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

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Abstract

For the past decade, the federal government and an increasing number of states and school districts across the US have begun to invest and focus on the social, learning, and working conditions (school climate) experienced by students, families, and teachers. Despite this trend, causal research on whether and how much various stakeholders value school climate is limited. In this paper, I investigate how publicizing school climate information is capitalized into the housing market and how it affects the sorting of homebuyers from different socioeconomic 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 an overall house price increase of 2% for a one-level-higher school climate rating. Additionally, I find a 2% increase in the average income of new homebuyers moving into neighborhoods assigned to a one-level-higher school climate rating. These effects are almost entirely driven by transactions in attendance zones with better-climate schools. These initial effects dissipate over time, as information becomes less salient. The effects are consistent across different types of schools and neighborhoods. I explore various potential mechanisms for these effects. I find evidence that homebuyers value this dimension of school quality that has been understudied in the revealed preferences literature.

*Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author and do not reflect the position of Zillow Group. Funding for this project comes from the National Academy of Education/Spencer Dissertation Fellowship. All errors are my own.

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1 Introduction

Organizations and institutions are showing a growing interest in the social conditions—both positive and negative—experienced by various stakeholders. This concept, broadly labeled *social climate*, addresses issues such as emotional support, safety, and discrimination. Examples include associations surveying the professional environment experienced by their members, employers addressing workplace issues specific to diversity and inclusion, and institutions like hospitals and universities committing to receive feedback from employees, as well as patients or students, about their social interactions.[1] That a growing number of organizations and institutions are making investments to measure, improve, and promote social climate suggests it is valuable to these organizations and to their constituents. However, causal research identifying how social climate is valued by stakeholders currently is limited.

Public K–12 schools offer a unique opportunity to study social climate in organizations, as many have begun to standardize its measurement and reporting. In this context, climate refers to the social, learning, and working conditions experienced by students, families, and teachers in schools. I refer to these conditions as *school climate*.[2] Educators and researchers argue that school climate provides a more complete picture of students' wellbeing, and is positively associated with child development, academic achievement, and educational attainment (Darling-Hammond, 2004; Gagnon and Schneider, 2019; Thapa et al., 2013). 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 growing focus on school climate can potentially have effects beyond internal school decision-making and improvement. Families' school quality preferences influence their residential decisions (Bayer et al., 2007; Bergman et al., 2020; Black, 1999; 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. 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

[1]Reporting on these and other examples include: Altimari (2021); American Economic Association (2019); Association of American Universities (2018); Brown (2021); Harte (2021); Isaac (2017); Mahoney (2021); Public Affairs (2021); Rhodes-Conway (2020); Wilensky (2018).

[2]School climate is a broad concept I discuss in detail in section 2.

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 socioeconomic backgrounds across neighborhoods. I leverage a plausibly exogenous shock of school climate information that took place in the Chicago Public Schools (CPS) district in fall of 2011. This climate information was based on surveys administered to students and teachers in the spring of 2011, which were then summarized into school climate reports. Before 2011, these biennial reports were privately provided to school administrators for internal use but were not released to the public (Levenstein, 2016). 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 executed home mortgage applications data that contain information on homebuyers' backgrounds. The breadth and depth of these two datasets combined allow me to investigate differential effects of school climate information on new homebuyers by socioeconomic 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 were only weakly correlated with school proficiency rates, poverty levels, and value-added rates. Additionally, they were difficult to predict based on these and other already public information. Furthermore, they were not positively capitalized into house prices before the information shock. 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.

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. After the information release, house prices zoned to a school with a one-level-higher climate rating experienced a 2% increase in sales prices, but this effect dissipates after six months. 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. Furthermore, I show that the effects differed on each side of the distribution. When focusing on average- and better-climate school zones, I show that there was a short-term statistically significant 6% increase in sales prices for homes zoned to a one-level-higher climate rating. On the other hand, I find smaller, and not statistically significant, impacts for homes in school zones with average or worse climate ratings. This finding is consistent with studies that find non-linear impacts of school quality on property values (Bibler and Billings, 2019; Ries and Somerville, 2010).

Additionally, I show that for the average or better climate ratings, there was a 7% to 8% increase in the average income of new homebuyers moving into school zones with a one-level-higher climate rating in the first two months after the information shock. There was no significant change overall nor in the school zones rated average or worse. These results suggest that higher-income homebuyers value and are able to quickly react to the best school climate ratings when the information is made available and salient.

Overall, my results indicate that releasing school climate ratings has short-term positive impacts on property values and that better ratings attract higher-income homebuyers. The effects dissipate by the sixth month after the information shock. I explore two main potential mechanisms: homebuyers may value school climate information only when it is highly salient and easily accessible, and homebuyers see unique value in school climate quality beyond it being just any quantitative measure.

The first potential mechanism for the short-term effects could be that homebuyers value school climate information when it is highly salient. Thus, 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. 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 (September through November), which return to pre-shock levels soon thereafter.

Another potential mechanism for the short term effects could be that homebuyers reacted to the information release as they would to any school quality measure, without caring about the actual school climate quality. Therefore, once the news coverage is over, the housing market effects dissipate. Although this could partially explain the patterns I find, research shows that housing markets do not react to just any school quality information. Prior work has shown short-term home price reactions to information shocks based on schools' average test scores (Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011). On the other hand, an information campaign for school value-added in Los Angeles in April 2011 did not affect the housing market (Imberman and Lovenheim, 2016). These findings suggest that there is something unique about school climate ratings that makes homebuyers value the information, at least more than value-added information.

This paper contributes to several areas of research.[3] It is most closely related to three papers on parental revealed preferences for social-learning conditions.[4] 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.[5] 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 after controlling for school value-added and test scores.

[3]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.

[4]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).

[5]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.

