suddenly public climate information as a unique opportunity to observe reactions in the housing market to a change in perceived relative school climate quality that was not associated with contemporaneous changes in school characteristics. The unexpected shock of information and the novelty of the school climate ratings allow me to identify the effect of publicly releasing this information through event studies and a difference-in-differences approach.

My event studies show no differential pre-trend in the relationship between school climate and housing market outcomes, suggesting that the information was not correlated with pre-release secular trends in home prices. The information shock led to a 9% to 19% price premium for homes assigned to better climate ratings relative to the worst rating in the first post-shock quarter, but these effects begin to dissipate after the second quarter. This dissipating effect is similar to those found by other relevant information campaign studies using school ratings based on student performance (Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011). I find evidence that the school climate information effects are independent of school proficiency and value-added rates.

Additionally, I show that there was an immediate 14% increase in the incomes of homebuyers purchasing homes in neighborhoods assigned to the best climate rating, compared to the incomes of those buying in the worst climate rating school zones. I also find suggestive evidence that information shock led more Asian and White homebuyers purchase homes assigned to better climate ratings. In heterogeneity analysis, I find suggestive evidence that families are willing to trade-off worse proficiency rates for a better climate rating.

Overall, my results indicate that releasing school climate ratings has short-term positive impacts on property values and that better ratings attract more advantaged homebuyers. The effects dissipate by the second quarter after the information shock. Prior work shows similar short-run reactions to other school quality information shocks (Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011). I then explore two potential mechanisms that can help explain the short-lived nature of these effects: (1) the information shock led to an immediate increase in demand that was met with a delayed response in the supply of available homes on the market; and (2) homebuyers may be able to value school climate information only when it is highly salient and easily accessible (low search costs).

The first potential mechanism could be based on the short- and long-run supply of houses available on the market. In the short-run, the information shock may have led to an increased demand for homes in better climate school zones. The supply of homes may not be able to react immediately to the increased demand, which would lead to an immediate increase in sales prices for in-demand properties that were already on the market. As time goes on, the initial price premium may lead to an increase in supply of available homes in in-demand

school zones to meet the increased demand for homes, bringing sales prices back down at the higher supply quantity. I provide suggestive evidence for the short-run mechanism using changes in the number of home sales transactions, but do not find significant supporting evidence for the long-run channel to help explain the dissipative nature of my results.

A second potential mechanism for the short-term effects could be that homebuyers value school climate information when it is highly salient and search costs are low. Thus, as CPS's information campaign ends and news coverage stops, the cost of obtaining school climate information increases, even though it is still publicly available and accessible. Homebuyers who enter the market after the information campaign may not be aware of the availability of the information. Prior work shows similar short-term reactions to other school quality information shocks (Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011), supporting this hypothesis. Further evidence for this hypothesis can be seen in online search patterns over time. Using Google Trends data, I find a spike in searches for relevant school climate terms during the months of the information campaign, which return to pre-shock levels soon thereafter.

This paper contributes to several areas of research.[1] It is most closely related to three papers on parental revealed preferences for social-learning conditions.[2] Jacob and Lefgren (2007) find that parents in a mid-size US school district, on average, strongly prefer teachers who are described by principals as able to promote student satisfaction, over their ability to improve student achievement. Relatedly, Hailey (2020) finds that in New York City, families are less willing to rank *disorderly* schools as their top choice in high school applications, controlling for other school characteristics.[3] On the other hand, Gibbons and Silva (2011) find that in England, families do not actually pay more for homes assigned to schools with higher rates of student-reported happiness, controlling for school value-added and test scores.

I make several contributions relative to this prior research on parental revealed preferences for social-learning conditions. First, I provide the first causal evidence of whether and how much families value school social conditions. I use a plausibly exogenous shock of new information that increased the salience of information about school climate quality across Chicago. By only changing the salience of school climate quality but not other school characteristics, I more credibly isolate the parental preferences for school climate from pref-

[1] There is a large literature on the revealed preferences for school characteristics. These studies consistently show that parents have a strong preference for schools with higher average test scores and those that are in closer proximity to the home, over other characteristics (Abdulkadiroğlu et al., 2020; Hastings and Weinstein, 2008). Very few studies focus on the revealed preferences for schools' social conditions.

[2] Studies consistently show that parents self-report having strong preferences for better social conditions in schools (Gibbons and Silva, 2011; Goyette, 2014; Hassan and Geys, 2016; Weininger, 2014); however, idealized perceptions and behavior may not necessarily manifest in real-life decisions through revealed preferences (Bruch and Mare, 2012; Gibbons and Silva, 2011; Parker and Souleles, 2017).

[3] Hailey (2020) defines *disorderly schools* based on school-reported violent and disruptive incidents, student perceptions of insecurity, teacher perceptions of disorder, and on neighborhood crime rates.

erences for other school characteristics. The prior studies relied on controlling for observed school characteristics to attempt to isolate parental preferences for school social conditions (Gibbons and Silva, 2011; Hailey, 2020; Jacob and Lefgren, 2007).

Second, I contribute to the literature by investigating families' revealed preferences for publicly available measures of school social and learning conditions. In my context, families are provided with quantitative and salient heuristics that can help them more easily compare schools and express their preferences. On the other hand, past relevant studies have relied on measures that are only observable to the researcher (Gibbons and Silva, 2011; Jacob and Lefgren, 2007).[4] In those cases, families are not able to easily compare a schools' social conditions. Under such imperfect information, families may not be able to fully express their preferences.

Third, I provide the first evidence of parental revealed preferences for a reliable multi-dimensional measure of school social conditions. The composite measure of school climate used in Chicago quantifies a more complete picture of the social climate experienced by students, compared to prior studies that have relied on singular dimensions of social conditions: student satisfaction, student happiness, or school safety (Gibbons and Silva, 2011; Hailey, 2020; Jacob and Lefgren, 2007). Furthermore, I contribute to the literature by using a more reliable and consistent measure of the social-learning conditions experienced by students to compare schools. In my context, the measures were established based on 20 years of research, and the ratings were only calculated for schools that had a majority of students and teachers respond to a 30-minute survey. The prior studies on this topic have relied on measures based on few respondents to a few survey questions.[5]

I also contribute to the literature that uses school quality information shocks to study the revealed preferences for school characteristics. Several studies examine how property values, student sorting, and teacher turnover are affected by the release of school performance ratings, school rankings, and school and teacher value-added information, but none use the release of school climate information (Bergman et al., 2020; Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011; Hastings and Weinstein, 2008; Imberman and Lovenheim, 2016; Pope, 2019; Rich and Jennings, 2015). Furthermore, because of data limitations, past papers examining the effects of school quality information on house prices have done so without being able to explore changes in the sorting of homebuyers from different backgrounds (Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011; Imberman and Lovenheim, 2016). This leaves open

[4] One exception to this is Hailey (2020), who uses already publicly available measures of school safety, but does not leverage plausibly exogenous variation.

[5] Jacob and Lefgren (2007) calculate their measures of teachers' ability to foster student satisfaction based on principals' responses to a survey question. Similarly, Gibbons and Silva (2011) calculate school-level student happiness based on at least 10 students responding to a single survey question.

an important question about the potential implications of school quality information on neighborhood demographics.

This paper is organized as follows: Section 2 discusses the concept of school climate, the school climate measures used in my context, and the institutional background of the information shock quasi-experiment. Sections 3 and 4 describe the data and the extent that school climate ratings were new information, respectively. Sections 5 and 6 describe the empirical approach and results of the school climate information shock, respectively. Section 7 discusses potential mechanisms that may explain the results, and Section 8 concludes.

2 Institutional Background

2.1 What is school climate?

For the past two decades, various educational institutions have focused on measuring, improving, and promoting the social, learning, and working conditions experienced by students, parents, and teachers in schools. Researchers and educators primarily refer to these school conditions as school climate. Despite intensive interest in *climate*, there is no consensus on how educational institutions define or measure this concept (Bradshaw et al., 2014; Thapa et al., 2013).

The National School Climate Council (2007) broadly suggests that school climate represents *patterns of school life experiences that reflect norms, goals, values, interpersonal relationships, teaching, learning and leadership practices, and organizational structures.* The recent school climate literature has emphasized that school climate is primarily based on stakeholders' perceptions of conditions (Gruenert, 2008; Zullig and Matthews, 2014). For example, school climate can include whether students feel academically supported by teachers or whether students feel socially supported by their peers.

Research and practice are not always aligned in their priorities and perceptions about what constitutes school climate and how to measure it. The literature broadly categorizes school climate into five main components: (1) safety, (2) relationships, (3) teaching and learning, (4) institutional environment, and (5) school improvement process (Cohen et al., 2008; Thapa et al., 2013).[6] Because school climate is a broad concept without a uniform definition, educational institutions take different approaches to measure, improve, and promote social climate. In 2010, the US Department of Education incentivized states to develop rigorous measurement systems to assess the social climate in their schools (Jennings, 2011).

[6]See Thapa et al. (2013) for a thorough literature review of research on each of these school climate components.

Through this process, along with guidance from researchers, the US Department of Education developed a school climate framework called the *Safe and Supportive Schools* model (U.S. Department of Education, 2013). This model focuses on three main components of school climate—engagement, safety, and environment—that covered some but not all components emphasized by the previous literature.

As of 2019, 16 states have started using or piloting various school climate surveys for accountability or public transparency purposes (Jordan and Hamilton, 2019). Different surveys in these states measure different components of school climate. In a review of the surveys used in these states, Jordan and Hamilton (2019) find that the main school climate components being evaluated are academic engagement, bullying, physical and emotional safety, and positive relationships. Some of these states have relied on surveys developed by the US Department of Education. Other states and school districts are using school climate surveys developed internally or by contracted evaluators.

2.2 Measuring school climate in CPS

One of the earliest implementers of a standardized school climate survey was the Chicago Public Schools district (CPS) in collaboration with the University of Chicago Consortium on School Research (CCSR). Since the early 1990s, CCSR has administered school climate surveys to CPS students in grades 6–12 and to all teachers across the district. The surveys are based on the *Five Essential Supports Framework*, which captures and summarizes characteristics of good-climate schools. Studies find that schools that perform well in this framework are associated with improved student performance (Bryk et al., 2010; Hart et al., 2020; Levenstein, 2016). The five components of school climate included in this framework are (1) supportive environment, (2) ambitious instruction, (3) involved families, (4) collaborative teachers, and (5) effective leadership.

CCSR's *Five Essential Supports Framework* is more comprehensive than the framework suggested by the US Department of Education, the main difference being that it includes measures of teacher collaboration and effective leadership. This framework has now been used by many school districts across the US. As of 2021, CCSR's *Five Essentials* survey has been administered in over 6,000 schools across 22 states (UChicago Impact, 2021).

Each school climate component in the *Five Essential Supports Framework* is measured based on a series of steps that combine survey responses by students and/or teachers. To start, researchers and psychoanalysts at CCSR combine individuals' responses to a series of related questions to obtain a score for subcomponents of school climate (Levenstein,

2016).[7] For example, five survey questions about students' interactions with their teachers are combined to create a score for the *student-teacher trust* experienced in school. This measure is then combined with measures of peer academic support, academic expectations, tailored instruction, and safety to create a score for the supportive environment experienced in school, one of the five school climate components in the framework (Klugman et al., 2015). This process is repeated for each of the other four school climate components.[8]

The ambitious instruction component is made up of subcomponents that measure students' perceived course clarity, course instruction, and quality of student discussions. The measure for involved families is based on students' perceived human and social resources in the community as well as teachers' perceived quality of interactions with parents. The collaborative teachers component measures teachers' trust and collaboration with each other. Lastly, the effective leadership component is based on teachers' perceived influence in the school and their trust in their principal's effectiveness.

For each of the five school climate components, if at least 50% of students and/or teachers in the school responded to questions that make up a school climate component, then that component's score is standardized to a 1–99 scale (Levenstein, 2016).[9] Each of these climate components is then given a color-coded rating from red to green. The red rating signifies that for that school climate component, the school is at least 1.5 standard deviations below the 2011 CPS average for schools serving similar grades. The orange rating signifies being between 1.5 and 0.5 standard deviations below the average. Yellow represents those between -0.5 and +0.5 standard deviations from the mean. Lime represents schools between 0.5 and 1.5 standard deviations above the mean, while dark green represents schools at least 1.5 standard deviations above the mean.

An overall school climate rating is then calculated by adding up the school's performance on each individual climate component. Being green or lime green on a component counts as +1, each neutral or missing component counts as 0, while being red or orange counts as -1. The sum of these component scores decides the overall climate rating. Green climate schools have an overall score of at least +3; lime green schools scored +1 or +2; yellow schools have a sum of 0; orange schools scored -1 or -2; and red climate schools scored -3 or lower.[10] The *Five*

[7] CCSR calculates measure scores using Rasch analysis, a method that uses statistical models to combine survey items together.

[8] See Klugman et al. (2015) for a more complete description of each of the school climate components measured in this framework.

[9] If less than 50% of students respond to the survey but more than 50% of teachers do so, then school climate components that only depend on teacher responses are assigned a score, but those that depend on student responses are left as missing, and vice-versa.

[10] The overall school climate rating is only calculated if the school met the response rate requirement to have at least three of the five school climate components generated. Of the neighborhood schools, 95% met the reporting requirements and received an overall school climate rating.

Essential Supports Framework is focused on measuring the combination of school climate components to determine whether a school is organized for improvement. Because of this, the overall climate ratings were labeled as "not yet organized" (red), "partially organized" (orange), "moderately organized" (yellow), "organized" (lime), or "well-organized" (green).

2.3 The release of school climate information in Chicago

From the early 1990s, CCSR administered school climate surveys in CPS in the spring (February through April) every two years through 2011. CCSR privately provided climate reports that included aggregate information about school climate components and subcomponents to principals and district administrators each year in the late summer to early fall after the survey was administered. Historically, principals were not obligated to share these reports with staff or parents (Chicago Tribune, 2011; Levenstein, 2016).[11] Additionally, the reports explicitly stated that they should not be distributed without permission from the school. These privacy requirements made it difficult for the public to access this information.

In September 2011, CPS and CCSR publicly released the school climate reports, allowing stakeholders, including parents and the community, to access them for the first time. The reports were presented through an online database and could be accessed without charge or registration.[12] The website included information about each climate component and subcomponent as well as instructions on how to read the reports. The database was searchable by school name, address, and zip code, which allowed anyone to access the reports of the nearest public school or anywhere in the district. Since 2011, the school climate surveys have been administered annually, with updated yearly climate reports publicly released ever since. Figure 1 outlines the timing of the school climate surveys and their initial public release.

Figure 2 shows a sample school climate report from the database website. The top of each report displays the overall school climate rating and a square graphic showing the rating for each of the five climate components. The overall climate rating and the ratings for each climate component are color-coded as red, orange, yellow, lime green, and green. For simplicity, I refer to these school climate ratings from worst to best as ratings 1, 2, 3, 4, and 5, respectively. No other information about school performance or characteristics were included in these reports.

CPS also distributed directly to families the same school climate information for all regular, noncharter schools. During student report card pickup days in November 2011,

[11] Example reports can be found at https://consortium.uchicago.edu/publications/ccsrs-2007-survey-reports-chicago-public-schools

[12] The original version of this database could be accessed at https://cps.5-essentials.org/.

CPS families received a physical two-sided school progress report card.[13] The front of these school report cards contained measures of the school's overall performance level, probation status, annual yearly progress (AYP) status, and proficiency rates as well as attendance rates, parent satisfaction, and student safety scores. The majority of this information was already publicly released annually before 2011. The back of the school report cards included color-coded climate ratings from the original September school climate reports website.

Additionally, Chicago news outlets covered the initial online database release in September and the physical school progress report cards distribution in November. These included large media outlets in the city, such as the Chicago Sun-Times and CBS Chicago.[14]

Google searches for school climate information increased around the information release. Figure 3 shows that Chicagoans had been searching online for terms related to school climate at least nine months before the information release, even though the reports were not publicly available.[15] The figure shows that starting in September, searches for the school climate-related terms began to rapidly rise and spiked in October. Searches remained relatively high in November, when parents received physical copies of the information at their schools. Search frequency for these terms returned to previous levels by the fourth month after the initial release.

3 Data

To investigate whether school climate information is capitalized into the housing market and whether it attracts homebuyers from different socioeconomic backgrounds, I require four main types of data. First, I need information about each neighborhood school, including demographics, student proficiency rates, school attendance boundaries, and the initial school climate ratings assigned in the fall of 2011. Second, I must have data on housing transactions that can be linked to each school attendance zone. Third, I need information about homebuyers' income and demographics. Fourth, I must have information about the neighborhoods where each property is sold. I therefore construct a dataset from multiple sources. The following subsections describe each data source in detail.

[13] See figures A1 and A2 in the appendix for an example school report card.

[14] This data release was not as controversial or as highly covered by the media as the 2011 value-added data release in the Los Angeles Unified School District (LAUSD) that was used by Imberman and Lovenheim (2016), but the Chicago release went a step further than LAUSD by providing the information during report card pickup days, which LAUSD did not do.

[15] I calculate Google Search Interest by adding together search trends for the terms "school climate," "school culture," and "school environment."

3.1 School Characteristics

I obtain school climate information directly from the school progress report cards that CPS publicly distributed in November 2011. CPS made the information from these report cards publicly available as a dataset through the Chicago Data Portal (2011). These data include the score for each of the five climate components assigned to each school as well as the color-coded rating assigned to each climate component. Unfortunately, these datasets did not contain the overall color-coded school climate ratings that were assigned to each school. Instead, I recreate the overall school climate ratings by combining the individual school climate component scores from the CPS progress report cards following the steps detailed in section 2.2. Of the neighborhood schools, 95% met the reporting requirements and receive an overall school climate rating.

The school progress report cards dataset also includes school-level subject-specific value-added measures for each school and grade-specific proficiency rates. CPS's school value-added measures were generated using value-added models created by the Value-Added Research Center at the University of Wisconsin–Madison. These models control for student-specific demographics and lagged test scores (Meyer, 2013). Value-added measures had been publicly released by CPS since the fall of 2008 (Myers, 2008, 2009). These measures were generated and reported separately for math and reading. For the purposes of this study, I create overall school-level value-added measures by taking the average of the math and reading value-added scores and then standardizing this score to have mean of zero with a standard deviation of one separately for elementary and middle schools.

Next, I obtain school-level demographics and proficiency information from the Illinois State Board of Education. These data contain school-level information on the number of students enrolled; the racial/ethnic composition of students; the fraction of students eligible for free- or reduced-price lunch (FRPL), classified as Limited English Proficiency (LEP), or who have an Individualized Education Plan (IEP); and the percentage of students meeting or exceeding proficiency levels on the Illinois Standards Achievement Test.

I obtain school attendance boundary maps from CPS through the Chicago Data Portal (CPS, 2016a). These data contain shapefiles with the exact street boundaries for each neighborhood school attendance zone. Neighborhood school admissions are based on students' residential location. CPS includes 394 elementary, 17 middle, and 50 high schools. Almost all elementary schools in Chicago serve grades K–8, and very few schools exclusively serve middle-school grades.[16] Thus, I exclude middle schools from my main analysis. Furthermore, my main analysis excludes high schools because about 70% of first-time ninth graders

[16]CPS states that middle schools are often established to relieve overcrowding at nearby elementary schools (CPS, 2016b).

in CPS attended a school outside their attendance zone in 2011 (Barrow and Sartain, 2017), making the link between homes and high schools weak. In the robustness section, I show that my results are consistent even when including high school climate effects.

3.2 Housing Transactions and Characteristics

I use detailed home sales transaction-level data from the Zillow Transaction and Assessment Dataset (ZTRAX, 2020). I focus on transactions between September 2009 and August 2012, which covers two years before the information shock and one year after. These data include sales prices and dates, geographic location, mortgage details, homeowner occupancy, and physical house characteristics, including the number of bedrooms and bathrooms, square footage, and year built. Following Billings et al. (2018), I focus on mortgage deeds, which identify home purchases that were acquired with a mortgage. These transactions can be linked to home mortgage applications data that provide socioeconomic and demographic information about homebuyers. I describe this process in the following subsection. For my analysis, I select the 44,099 transactions geocoded as being located within one of the 2011–2012 elementary school attendance boundaries in CPS. I limit the sample to single-family residences, townhouses, condominiums, and rowhouses, which includes 35,324 transactions. I exclude intrafamily, dissolution, non-arm's length, and re-recorded deed transactions. Furthermore, I exclude transactions with missing sales price and those with a price of zero. These limitations bring the sample size to 29,950. I identify and exclude 1,584 duplicate records for the same transactions. To limit potential outliers, I winsorize sales prices lower than $38,500 (1st percentile) and higher than $1,500,000 (99th percentile). Lastly, I limit the sample to the 24,618 homeowner-occupied transactions for which the borrower mailing address matches the property address.

While these data include a rich set of housing characteristics, they lack unit-specific characteristics for condominiums because the Cook County Assessor's Office does not collect this information. This affects 38% of my sample. To ameliorate this issue, I impute the number of bedrooms, bathrooms, and half bathrooms and/or the square footage for properties missing any of these characteristics based on the average in the corresponding Census block-group. I interact these imputed characteristics with a missing indicator in my regressions to allow for different slopes. In Section 6.4, I show that my results are similar with or without condominium transactions.