I make several contributions relative to this prior research on parental revealed preferences for social-learning conditions. First, the prior three studies relied on selection-on-observables models that control for observed school characteristics to attempt to isolate parental preferences for school social conditions (Gibbons and Silva, 2011; Hailey, 2020; Jacob and Lefgren, 2007). However, school climate may be correlated with unobserved school factors, which would impede researchers from reliably distinguishing between families preferring better school climate over other correlated school factors. I provide the first causal evidence of whether and how much families value the social-learning conditions experienced by students in schools. I use a plausibly exogenous shock of new information that increased the salience of information about school climate quality across CPS. 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 preferences for other school characteristics.

Second, past relevant studies have relied on measures that are only observable to the researcher (Gibbons and Silva, 2011; Jacob and Lefgren, 2007).[6] In those cases, families may not be able to easily compare a school's social conditions relative to those in other schools. Under this imperfect information, families may not be able to fully express their preferences. Research in psychology and behavioral economics argues that stakeholders use heuristics, or cognitive shortcuts, to make reasonable decisions (Kahneman, 2003). While families may have prior beliefs about a school's climate, providing them with heuristics, such as salient and direct quantitative measures of school quality, can help them easily and reliably compare schools across the district to express their preferences. I contribute to the literature by investigating families' revealed preferences for publicly available measures of school social and learning conditions.

Third, each of the three prior studies on the revealed preference for school social conditions have relied on singular dimensions of school climate, focusing on student satisfaction, student happiness, or school safety (Gibbons and Silva, 2011; Hailey, 2020; Jacob and Lefgren, 2007). Comparatively, I provide the first evidence of parental revealed preferences for a multidimensional measure of school social conditions. The composite measure of school climate used in Chicago quantifies a more complete picture of the social-learning conditions experienced by students. Furthermore, most studies on the revealed preference for school social conditions have relied on measures based on few respondents to a few survey questions. 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. I contribute to this literature by using a more reliable and consistent

[6]One exception to this is Hailey (2020), who uses publicly available measures of school safety.

measure of the social-learning conditions experienced by students to compare schools. These 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.

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

My findings offer evidence that families value school climate quality, leading to potential policy implications. Schools and school districts may want to promote and increase the salience of school climate quality information in order to attract more families. However, because climate ratings can affect house prices and attract higher-income 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 by having students, teachers, families, and principals choose and implement school climate interventions. 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 and this way improve school climate (Gonzalez et al., 2020).

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).[7] 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). 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,

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

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 improving 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).[8] 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.[9]

The ambitious instruction component is made up of subcomponents that measure students' perceived course clarity, course instruction, and quality of student discussions. The

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

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

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' perceived trust with other teachers. 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).[10] 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.[11] The *Five 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 green), 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 the school climate components and sub-components to principals and district administrators each year in the late summer to early

[10]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.

[11]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.

fall after the survey was administered. Historically, principals were not obligated to share these reports with staff or parents (Chicago Tribune, 2011; Levenstein, 2016).[12] 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 community groups, to access them for the first time. The reports were presented through an online database and could be accessed without charge or registration.[13] 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 public schools nearest them 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 **??** outlines the timing of the school climate surveys and their initial public release.

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. Figure 1 shows a sample school climate report from the database website. 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, CPS families received a physical two-sided school progress report card. [14] 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.[15]

Additionally, Chicago news outlets covered the initial online database release in September and the physical school progress report cards distribution in November. These included

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

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

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

[15]For high schools, these also contained high school test score averages, growth, and graduation rates.

large media outlets in the city, such as the Chicago Sun-Times and CBS Chicago.[16]

Google searches for school climate information increased around the information release. Figure 2 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.[17] 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, 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.

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 (CPS, 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

[16]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.

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

school climate component scores from the CPS progress report cards following the steps detailed in section 2.2.

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.[18] Consequently, of this, I exclude middle schools from my main analysis. Furthermore, my main analysis excludes high schools because about 70% of first-time ninth graders 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

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

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 year loan amount, Census tract, and lender's name.[19] 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.

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 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.[20] 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.

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

[20] I categorize drug-related crimes as those based on liquor law violations, narcotics, or other narcotic violation. 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.

3.5 Summary Statistics

I present summary statistics of some key variables between September 2009 and August 2011 (pre-shock period) in Table 1. The table displays averages and standard deviations for the overall sample, as well for the sample with average or worse climate ratings, and the sample with average or better ratings. Overall, the average home in Chicago sold for about \$200,000, with an average homebuyer income of about \$74,000 and 31% of these transactions having both homebuyers being white. Furthermore, the average home was zoned to a neighborhood school with below average proficiency rates and about average value-added score, and which are majority non-white and majority FRPL. Homes in the overall sample were located in neighborhoods with an average median household income of \$48,000.

The second and third columns show that school climate ratings are correlated with higher sales prices, homebuyer incomes, white homebuyers. On average, homes in better-climate school zones sold for about \$27,500 more than homes in worse-climate school zones, but the difference in homebuyer income was only about \$7,500. Better school climate ratings also had higher proficiency and value-added rates, more white students, fewer FRPL-eligible students, and lower school crime rates than worse climate school zones. Additionally, on average, properties in better-climate school zones were in neighborhoods with higher median household incomes, slightly more condominiums, and lower crime rates.

4 Did School Climate Ratings Provide New Information?

Before discussing the effects of publicly releasing school climate information in Chicago, it is important to describe how new and unexpected school climate ratings were before the information shock relative to other school characteristics. 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 the ratings were not positively capitalized into house prices before the information release.

4.1 Was school climate predictable before the information release?

First, 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 rate is negatively correlated with school proficiency rates (correlation coefficient of -0.69). Suggesting that if stakeholders found a school with higher rates of low-income students, it is likely that school would have low proficiency rates. 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 suggests that schools with higher-rates of low-income students and lower-proficiency rates are not substantially more likely to have a bad school climate rating. This is in line with a recent pilot study of school climate measures in a mid-sized urban district in Massachusetts (Gagnon and Schneider, 2019). These correlations can be seen graphically in figure 3. 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.[21] 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 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, which 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 right map in figure 3 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 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. This allows 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.[22] Columns (1) and (2) show that school proficiency rates and FRPL-rates are highly

[21] 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.