3.3 Homebuyer Income and Demographic Characteristics

Homebuyer income and demographic data come from the Home Mortgage Disclosure Act dataset (HMDA, 2018). These data provide transaction-level information, including Census tract property location, mortgage details, and applicants' self-reported income, race/ethnicity, and gender. While these data do not include the exact property address or the sales price, they contain key information that allows me to link them to the sales data. This linking process is based on the procedure outlined in Billings (2019).

To link the data, I first obtain the full sample of home sales transactions with concurrent mortgages that had a positive loan amount and for which the Census tract can be identified based on the property location. I use three rounds of linking, each round being fuzzier than the prior. First, I link transactions that are uniquely identified in each of the two datasets based on sale year, loan amount, and Census tract. Second, I link those that remain unmatched based on sale year, loan amount, Census tract, and lender's name.[17] The third linking step matches based on sale year, loan amount, Census tract, and a phonically based representation of the lender's name, which is created using the R package *Soundex*.

Once I obtain these linked data, I merge them back into my final transactions sample created above. I am able to identify borrowers' background information using the linking process for about 82% of the final transactions in my sample.[18]

3.4 Neighborhood Characteristics

I link each transaction to its corresponding Census block-group and obtain neighborhood sociodemographic characteristics from the 2011 American Community Survey (ACS) 5-year estimates. I specifically obtain information on racial/ethnic composition, single-mother households, educational attainment, age composition, and median household income. These data were collected before September 2011 and, hence, would not be affected by the school climate information shock.

Additionally, I obtain data on reported incidents of crime from the Chicago Police Department (CPD, 2020). These data include the location, date, and type of crime for each incident. I link each incident to its corresponding Census block-group, which allows me to count the total number of crimes reported each school-year in each block-group. Using ACS block-group population estimates, I calculate the crime rate by dividing the number of reported crimes in the block-group in a school-year by the total population in that block-group

[17] HMDA provides lender IDs without actual names. These can be matched to the lender names based on the first step of the linking process.

[18] Of those matched, 76.45% were based on the first round of HMDA matching, 23.55% were based on the second round, and only 0.01% were from the third round of linking.

as of 2011. To create more stable crime rates, I calculate the average 5-year crime rate based on the 2006–2007 through the 2010–2011 school-years. I use this same process to obtain an overall crime rate, a drug-related crime rate, a physical crime rate, a weapon-involved crime rate, and a property crime rate.[19] Lastly, I standardize each of these crime rates across neighborhoods to have a mean of zero and a standard deviation of one.

Finally, I remove transactions still missing property characteristics; those missing school demographics, performance, or climate information; and those missing neighborhood income, demographic, or crime information. My final sample comprises 20,621 home sales transactions. Of these, 16,952 transactions also contain homebuyer income information.

3.5 Summary Statistics

I present summary statistics of some key variables in Table 1. The table displays averages and standard deviations for the overall sample, the sample of properties zoned to schools with average or better climate ratings, and the sample with average or worse ratings. Overall, the average home in Chicago sold for $286,011. The average homebuyer income was $100,804, and more than half these purchases were by white homebuyers. Furthermore, the average home was zoned to schools with above average proficiency rates and about average value-added. These schools are majority non-white and majority FRPL-eligible. Homes in the overall sample were located in neighborhoods with an average median household income of $65,885.

The second and third columns show that the school climate ratings were not completely uncorrelated with school and neighborhood demographics. The better-climate school zones tend to have higher sales prices, homebuyer incomes, and fraction of homebuyers who are white than worse-climate school zones. On average, homes in better-climate school zones sold for about $35,000 more than homes in worse-climate school zones, but the difference in homebuyer income was only about $10,500. Better school climate ratings also had higher proficiency and value-added rates, a smaller composition of black and white students, and fewer FRPL-eligible students. Additionally, on average, properties in better-climate school zones were in neighborhoods with higher levels of education and median household incomes. Homes in better climate school zones were slightly bigger and more likely to be condos.

[19] I categorize drug-related crimes as those based on liquor law violations, narcotics, or other narcotic violations. Physical crimes include those based on assault, battery, homicide, or kidnapping. Property crimes include those based on arson, burglary, criminal damage, motor vehicle theft, robbery, or theft. Weapon-involved crimes include concealed carry license violations or other weapons violations.

4 Did Climate Ratings Provide New Information?

In this section, I provide suggestive evidence that school climate ratings provided new information about schools and, hence, would have been difficult to predict by the public prior to the information release. Furthermore, I show that better climate ratings were not positively capitalized into house prices and, in general, did not attract higher income homebuyers pre-release. However, I find that Black and Hispanic homebuyers were more likely than Asian and White families to sort into better climate school zones before the information was publicly available.

4.1 Was school climate predictable before the information release?

The initial publicly available school climate ratings were not strongly correlated with traditionally measured school characteristics that are generally available to the public. Using data from the academic year before the initial information release, I find that school poverty rates were much less correlated with school climate ratings than with school proficiency rates. School proficiency rates in Chicago were strongly correlated with schools' rates of low-income students, as proxied by free- and reduced-price lunch (FRPL) eligibility. School FRPL-eligibility rates are negatively correlated with school proficiency rates (correlation coefficient of -0.69). This suggests that schools with higher percentages of low-income students tend to have low proficiency rates. This relationship has been thoroughly documented in the education literature. On the other hand, school climate ratings are only weakly correlated with school FRPL rates (correlation coefficient of -0.22). Similarly, school climate ratings were weakly correlated with school proficiency rates, with a correlation coefficient of 0.36. This finding suggests that schools with higher percentages of low-income students and lower proficiency rates are not substantially more likely to have a bad school climate rating. This result is in line with a recent pilot study of school climate measures in a mid-sized urban district in Massachusetts (Gagnon and Schneider, 2019).

Figure 4 presents these correlations graphically. The polygons in the background represent elementary school attendance zones across CPS. Purple zones represent schools where more than 90% of students in those schools are FRPL-eligible.[20] The dots represent the location of each traditional neighborhood school in the district. The colors of the dots in the left map represent school proficiency rates relative to the average proficiency rates across all elementary schools in the district. Blue circles are schools with some of the highest proficiency rates in the city, while red circles represent some of the worst-performing schools in

[20] I chose 90% as the cutoff for display purposes because only about a quarter of traditional neighborhood schools in Chicago are composed of less than 90% FRPL-eligible students.

the city in terms of test scores. This map makes it visually clear that there is a strong relationship between school poverty rates and school proficiency rates, as is widely documented in the education literature. Blue and light-blue circles are almost always in polygons serving fewer poor students, while yellow, orange, and red proficiency schools are almost always in attendance zones with high FRPL-rates.

On the other hand, the map on the right side of figure 4 shows that the best climate schools (blue is a rating of 5 and light-blue is a rating of 4) can be found all across the district. Schools can have excellent school climate and yet have higher- or lower-FRPL rates. Similarly, schools with some of the worst climate ratings can also have high- or low-FRPL rates. This relationship leads to the weak correlation coefficient of -0.21.

To further quantify these findings, I use regression models to predict various school characteristics based on easily accessible school data. These prediction models allow me to examine how easily savvy parents would have been able to predict school quality and how new some of this information may have been to them. Table 2 shows the estimated R^2 from the regression models.[21] Columns (1) and (2) show that school proficiency rates and FRPL-rates are highly predictable. The models estimate that 70% to 77% of the variation in school proficiency rates and FRPL-eligibility rates, respectively, can be explained by other school characteristics. Column (3) shows that school value-added is much less predictable, with only about 24% of the school value-added variation being explained by the model, which is similar to the percentage found by Imberman and Lovenheim (2016). Columns (4)–(6) show that school climate ratings are slightly less predictable than school value-added, and substantially less predictable than school proficiency rates or FRPL-rates. Only about 7% to 21% of the variation in school climate can be explained by these models.

4.2 Were school climate ratings capitalized into house prices before the information release?

Next, I employ two commonly used methods to describe how different measures of school quality were capitalized into house prices before the school climate information release. First, I use a simple hedonic model that compares properties across the district with different school qualities (e.g., proficiency and value-added rates, as well as school climate ratings), controlling for house characteristics and neighborhood sociodemographics. Second, I follow Black (1999) by using school attendance boundary discontinuity methods, which compare properties that are on opposite sides of an attendance zone boundary where one side is served

[21] Refer to appendix Table B1 for full table with coefficients.

by one school and the other is served by a different school.[22] Due to the close proximity of the properties being compared, this latter method may be better able to control for unobservable neighborhood characteristics than the hedonic model. For this analysis, I limit the sample to homes sold within two years prior to the climate information campaign to examine the relationship before school climate ratings were publicly available.

CPS has been at the forefront of school choice (Chicago Reporter, 2015; Zotti, 2020), weakening the link between home address and school assignments. Nevertheless, I show that neighborhood school proficiency rates are significantly and positively capitalized into house prices, suggesting that if school climate is valued by residents, then this school quality measure would be capitalized as well.

Table 3 presents simple descriptive estimates whether future school climate ratings were capitalized into house prices before any school climate information was publicly available. Panel A presents hedonic regression estimates for all school zones that are eventually assigned a school climate rating. Column (1), which only includes property characteristics controls, shows that houses zoned to schools with the two best climate ratings sell for about 25% more than homes zoned to the worst climate rating. The price premium is about 12% to 18% for climate ratings 2 and 3. Most of this value is due to neighborhood characteristics, because, as column (2) shows, the estimated coefficient decreases to a 0% to 4% price premium once I control for Census block-group characteristics. This is supported further by the boundary discontinuity models in panel B, which compare properties within 0.2 miles from the nearest boundary, as shown in columns (1) and (2) of table 3. In these models the premium is consistently negative and not statistically significant. Gibbons and Silva (2011) similarly find that school-level student happiness is associated with higher sales prices, but this premium is completely explained by neighborhood and other school quality characteristics.

In column (3) of Table 3, I add a standardized measure of school proficiency rates to the model and find that houses assigned to schools with a one standard deviation higher proficiency rate are correlated with 4% to 5% higher sales prices (statistically significant at the 1% level). These estimates are similar to those found in the literature regarding the valuation of school test scores (Black and Machin, 2011). The fact that the coefficients on better climate ratings become slightly more negative suggests that homebuyers are willing to trade-off having a worse school climate in exchange for having higher average test scores.

[22] More specifically, I estimate $Y_{inst} = \alpha_0 + \sum_{r=2}^{5}(\alpha_r Climate_{r,s}) + \Gamma \mathbf{X}_{it} + \mathbf{Z}_{in} + \theta_t + \nu_{s_j,s_k} + \varepsilon_{inst}$, where Y_{ist} is the outcome of interest for property i in school zone s in month-year t. $Climate_{r,s}$ represents climate rating r at school s based on characteristics from the 2010–2011 school year (worst rating is the reference). $\mathbf{X}_{it}$ represents property characteristics; $\mathbf{Z}_{in}$ is a set of neighborhood characteristics; θ_t is a set of month-by-year fixed effects; and ν_{s_j,s_k} is a set of attendance boundary fixed effects that separate school zone s_i from school zone s_j. The hedonic model is identical to the boundary fixed effects model but does not include the set of boundary fixed effects.

Lastly, in column (4) I include a standardized measure of school value-added. I find that houses assigned to schools with better value-added are correlated with 3% to 4% lower sales prices (statistically significant at the 1% level, conditional on school proficiency and climate). The strong price premium for higher average test scores and the nonpositive value-added capitalization is in line with much of the value-added capitalization literature (Brasington, 1999; Brasington and Haurin, 2006; Downes and Zabel, 2002; Hayes and Taylor, 1996; Imberman and Lovenheim, 2016), though Gibbons et al. (2013) and Yinger (2015) find that school test scores and value-added are similarly valued in their contexts.[23]

In summary, this pre-shock analysis provides evidence that better school climate ratings were not positively capitalized into house prices in the period before the school climate information shock. However, traditional school quality measures are capitalized into Chicago's housing market, as expected based on the literature.

4.3 Were school climate ratings attracting different demographic homebuyers before the information release?

The level of neighborhood amenity capitalization does not perfectly align with attracting higher income homebuyers. For example, Billings et al. (2018) find that providing neighborhoods with better school choice options increases home sales prices by 8.4%, which in turn attracts homebuyers with incomes 20.2% higher than before. Therefore, even though I find that better school climate ratings were not positively capitalized into house prices before the information release, the social climate might have already been attracting higher income or minority homebuyers. I test for whether future school climate rating information was already differently attracting different income and race homebuyers, using the same regression models and school attendance boundary discontinuity methods from above.

Table 4 shows similar patterns between school climate ratings and homebuyer incomes, to those using log sales prices. Conditional on proficiency rates, and property and neighborhood characteristics, homebuyers in school zones that will be assigned better climate ratings tend to have lower-income. This again suggests that higher income homebuyers are willing to trade-off better school value-added and social climate in exchange for higher test proficiency rates.

Panel A of Table 5 shows that conditional on property and neighborhood characteristics, Asian and White homebuyers are slightly more likely to avoid properties in neighborhoods that will be assigned better climate ratings, although these estimates are noisy. On the

[23]Table B2 shows consistent results when the maximum distance to the nearest boundary varies from 0.35 to 0.15 miles. These distances have been used in prior related work (Bayer et al., 2007; Black, 1999).

other hand, panel B shows that across specifications using boundary FEs, Asian and White homebuyers are significantly less likely to purchase a home in school zones with better future climate ratings (about 5% to 6% less likely). The results are reversed for Black and Hispanic homebuyers, who are 5% more likely to purchase homes in better climate school zones before the information is publicly available (refer to Table 6).

5 Identification Strategy

I now turn to the causal effects of providing school climate information. I specifically study the effects of publicly releasing school climate ratings on home prices and on homebuyers' demographics using a difference-in-differences (DID) framework.

More specifically, I employ a dynamic DID approach that compares the cross-sectional difference in housing market outcomes between climate ratings before and in each quarter after the climate rating information shock. For this analysis, I estimate regressions of the following form:

$$Y_{inst} = \alpha_0 + \sum_{q=1}^{4} \Big(\sum_{r=2}^{5} (\alpha_{r,q} Climate_{r,s} * 1(Qtr_t = q)) \Big) + \Phi \mathbf{W}_{st} + \Gamma \mathbf{X}_{it} + \Lambda \mathbf{Z}_{in} + \theta_t + \nu_{s_j,s_k} + \mu_s + \varepsilon_{inst}, \quad (1)$$

where Y_{nist} is the outcome of interest for property i in neighborhood n in school zone s in month-year t. The key variable of interest, $Climate_{r,s}$, represents an indicator for each climate rating from orange ($r = 2$) to the best rating ($r = 5$), which are only activated for the corresponding rating that will be assigned to school s starting in September 2011. The worst climate rating ($r = 1$) is excluded to serve as the reference rating.

The model allows for semi-parametric school climate effects in each quarter of the post-shock school year by interacting the climate ratings with each of the four post-shock quarter indicators. I do not include a climate effect in the pre-shock period because this would be captured by the school fixed effect since this measure does not vary over time. It is important to study information shock effects dynamically because related studies find dissipating effects soon after school quality information is released (Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011). The initial post-shock quarter (September–November 2011) encapsulates the main school climate information campaign that included news media coverage, although the climate reports remained publicly available online afterward. To my knowledge, CPS and local news media did not actively promote climate information during the rest of the school-year after November. However, the administration of the spring 2012 climate surveys

could have indirectly nudged parents to seek out the information in the second and third quarters after the original information shock.

In this model, I include month-by-year fixed effects, θ_t, to control for any time-varying changes in house prices that are experienced across the school district, including seasonal changes. I also include boundary fixed effects, ν_{s_j,s_k}, which represent streets that separate houses in very close proximity to each other, where one side of the street is served by school s_j and the other side of the street is served by a different school, s_k. In my main specification, I follow the literature and link property transactions to their nearest boundary within 0.2 miles (Bayer et al., 2007; Black, 1999; Zheng, 2021). Additionally, I include school fixed effects, μ_s, which control for time-invariant school quality and zone differences. The inclusion of both month-year and boundary fixed effects means the estimates are identified off of changes in the difference in outcomes between properties across a given boundary line before and after the information shock, while the school fixed effects account for any school zone information already known by residents.

The $\alpha_{r,q}$ coefficients represent the semi-parametric DID estimates of the impact on the difference in the outcome between climate rating r and the worst climate rating in quarter q after the information release, relative to before the release. Specifically, $\alpha_{r,1}$ represents the impact of having the fully active information campaign in the first quarter, while $\alpha_{r,4}$ represents the climate rating effect by the fourth post-shock quarter. Additionally, I cluster standard errors at the school zone level to account for there being multiple transactions per school attendance zone.

I also control for various school, property, and neighborhood characteristics to capture the existing conditions attached to a property that homebuyers would be aware of. I include a vector of school-year-specific school characteristics, $\mathbf{W}_{st}$, which includes two years of lagged test scores and the school demographic characteristics described in the data section. The vector of property-specific characteristics, $\mathbf{X}_{it}$, includes the number of bedrooms and bathrooms, square footage, age, distance to downtown, and an indicator for condo. As detailed in section 3, I imputed the property characteristics for condominiums. Therefore, I interact property characteristics with a condominium indicator in the regressions to allow for different slopes for each property characteristic between condominiums and non-condos.[24] I include a vector of neighborhood-specific characteristics, $\mathbf{Z}_{in}$, which includes racial composition, levels of education, age composition, median income level, and crime rates.[25] Additionally, since the cheapest neighborhoods may be increasing in price faster than the most expensive

[24] In Section 6.4, I show that my estimates are qualitatively similar with and without including the condominium transactions.

[25] Neighborhood characteristics are based on 5-year ACS estimates from 2006 through 2011, and, hence, would not be affected by the school climate information shock.

neighborhoods, and vice versa, I include neighborhood price trends.

Two main assumptions underlie this DID approach. The first is that there are no differential pre-release trends in outcomes that vary by school climate. The close proximity of the properties being compared in my model makes this assumption more likely to hold, as the outcomes for properties so close to each other are likely to trend similarly. I test this assumption by conducting event study analyses that explore the school climate effect on the housing market in each of the eight quarters before the information release and in the four quarters after. These models are based on regressions of the following form:

$$Y_{inst} = \kappa_0 + \sum_{\tau}^{T} \Big(\sum_{r=2}^{5} (\gamma_{r,t} Climate_s * 1(t = \tau)) \Big) + \Phi \mathbf{W}_{st} + \Gamma \mathbf{X}_{it} + \Lambda \mathbf{Z}_{in} + \theta_t + \nu_{s_j,s_k} + \mu_s + \varepsilon_{inst}, \quad (2)$$

where the variables are the same as in equation 1, except that the $\gamma_{r,t}$ coefficients represent the difference in the outcome of interest between climate rating r and the worst climate rating in relative period t. To minimize the sensitivity of these estimates to the choice of the reference period, I use constrained regressions to estimate these models, where pre-shock coefficients average to zero. Thus, each $\gamma_{r,t}$ represents the school climate effect in period t, relative to the average relationship in the pre-shock period (Miller, 2023).[26] Moreover, constrained regressions allow my coefficients to be more directly comparable to the DID estimates.

The DID approach also assumes that there are no contemporaneous unobservable shocks to the outcomes of interest that are correlated with the initial school climate ratings. Again, the close proximity of the properties being compared in my model makes this assumption more likely to hold, since if there are contemporaneous shocks affecting a property, these shocks would likely affect properties on both sides of the street similarly due to their proximity. Although this assumption is not directly testable, I note that CPS publicly stated that school climate ratings were only for informational purposes and would not initially be used for accountability, suggesting that there were no other intentional concurrent changes attached to the release of this information that may affect the housing market (Levenstein, 2016).

[26] This approach is similar to that used by Borgschulte et al. (2022) and Deryugina and Molitor (2020).

6 Results

I now turn to my key findings regarding the effects of a school climate information shock on house prices and on incoming homebuyer demographics. In each subsection, I present results for nonparametric event studies as well as semi-parametric difference-in-difference estimates.

6.1 School climate information effects on housing values

Figure 5 presents the quarterly dynamics of log house prices for each school climate rating relative to the worst rating two years before and one year after the information shock. All four panels are estimated in the same regression through equation 2. The dots represent the estimated coefficients from the event study model in each relative quarter, while the lines extending from the dots represent the 95% confidence intervals.

Across all four climate rating event studies, house prices are relatively flat as a function of future school climate ratings before the information is publicly released. Thus, the figures show no evidence of differential pre-trends that would bias the estimates. Each panel shows that there is a visually clear and significant positive change in the initial post-shock quarter relative to the pre-shock average estimates.

Table 7 represents analogous semi-parametric quarterly estimates based on DID models from equation 1.[27] The first column shows that the information shock led to a 19% price premium for homes assigned to the best climate rating relative to the worst rating in the first post-shock period (statistically significant at the 1% level). For climate ratings 2, 3, and 4, there were also immediate price premiums between 8.6% and 12.9% relative to the worst rating, all of which are statistically significant.