[22] I use the following school characteristics as predictors in the models: school standardized proficiency rate (except in column 1); % Asian, % Black, % Hispanic, % White, % 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 proficiency rates.

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 that found by Imberman and Lovenheim (2016). Columns (4) through (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 use two very 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, and 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 by one school and the other is served by a different school.[23] Due to the close proximity of the properties being compared in the latter model, this model may be better able to control for unobservable neighborhood characteristics, compared to the prior 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 house to school assignments. Nevertheless, I show that neighborhood school proficiency rates significantly and positively capitalized into house prices,

All models except for % FRPL outcome model control for % FRPL. To make fair comparisons, columns models estimating FRPL, proficiency, or VA 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 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.

[23] More specifically, I estimate $Y_{inst} = \alpha_0 + \alpha_1 Quality_s + \Gamma \mathbf{X}_{it} + \mathbf{Z}_{in} + \theta_t + \nu_{s_j,s_k} + \varepsilon_{inst}$, where Y_{ist} is the outcome of interest for property i in school zone s in month-year t, $Quality_s$ represents the measure of school quality of interest at school s based on characteristics from the 2010-2011 school year, $\mathbf{X}_{it}$ 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.

suggesting that if school climate is valued by residents, then this school quality would be capitalized as well.

Table 3 presents simple hedonic regression estimates of the relationship between the school climate rating and house prices. Panel A of the table presents estimates including school zones in CPS with any of the five school climate ratings. Column (1), which only includes property characteristics controls, shows that houses zoned to a standard deviation higher proficiency schools are associated with 24.2% higher sales prices across the district. Most of this value is due to neighborhood characteristics, because, as column (2) shows, the estimated coefficient decreases to a 4.2% premium once I control for Census block-group characteristics. This is supported further by boundary discontinuity models, which compare properties within 0.2 miles from the nearest boundary, as shown in columns (1) and (2) of table 4. In these models the premium is slightly smaller, where a one standard deviation higher proficiency rate is associated with a 2.6% and 3.3% higher sales price. These estimates are similar to those found in the school quality capitalization literature (see Black and Machin (2011)).

In column (3) of Table 3, I add a standardized measure of school value-added to the models, which shows that houses assigned to better value-added schools are correlated with 4.1% lower sales prices (statistically significant at the 1% level). The boundary discontinuity model estimates a similar relationship. The strong preference for schools with higher average test scores and the non-positive value-added capitalization is in line with the value-added capitalization literature (Brasington, 1999; Brasington and Haurin, 2006; Downes and Zabel, 2002; Hayes and Taylor, 1996; Imberman and Lovenheim, 2016). Although, Gibbons et al. (2013) and Yinger (2015) find that school test scores and value-added are similarly valued in their contexts.

Column (4) of Table 3 adds the climate rating measure into the model to test whether school climate ratings were capitalized into house prices before any school climate information was publicly available. On average, controlling for house, neighborhood, and school characteristics, houses zoned to what would be assigned a one-level-higher climate rating school were associated with 0.5% lower prices in the simple hedonic models. The boundary disconuity model estimates 1.8% lower prices (column 4 of Table 4).

Panel B of Tables 3 and 4 focuses on school zones with better-climate ratings (yellow to green ratings), while panel C focuses on school zones with worse climate ratings (red to yellow ratings). For both of these subsamples the relationships between proficiency and value-added rates with house prices are the same as the overall sample, but the climate effect is more nuanced. In school zones with better-climate ratings, there is a near zero relationship between the climate rating and house prices. On the other hand, I find that in school zones with the worse-climate ratings there was a negative, but not statistically significant, relationship between climate ratings and house prices. In all three panels, adding school climate to the regression models does not significantly change the coefficients for proficiency or value-added rates. This suggests that school test score capitalization is not driven by school climate, and instead school climate ratings provide their own separate aspect of school quality that is different from proficiency rates.

This pre-shock analysis provides evidence that traditional school quality measures are capitalized into Chicago's housing market at similar rates to those found in the literature. Furthermore, both the simple hedonic model and the boundary discontinuity model, and all three samples, show that the initial school climate ratings were not positively capitalized into house prices in the period before the school climate information shock.

5 Identification Strategy

Having provided evidence that the original school climate ratings released by CPS provided information about a different aspect of schools that was not well captured by traditional school characteristics, were not easily predictable, and were not positively capitalized in the housing market, 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' income using two versions of a difference-in-differences (DID) framework: DID with school zone fixed effects and DID with school zone and boundary fixed effects, which I describe in the following subsections.

5.1 DID approach with school zone fixed effects

I first employ a dynamic DID approach that compares the cross-sectional relationship between climate ratings and housing market outcomes in the pre-period before climate ratings were publicly available, to the relationship in each quarter of the post-period. This means that I am measuring the net change in the relationship surrounding the release of the information. For this analysis, I estimate regressions of the following form:

$$Y_{inst} = \alpha_0 + \sum_{q=1}^{4} \Big(\alpha_q Climate_s * 1(Qtr_t = q) \Big) + \Phi \mathbf{W}_{st} + \Gamma \mathbf{X}_{it} + \Lambda \mathbf{Z}_{in} + \theta_t + \mu_s + \varepsilon_{inst}, \quad (1)$$

where Y_{ist} is the outcome of interest for property i in neighborhood n in school zone s in month-year t. The key variable of interest, $Climate_s$, represents the climate rating that will be assigned to school s starting in September 2011. By including a single climate measure, I impose a linear in means assumption for climate rating effects. Instead of measuring specific effects for each individual climate rating difference, I measure the average difference between each climate rating. To rely less on this assumption, I also separate my analysis to better- (ratings 3, 4, 5) and worse- (ratings 1, 2, 3) climate schools to allow there to be different effects for a one-level-higher climate rating on each side of the scale. This parameterization also allows for more statistical power and is less demanding of the data.