More specifically, the best climate rating led to a 11% increase in house prices relative to second best climate schools (p-value of 0.016). This estimate is consistent with results by Figlio and Lucas (2004), who find that housing markets respond to the assignment of letter grades for school quality that was based on student test scores. They specifically find a grade of "A" is associated with a 19.5% increase in sales prices relative to "B" grades in the year of the information shock. On the other hand, I find that the best climate rating led to a price premium of 12% relative to the yellow climate rating (p-value of 0.011), which is only a third of the 35% effect for a grade of "A" relative to a grade of "C" found by Figlio and Lucas (2004).

The differences between the estimate for the best climate rating and for each of the other three estimates are all statistically significant at the 5% to 10% levels, based on F-tests of the null hypothesis that the differences are zero. On the other hand, the estimated effects

[27] For ease of comparison, I present these same estimates visually in Figure A3.

for climate ratings 2, 3, and 4 are not statistically different from each other. This suggests that homebuyers react distinctly for the best climate rating compared to the other ratings, but respond similarly between climate ratings that are around average. These differential effects are consistent with studies that find non-linear impacts of school quality on property values (Bibler and Billings, 2019; Ries and Somerville, 2010).

The effects begin to dissipate by the second quarter, at which point only the best climate rating effect remains statistically significant at the 10% level. By the third and fourth post-shock quarters all estimates return to pre-shock levels. Similarly, Fiva and Kirkebøen (2011) find that school quality information shock effects on house prices quickly dissipate and return to pre-publication levels two quarters after the shock.

6.2 School climate information effects on buyer demographics

A growing literature in economics emphasizes differences in linking residential decisions to school options by families from different demographic backgrounds (Barrow, 2002; Billings et al., 2018). Research has also shown socioeconomic and racial/ethnic differences in parents' preferences for different school qualities (Hastings et al., 2009; Jacob and Lefgren, 2007). Therefore, in this subsection, I examine the effects of the school climate information shock on the sorting of homebuyers from different socioeconomic and racial/ethnic backgrounds.

Figure 6 presents event study estimates comparing log homebuyer incomes in neighborhoods with each climate rating relative to those with the worst climate rating over time. The new homebuyer incomes are relatively flat as a function of future school climate ratings before the information is publicly released–providing support for the assumption of no differential pre-trends. The top left panel shows that there is an immediate and statistically significant effect on homebuyer incomes in response to the best climate rating in the first post-shock quarter, but the other panels show that for other climate ratings the reaction was more muted.

Column 2 of Table 7 represents analogous semi-parametric DID estimates based on equation 1.[28] In the quarter the information was released, there was a 14.4% increase in the incomes of homebuyers purchasing homes in neighborhoods assigned to the best climate rating, compared to the incomes of those buying in the worst climate rating school zones, which is statistically significant at the 10% level (p-value of 0.052). This result is in line with past research showing that higher-income families strongly value teachers' ability to promote student satisfaction (Jacob and Lefgren, 2007).[29] This change quickly dissipates by

[28]For ease of comparison, I present these same estimates visually in Figure A4.

[29]Relatedly, Figlio and Lucas (2004) find that a school grade information shock differentially attracted higher income students (as proxied by FRPL-eligibility) differentially into "B" schools relative to "C", but

the second post-shock quarter. The other climate ratings experienced an immediate increase in homebuyer income of 4.2% to 5.4%, but the standard errors are larger than the estimated coefficients in all post-shock periods.

I now present the effects on homebuyer race/ethnicity. Figures 7 and 8 again show that the difference in homebuyer race between each climate rating and the worst climate rating is relatively flat before the information shock. Columns 3 and 4 of Table 7 summarize the dynamic DID results, which are summarized graphically in figures A5 and A6, respectively.

The estimates suggest that by the second post-shock quarter (soon after CPS distributed physical school report cards), the climate information led to a short-lived 6 to 11 percentage point (pp) increase in Asian and White homebuyers to neighborhoods with better climate schools relative to neighborhoods with the worst climate schools. This suggests that Asian and White homebuyers were avoiding the worst climate schools, although these estimated effects are not statistically significant. In turn, this change led to a short-lived 9 to 16pp decline in Black and Hispanic homebuyers in better climate neighborhoods. The estimated negative impact is only statistically significant for the second-best climate rating, although none of the estimated impacts in the second quarter are statistically different from each other. All estimated impacts decline by the third quarter.

In general, the estimated school climate impacts on homebuyer income and race/ethnicity are in line with results from previous studies. First, Barrow (2002) finds that in Washington, DC, higher-income, White, and Asian families choose schools through residential choice to a greater extent than their Black counterparts. Furthermore, Jacob and Lefgren (2007) find that higher-income and non-minority families strongly value teachers' ability to promote student satisfaction, which is a component of social climate.

6.3 Heterogeneous Effects

Families face trade-offs between various school characteristics when deciding where to live and where to send their children to school (Bayer et al., 2007; Black, 1999). Prior research shows that families prefer schools with higher achieving peers, and, to a certain extent, schools with better impacts on non-test-score outcomes (Abdulkadiroğlu et al., 2020; Beuermann et al., 2022; Hastings and Weinstein, 2008).

I explore heterogenous climate information effects on properties with varying levels of neighborhood school characteristics. To do this, I modify equation 1 to include separate effects for schools with different proficiency rates, FRPL-rates, or racial composition. I separate these effects by interacting the post-shock climate score with an indicator for each

find no difference between "A" and "B" schools.

school characteristic quartile. In order to increase statistical power, I combine ratings 4 and 5 to a single rating (best climate), and do the same for ratings 2 and 3 (medium climate). In the interest of brevity, I graphically present the estimated impacts across post-shock quarters in figures A7, A8, A9, and A10

I find evidence that families may be willing to trade-off low proficiency rates in exchange for better climate ratings. Panels A and B of Figure A7 show that the estimated climate information impacts for properties in the lowest proficiency quartile school zones are 1.3 to 1.8 times that for the highest proficiency quartile. In terms of magnitude, there is an estimated impact of 4% to 5% for properties in the lowest proficiency school zones and an impact of 2% in the highest proficiency zones, all of which are statistically significant. By the second quarter, the difference in the estimates between the top and bottom quartiles is statistically significant at the 5% level, based on F-tests of the null hypothesis that the difference is zero. For the best climate ratings, the information effect is sustained through the fourth quarter in the least proficient school zones, but the climate impact dissipates for the most proficient schools. The information effects dissipate for all proficiency levels for the medium climate ratings.

These heterogeneous effects suggest that people have different expectations for climate at differently performing schools. People may have expected particularly inadequate climate at the least proficient schools and slightly better climate at the most proficient schools. Once the lowest proficiency schools receive an above average climate rating, people significantly update their beliefs. While when the highest proficiency schools receive an above average rating, people update their priors, but to a lesser extent since they were not expecting the worst climate. The sample of schools with average or worse climate ratings exhibit similar patterns, but with smaller belief updates.

School test scores, non-FRPL-eligibility, and non-minority enrollment shares all have a strong and positive correlation. Therefore, parents might use a school's income and racial-demographics as a proxy for school test scores. Panels (c) through (d) show slightly similar but noisier heterogeneous patterns by school demographics. Panels (c) and (d) display heterogeneity by non-FRPL rates, and panels (e) and (f) show them by White enrollment shares. The lowest-income and the least White schools (first quartiles) tend to have a higher price premium for a better climate rating in the first two post-shock periods, although these differences are not statistically significant. Again these provide suggestive evidence that families pay more for better climate schools when their prior information about the school updates.

Figure A8 shows heterogeneity in climate information impacts on homebuyer incomes. Panels (a) and (b) show that the buyer income impacts are more consistent across school

proficiency quartiles. But panels (c) through (f) suggest that in the first two post-shock periods, higher income families are more likely to move into better climate school zones when the school had fewer non-FRPL (more low-income) and White students, although again these differences are not statistically significant.

Lastly, Figure A9 suggests that in general, more Asian and White families move into better climate school zones when the proficiency rates are lower. On the other hand, Figure A10 shows that the patterns are reversed for Black and Hispanic families. The impacts are more consistent across non-FRPL and White enrollment quartiles.

Taken together these results show that the school climate rating information had a large and sustained impact on house prices and on entering homebuyer incomes when the local school had low test proficiency rates. These findings suggest that families are willing to trade-off lower proficiency rates and their associated demographics for better climate quality.

6.4 Robustness Checks

I now test the sensitivity of my main findings by conducting a series of robustness checks. Appendix tables B4 and B5 show the results from various specifications for the effects of releasing school climate ratings on house prices and homebuyers' incomes. These robustness tests show that my main estimates are robust to DID models that only control for main climate effects; the inclusion of controls for property and neighborhood characteristics, neighborhood latent price trend, and school characteristics; the inclusion of school border fixed effects; and the inclusion of both school fixed effects and border fixed effects.

In order to identify home transactions that are more likely to be occupied by families with children and who are more likely to attend the neighborhood school, I next focus on homes that were not condominiums and had three or more bedrooms. Column (2) of Appendix Table B8 shows consistent effects on home sales prices, but the impacts dissipate more quickly than in the overall sample of property types. On the other hand, column (2) of Appendix Table B9 shows larger immediate impacts on homebuyer incomes. In the initial post-shock quarter, higher income families move into neighborhoods with better climate ratings. By the next quarter, there is a significant decline in homebuyer incomes, suggesting that lower-income families move into neighborhoods with better climate ratings. These consistent estimates suggests that properties intended for families are the ones reacting to the neighborhood school climate quality. Furthermore, this provides supporting evidence that imputing property characteristics for condominiums does not drive my results, as even focusing on a sample with only non-condominiums still estimates consistent effects.

As detailed in Section 2, CPS distributed additional school quality information through

physical report cards starting in November 2011 (two months after the climate reports). These additional pieces of information may affect how the school climate ratings affected the housing market, since school climate is positively correlated with school proficiency and value-added rates. However, the event studies in figures 5 and 6 show that the school climate ratings impacts start taking immediate effect in September and October, before the physical school progress report cards. This suggests that the school climate ratings had independent effects that were not driven by the release of other school quality information. To formally test the impacts of the school progress report cards, I run models that include proficiency and value-added information shocks that are initiated in November 2011. Column (3) of Appendix tables B8 and B9 show consistent price and income effects, respectively, over time. This makes sense since the school climate ratings were only weakly correlated with school proficiency and value-added.

The analysis in this study has focused on the school climate ratings effects for elementary school zones. CPS also administered and publicly released school climate survey results for almost all high schools in the district. Therefore, each property received school climate information for both the neighborhood elementary school and the neighborhood high school. To test whether the high school climate rating shocks drive my main results, I conduct models that include quarterly effects for the high school climate ratings in my main models. In column (4) of Appendix Tables B8 and B9, I show that the climate rating effects for the neighborhood elementary schools are consistent but noisier to those in my main models. This suggests that the neighborhood elementary schools climate rating effects were not driven by the climate ratings assigned to neighborhood high schools.

7 Potential Mechanisms

In this section, I explore two main potential mechanisms: (1) the school climate information shock leads to an increased demand for homes with better climate ratings with a delayed response in the supply of available homes on the market and (2) homebuyers may be able to value school climate information only when it was highly salient and easily accessible (low search costs).

7.1 Supply and demand mechanism

The climate information effect on house prices and its ensuing fadeout could potentially be explained by the short- and long-run supply of houses available on the market. I find suggestive evidence for the short-run channel, but not for the long-run. Figure A11 graphically

shows this potential mechanism. In the short-run, the information shock may have led to an increased demand for homes assigned to better climate schools than for homes assigned to worse climate schools (from demand curve D to D'). The supply of homes (S_{SR}) may not be able to react immediately to the increased demand, which would lead to an immediate increase in sales prices for in-demand properties that were already on the market (from equilibrium point A to B). As time goes on, the initial price premium may lead to an increased supply of available homes assigned to in-demand schools to meet the increased demand for homes with access to better climate ratings (from supply curve S_{SR} to S'_{SR}), bringing sales prices back down at the higher supply quantity (from equilibrium point B to C).

To explore this potential channel, I study the climate information shock effects on the number of executed sales transactions. Although I cannot directly observe changes in the supply of or demand for houses, the number of home sales transactions may represent the quantity of transactions where supply meets demand at different points in time. Using transaction quantities, I find that the climate information shock did not lead to an immediate change in the quantity of home sales transactions. This provides supporting evidence that the price effects were driven by an increase in housing demand without a short-run increase in available houses on the market. However, the number of transactions was relatively stable in the months following the information shock, suggesting the dissipating climate rating effects on prices were not driven by an increase in supply of available properties.

For this analysis I create a balanced monthly panel of the number of transactions in each school zone and in each school zone by nearest border area during my sample period.[30] I use Poisson model versions of equation 1, where the outcome of interest is the number of nearest border-by-school zone-by-month level transactions, respectively.

Figure A12 shows event studies of the difference in the number of transactions between each respective rating and the worst rating in each quarter around the information shock (based on Poisson model versions of equation 2). In the pre-shock period, all ratings follow a smooth and mostly flat relationship with the number of transactions.

There is no significant break in trend immediately after the information shock that would explain the initial sales price response to the climate ratings. For the top two climate ratings, the price premium increases slightly by the third post-shock period, but this increase is not statistically significant. There is no similar increase in the number of transactions for the other two climate ratings. Therefore, the longer-run housing supply channel cannot fully explain the dissipating price premiums.

[30] I do not require homebuyer income information nor homeowner occupancy for these transactions in order to account for relevant and available properties. Furthermore, I limit the sample to units within 0.2 miles from the nearest border. The results are consistent across these sample selection rules.

Generally, studies of school quality information shock capitalization find short-run effects that dissipate over time. The supply mechanism may help explain the short-lived nature of these effects in the literature, but this mechanism has been understudied up to this point (Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011).

7.2 Information salience and search costs mechanism

The efficient market hypothesis would suggest that once valuable information is made publicly available it should be consistently capitalized in the housing market, assuming perfect information. The 2011 Chicago school climate ratings provided information that stakeholders did not expect to receive or access, unlike school test performance information that has been publicly accesible since the No Child Left behind Act of 2001. Climate information salience and search costs may play a role in people's ability to access and value the information.

Therefore, a second potential mechanism for the immediate—and then dissipating—effects could be that homebuyers value school climate, but only pay for it when they can observe the information. This would suggest that as CPS's information campaign ends and news coverage stops, the cost of obtaining school climate information increases, even though the reports are still publicly available and accessible. Homebuyers who enter the market after the information campaign may not be aware of the availability of the information, making it costlier to access the information. Prior work shows similar short-term reactions to other school quality information shocks (Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011), supporting this hypothesis.

Further evidence for this mechanism can be seen in online search patterns over time. Google Search Trends data (see figure 3) shows how Chicagoans searched for school climate related terms (school climate, school culture, and school environment) between January 2011 and December 2013. The dashed red lines identify the time right before September of each school year when the school climate reports were released on a yearly basis. The first bunching occurs around the time the 2011 school climate survey was administered, the second was around the time of the initial school climate information release, and the third was around the time that the 2012 school climate survey was administered.[31] Among these three periods, the largest spike in searches for relevant school climate terms occurred during the months of the information campaign (September through November). Looking at the following two school climate information campaigns in 2012 and 2013, neither led to as large of a spike in related search terms than the September 2011 information campaign. Notably,

[31] My Google Search Trends time series starts in January 2011 because Google changed how geographies were defined before this time period. Making search patterns before and after January 1, 2011 difficult to compare.

fall 2012 had the smallest increase around the information campaign. This may have been driven by the fact that in the same week of September 2012, the Chicago Teachers Union went on the longest strike in the district's history, leading the local and national news media to focus on this topic.

8 Conclusion and Discussion

A growing body of research emphasizes the importance of school climate on students' outcomes. For the past decade, the federal government and an increasing number of states and districts across the US have begun to focus on measuring, improving, and promoting school climate. If families value this school quality, then providing this information can affect families school choice, residential decisions, and equity in access to good schools. Despite growing interest, causal research on whether stakeholders value school climate is limited.

In this paper, I present evidence that school climate ratings can provide new insights about schools that would not be otherwise easily observable by parents and homebuyers without publicly available information. I demonstrate that school climate ratings were difficult to predict using previously public information. Additionally, they are only weakly correlated with school poverty levels and proficiency rates, showing that good social climate quality can be found in historically underperforming and underserved schools. Furthermore, better school climate was not significantly capitalized into house prices before the information was publicly available. However, I find that lower-income and Black and Hispanic families were more likely to purchase homes assigned to better climate schools without publicly available information.

I provide the first causal evidence of how publicizing school climate information is capitalized into the housing market and how it attracts homebuyers from different demographic backgrounds. To do this, I link home transactions data with home loan applications data and use a plausibly exogenous shock of school climate information that occurred in the Chicago Public Schools district in 2011. Employing event studies and a difference-in-differences framework, I find that the school climate information shock led to an immediate and statistically significant increase in sales prices for homes assigned to better climate schools. This effect dissipated soon after the information campaign. Additionally, I find an immediate but quickly dissipating increase in the incomes of new homebuyers moving into neighborhoods zoned to schools with a one-level-higher climate rating. I also find suggestive evidence that Asian and White families are attracted to better climate ratings but only when these are publicly available. In heterogeneity analysis, I find evidence that families may be willing to trade-off low proficiency rates in exchange for better climate ratings.

The immediate and significant effects, which dissipate soon after, can be due to different mechanisms. First, I find suggestive evidence that the information shock led to an immediate increase in demand without changing housing supply available on the market—leading to the immediate increase in sales prices for in-demand properties that were already on the market. However, there was not a significant increase in supply quantity of available homes in in-demand neighborhoods, therefore this cannot fully explain the dissipating impacts over time. Second, I find evidence that suggests the information campaign increased the salience of school climate information, which in turn decreased the cost of finding the information. On the other hand, as the salience of the information declined, the cost of knowing about the data and finding it increased, especially for homebuyers entering the housing market without an active climate information campaign.

My findings offer evidence that families value school climate quality when this information is highly salient and freely accessible, leading to potential policy implications. Schools and school districts may want to promote school climate quality information in order to attract more families. As past studies have shown, information about schools' average tests scores is highly valued by families, and such data are so common that stakeholders know the information exists and is accessible. On the other hand, school climate information is a newer metric that is not as widely known. Thus, if school districts want families to use school climate information to help form their decisions for school choice, then they should make the information clear, easily accessible, and highly salient.

However, because climate ratings can affect house prices and attract more advantaged families, districts must be aware of the potential impacts on equitable access to neighborhood schools. Widely accessible climate data can lead to inequality in access to better-climate schools. School districts may provide all students better school climate conditions by fostering positive relationships among all stakeholders in schools, without limiting which students get access to better climate quality. The National Center on Safe Supportive Learning Environments (U.S. Department of Education, 2018) and other organizations have developed resources for individual schools to improve their social environments. Some of these strategies include having students, teachers, families, and principals choose and implement school climate interventions to improve on. On the other hand, some school districts have implemented social and emotional learning programs in order to improve the socioemotional skills of both students and teachers, in this way improving school climate (Gonzalez et al., 2020).

My analysis is limited in its ability to measure the effects on families who may be renting and are not homeowners. Future work should explore this question by using administrative student-level data or migration data to track individuals from school to school or residence to residence, whether or not they own their home. This additional data will help provide a

clearer picture of how families, independent of wealth, value school climate information.

The information experiment in this study allows me to explore the immediate effects of publicly releasing available school climate information, but I am unable to explore the long-term effects. Annual releases of new waves of school climate information mean that the information is no longer unexpected and, hence, not exogenous. Furthermore, the Chicago Teachers' Union went on its first strike in 25 years during the second annual climate information release, and during the third annual information release the district closed more than 50 schools—each event complicating the salience of the annual climate information. New information experiments may be necessary to fully understand how school climate is valued by stakeholders once information is already publicly available.

As more states and school districts across the US collect and publish school climate information, local house prices and districts' tax bases could be affected. Furthermore, such changes may affect neighborhood and school socioeconomic demographics, which may limit access to good-quality schools by all students. Educational institutions can use this information to help improve their schools, but they may want to be careful not to limit access to already underserved students.