The model allows for semi-parametric school climate effects in each quarter of the post-shock school year by interacting the climate rating 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 first post-shock quarter (September through November 2011) encapsulates the main school climate information campaign that included news media coverage, although the climate reports remained publicly available online afterwards. To my knowledge, CPS and local news media did not actively promote climate information for the rest of the school-year after November, although administering the spring 2012 climate surveys could have indirectly nudged parents to seek out the information in the second quarter 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 housing prices that are experienced across the school district, including seasonal changes. Additionally, I include school fixed effects, μ_s, which control for time-invariant school quality differences. The school fixed effect accounts for any school climate information that may have been privately known by residents before the public information release. The inclusion of both month-year and school fixed-effects means the estimates are identified off of within-school changes in outcomes before and after the climate ratings information shock.

The α_q coefficients represent the semi-parametric DID estimates of the impact of having a one-level better climate rating on the outcome of interest in quarter q after the information release, relative to before the release. Specifically, α_1 represents the impact of having the fully active information campaign in the first quarter, while α_4 represents the shock effect four quarters after the information campaign. Additionally, I cluster the 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 that would capture the existing conditions attached to a property that homebuyers would be aware of. I include a vector of school-year specific school characteristics, $\mathbf{W}_{st}$. This 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, bathrooms, square feet, age, distance to downtown, and an indicator for condominium. 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 between for each property characteristics between condominiums and non-condominiums.[24] I include a vector of neighborhood-specific characteristics, $\mathbf{Z}_{in}$, which includes racial composition, levels of education, age composition, median income levels, and crime rates.[25]

There are two main assumptions underlying this DID approach. The first is that there are no differential pre-release trends in outcomes that vary by school climate. I test this assumption by conducting event study analyses that explore the school climate effect on the housing market in each of the 12 two-month periods before the information release and in the six two-month periods after.[26] These models are based on regressions of the following form:

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

where the variables are the same as in the equation above; however, the γ_t coefficients represent the relationship between school climate ratings and the outcome of interest 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 γ_t represents the school climate effect in period t, relative to the average relationship in the pre-shock period.[27] Moreover, constrained regressions allow my coefficients to be more directly comparable to the DID estimates.

In addition to the parallel trends assumption, the validity of my results require that there are no contemporaneous unobservable shocks on the outcomes of interest that are correlated with the initial school climate ratings. 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 (Levenstein,

[24] In the robustness tests section, 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.

[26] I do this at the two-month period because the data is very noisy at the monthly level, but the results are qualitatively similar.

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

2016) that may affect the housing market.

5.2 DID approach with school and boundary fixed effects

In order to rely less on the assumptions in models (1), I employ DID models with boundary fixed effects. These models are based on the following regression:

$$Y_{inst} = \alpha_0 + \sum_{q=1}^{4} \Big(\alpha_q Climate_s * 1(Qtr_t = q)\Big) + \Phi \mathbf{W}_{st} + \Gamma \mathbf{X}_{it} + \Lambda \mathbf{Z}_{in} + \theta_t + \mu_s + \nu_{s_j,s_k} + \varepsilon_{inst}, \quad (3)$$

where variables are defined as in equation 1. In this specification, I include boundary fixed effects, ν_{s_j,s_k}. These boundary fixed effects represent streets that separate houses at 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 link property transactions to their nearest boundary within 0.2 miles. The inclusion of both month-year and boundary fixed-effects means the estimates are identified off of changes in the difference in outcomes across boundary lines surrounding the information release. The identifying assumptions in this model are the same as in model (1), but the close proximity of the properties being compared makes the assumptions more likely to hold. The outcomes for properties that are so close to each other are likely to trend similarly. Moreover, 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.

6 Results

Having provided evidence that the school climate ratings were not easily predictable and were not positively capitalized into housing prices before the information release, I now turn to my key findings regarding the effects of a school climate information shock on housing prices and on average homebuyer income. In each subsection, I present non-parametric event studies, as well as parametric difference-in-difference estimates.

6.1 School Climate Information Shock Effects on Housing Values

Figure 4 presents event study estimates, based on equation 2, of the relationship between school climate ratings and the log sales prices in each two-month relative time period. The solid bold lines represent the coefficients from the event study models in each relative time two-month period, while the dotted lines represent the 95% confidence intervals. The estimates in all six event studies are fairly noisy, as would be expected from such a data intensive estimation, but house prices are relatively flat as a function of future school climate ratings before the information is publicly released. This suggests that there is no evidence of differential pre-trends that would bias the estimates.

Panels (a) and (b) present estimates of the overall relationship between school climate ratings and log sales prices based on the school zone fixed effects model or the school and boundary fixed effects model, respectively. In each figure, there is a slight break in trend in the first two-month period when the school climate ratings were first released. The effect in the first three two-month periods is positive and sustained relative to the pre-shock average estimates, although not statistically significant. The effect dissipates and returns to normal levels by the fourth two-month period after the information release.

Table 5 represents analogous semi-parametric estimates based on DID models from equations 1 and 3. The first two columns include all school zones in the district, the second pair of columns represent estimates focusing on the sample of transactions in the better climate attendance zones (ratings 3, 4, and 5), and the third pair of columns represent estimates based on the sample of transactions in worse climate zones (ratings 1, 2, and 3). Estimates in the odd numbered columns are based on the school fixed effects model (equation 1). The estimates in the even numbered columns are based on the school and boundary fixed effects model (equation 3), which limit the sample to properties within 0.2 miles from the nearest school attendance boundary.

The school zone fixed effects model (column 1), based on all schools in the district, estimates a 1.8% increase in home sales prices for a one-level-higher school climate rating in the first quarter after the information shock. Similarly, the school zone and border fixed effects model (column 2) estimates a 2.2% premium for homes on the side of the street with better climate ratings, relative to those on the other side of the street. Both estimates are significant at the 5% level. By the second post-shock quarter, the effect is sustained in the first model and it declines to 1.4% in the second model, but both estimates are noisier than in the first quarter. By the third and fourth post-shock periods, both models estimate effects near zero. This suggests that the difference in home sales prices between school climate ratings returns to levels similar to the difference before the information shock. Similarly, Fiva and Kirkeboen (2011) find that school quality information shock effects on house prices return to pre-publication levels two quarters after a school quality information shock.

Panels (c) and (d) of figure 4 present event studies that focus on the sample of sales transactions in better-climate school zones (ratings 3, 4, and 5). Both event studies show that there is a visually clear break in trend in the first two periods after the information release. In both models, the information shock led to about a 7% sales premium for homes assigned to a one-level-higher school climate rating in the first post-shock period (statistically significant at the 1% level). The estimates return to the pre-shock average by the fourth post-shock period. Columns (3) and (4) of table 5 summarize these findings and shows that house prices rose by about 6% for a one-level-higher climate rating in the first quarter after the information campaign. By the second quarter, the effect declines to 4.6% to 5.5% for a one-level-higher school climate rating, based on the school zone FE model or the school and boundary FE model, respectively. The effects further dissipate to near zero by the third quarter.

Panels (e) and (f) of figure 4 show that there was no break in trend from the information shock in the worse-climate school zones (ratings 1, 2, 3). Columns (5) and (6) of table 5 estimate coefficients of 1.2% to 3.1%, but these have large standard errors relative to the coefficients and are not statistically significant. This suggests that the school climate information shock did not have a significant impact on the relationship between climate ratings and house prices in areas where school climate was negatively capitalized before the information campaign, but had short-term positive impacts on house prices in areas where school climate was positively associated with higher sales prices before the information shock.

The result showing that the school climate information shock led to sales price increases for homes assigned to a one-level-higher school climate rating is consistent with the notion that relative housing demand increases in school zones with better climate rating information. Home prices may increase due to an increased demand that exceeds the supply of houses, or because both the supply and demand of houses in better climate rating school zones increase together.[28] Although I cannot directly observe changes in the supply or demand of houses, I investigate changes in the number of transactions. The number of transactions can be thought of as the quantity of houses where supply meets demand.

To do this, I create a balanced monthly panel of the number of transactions in each school zone during my sample period. Using a Poisson model version of equation 1, where the outcome of interest is the number of school-by-school-year level transactions, including month-by-year and school zone-fixed effects, I find that the information shock did not have an immediate effect on sales counts.[29] Figure 5 shows that the trend was relatively flat across the shock period in each of the three school ratings samples and there is no visible break in trend around the information shock. Table 6 summarizes these results and shows that there

[28]Homeowners may have been more or less willing to place their properties on the market in response to the information shock if they wanted the price premium, or if they wanted to maintain access to the better climate rating zone.

[29]I find similar results using standard OLS regressions with the raw count as the outcome, as well as when using $log(1 + y)$ as the outcome.

were no significant effects on sales counts in the first quarter of the information campaign. The significant positive sales price effects in the first two periods of the information shock were not attached to a change in housing transactions. This suggests that homeowners did not increase the supply of houses on the market, or if they did increase the supply it was at a similar rate to the increase in demand leaving the number of executed transactions steady but leading to the short-term increase in house prices. By the third quarter after the information campaign, there is a 9% increase in sales transactions in zones with a one-level-higher climate rating, but this is only the case in the better-climate school zones (ratings 3, 4, and 5) and it is only statistically significant at the 10% level. This slight change happens at a time when the effects on house prices had already dissipated. One possible interpretation of this is that sales prices returned to pre-shock levels because more properties zoned to better-climate ratings were sold, increasing the supply to meet the demand.

6.2 School Climate Information Shock Effects on Homebuyer Incomes

I now turn to the effects of the school climate information shock on the sorting of homebuyers from different socioeconomic backgrounds. Figure 6 presents event study estimates of the relationship between school climate ratings and homebuyer income over time. The estimates in all six event studies are fairly noisy, as would be expected from such a data intensive estimation, but new homebuyer incomes are relatively flat as a function of future school climate ratings before the information is publicly released. This suggests that there is no evidence of differential pre-trends that would bias the estimates.

Panels (a) and (b) present estimates of the overall relationship between school climate ratings and log homebuyer incomes prices based on the school zone fixed effects model or the school and boundary fixed effects model, respectively. There is no statistically significant break in trend after the information shock takes place, but there is suggestive evidence in the school zone and boundary fixed effects model that there was a slight uptick in the first two months of the information campaign, which dissipates quickly.

Table 7 represents analogous semi-parametric estimates based on DID models. The school zone fixed effects model (column 1) and the zone and boundary fixed effects model (column 2), estimate a 1% to 2% increase in home sales prices for a one-level-higher school climate rating in the first quarter after the information shock, but these estimates are not statistically significant at conventional levels. The estimates are close to zero by the second quarter after the information campaign.

Panels (c) and (d) of figure 6 present event studies that focus on the sample of transactions in better-climate school zones (ratings 3, 4, and 5). Both event studies show that there is a visually clear break in trend in the first period after the information release. The school zone fixed effects model estimates a 9% increase in average homebuyer income in zones with a one-level-higher rating, which is statistically significant at the 1%. Similarly, the school and boundary fixed effects model estimates a 7.5% increase that is statistically significant at the 5% level. In both cases the estimates return to the pre-shock average by the second or third post-shock period. Columns (3) and (4) of table 7 summarize these findings and shows that the average incoming homebuyer income rose by about 5% to 6% for a one-level-higher climate rating in the first quarter after the information campaign, which are statistically significant at the 10% and 5% level, respectively. By the second quarter, the effect declines to 3% to 4% for a one-level-higher school climate rating, but are no longer statistically significant.

Panels (e) and (f) of figure 6 show that there was no break in trend from the information shock in the worse-climate school zones (ratings 1, 2, 3). Columns (5) and (6) of table 7 estimate coefficients of -3% to 1%, but these have large standard errors relative to the coefficients and are not statistically significant. This suggests that the school climate information shock did not have a significant impact on the relationship between climate ratings and average homebuyer income in school zones with the worst climate ratings in the district.