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Figures

Figure 1: Timeline of school climate information release

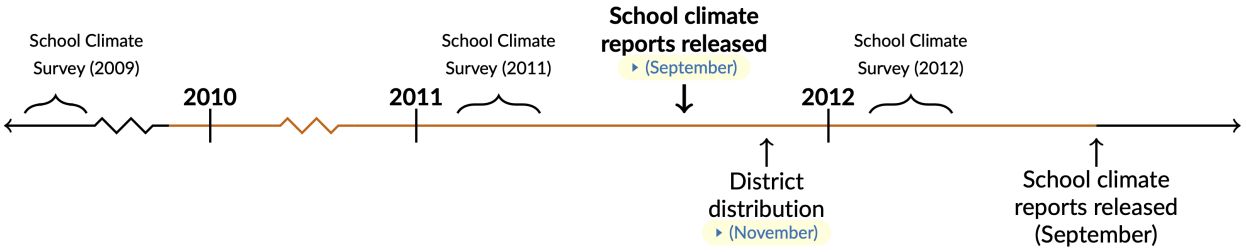


Figure 2: Example of school climate reports website

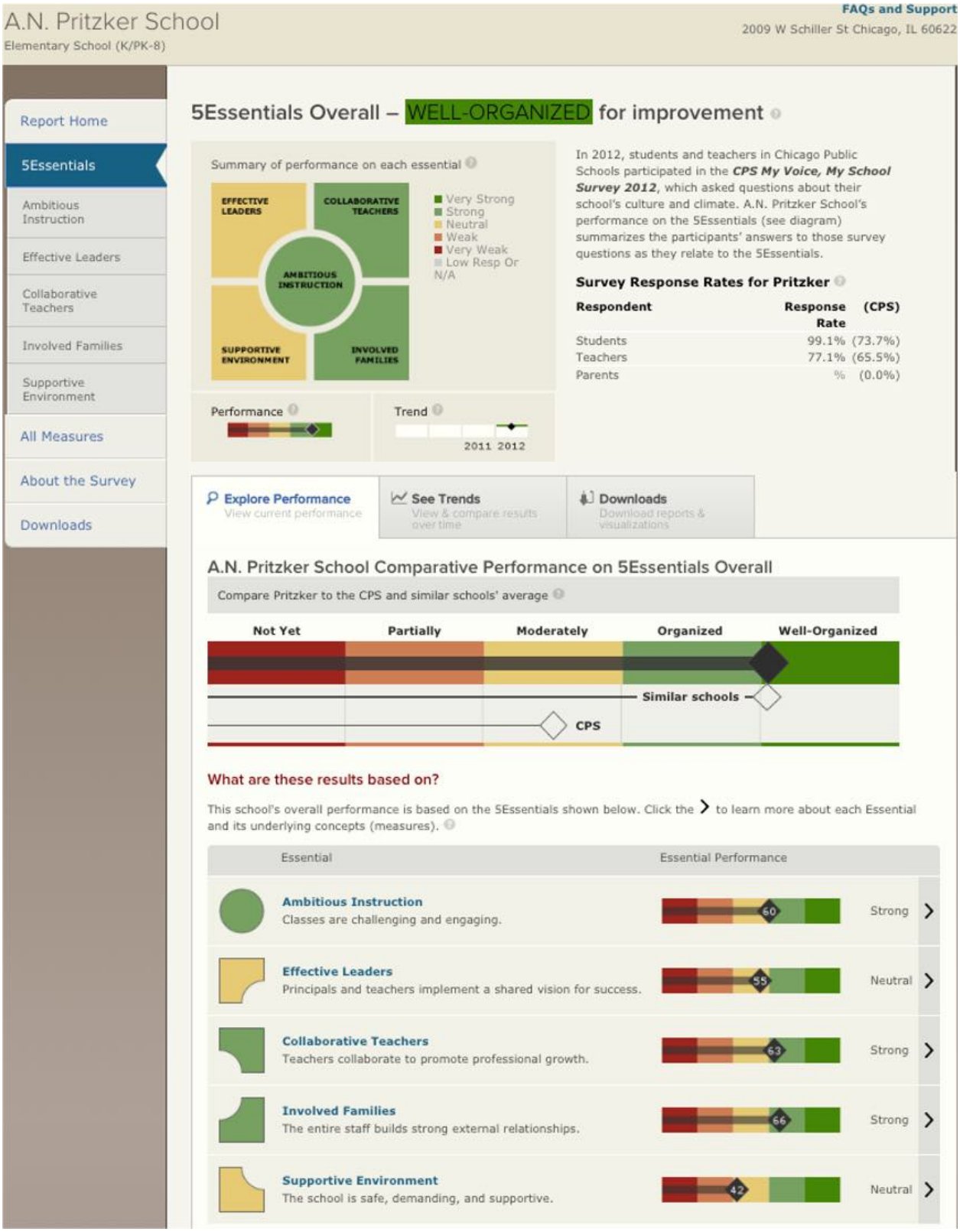
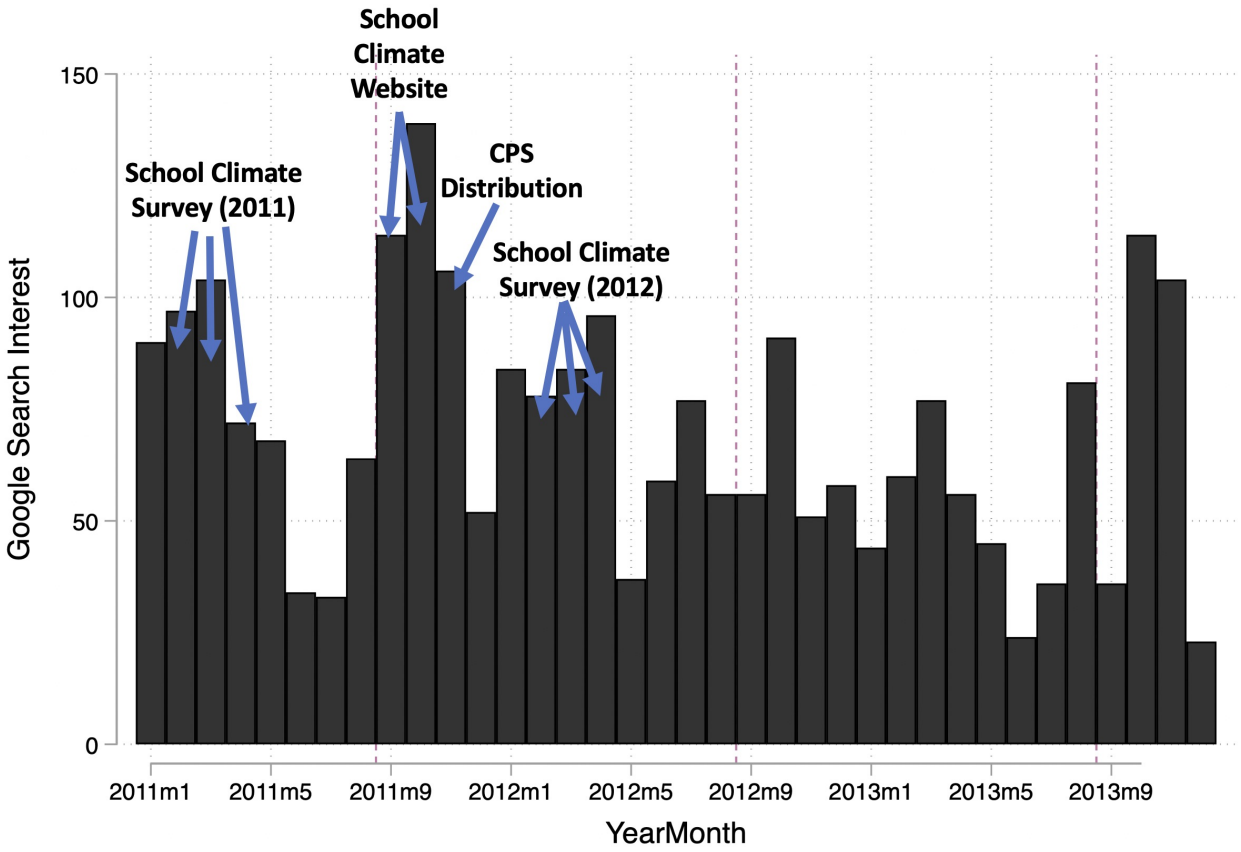
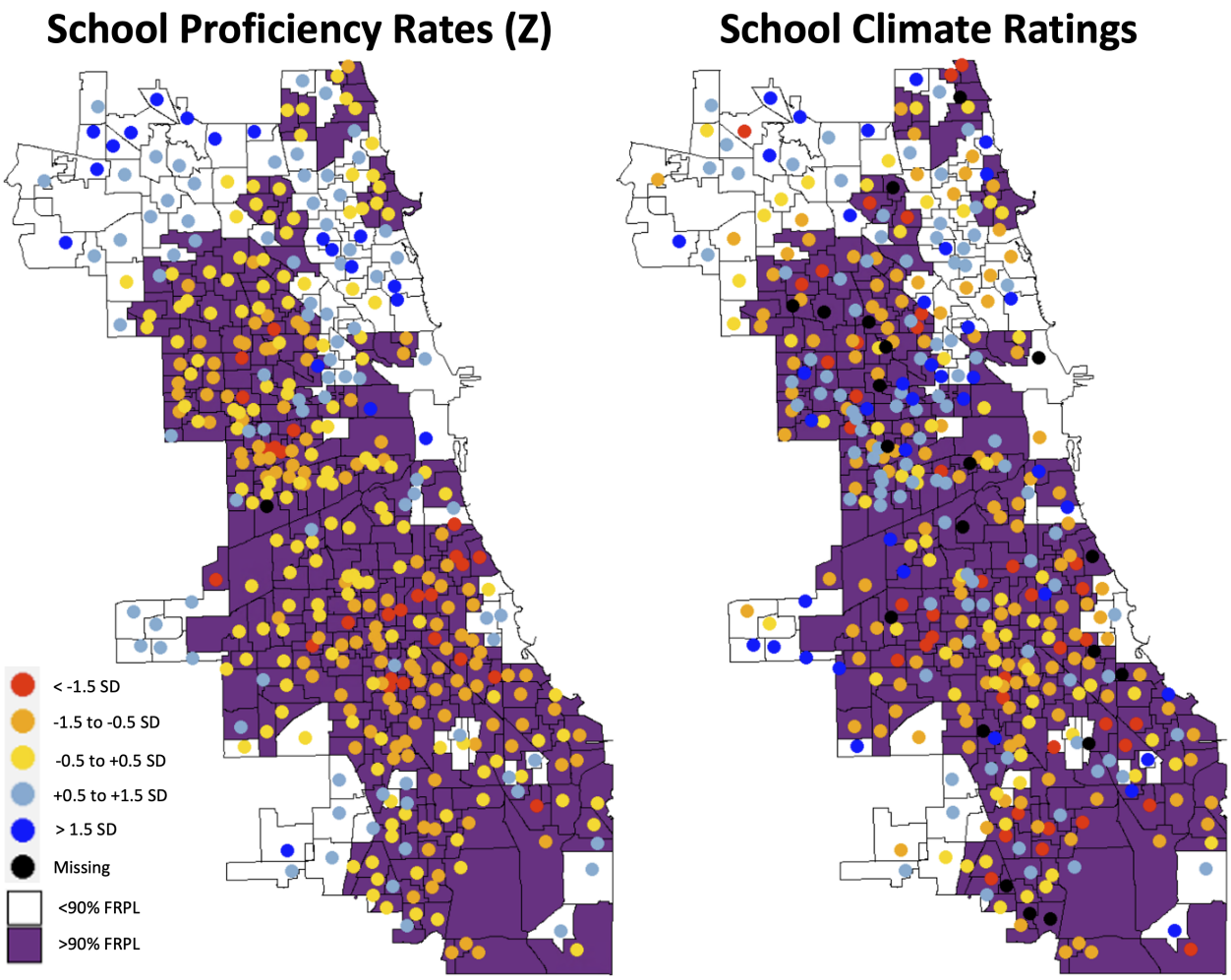


Figure 3: Google Search Trends for School Climate Related Keywords: school climate, school culture, and school environment



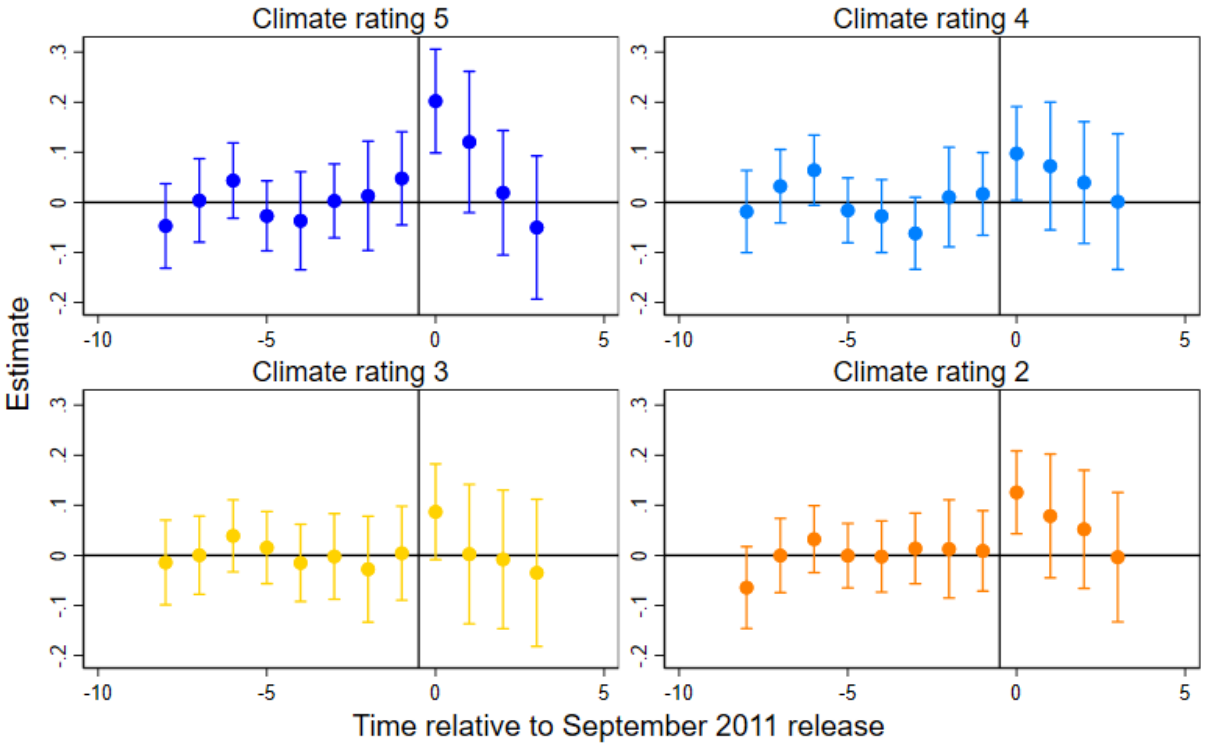
Notes: Google Trends search results based on keywords *school climate*, *school culture*, and *school environment*, for the Chicago, Illinois area between January 1, 2011 and August 1, 2016. The Google Trends website changed geographic definitions in January 1, 2011, making it difficult to compare before and after this time period. I create the monthly Google Search Interest measure by adding the hit rates for each of the three terms together in each month.

Figure 4: School proficiency rates (left) and School Climate ratings (right) overlayed on school FRPL rates by school attendance zones



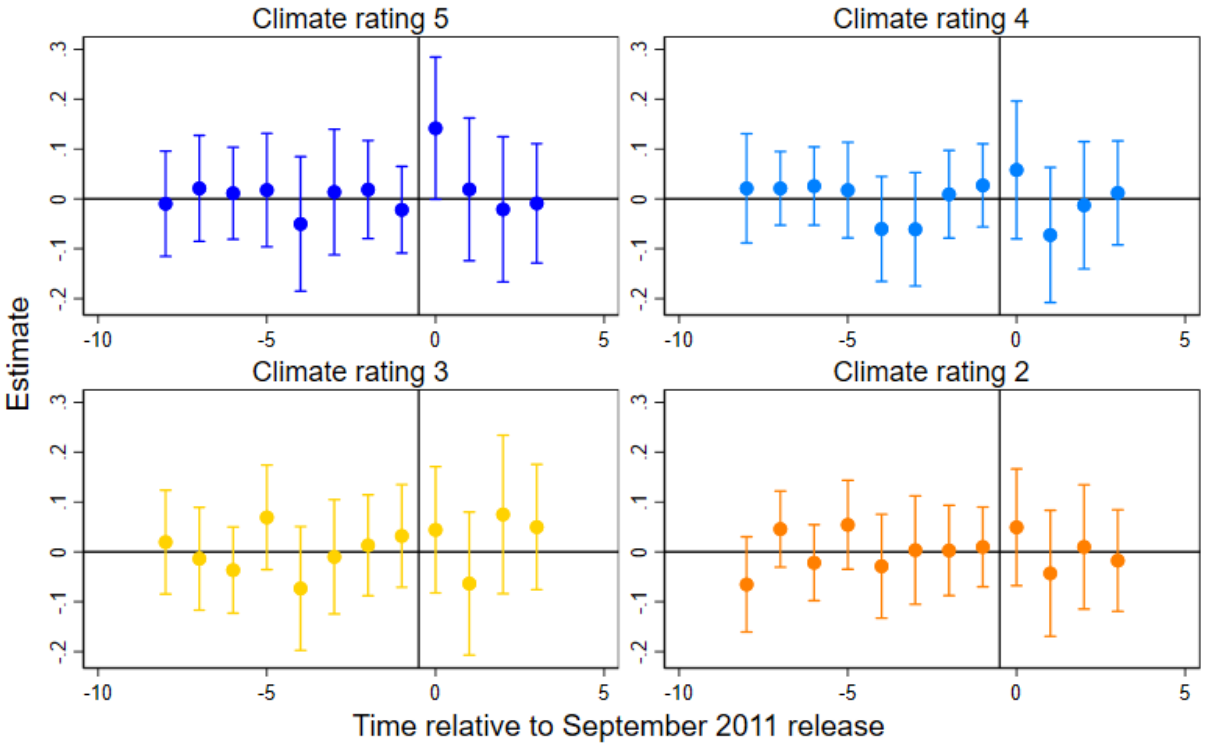
Notes: The purple polygons represent the attendance boundaries for schools serving a population of students that is more than 90% eligible for free-or-reduced-price lunch (FRPL), a measure of student income. The white polygons represent neighborhood schools serving higher-income students. I choose a 90% cutoff for display purposes, because only about a quarter of neighborhood elementary schools in CPS have less than 90% FRPL eligibility.

Figure 5: Quarterly event study estimates: Log Home Sales Price



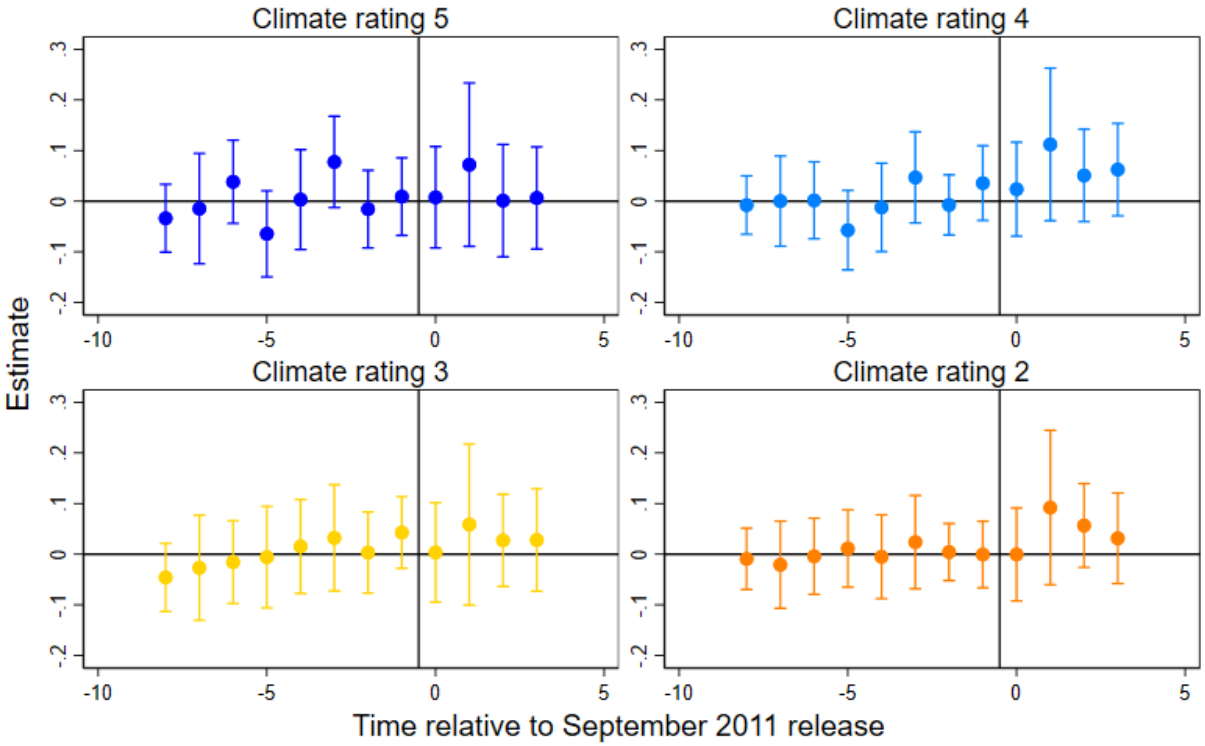
Notes: These event studies are based constrained regressions where the pre-shock coefficients average to zero (refer to equation 2 for details). Constrained regressions allow coefficients to be more directly comparable to DID estimates.