6.3 Heterogeneous Effects

In this subsection, I follow the previous literature and explore heterogeneous effects by school and neighborhood characteristics. Exploring heterogeneity in these ways is important because of the strong link between how families choose schools and neighborhoods, and the interaction between the two.

6.3.1 Heterogeneity by school characteristics

First, Jacob and Lefgren's (2007) choice model of parental preferences for educational inputs suggests that parents only value better climate in schools with lower-poverty levels and those with better academic performance, but is not valued by parents in higher-poverty schools. To examine this, I slightly modify equation 1 to include separate effects for school zones with different levels of student affluence (proxied by non-FRPL rate), and by proficiency and value-added rates. I do this by interacting each post-shock climate score with an indicator for each quintile of the school characteristic of interest.

The top three rows of figure 7 present the first post-shock quarter effects of school climate ratings on house prices by different school characteristics. Although the estimated precision of the effect for each subgroup varies somewhat, the estimates are overall consistent across subgroup, and none are statistically significantly different from each other. On average, when using the sample school zones with any of the five climate ratings, I find that there are varying but positive effects on house prices from a one-level-higher school climate rating across school characteristics. I consistently find positive and statistically significant sales price effects for properties zoned to better climate schools (ratings 3, 4, and 5). On the other hand, the third column shows that in the worse climate school zones (ratings 1, 2, and 3) the effects were noisier and smaller, but the coefficients are generally positive.

The top three rows of figure 8 shows comparable plots when log buyers' income is the outcome of interest. Here I find small positive, but statistically insignificant, effects for the overall sample of transactions zoned to schools with any of the five climate ratings, by affluence of students served, and proficiency and value-added rates. The information shock led to statistically significantly higher-income homebuyers in zones for better-climate schools across school types, but null effects in the worse climate school zones. I find that the houses zoned to better-climate schools (ratings 3, 4, and 5) that have the worse proficiency rates (bottom quintile) experienced an increase in buyer incomes of 11.9% for a one-level-higher climate rating in the first period after the information campaign. This estimate is statistically significantly higher than the estimated 8% effect for comparable schools within the highest proficiency quintile. This difference may suggest that higher-income families are more willing to purchase houses zoned to low-proficiency schools once they know these schools have better climate, relative to places where proficiency rates were already high.

6.3.2 Heterogeneity by historical neighborhood prices

A small but growing literature shows that households are willing to tradeoff neighborhood amenities for access to better quality schools. First, Bergman et al. (2020) show that low-income families who are provided information on apartments' zoned school quality are more likely to search for and move to apartments in school zones with higher performance. Additionally, they estimate that families with more school quality information are willing to trade proximity to downtown in exchange for being zoned to a better performing school. Similarly, Billings et al. (2018) and Cortes and Friedson (2014) find that housing prices increase in lower-price neighborhoods with lower-performing schools once families can strategically access better performing schools due to No Child Left Behind or in order to improve their odds of admissions through the Texas "Top 10% Plan", respectively. Furthermore, Billings et al. (2018) show that higher-income families are willing to gentrify neighborhoods in order to access better quality schools.

To explore heterogeneous school climate information shock effects on the housing market in different neighborhoods, I allow for heterogeneous effects by historical neighborhood prices, which are proxies for neighborhood amenities. I categorize neighborhoods (based on Census block-group) into quintiles based on average house prices in each neighborhood between the 2006-2007 and 2010-2011 school years. Figure A3 shows that the historically cheapest neighborhoods tend to be in the south and west sides of the city. These neighborhoods have been predominantly made up of Black and Latine working-class families. On the other hand, the most expensive neighborhoods in the city tend to be concentrated downtown and in the north side of Chicago, which tend to have higher concentrations of white and higher-income families.

The bottom row of figure 7 displays school climate rating effects in the first quarter of the information campaign in each of the neighborhood price quintiles. Panel (j) shows that the strongest reaction to better climate occurred in neighborhoods in the top price quintile, with an estimated effect of 4%, while the estimated effect was around 1% to 2% in the other four quintiles. The estimated effect in the top price quintile neighborhoods is statistically significantly different (at 10% level) from the estimated effects at the bottom two quintiles. Panel (k) shows that in the better-climate school zones (ratings 3, 4, and 5) the estimated effect is similarly positive and significant in all five neighborhood price quintiles, with the strongest estimated effect being 7.1% in the most expensive neighborhoods and 4.8% in the least expensive neighborhoods. These coefficients are not statistically different form each other. Moreover, in the school zones with the worse climate ratings there were smaller and statistically insignificant effects in response to the climate ratings, but the estimated effect is more positive in more expensive neighborhoods going from a noisy effect of 1% in the cheapest neighborhoods to about 4% in the most expensive neighborhoods.

The buyer income effects do not vary much by historical neighborhood prices. The bottom row of figure 7 shows that across all school climate rating zones the estimated effect on buyer incomes was negligible. Panel (k) shows that the effect was positive and statistically significant in the better-climate school zones (ratings 3, 4, 5), with an estimated effect of 9.7% in the cheapest neighborhoods and an estimated effect of 8.2% in the most expensive neighborhoods. The fact that I find that a one-level-higher school climate rating leads to an 9.7% increase in buyer incomes in the cheapest neighborhoods in the city, suggests that higher-income families are willing to gentrify cheaper neighborhoods in exchange for better school climate quality. This is about half of the effect found by Billings et al (2018) of high-income families' willingness to move into cheaper neighborhoods in order to gain access to better quality schools by opting out through a school choice policy. Furthermore, school climate is a school quality that families are willing to pay for in neighborhoods with the most and least amenities already in place. On the other hand, panel (l) shows that there was a generally null effect across all neighborhoods with the worse climate ratings.

6.4 Robustness Checks

I now test the sensitivity of my main findings by conducting a series of robustness checks. Tables A1 and A2 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; inclusion of controls for main climate effects, property and neighborhood characteristics, neighborhood latent price trend, and school characteristics; inclusion of school border fixed effects; and inclusion of both school fixed effects and border fixed effects. The findings hold overall, as well as separately in both better- and worse-climate school zones.