Figure 6: Quarterly event study estimates: Log Homebuyer Income



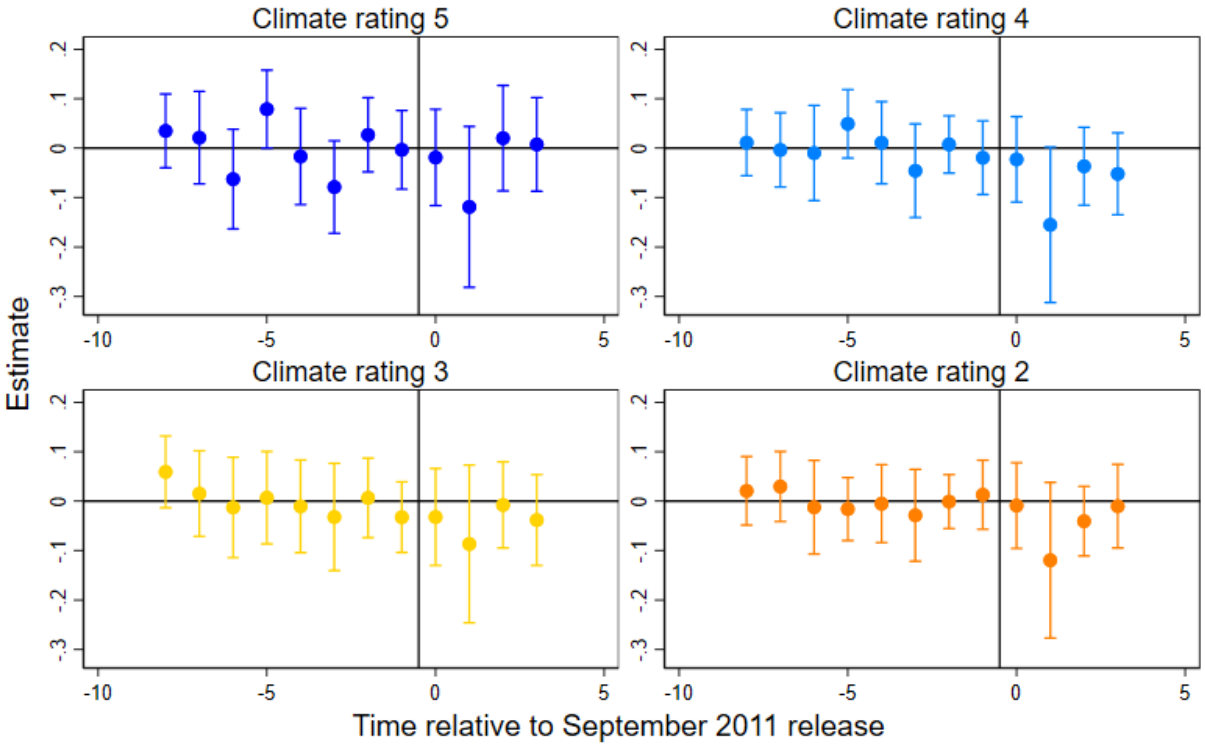
Notes: These event studies are based constrained regressions where the pre-shock coefficients average to zero (refer to equation 2 for details). Constrained regressions allow coefficients to be more directly comparable to DID estimates.

Figure 7: Quarterly event study estimates: Homebuyer is Asian or White



Notes: These event studies are based constrained regressions where the pre-shock coefficients average to zero (refer to equation 2 for details). Constrained regressions allow coefficients to be more directly comparable to DID estimates.

Figure 8: Quarterly event study estimates: Homebuyer is Black or Hispanic



Notes: These event studies are based constrained regressions where the pre-shock coefficients average to zero (refer to equation 2 for details). Constrained regressions allow coefficients to be more directly comparable to DID estimates.

Tables

Table 1: Summary statistics of select property, school, and neighborhood variables

Characteristics	All schools	Yellow to Green Climate	Red to Yellow Climate
Key regression variables			
Sale price	286,011	296,376	261,135
	(225,906)	(229,774)	(207,366)
Mortgage Income	100,804	103,711	93,197
	(92,477)	(93,548)	(85,856)
Mortgage Both White	.554	.598	.5
	(.497)	(.49)	(.5)
Avg. School Performance			
Proficiency rates (Z)	.58	.772	.343
	(.836)	(.793)	(.797)
Value-Added (Z)	.0518	.297	-.143
	(.843)	(.782)	(.826)
Avg. School Characteristics			
% Black	24.5	23.9	27.6
	(32.9)	(32.7)	(34.8)
% Latino	44.4	39.9	47.8
	(31.5)	(28)	(33.5)
% FRPL	72.1	67	79
	(27.5)	(28.9)	(23.4)
Enrollment	710	654	760
	(316)	(263)	(350)
Parcels' Census Block-Group Characteristics			
% Black	.17	.152	.197
	(.299)	(.281)	(.323)
% Latino	.238	.208	.27
	(.25)	(.224)	(.271)
% Single mother household	.217	.21	.238
	(.235)	(.232)	(.247)
% Adults with college+	.429	.445	.394
	(.27)	(.256)	(.272)
Median HH income	65,885	68,043	62,007
	(27,072)	(26,917)	(26,133)
Avg. Property Characteristics			
Square Feet	1614	1649	1552
	(672)	(692)	(636)
Condo	.384	.382	.373
	(.486)	(.486)	(.484)
N-Observations	16,952	9,176	10,352
N-Schools	340	182	220

Notes: Summary statistics are based on sample described in section 3. The first column includes the full sample, the second column only includes the sample with average or better climate ratings (yellow to green), while the third column includes the sample with average or worse climate ratings (red to yellow). Standard deviations are shown in parentheses.

Table 2: Predictability of elementary school proficiency, FRPL, value-added, and climate ratings before initial school climate information release

	(1) Proficiency Rates (Z)	(2) % FRPL (Z)	(3) Value-Added (Z)	(4) Overall Climate	(5) Best Climate	(6) Worst Climate
Observations	335	335	335	335	180	217
R-squared	0.712	0.770	0.235	0.211	0.172	0.074
Adj. R-squared	0.699	0.759	0.196	0.171	0.091	-0.001

Notes: Refer to appendix Table B1 for full table with coefficients. These regressions also include: school standardized proficiency rate (except in column 1); % Asian, % Black, % Hispanic, % Native American, % Multi-Race; % FRPL (except in column 2); % LEP, % IEP; enrollment; average yearly school crimes (based on 2007 through 2011 FY); parent perceived school safety; and block-group education levels (HS, some college, college, and graduate). All models except for proficiency rates outcome model control for profiency rates. All models except for % FRPL outcome model control for % FRPL. To make fair comparisons, columns (1) through (3) use versions of the outcome variables that have five levels that are comparable to the climate levels (estimates are very similar whether I use the 5-level outcome outcome or the continuous measures). These levels are created by grouping the following standardized values into five ratings: rating of 1 if less than -1.5 SD; rating of 2 if between -1.5 SD and -0.5 SD; rating of 3 if between -0.5 SD and +0.5 SD; rating of 4 if between +0.5 SD and +1.5 SD; rating of 5 if greater than +1 SD. Columns (1) through (4) include all school zones in the sample, while column (5) only includes yellow or better climate school zones, and column (6) includes the sample of yellow or worse climate school zones.

Table 3: Hedonic regression estimates of school climate relationships with log sales price during prerelease period

	(1)	(2)	(3)	(4)
Panel A: Hedonic regression estimates				
Climate Rating 5	0.249***	-0.017	-0.054	-0.048
	(0.082)	(0.036)	(0.036)	(0.037)
Climate Rating 4	0.251***	-0.011	-0.038	-0.030
	(0.079)	(0.035)	(0.036)	(0.037)
Climate Rating 3	0.122	-0.040	-0.052	-0.042
	(0.077)	(0.037)	(0.037)	(0.037)
Climate Rating 2	0.178**	-0.008	-0.024	-0.034
	(0.079)	(0.033)	(0.033)	(0.034)
Proficiency Rates (Z)			0.047***	0.067***
			(0.014)	(0.014)
Value-Added (Z)				-0.040***
				(0.010)
Observations	12237	12237	12237	12237
Panel B: Attendance boundary FE estimates ($\leq$0.2mi from border)				
Climate Rating 5	-0.009	-0.021	-0.052*	-0.045
	(0.031)	(0.030)	(0.029)	(0.029)
Climate Rating 4	-0.024	-0.035	-0.055*	-0.051*
	(0.029)	(0.029)	(0.029)	(0.028)
Climate Rating 3	-0.032	-0.034	-0.038	-0.030
	(0.030)	(0.028)	(0.027)	(0.027)
Climate Rating 2	0.032	0.024	0.019	0.006
	(0.028)	(0.027)	(0.027)	(0.026)
Proficiency Rates (Z)			0.041***	0.056***
			(0.011)	(0.010)
Value-Added (Z)				-0.032***
				(0.007)
Observations	9721	9721	9721	9721
Housing Characteristics	Y	Y	Y	Y
Block-Group characteristics		Y	Y	Y

Notes: Estimates are based on simple hedonic regression models described in Section 4.2. Each panel and column represents a separate estimation. House transactions are from September 2009 through August 2011. All models include month-year FE. Standard errors are clustered at the school level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table 4: Hedonic regression estimates of school climate relationships with log homebuyer income during prerelease period

	(1)	(2)	(3)	(4)
Panel A: Hedonic regression estimates				
Climate Rating 5	0.167**	-0.043	-0.064*	-0.058*
	(0.066)	(0.031)	(0.033)	(0.033)
Climate Rating 4	0.187***	-0.025	-0.040	-0.032
	(0.065)	(0.031)	(0.031)	(0.033)
Climate Rating 3	0.076	-0.058*	-0.065**	-0.055*
	(0.065)	(0.031)	(0.031)	(0.032)
Climate Rating 2	0.121*	-0.028	-0.037	-0.047
	(0.066)	(0.029)	(0.029)	(0.031)
Proficiency Rates (Z)			0.027**	0.046***
			(0.011)	(0.011)
Value-Added (Z)				-0.039***
				(0.009)
Observations	12237	12237	12237	12237
Panel B: Attendance boundary FE estimates (≤0.2mi from border)				
Climate Rating 5	-0.026	-0.034	-0.056*	-0.043
	(0.032)	(0.031)	(0.032)	(0.028)
Climate Rating 4	-0.009	-0.018	-0.032	-0.026
	(0.029)	(0.028)	(0.029)	(0.027)
Climate Rating 3	-0.054*	-0.056**	-0.059**	-0.046*
	(0.028)	(0.027)	(0.027)	(0.026)
Climate Rating 2	0.039	0.033	0.029	0.007
	(0.028)	(0.027)	(0.027)	(0.025)
Proficiency Rates (Z)			0.029**	0.054***
			(0.014)	(0.013)
Value-Added (Z)				-0.053***
				(0.007)
Observations	9721	9721	9721	9721
Housing Characteristics	Y	Y	Y	Y
Block-Group characteristics		Y	Y	Y

Notes: Estimates are based on simple hedonic regression models described in Section 4.2. Each panel and column represents a separate estimation. House transactions are from September 2009 through August 2011. All models include month-year FE. Standard errors are clustered at the school level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Table 5: Hedonic regression estimates of school climate relationships with homebuyer being Asian or White during prerelease period

	(1)	(2)	(3)	(4)
Panel A: Hedonic regression estimates				
Climate Rating 5	0.219***	-0.025	-0.032	-0.030
	(0.084)	(0.046)	(0.049)	(0.048)
Climate Rating 4	0.219***	-0.004	-0.009	-0.007
	(0.081)	(0.042)	(0.043)	(0.042)
Climate Rating 3	0.123	-0.025	-0.027	-0.024
	(0.083)	(0.043)	(0.043)	(0.042)
Climate Rating 2	0.116	-0.045	-0.048	-0.051
	(0.080)	(0.042)	(0.042)	(0.042)
Proficiency Rates (Z)			0.009	0.015
			(0.011)	(0.013)
Value-Added (Z)				-0.012
				(0.011)
Observations	11316	11316	11316	11316
Panel B: Attendance boundary FE estimates ($\leq$ 0.2mi from border)				
Climate Rating 5	-0.038**	-0.046**	-0.051**	-0.049**
	(0.019)	(0.019)	(0.020)	(0.020)
Climate Rating 4	-0.055***	-0.058***	-0.061***	-0.060***
	(0.019)	(0.019)	(0.020)	(0.020)
Climate Rating 3	-0.052***	-0.051***	-0.052***	-0.050***
	(0.019)	(0.018)	(0.018)	(0.018)
Climate Rating 2	-0.025	-0.029	-0.029	-0.032
	(0.021)	(0.021)	(0.021)	(0.020)
Proficiency Rates (Z)			0.006	0.009
			(0.006)	(0.007)
Value-Added (Z)				-0.007
				(0.006)
Observations	8979	8979	8979	8979
Housing Characteristics	Y	Y	Y	Y
Block-Group characteristics		Y	Y	Y

Notes: Estimates are based on simple hedonic regression models described in Section 4.2. Each panel and column represents a separate estimation. House transactions are from September 2009 through August 2011. All models include month-year FE. Standard errors are clustered at the school level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table 6: Hedonic regression estimates of school climate relationships with homebuyer being Black or Hispanic during prerelease period

	(1)	(2)	(3)	(4)
Panel A: Hedonic regression estimates				
Climate Rating 5	-0.198**	0.037	0.043	0.041
	(0.081)	(0.046)	(0.048)	(0.048)
Climate Rating 4	-0.206***	0.011	0.015	0.012
	(0.079)	(0.041)	(0.043)	(0.042)
Climate Rating 3	-0.114	0.029	0.031	0.027
	(0.081)	(0.042)	(0.043)	(0.042)
Climate Rating 2	-0.104	0.052	0.054	0.058
	(0.079)	(0.042)	(0.042)	(0.042)
Proficiency Rates (Z)			-0.007	-0.014
			(0.011)	(0.013)
Value-Added (Z)				0.014
				(0.011)
Observations	11316	11316	11316	11316
Panel B: Attendance boundary FE estimates ($\leq$ 0.2mi from border)				
Climate Rating 5	0.038**	0.045**	0.048**	0.047**
	(0.019)	(0.019)	(0.020)	(0.020)
Climate Rating 4	0.049***	0.050***	0.052***	0.052***
	(0.018)	(0.018)	(0.018)	(0.018)
Climate Rating 3	0.048**	0.046**	0.046**	0.045**
	(0.019)	(0.018)	(0.018)	(0.018)
Climate Rating 2	0.019	0.022	0.023	0.024
	(0.019)	(0.019)	(0.019)	(0.019)
Proficiency Rates (Z)			-0.003	-0.005
			(0.006)	(0.007)
Value-Added (Z)				0.004
				(0.006)
Observations	8979	8979	8979	8979
Housing Characteristics	Y	Y	Y	Y
Block-Group characteristics		Y	Y	Y

Notes: Estimates are based on simple hedonic regression models described in Section 4.2. Each panel and column represents a separate estimation. House transactions are from September 2009 through August 2011. All models include month-year FE. Standard errors are clustered at the school level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table 7: Effect of school climate rating information on log sale prices and log buyer income

	(1)	(2)	(3)	(4)
	Log Price	Log Income	Asian/White	Black/Latino
Climate Rating 5 x PostQ0	0.205***	0.144*	0.010	-0.022
	(0.053)	(0.074)	(0.050)	(0.049)
Climate Rating 4 x PostQ0	0.096**	0.054	0.025	-0.026
	(0.048)	(0.071)	(0.046)	(0.043)
Climate Rating 3 x PostQ0	0.086*	0.042	0.007	-0.036
	(0.049)	(0.065)	(0.049)	(0.049)
Climate Rating 2 x PostQ0	0.129***	0.054	0.001	-0.011
	(0.042)	(0.060)	(0.046)	(0.044)
Climate Rating 5 x PostQ1	0.121*	0.021	0.074	-0.120
	(0.073)	(0.074)	(0.082)	(0.083)
Climate Rating 4 x PostQ1	0.069	-0.077	0.113	-0.157*
	(0.066)	(0.070)	(0.077)	(0.080)
Climate Rating 3 x PostQ1	0.003	-0.064	0.060	-0.088
	(0.072)	(0.074)	(0.081)	(0.081)
Climate Rating 2 x PostQ1	0.082	-0.038	0.092	-0.120
	(0.064)	(0.065)	(0.077)	(0.080)
Climate Rating 5 x PostQ2	0.021	-0.017	0.004	0.016
	(0.065)	(0.074)	(0.056)	(0.053)
Climate Rating 4 x PostQ2	0.037	-0.017	0.053	-0.039
	(0.064)	(0.065)	(0.047)	(0.040)
Climate Rating 3 x PostQ2	-0.008	0.074	0.031	-0.011
	(0.072)	(0.082)	(0.046)	(0.044)
Climate Rating 2 x PostQ2	0.055	0.015	0.059	-0.043
	(0.062)	(0.063)	(0.043)	(0.037)
Climate Rating 5 x PostQ3	-0.050	-0.006	0.009	0.005
	(0.074)	(0.061)	(0.050)	(0.047)
Climate Rating 4 x PostQ3	-0.002	0.008	0.064	-0.054
	(0.071)	(0.054)	(0.045)	(0.041)
Climate Rating 3 x PostQ3	-0.035	0.049	0.030	-0.040
	(0.077)	(0.064)	(0.050)	(0.045)
Climate Rating 2 x PostQ3	-0.002	-0.014	0.032	-0.011
	(0.068)	(0.053)	(0.045)	(0.042)
Observations	13586	13586	12581	12581

Notes: Estimation is based on equation 1. The model includes month-by-year fixed-effects and school fixed-effects; property controls including squared-feet, squared-feet squared, lot size square feet,number of bedrooms, number of full/half bathrooms, age, age squared, age cubed, garage indicator, garage size, distance to downtown; Census block-group controls including percent black, percent Latine, percent of households with single mothers, percent of adults with less than a HS diploma, a high school diploma, and some college, fraction of people who are children or adults, median income; and Census block-group latent price time-trend; school controls include lagged and twice-lagged proficiency rates, fraction Black, Hispanic, Asian, and Native American students, and fraction LEP, IEP and FRPL-eligible students. Standard errors are clustered at the school zone level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Appendix A Figures

Figure A1: Front of school report card provided to parents by CPS



SY2011 School Progress Report

Sample CPS Elementary School

101 S. Sample Street, Chicago IL, 60603 | (773) 555-1001 | SAMPLE

MADE AYP IN 2011? Y

HEALTHY SCHOOLS CERTIFIED? N

ES

100001 | .

Overall Performance Summary

Overall Performance Level	LEVEL 1	This symbol helps you understand how your school is performing both this year and over the past few years. **Level 1** indicates the highest performing schools. **Level 2** indicates a middle-performing school that needs improvement. **Level 3** indicates the lowest performing schools. **NDA** indicates no data available.
Current Probation Status	NOT ON PROBATION	This reflects whether or not your school is on probation this year. More information on the CPS Performance Policy may be found online at **www.cps.edu.** **N/A:** Not applicable **NDA:** No data available

WHAT DO YOU THINK?

Although we have redesigned this year's **School Progress Report** to be easier to understand and use, *we're not done yet!* Based on the feedback we receive from families, schools, and staff, we will continue to improve this report for next year.

Please share your feedback on this report by visiting:

www.cps.edu/SPRfeedback2011

Academic Achievement | Pathway to College and Career Success

Pre-K - 2nd Grade		3rd - 5th Grade		6th - 8th Grade		8th Grade	
Early Literacy | % of Students at Benchmark on DIBELS or IDEL (End of Year)	74.8	**Grade Level Performance - Reading** % of Students At or Above Grade Level on Scantron/NWEA	57	**Grade Level Performance - Reading** % of Students At or Above Grade Level on Scantron/NWEA	53.3	**8th Grade EXPLORE - Reading** | % of Students at College Readiness Benchmark (End of Year)	34.6
Early Math | % of Students at Benchmark on mClass (End of Year)	63.8	**Grade Level Performance - Math** % of Students At or Above Grade Level on Scantron/NWEA	71.6	**Grade Level Performance - Math** % of Students At or Above Grade Level on Scantron/NWEA	77.8	**8th Grade EXPLORE - Math** | % of 8th Graders at College Readiness Benchmark (End of Year)	44.2
		Keeping Pace - Reading | % of Students Making Growth Targets on Scantron/NWEA	NDA	**Keeping Pace - Reading** | % of Students Making Growth Targets on Scantron/NWEA	NDA		
		Keeping Pace - Math | % of Students Making Growth Targets on Scantron/NWEA	80.6	**Keeping Pace - Math** | % of Students Making Growth Targets on Scantron/NWEA	NDA		

NDA: No data available

For more information about the metrics described above, please see the glossary (reverse) or visit **www.cps.edu/performance**.