On potential argument is that house prices were already increasing for what would be rated as better-climate school zones. To test for this, I directly control for pre-trends in the relationship between school climate ratings and house prices or homebuyers' incomes.[30] Table A3 shows that the coefficient on the pre-trend control in each of the columns is consistently near zero and statistically insignificant. Furthermore, these models only slightly affect the estimated coefficients and support the same qualitative conclusions.

In order to identify home transactions that are more likely to be for families with children who are more likely to attend the neighborhood school, I next focus on homes that were not condominiums and had 3 or more bedrooms. Table A5 shows consistent effects on home sales prices, while Table A6 shows consistent overall results on homebuyer incomes. This suggests that properties intended for families react 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. 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 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,

[30] I use a slightly modified version of equation 1, which is specified as follows: $Y_{ist} = \beta_0 + \sum_{q=1}^{4} \Big(\beta_q Climate_s * 1(PostQuarter_t = q) \Big) + \Lambda Climate_s * (t - 5.5) * 1(t < 0) + \Gamma \mathbf{X}_{it} + \theta_t + \mu_s + \varepsilon_{ist}$.

I run models that include proficiency and value-added information shocks that are initiated in November 2011. Tables A7 and A8 show consistent price and income effects over time. This makes sense since the school climate ratings were only weakly correlated with school proficiency and value-added rates.

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 ratings shocks drive my main results, I conduct models that include quarterly effects for the high school climate ratings in my main models. In Tables A9 and **??**, I show that the climate ratings effects for the neighborhood elementary schools are almost identical 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.

I test various specifications that would allow me to identify individual climate ratings effects relative to a reference group, but due to the heavy data demands for estimating dynamic effects for five individual climate ratings effects, I find underpowered noisy estimates. I use three discrete specifications, which I detail in Appendix 8. First, I compare housing market outcomes in school zones that were assigned the yellow (average) climate rating (reference group) to the housing outcomes in school zones with each of the other climate ratings (blue, light blue, orange, and red), before and after the information campaign. A second approach I implement is to compare the housing market outcomes for school zones in CPS that were assigned one of the five school climate ratings to the housing outcomes across suburban school zones, which did not receive school climate ratings information, before and after the information campaign. A third approach is to compare school zones with each of the five climate ratings to suburban school zones that would receive that same climate rating three years later (separate control groups for each of the five treatment groups), but did not receive it in September 2011.[31]

Table A10 presents results from each of these three specifications and shows that transactions zoned to the best climate rating schools experienced an immediate increase in sales prices, those zoned to the second best experienced a small or negligible increase in prices, while the yellow climate ratings experienced a slight decrease in sales prices. This supports my main finding that the net effect in the best climate school zones was a stronger rela-

[31] The Illinois State Board of Education began to publicly release school climate ratings for the majority of public school systems across the state in November 2014. Only about half of public schools received school climate ratings for the 2014-2015 school year, while about 80% received climate ratings for the 2015-2016 school year. I use suburban schools' first publicly available school climate ratings in this subanalysis.

tionship between climate ratings and housing outcomes. On the other hand, in the worse climate school zones, the orange rating had a small negligible effect on house prices, while the red climate rating had a stronger negative effect on house prices. All in all, this helps explain the small net effects that I find in the worse climate ratings school zones, since the yellow and orange climate ratings were not linearly negative.

7 Potential Mechanisms

Overall, my results indicate that releasing school climate ratings has short-term positive impacts on property values, and that better ratings attract higher-income homebuyers. The effects dissipate by the sixth month after the information shock. In this section, I explore two main potential mechanisms: homebuyers may be able to value school climate information only when it is highly salient and easily accessible (low search costs), or homebuyers may react to any school quality information rather than actual concern about school climate quality.

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. One potential mechanism for the immediate—and then dissipating—effects could be that homebuyers value school climate information when it is highly salient, but not when less salient. 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 2) 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 of the 2012 school climate survey was administered.[32] Out these

[32]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

three periods, the largest spike in searches for relevant school climate terms occured 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 the fall 2012 actually 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.

Another potential mechanism for the short term effects could be that homebuyers reacted to the information release as they would to any school quality measure, without caring about the actual school climate quality. Therefore, once the news coverage is over, the housing market effects dissipate. Although this could be a partial explanation, research shows that housing markets do not react to just any school quality information. Prior work has shown short-term home price reactions to information shocks based on schools' average test scores (Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011). On the other hand, an information campaign for school value-added in Los Angeles in April 2011 did not have effects on the housing market (Imberman and Lovenheim, 2016). This suggests that there is something special about school climate ratings that makes homebuyers value the information, at least more than value-added information.

8 Conclusion

Organizations, institutions, and industries are showing a growing interest in the social conditions experienced by stakeholders. For the past decade, the federal government and an increasing number of states and school districts across the US have begun to focus on the social, learning, and working conditions experienced by students, families, and teachers. Despite this trend, causal research on whether or how much various 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, suggesting that good climate quality can be found in historically underperforming and underserved schools. Furthermore, school climate was not strongly or significantly capitalized into housing prices before the

compare.

information was publicly available.

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 socioeconomic 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 a school with a one-level-higher climate rating. 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.

The main effects of school climate information on house prices and new homebuyer incomes are consistent across schools with differing proportions of low-income students, proficiency rates, and value-added. Furthermore, the information shock effects are similar across less- and more-expensive neighborhoods.

The immediate and significant effects, which dissipate soon after, can be due to different mechanisms. I find evidence that the increasing salience of the information from news coverage and district promotion led to an increase in Chicagoans searching for the school climate information online. Concurrently, there was an increase in sales prices and higher-income homebuyers moving into neighborhoods with better-climate schools. As soon as the information campaign ended and the information was no longer salient, searches for the information returned to previous levels and the premium for houses zoned to a better-climate school return to previous levels. This relationship suggests that 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 that were 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 higher-income 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 and this way improve 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. In future work, I plan to explore this question by using migration data to track individuals from 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. 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 impacted. 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 should be careful not to limit access to already underserved students.