Figure A2: back of school report card provided to parents by CPS

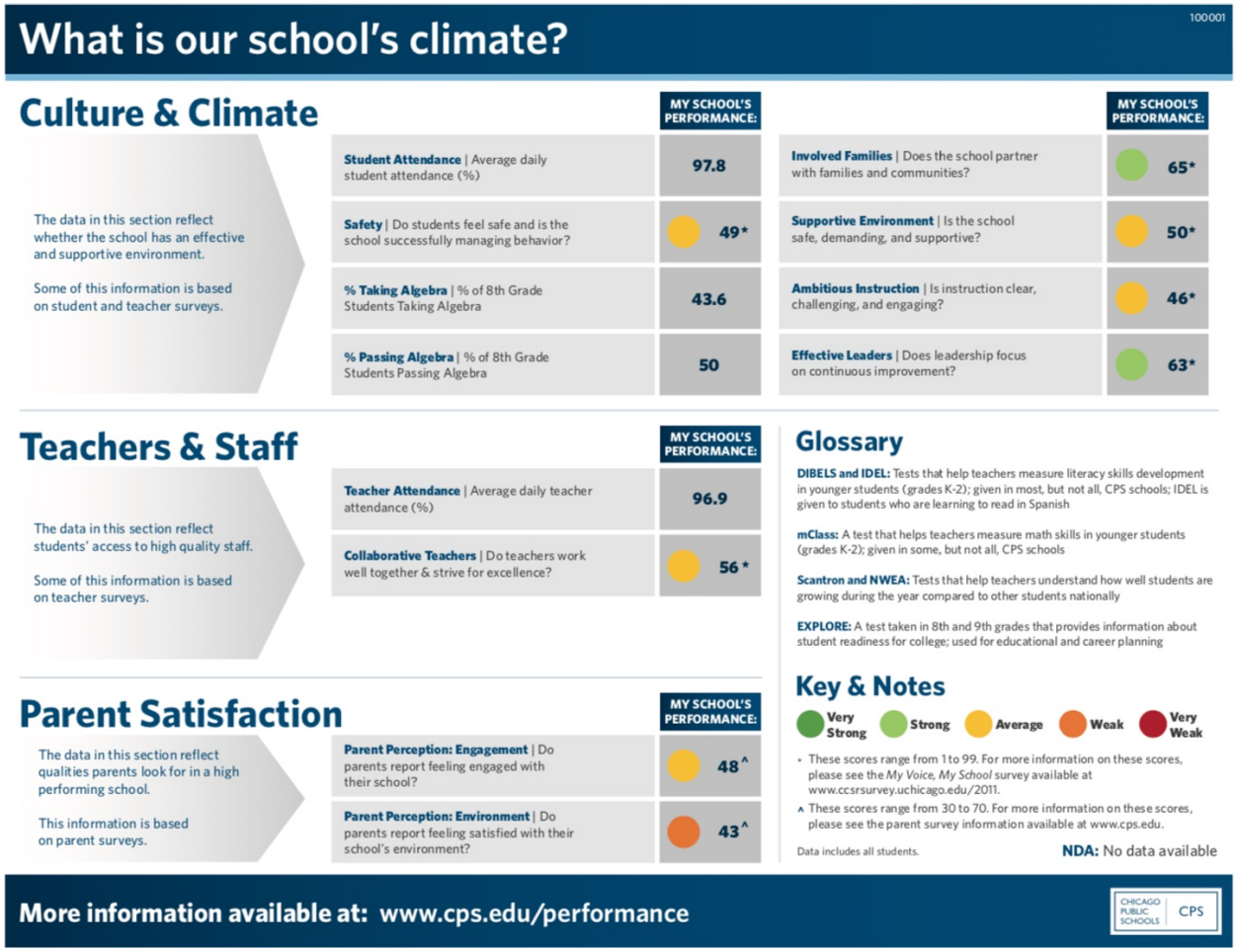
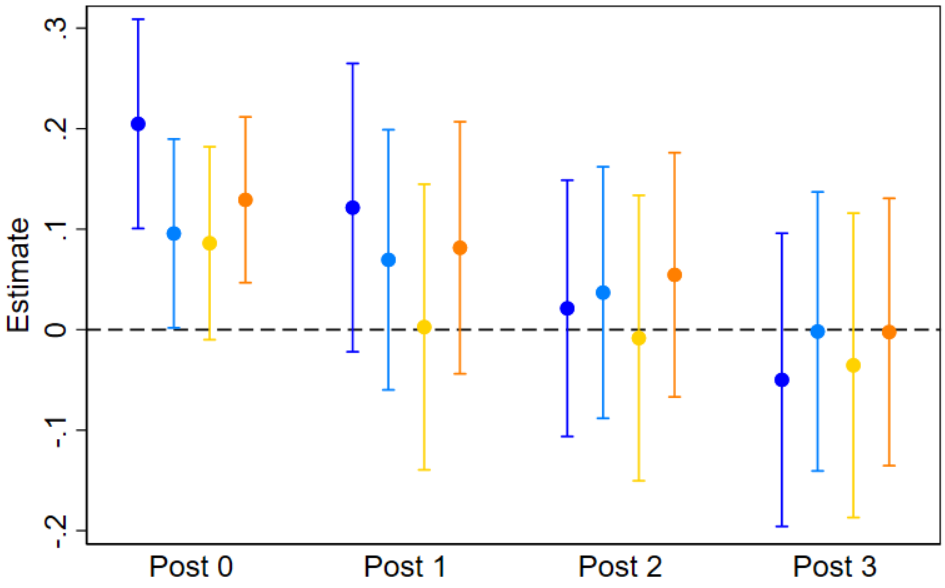
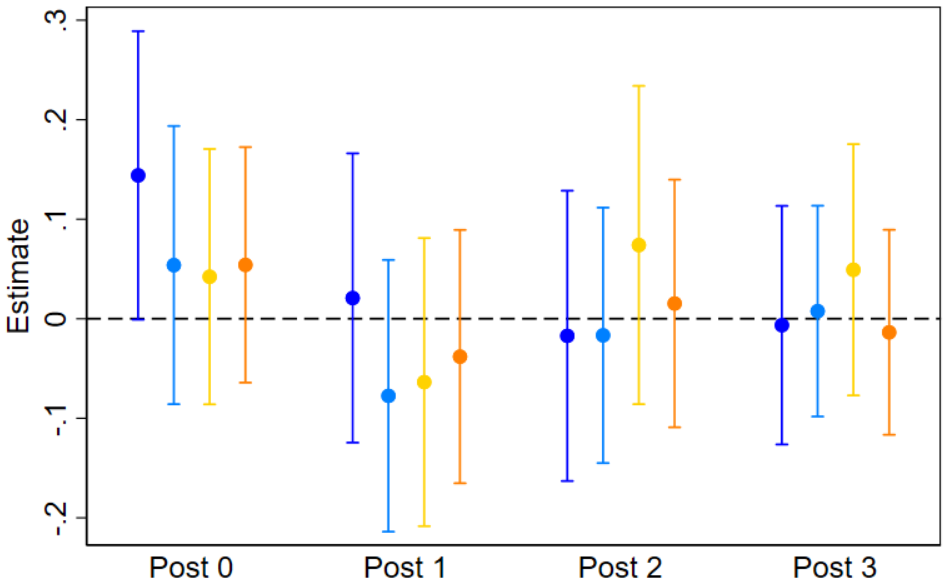


Figure A3: Quarterly DID estimates: Log Sales Price



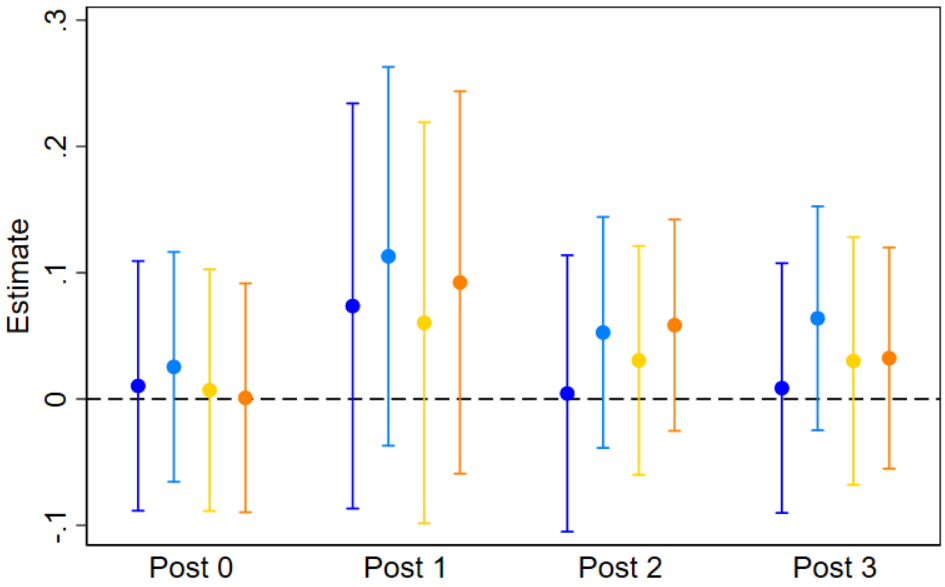
Notes: These estimates are based on equation 1.

Figure A4: Quarterly DID estimates: Log Homebuyer Income



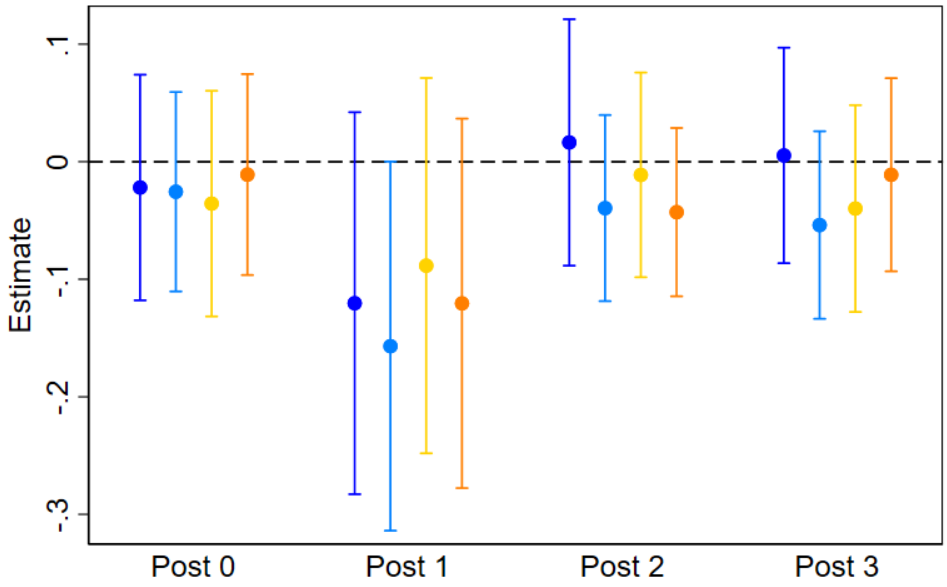
Notes: These estimates are based on equation 1.

Figure A5: Quarterly DID estimates: Homebuyer is Asian or White



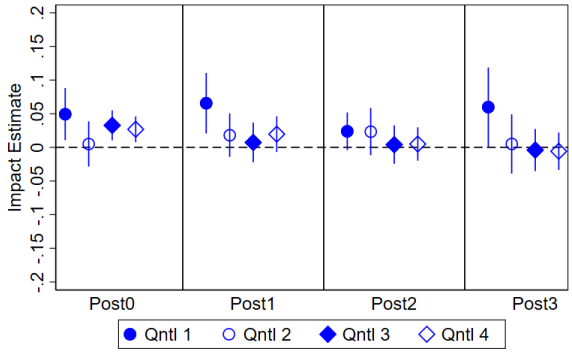
Notes: These estimates are based on equation 1.

Figure A6: Quarterly DID estimates: Homebuyer is Black or Hispanic

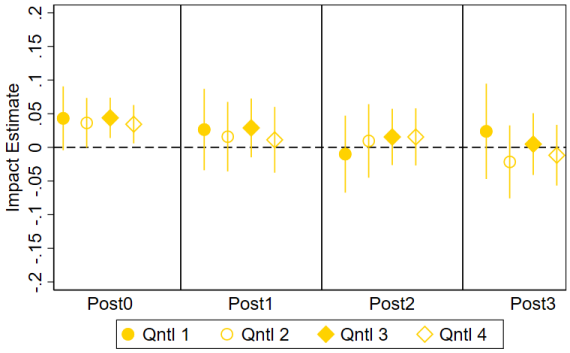


Notes: These estimates are based on equation 1.

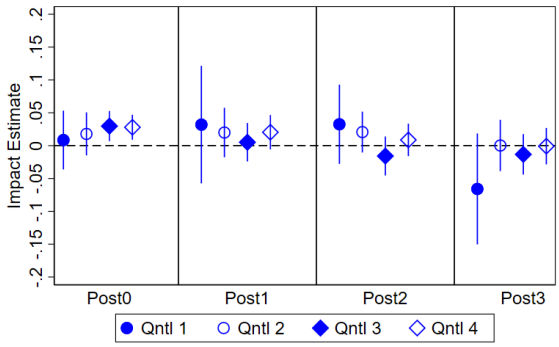
Figure A7: Heterogeneous climate rating effects on Log Sales Prices in each post-shock quarter, by school proficiency rate, non-FRPL rate, and White enrollment share quartiles



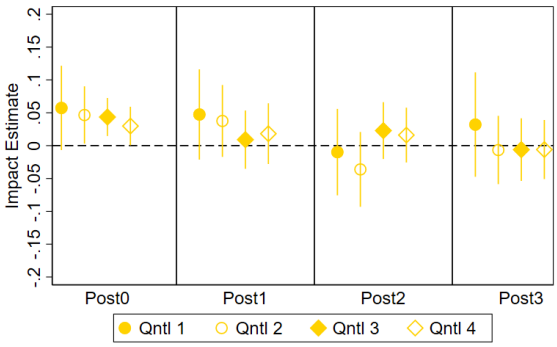
(a) Proficiency Quartiles (best climate)



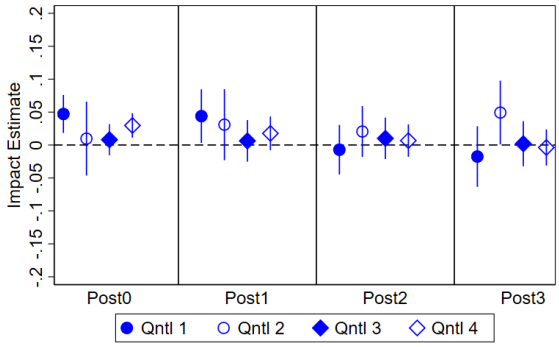
(b) Proficiency Quartiles (medium climate)



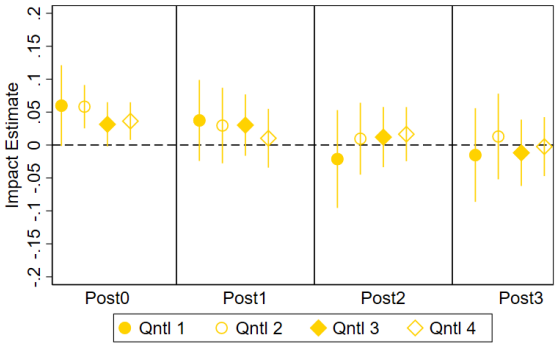
(c) Non-FRPL Quartiles (best climate)



(d) Non-FRPL Quartiles (medium climate)



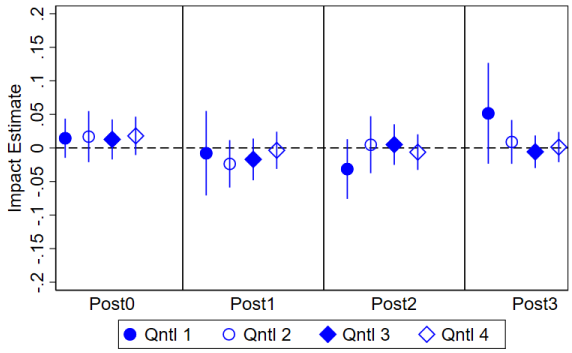
(e) White Share Quartiles (best climate)



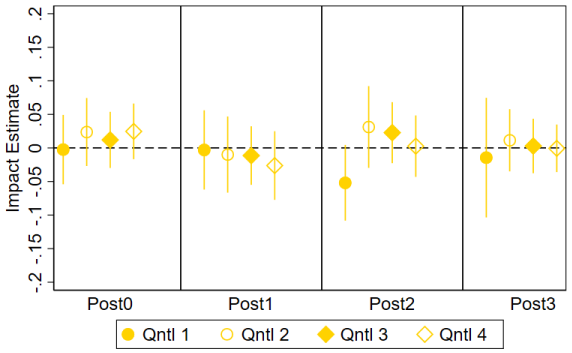
(f) White Share Quartiles (best climate)

Notes: These figures display post-shock estimates based on modified versions of equations 1, which include separate effects for school zones with different proficiency rates, non-FRPL rates, and White enrollment shares. This is done by interacting each post-shock climate score with an indicator for each quartile of the school characteristic of interest. Refer to section 6.3 for more details. Each pair of panels is based on a separate regression estimation.

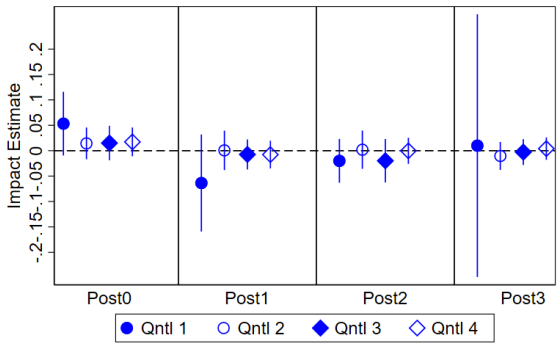
Figure A8: Heterogeneous climate rating effects on Log Homebuyer Incomes in each post-shock quarter, by school proficiency rate, non-FRPL rate, and White enrollment share quartiles



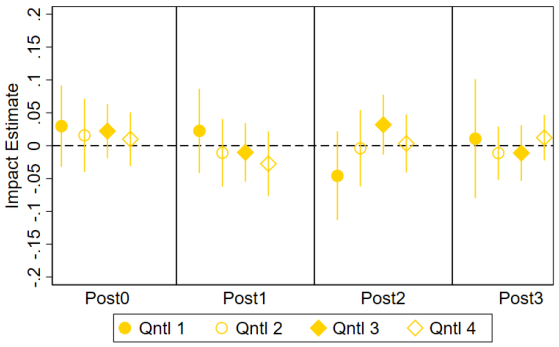
(a) Proficiency Quartiles (best climate)



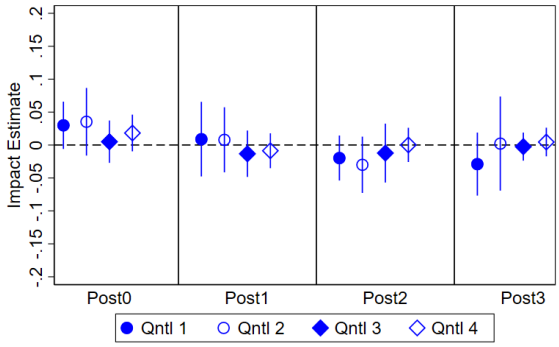
(b) Proficiency Quartiles (medium climate)



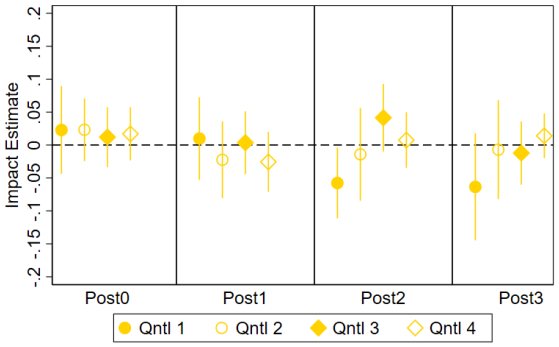
(c) Non-FRPL Quartiles (best climate)



(d) Non-FRPL Quartiles (medium climate)



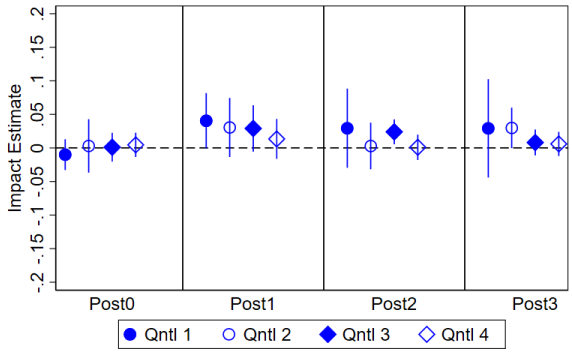
(e) White Share Quartiles (best climate)



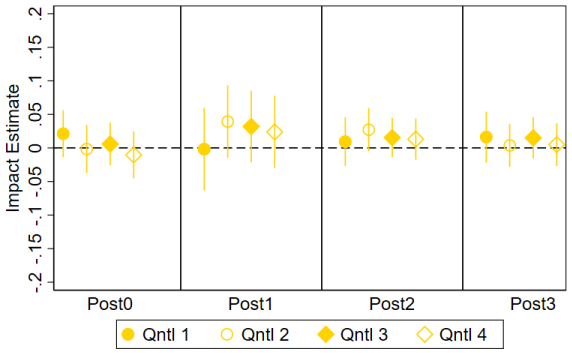
(f) White Share Quartiles (best climate)

Notes: These figures display post-shock estimates based on modified versions of equations 1, which include separate effects for school zones with different proficiency rates, non-FRPL rates, and White enrollment shares. This is done by interacting each post-shock climate score with an indicator for each quartile of the school characteristic of interest. Refer to section 6.3 for more details. Each pair of panels is based on a separate regression estimation.

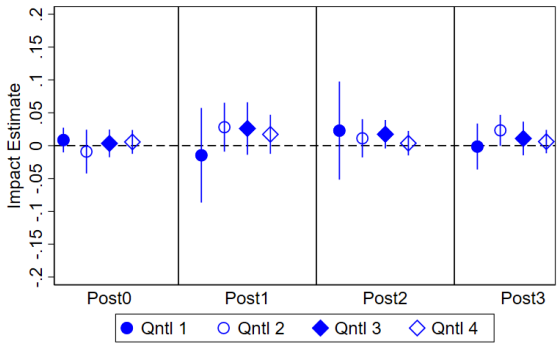
Figure A9: Heterogeneous climate rating effects on Homebuyer being Asian or White in each post-shock quarter, by school proficiency rate, non-FRPL rate, and White enrollment share quartiles



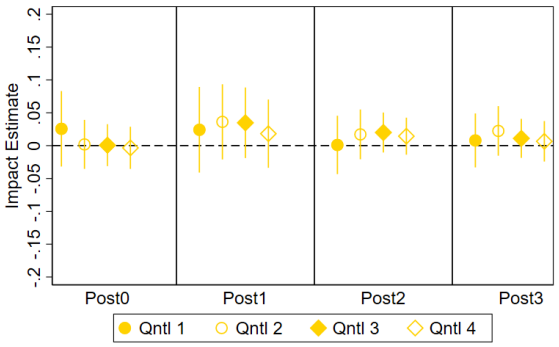
(a) Proficiency Quartiles (best climate)



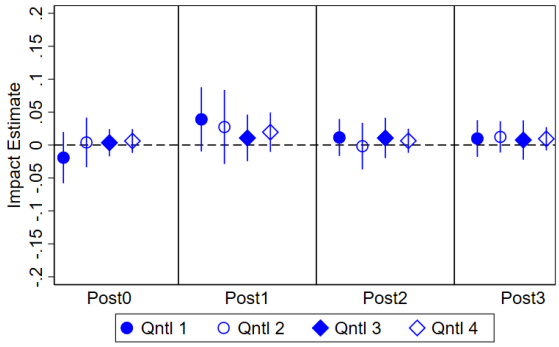
(b) Proficiency Quartiles (medium climate)



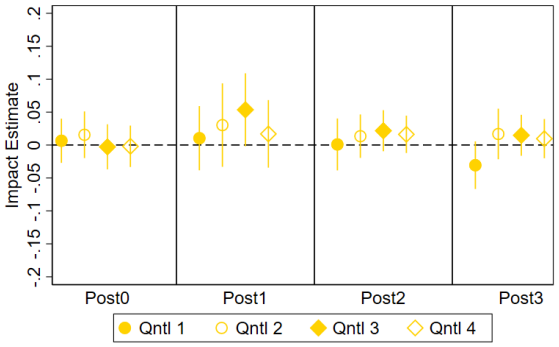
(c) Non-FRPL Quartiles (best climate)



(d) Non-FRPL Quartiles (medium climate)



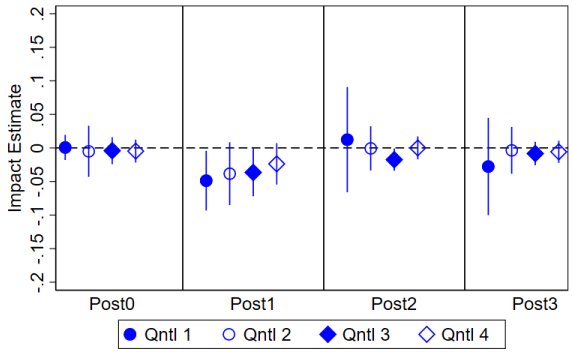
(e) White Share Quartiles (best climate)



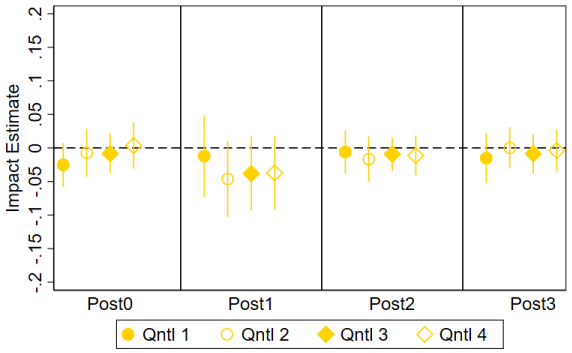
(f) White Share Quartiles (best climate)

Notes: These figures display post-shock estimates based on modified versions of equations 1, which include separate effects for school zones with different proficiency rates, non-FRPL rates, and White enrollment shares. This is done by interacting each post-shock climate score with an indicator for each quartile of the school characteristic of interest. Refer to section 6.3 for more details. Each pair of panels is based on a separate regression estimation.

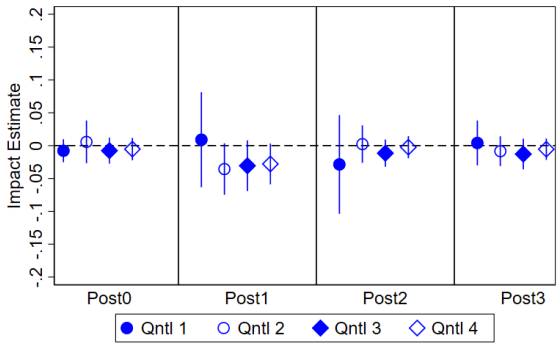
Figure A10: Heterogeneous climate rating effects on Homebuyer being Black or Hispanic in each post-shock quarter, by school proficiency rate, non-FRPL rate, and White enrollment share quartiles



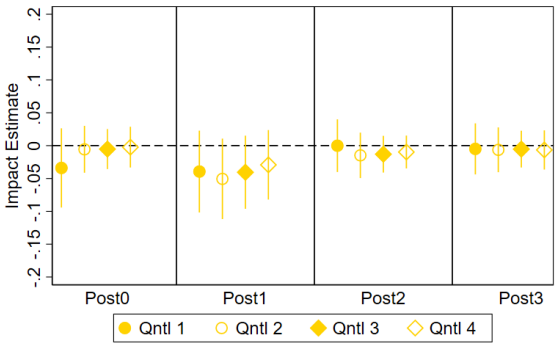
(a) Proficiency Quartiles (best climate)



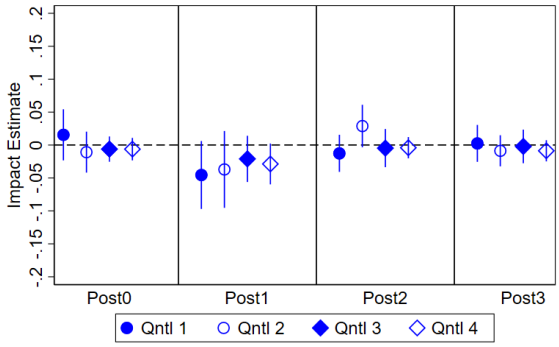
(b) Proficiency Quartiles (medium climate)



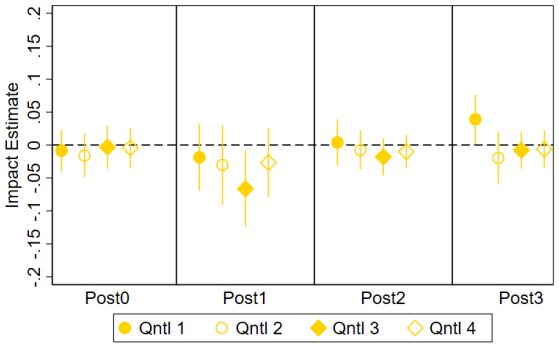
(c) Non-FRPL Quartiles (best climate)



(d) Non-FRPL Quartiles (medium climate)



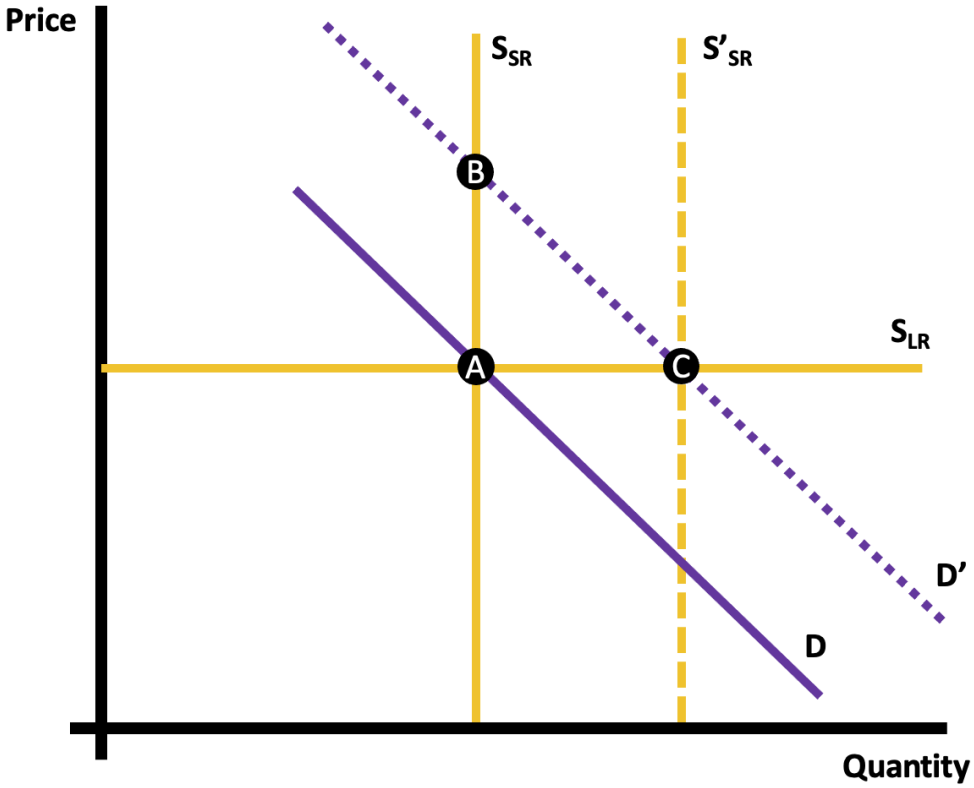
(e) White Share Quartiles (best climate)



(f) White Share Quartiles (best climate)

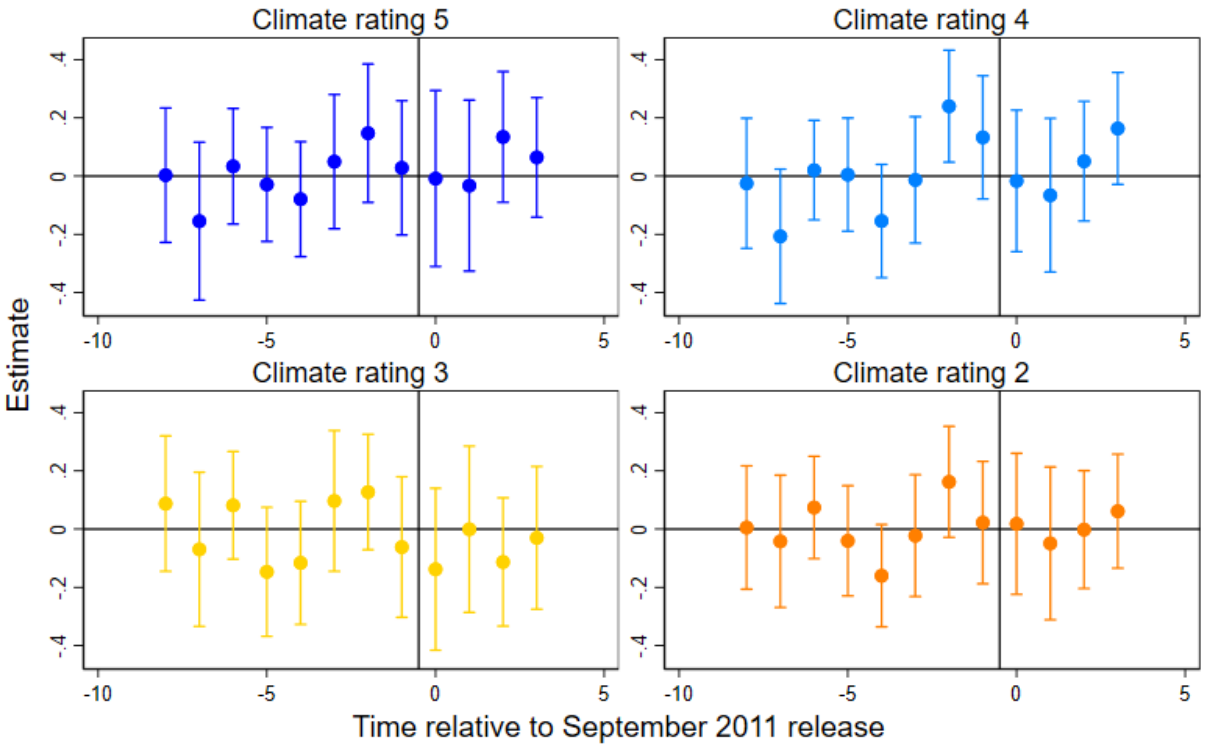
Notes: These figures display post-shock estimates based on modified versions of equations 1, which include separate effects for school zones with different proficiency rates, non-FRPL rates, and White enrollment shares. This is done by interacting each post-shock climate score with an indicator for each quartile of the school characteristic of interest. Refer to section 6.3 for more details. Each pair of panels is based on a separate regression estimation.

Figure A11: Graphical model of supply and demand mechanism



Notes: Graphical model showing the potential supply reactions to a shock in demand for properties on the market. Where D is the pre-shock demand curve, D' is the post-shock demand curve, S_{SR} is the immediate short run supply curve, and S'_{SR} is the updated short run supply curve that develops over time in reaction to D'. Point A is the pre-shock supply and demand equilibrium, point B is the immediate post-shock equilibrium, while point C is the post-shock equilibrium that develops over time.

Figure A12: Bi-monthly-level event study estimates: Number of Transactions (based on school zone fixed effects Poisson model)



Notes: Estimation is based on Poisson regression models based on equation 1, where the outcome of interest is the number of transactions. Models are based on data at the school zone-by-month level for the number of transactions. Each figure is a separate regression. Each model includes month-by-year and school zone fixed-effects. The black lines represent estimates using the overall sample of schools, the blue lines represent estimates from a sample that only includes schools that were assigned a climate rating of 3, 4, or 5, while the red lines represent estimates from a sample of schools rated 1, 2, or 3 for their climate quality. Estimates adjusted such that the reference period is the average of the pre-shock period. Standard errors are clustered at the school zone level.

Appendix B Tables

Table B1: Predictability of elementary school proficiency, FRPL, value-added, and climate ratings before initial school climate information release

	(1) Proficiency Rates (Z)	(2) FRPL Rate (Z)	(3) Value-Added (Z)	(4) Overall Climate	(5) Best Climate	(6) Worst Climate
% FRPL	-0.0123**		0.00600	-0.00669	0.00828	-0.00523
	(0.00450)		(0.00784)	(0.00951)	(0.00997)	(0.00677)
Enrollment	-0.0000145	-0.000228	-0.000238	-0.000872**	-0.000608*	-0.000227
	(0.000137)	(0.000122)	(0.000261)	(0.000280)	(0.000239)	(0.000212)
Attendance Rate	0.190***	-0.0189	-0.00669	0.0805	0.0450	0.0293
	(0.0251)	(0.0189)	(0.0390)	(0.0485)	(0.0415)	(0.0330)
% Asian	0.00667	0.0245***	-0.00526	0.00560	0.00359	0.00364
	(0.00671)	(0.00454)	(0.0107)	(0.0160)	(0.0172)	(0.00805)
% Black	-0.00946*	0.0242***	0.0109	0.00599	-0.00646	0.00487
	(0.00447)	(0.00185)	(0.00751)	(0.00967)	(0.0101)	(0.00619)
% Hispanic	0.0000852	0.0218***	-0.00317	0.00441	-0.000238	0.00232
	(0.00472)	(0.00240)	(0.00819)	(0.0102)	(0.0111)	(0.00588)
% Native	-0.0405	0.0172	-0.235	-0.283*	-0.0521	-0.0535
	(0.0763)	(0.0536)	(0.125)	(0.137)	(0.167)	(0.0950)
% Multi-race	0.00358	-0.118***	-0.0228	0.0310	0.00787	0.00516
	(0.0327)	(0.0243)	(0.0452)	(0.0515)	(0.0466)	(0.0529)
% LEP	-0.0188***	0.00311	0.0191*	-0.000980	-0.0125	0.000519
	(0.00477)	(0.00346)	(0.00767)	(0.0103)	(0.00929)	(0.00661)
% IEP	-0.00199	-0.0121	-0.00213	-0.00188	0.00688	-0.0161
	(0.00895)	(0.00692)	(0.0131)	(0.0161)	(0.0125)	(0.0124)
Nbhd HS Education	2.314***	-1.031*	-0.553	-0.833	-0.156	-0.00225
	(0.636)	(0.415)	(1.101)	(1.172)	(1.061)	(0.866)
Nbhd Some Coll. Educ.	0.621	-1.595***	-2.023*	-0.777	-0.375	-0.183
	(0.556)	(0.369)	(0.932)	(1.011)	(0.773)	(0.670)
Nbhd College Educ.	1.204	-0.179	-0.351	0.543	-0.294	0.334
	(0.707)	(0.399)	(0.934)	(1.114)	(1.087)	(0.760)
Nbhd Graduate Educ.	1.363	-2.330***	-1.160	-2.954*	-0.0282	-1.043
	(0.865)	(0.498)	(1.203)	(1.292)	(1.221)	(0.924)
Avg yearly school crimes	-0.0264***	0.00110	0.0215**	0.000117	-0.00959	0.00671
	(0.00619)	(0.00414)	(0.00823)	(0.00982)	(0.00938)	(0.00708)
Proficiency Rates (Z)		-0.128**	0.836***	0.473***	0.169	0.180
		(0.0464)	(0.0952)	(0.130)	(0.111)	(0.0940)
Observations	335	335	335	335	180	217
R-squared	0.712	0.770	0.235	0.211	0.172	0.074
Adjusted R-squared	0.699	0.759	0.196	0.171	0.091	-0.001

Notes: Refer to Table 2. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Table B2: School attendance boundary fixed-effect estimates of school climate relationship with log sales price during prerelease period (various distances from nearest border)

	(1)	(2)	(3)
Climate Rating 5	-0.030	-0.045	-0.071**
	(0.025)	(0.029)	(0.030)
Climate Rating 4	-0.043	-0.051*	-0.054*
	(0.026)	(0.028)	(0.031)
Climate Rating 3	-0.017	-0.030	-0.045
	(0.027)	(0.027)	(0.031)
Climate Rating 2	0.014	0.006	-0.009
	(0.024)	(0.026)	(0.028)
Proficiency Rates (Z)	0.058***	0.056***	0.052***
	(0.009)	(0.010)	(0.012)
Value-Added (Z)	-0.031***	-0.032***	-0.034***
	(0.007)	(0.007)	(0.008)
Observations	11631	9721	8120
Housing Characteristics	Y	Y	Y
Block-Group characteristics	Y	Y	Y
$\leq$0.35 miles from border	Y		
$\leq$0.20 miles from border		Y	
$\leq$0.15 miles from border			Y

Notes: Refer to Table 7.

Table B3: School attendance boundary fixed-effect estimates of school climate relationship with log sales price during prerelease period (various distances from nearest border)

	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	Log Homebuyer Income			Buyer is Asian/White			Buyer is Black/Hispanic		
Panel A: Pre-Shock									
Climate Rating 5	-0.043*	-0.043	-0.075**	-0.026	-0.049**	-0.039*	0.038*	0.047**	0.041*
	(0.026)	(0.028)	(0.034)	(0.019)	(0.020)	(0.022)	(0.020)	(0.020)	(0.023)
Climate Rating 4	-0.021	-0.026	-0.028	-0.037*	-0.060***	-0.052**	0.032*	0.052***	0.044**
	(0.026)	(0.027)	(0.030)	(0.019)	(0.020)	(0.021)	(0.019)	(0.018)	(0.020)
Climate Rating 3	-0.040	-0.046*	-0.062**	-0.038**	-0.050***	-0.037*	0.038**	0.045**	0.036*
	(0.027)	(0.026)	(0.031)	(0.018)	(0.018)	(0.020)	(0.019)	(0.018)	(0.021)
Climate Rating 2	0.009	0.007	-0.007	-0.025	-0.032	-0.024	0.021	0.024	0.017
	(0.024)	(0.025)	(0.028)	(0.020)	(0.020)	(0.022)	(0.019)	(0.019)	(0.021)
Proficiency Rates (Z)	0.053***	0.054***	0.050***	0.013*	0.009	0.005	-0.012	-0.005	-0.000
	(0.012)	(0.013)	(0.014)	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)
Value-Added (Z)	-0.047***	-0.053***	-0.056***	-0.009	-0.007	-0.003	0.007	0.004	-0.004
	(0.007)	(0.007)	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	11631	9721	8120	10733	8979	7491	10733	8979	7491
Housing Characteristics	Y	Y	Y	Y	Y	Y	Y	Y	Y
CBG characteristics	Y	Y	Y	Y	Y	Y	Y	Y	Y
≤0.35 miles from border	Y			Y			Y		
≤0.20 miles from border		Y			Y			Y	
≤0.15 miles from border			Y			Y			Y

Notes: Refer to Table 7.

Table B4: Robustness tests of DID estimates of school climate rating information on log sale prices

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Climate Rating 5 x PostQ0	0.167***	0.159***	0.184***	0.190***	0.176***	0.205***
	(0.048)	(0.052)	(0.053)	(0.050)	(0.052)	(0.053)
Climate Rating 4 x PostQ0	0.083**	0.063	0.088*	0.083*	0.078*	0.096**
	(0.040)	(0.046)	(0.047)	(0.046)	(0.046)	(0.048)
Climate Rating 3 x PostQ0	0.039	0.042	0.075	0.067	0.062	0.086*
	(0.039)	(0.043)	(0.046)	(0.047)	(0.047)	(0.049)
Climate Rating 2 x PostQ0	0.089**	0.067	0.102**	0.117***	0.097**	0.129***
	(0.037)	(0.041)	(0.040)	(0.040)	(0.040)	(0.042)
Climate Rating 5 x PostQ1	0.187***	0.177**	0.121*	0.160**	0.107	0.121*
	(0.070)	(0.073)	(0.073)	(0.066)	(0.071)	(0.073)
Climate Rating 4 x PostQ1	0.130**	0.109*	0.084	0.078	0.074	0.069
	(0.059)	(0.062)	(0.064)	(0.060)	(0.064)	(0.066)
Climate Rating 3 x PostQ1	0.056	0.022	0.002	0.020	-0.005	0.003
	(0.069)	(0.073)	(0.070)	(0.067)	(0.070)	(0.072)
Climate Rating 2 x PostQ1	0.100*	0.094	0.074	0.094	0.069	0.082
	(0.058)	(0.060)	(0.063)	(0.058)	(0.063)	(0.064)
Climate Rating 5 x PostQ2	0.064	0.061	0.028	0.060	0.017	0.021
	(0.066)	(0.065)	(0.061)	(0.064)	(0.061)	(0.065)
Climate Rating 4 x PostQ2	0.073	0.082	0.051	0.058	0.038	0.037
	(0.058)	(0.060)	(0.059)	(0.063)	(0.061)	(0.064)
Climate Rating 3 x PostQ2	-0.005	0.000	0.005	0.012	-0.006	-0.008
	(0.060)	(0.066)	(0.067)	(0.069)	(0.069)	(0.072)
Climate Rating 2 x PostQ2	0.073	0.079	0.064	0.081	0.058	0.055
	(0.054)	(0.057)	(0.057)	(0.061)	(0.058)	(0.062)
Climate Rating 5 x PostQ3	0.088	0.077	-0.027	-0.005	-0.038	-0.050
	(0.096)	(0.076)	(0.071)	(0.073)	(0.070)	(0.074)
Climate Rating 4 x PostQ3	0.099*	0.149**	0.016	0.045	0.003	-0.002
	(0.060)	(0.064)	(0.066)	(0.070)	(0.066)	(0.071)
Climate Rating 3 x PostQ3	0.008	0.055	-0.014	-0.010	-0.024	-0.035
	(0.068)	(0.075)	(0.072)	(0.077)	(0.073)	(0.077)
Climate Rating 2 x PostQ3	0.075	0.115*	0.014	0.030	0.007	-0.002
	(0.058)	(0.063)	(0.063)	(0.067)	(0.063)	(0.068)
Observations	16952	13586	13586	13586	13586	13586
Main climate effects	Y	Y	Y		Y	
Property & Nbhd Controls	Y	Y	Y	Y	Y	Y
School Controls				Y	Y	Y
School FE				Y		Y
Boundary FE			Y		Y	Y
≤0.2mi of Boundary		Y	Y	Y	Y	Y

Notes: Estimation is based on equation 1. All models include month-by-year fixed-effects and school fixed-effects. Some models include property, Census block-group, and school controls as defined in the notes for table 7. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table B5: Robustness tests of DID estimates of school climate rating information on log buyer income

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Climate Rating 5 x PostQ0	0.084	0.078	0.137*	0.125*	0.121*	0.144*
	(0.073)	(0.077)	(0.072)	(0.072)	(0.070)	(0.074)
Climate Rating 4 x PostQ0	0.012	0.024	0.059	0.049	0.045	0.054
	(0.059)	(0.069)	(0.066)	(0.066)	(0.067)	(0.071)
Climate Rating 3 x PostQ0	-0.052	-0.021	0.047	0.017	0.033	0.042
	(0.055)	(0.063)	(0.060)	(0.061)	(0.061)	(0.065)
Climate Rating 2 x PostQ0	0.004	-0.004	0.040	0.053	0.036	0.054
	(0.052)	(0.061)	(0.055)	(0.057)	(0.056)	(0.060)
Climate Rating 5 x PostQ1	0.105	0.068	0.036	0.047	0.014	0.021
	(0.087)	(0.086)	(0.075)	(0.072)	(0.073)	(0.074)
Climate Rating 4 x PostQ1	-0.037	-0.037	-0.053	-0.066	-0.066	-0.077
	(0.075)	(0.076)	(0.068)	(0.067)	(0.069)	(0.070)
Climate Rating 3 x PostQ1	-0.010	-0.060	-0.073	-0.052	-0.082	-0.064
	(0.078)	(0.078)	(0.070)	(0.072)	(0.071)	(0.074)
Climate Rating 2 x PostQ1	-0.002	-0.028	-0.040	-0.028	-0.045	-0.038
	(0.072)	(0.072)	(0.065)	(0.062)	(0.064)	(0.065)
Climate Rating 5 x PostQ2	0.032	-0.007	-0.001	-0.013	-0.020	-0.017
	(0.071)	(0.057)	(0.068)	(0.069)	(0.069)	(0.074)
Climate Rating 4 x PostQ2	-0.008	-0.001	-0.010	-0.023	-0.028	-0.017
	(0.053)	(0.054)	(0.061)	(0.062)	(0.063)	(0.065)
Climate Rating 3 x PostQ2	0.031	0.064	0.081	0.067	0.068	0.074
	(0.065)	(0.065)	(0.077)	(0.075)	(0.079)	(0.082)
Climate Rating 2 x PostQ2	0.021	0.018	0.019	0.014	0.013	0.015
	(0.048)	(0.049)	(0.058)	(0.059)	(0.061)	(0.063)
Climate Rating 5 x PostQ3	0.145*	0.092	0.015	0.023	-0.004	-0.006
	(0.084)	(0.068)	(0.060)	(0.062)	(0.059)	(0.061)
Climate Rating 4 x PostQ3	0.103**	0.120**	0.020	0.036	0.006	0.008
	(0.045)	(0.058)	(0.053)	(0.055)	(0.053)	(0.054)
Climate Rating 3 x PostQ3	0.088	0.115	0.064	0.069	0.054	0.049
	(0.059)	(0.070)	(0.063)	(0.065)	(0.063)	(0.064)
Climate Rating 2 x PostQ3	0.104**	0.090	0.000	0.016	-0.005	-0.014
	(0.046)	(0.060)	(0.053)	(0.053)	(0.052)	(0.053)
Observations	16952	13586	13586	13586	13586	13586
Main climate effects	Y	Y	Y		Y	
Property & Nbhd Controls	Y	Y	Y	Y	Y	Y
School Controls				Y	Y	Y
School FE				Y		Y
Boundary FE			Y		Y	Y
≤0.2mi of Boundary		Y	Y	Y	Y	Y

Notes: Estimation is based on equation 1. All models include month-by-year fixed-effects and school fixed-effects. Some models include property, Census block-group, and school controls as defined in the notes for table 7. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table B6: Robustness tests of DID estimates of school climate rating information on buyer being Asian or White

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Climate Rating 5 x PostQ0	-0.009	-0.043	0.003	-0.013	0.003	0.010
	(0.060)	(0.057)	(0.049)	(0.047)	(0.049)	(0.050)
Climate Rating 4 x PostQ0	0.015	-0.024	0.021	0.010	0.018	0.025
	(0.057)	(0.054)	(0.046)	(0.043)	(0.046)	(0.046)
Climate Rating 3 x PostQ0	-0.013	-0.045	-0.007	-0.010	-0.009	0.007
	(0.060)	(0.059)	(0.048)	(0.047)	(0.047)	(0.049)
Climate Rating 2 x PostQ0	-0.026	-0.048	-0.004	-0.009	-0.004	0.001
	(0.057)	(0.055)	(0.046)	(0.045)	(0.045)	(0.046)
Climate Rating 5 x PostQ1	0.067	0.087	0.067	0.061	0.066	0.074
	(0.067)	(0.068)	(0.079)	(0.072)	(0.079)	(0.082)
Climate Rating 4 x PostQ1	0.135**	0.157**	0.114	0.108	0.110	0.113
	(0.064)	(0.063)	(0.075)	(0.067)	(0.075)	(0.077)
Climate Rating 3 x PostQ1	0.072	0.061	0.055	0.048	0.052	0.060
	(0.063)	(0.069)	(0.080)	(0.072)	(0.079)	(0.081)
Climate Rating 2 x PostQ1	0.106*	0.102	0.089	0.085	0.088	0.092
	(0.062)	(0.063)	(0.075)	(0.068)	(0.075)	(0.077)
Climate Rating 5 x PostQ2	0.013	0.042	0.000	0.007	-0.001	0.004
	(0.061)	(0.065)	(0.055)	(0.056)	(0.054)	(0.056)
Climate Rating 4 x PostQ2	0.076	0.104*	0.052	0.065	0.050	0.053
	(0.054)	(0.053)	(0.046)	(0.048)	(0.045)	(0.047)
Climate Rating 3 x PostQ2	0.008	0.058	0.039	0.047	0.037	0.031
	(0.053)	(0.053)	(0.044)	(0.049)	(0.044)	(0.046)
Climate Rating 2 x PostQ2	0.059	0.087*	0.057	0.065	0.058	0.059
	(0.050)	(0.051)	(0.041)	(0.045)	(0.041)	(0.043)
Climate Rating 5 x PostQ3	0.047	0.042	0.021	0.008	0.020	0.009
	(0.045)	(0.046)	(0.049)	(0.049)	(0.049)	(0.050)
Climate Rating 4 x PostQ3	0.132***	0.117***	0.070	0.066	0.068	0.064
	(0.042)	(0.043)	(0.045)	(0.045)	(0.044)	(0.045)
Climate Rating 3 x PostQ3	0.080	0.062	0.034	0.024	0.032	0.030
	(0.049)	(0.048)	(0.048)	(0.050)	(0.048)	(0.050)
Climate Rating 2 x PostQ3	0.072*	0.062	0.037	0.032	0.039	0.032
	(0.042)	(0.042)	(0.043)	(0.045)	(0.043)	(0.045)
Observations	15685	12581	12581	12581	12581	12581
Main climate effects	Y	Y	Y		Y	
Property & Nbhd Controls	Y	Y	Y	Y	Y	Y
School Controls				Y	Y	Y
School FE				Y		Y
Boundary FE			Y		Y	Y
≤0.2mi of Boundary		Y	Y	Y	Y	Y

Notes: Estimation is based on equation 1. All models include month-by-year fixed-effects and school fixed-effects. Some models include property, Census block-group, and school controls as defined in the notes for table 7. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table B7: Robustness tests of DID estimates of school climate rating information on buyer being Black or Latino

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Climate Rating 5 x PostQ0	-0.032	0.014	-0.020	-0.010	-0.019	-0.022
	(0.053)	(0.046)	(0.047)	(0.046)	(0.047)	(0.049)
Climate Rating 4 x PostQ0	-0.032	0.011	-0.027	-0.017	-0.022	-0.026
	(0.049)	(0.042)	(0.042)	(0.039)	(0.041)	(0.043)
Climate Rating 3 x PostQ0	-0.032	0.006	-0.027	-0.020	-0.024	-0.036
	(0.053)	(0.050)	(0.047)	(0.045)	(0.047)	(0.049)
Climate Rating 2 x PostQ0	-0.007	0.025	-0.012	-0.007	-0.011	-0.011
	(0.050)	(0.043)	(0.042)	(0.041)	(0.042)	(0.044)
Climate Rating 5 x PostQ1	-0.106	-0.135*	-0.118	-0.110	-0.116	-0.120
	(0.072)	(0.070)	(0.080)	(0.073)	(0.081)	(0.083)
Climate Rating 4 x PostQ1	-0.174**	-0.198***	-0.159**	-0.150**	-0.154*	-0.157*
	(0.071)	(0.066)	(0.078)	(0.071)	(0.078)	(0.080)
Climate Rating 3 x PostQ1	-0.097	-0.094	-0.084	-0.075	-0.081	-0.088
	(0.068)	(0.069)	(0.080)	(0.072)	(0.080)	(0.081)
Climate Rating 2 x PostQ1	-0.135*	-0.132**	-0.117	-0.116	-0.116	-0.120
	(0.069)	(0.065)	(0.078)	(0.071)	(0.079)	(0.080)
Climate Rating 5 x PostQ2	0.004	-0.014	0.021	0.017	0.023	0.016
	(0.058)	(0.061)	(0.052)	(0.053)	(0.052)	(0.053)
Climate Rating 4 x PostQ2	-0.056	-0.083*	-0.036	-0.047	-0.033	-0.039
	(0.048)	(0.046)	(0.039)	(0.042)	(0.039)	(0.040)
Climate Rating 3 x PostQ2	0.019	-0.030	-0.018	-0.021	-0.016	-0.011
	(0.051)	(0.048)	(0.041)	(0.047)	(0.042)	(0.044)
Climate Rating 2 x PostQ2	-0.046	-0.068	-0.040	-0.046	-0.041	-0.043
	(0.046)	(0.044)	(0.035)	(0.039)	(0.035)	(0.037)
Climate Rating 5 x PostQ3	-0.049	-0.037	-0.011	-0.004	-0.010	0.005
	(0.044)	(0.045)	(0.047)	(0.047)	(0.046)	(0.047)
Climate Rating 4 x PostQ3	-0.132***	-0.112***	-0.061	-0.063	-0.059	-0.054
	(0.042)	(0.041)	(0.041)	(0.042)	(0.040)	(0.041)
Climate Rating 3 x PostQ3	-0.093**	-0.076*	-0.044	-0.038	-0.042	-0.040
	(0.047)	(0.045)	(0.044)	(0.046)	(0.044)	(0.045)
Climate Rating 2 x PostQ3	-0.063	-0.048	-0.020	-0.017	-0.022	-0.011
	(0.042)	(0.041)	(0.041)	(0.043)	(0.041)	(0.042)
Observations	15685	12581	12581	12581	12581	12581
Main climate effects	Y	Y	Y		Y	
Property & Nbhd Controls	Y	Y	Y	Y	Y	Y
School Controls				Y	Y	Y
School FE				Y		Y
Boundary FE			Y		Y	Y
≤0.2mi of Boundary		Y	Y	Y	Y	Y

Notes: Estimation is based on equation 1. All models include month-by-year fixed-effects and school fixed-effects. Some models include property, Census block-group, and school controls as defined in the notes for table 7. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table B8: Effect of school climate rating information on log sale prices, across samples and controls

	(1)	(2)	(3)	(4)
	Log Price	Log Price	Log Price	Log Price
Climate Rating 5 x PostQ0	0.205***	0.220***	0.203***	0.189***
	(0.053)	(0.068)	(0.053)	(0.055)
Climate Rating 4 x PostQ0	0.096**	0.110	0.094*	0.083
	(0.048)	(0.074)	(0.048)	(0.051)
Climate Rating 3 x PostQ0	0.086*	0.118*	0.086*	0.071
	(0.049)	(0.067)	(0.049)	(0.053)
Climate Rating 2 x PostQ0	0.129***	0.151**	0.130***	0.114**
	(0.042)	(0.059)	(0.042)	(0.045)
Climate Rating 5 x PostQ1	0.121*	-0.073	0.111	0.091
	(0.073)	(0.094)	(0.073)	(0.071)
Climate Rating 4 x PostQ1	0.069	-0.035	0.064	0.036
	(0.066)	(0.087)	(0.067)	(0.065)
Climate Rating 3 x PostQ1	0.003	-0.025	-0.001	-0.050
	(0.072)	(0.090)	(0.072)	(0.072)
Climate Rating 2 x PostQ1	0.082	-0.020	0.085	0.046
	(0.064)	(0.083)	(0.064)	(0.061)
Climate Rating 5 x PostQ2	0.021	-0.083	0.014	0.049
	(0.065)	(0.080)	(0.067)	(0.070)
Climate Rating 4 x PostQ2	0.037	-0.011	0.030	0.059
	(0.064)	(0.072)	(0.065)	(0.069)
Climate Rating 3 x PostQ2	-0.008	-0.042	-0.013	0.006
	(0.072)	(0.091)	(0.072)	(0.077)
Climate Rating 2 x PostQ2	0.055	-0.007	0.058	0.074
	(0.062)	(0.071)	(0.063)	(0.067)
Climate Rating 5 x PostQ3	-0.050	-0.093	-0.057	-0.048
	(0.074)	(0.074)	(0.077)	(0.084)
Climate Rating 4 x PostQ3	-0.002	-0.082	-0.007	0.002
	(0.071)	(0.061)	(0.074)	(0.081)
Climate Rating 3 x PostQ3	-0.035	-0.079	-0.038	-0.037
	(0.077)	(0.064)	(0.079)	(0.086)
Climate Rating 2 x PostQ3	-0.002	-0.035	0.003	-0.002
	(0.068)	(0.064)	(0.068)	(0.078)
Observations	13586	6237	13586	12940
No Condos, 3+ bdrms		Y		
Control for proficiency, VA shocks			Y	
Control for HS climate info shock				Y

Notes: See notes in table 7.

Table B9: Effect of school climate rating information on log homebuyer income, across samples and controls

	(1)	(2)	(3)	(4)
	Log Income	Log Income	Log Income	Log Income
Climate Rating 5 x PostQ0	0.144*	0.202**	0.120*	0.133
	(0.074)	(0.078)	(0.071)	(0.081)
Climate Rating 4 x PostQ0	0.054	0.120*	0.044	0.045
	(0.071)	(0.069)	(0.066)	(0.076)
Climate Rating 3 x PostQ0	0.042	0.221***	0.015	0.021
	(0.065)	(0.072)	(0.061)	(0.072)
Climate Rating 2 x PostQ0	0.054	0.097	0.053	0.055
	(0.060)	(0.059)	(0.057)	(0.067)
Climate Rating 5 x PostQ1	0.021	-0.102	0.014	0.026
	(0.074)	(0.111)	(0.069)	(0.070)
Climate Rating 4 x PostQ1	-0.077	-0.348***	-0.087	-0.077
	(0.070)	(0.097)	(0.065)	(0.068)
Climate Rating 3 x PostQ1	-0.064	-0.210**	-0.063	-0.069
	(0.074)	(0.105)	(0.071)	(0.074)
Climate Rating 2 x PostQ1	-0.038	-0.187*	-0.030	-0.034
	(0.065)	(0.099)	(0.060)	(0.062)
Climate Rating 5 x PostQ2	-0.017	0.019	-0.042	0.001
	(0.074)	(0.100)	(0.075)	(0.078)
Climate Rating 4 x PostQ2	-0.017	-0.021	-0.047	0.014
	(0.065)	(0.090)	(0.066)	(0.070)
Climate Rating 3 x PostQ2	0.074	0.083	0.054	0.083
	(0.082)	(0.105)	(0.075)	(0.083)
Climate Rating 2 x PostQ2	0.015	0.049	0.011	0.033
	(0.063)	(0.089)	(0.062)	(0.064)
Climate Rating 5 x PostQ3	-0.006	-0.044	-0.009	-0.011
	(0.061)	(0.090)	(0.068)	(0.069)
Climate Rating 4 x PostQ3	0.008	0.050	0.011	0.008
	(0.054)	(0.064)	(0.058)	(0.061)
Climate Rating 3 x PostQ3	0.049	0.028	0.055	0.051
	(0.064)	(0.066)	(0.068)	(0.068)
Climate Rating 2 x PostQ3	-0.014	-0.031	0.012	-0.024
	(0.053)	(0.063)	(0.055)	(0.058)
Observations	13586	6237	13586	12940
No Condos, 3+ bdrms		Y		
Control for proficiency, VA shocks			Y	
Control for HS climate info shock				Y

Notes: See notes in table 7.