References

Abdulkadiroğlu, A., Pathak, P. A., Schellenberg, J., and Walters, C. R. (2020). Do Parents Value School Effectiveness? *American Economic Review*, 110(5):1502–1539.

Altimari, D. (2021). A report finds a pattern of "culture/climate issues with racial undertones" at Manchester Community College. *Hartford Courant*. Section: Politics.

American Economic Association (2019). AEA Member Announcements: Final report on AEA professional climate survey now available.

Association of American Universities (2018). 33 Universities to Participate in AAU Campus Climate Survey on Sexual Assault and Misconduct | Association of American Universities (AAU). Technical report.

Barrow, L. and Sartain, L. (2017). The Expansion of High School Choice in Chicago Public Schools. *Economic Perspectives*, 41(5).

Bayer, P., Ferreira, F., and McMillan, R. (2007). A Unified Framework for Measuring Preferences for Schools and Neighborhoods. *journal of political economy*, page 51.

Bergman, P., Chan, E., and Kapor, A. (2020). Housing Search Frictions: Evidence from Detailed Search Data and a Field Experiment. Technical Report w27209, National Bureau of Economic Research, Cambridge, MA.

Bibler, A. and Billings, S. B. (2019). Win or Lose: Residential Sorting After a School Choice Lottery. *The Review of Economics and Statistics*, pages 1–45.

Billings, S. B. (2019). Technical Summary - Merging Home Mortgage Disclosure Data to Property Records from Zillow (Ztrax) 1995-2016. page 17.

Billings, S. B., Brunner, E. J., and Ross, S. L. (2018). Gentrification and Failing Schools: The Unintended Consequences of School Choice under NCLB. *The Review of Economics and Statistics*, 100(1):65–77.

Black, S. E. (1999). Do Better Schools Matter? Parental Valuation of Elementary Education. *The Quarterly Journal of Economics*, 114(2):577–599.

Black, S. E. and Machin, S. (2011). Chapter 10 - Housing Valuations of School Performance. In Hanushek, E. A., Machin, S., and Woessmann, L., editors, *Handbook of the Economics of Education*, volume 3, pages 485–519. Elsevier.

Borgschulte, M., Molitor, D., and Zou, E. Y. (2020). Air Pollution and the Labor Market: Evidence from Wildfire Smoke. *Working Paper*.

Bradshaw, P., E, W. T., J, D. K., and Lindstrom, J. S. (2014). Measuring School Climate in High Schools: A Focus on Safety, Engagement, and the Environment. *Journal of School Health*, 84(9):593–604.

Brasington, D. (1999). Which measures of school quality does the housing market value? *Journal of Real Estate Research*, page 18.

Brasington, D. and Haurin, D. R. (2006). Educational Outcomes and House Values: A Test of the value added Approach*. *Journal of Regional Science*, 46(2):245–268.

Brown, L. (2021). Los Angeles schools eliminating some police officers for 'school climate coaches'. *New York Post*.

Bruch, E. E. and Mare, R. D. (2012). METHODOLOGICAL ISSUES IN THE ANALYSIS OF RESIDENTIAL PREFERENCES, RESIDENTIAL MOBILITY, AND NEIGHBORHOOD CHANGE. *Sociological methodology*, 42(1):103–154.

Bryk, A. S., Penny, S. B., Allensworth, E., Luppescu, S., and Easton, J. Q. (2010). *Organizing Schools for Improvement: Lessons from Chicago*. The University of Chicago Press, Chicago.

Chicago Reporter (2015). History of Chicago Public Schools.

Chicago Tribune (2011). Engaging parents. *Chicago Tribune*. Editorial.

Cohen, J., McCabe, L., Michelli, N. M., and Pickeral, T. (2008). School Climate: Research, Policy, Practice, and Teacher Education. *Teachers College Record*, pages 180–213.

Cortes, K. E. and Friedson, A. I. (2014). Ranking Up by Moving Out: The Effect of the Texas Top 10% Plan on Property Values. *National Tax Journal*, 67(1):51–76.

CPD (2020). Crimes - 2001 to Present.

CPS (2016a). Chicago Public Schools - Elementary School Attendance Boundaries SY1112.

CPS (2016b). Chicago Public Schools - Middle School Attendance Boundaries SY1112.

Darling-Hammond, L. (2004). Teachers College Record: Standards, Accountability, and School Reform. Technical report, Teachers College Record.

Deryugina, T. and Molitor, D. (2020). Does When You Die Depend on Where You Live? Evidence from Hurricane Katrina. *American Economic Review*, 110(11):3602–3633.

Downes, T. and Zabel, J. (2002). The impact of school characteristics on house prices: Chicago 1987–1991. *Journal of Urban Economics*, 52(1):1–25.

Figlio, D. N. and Lucas, M. E. (2004). What's in a Grade? School Report Cards and the Housing Market. *American Economic Review*, 94(3):591–604.

Fiva, J. H. and Kirkebøen, L. J. (2011). Information Shocks and the Dynamics of the Housing Market. *The Scandinavian Journal of Economics*, 113(3):525–552.

Gagnon, D. J. and Schneider, J. (2019). Holistic School Quality Measurement and the Future of Accountability: Pilot-Test Results. *Educational Policy*, 33(5):734–760.

Gibbons, S., Machin, S., and Silva, O. (2013). Valuing school quality using boundary discontinuities. *Journal of Urban Economics*, 75:15–28.

Gibbons, S. and Silva, O. (2011). School quality, child wellbeing and parents' satisfaction. *Economics of Education Review*, 30(2):312–331.

Gonzalez, G. C., Cerully, J. L., Wang, E. L., Schweig, J., Todd, I., Johnston, W. R., and Schnittka, J. (2020). Social and Emotional Learning, School Climate, and School Safety: A Randomized Controlled Trial Evaluation of Tools for Life® in Elementary and Middle Schools. Technical report, Rand Corporation, Santa Monica, CA.

Goyette, K. (2014). Setting the Context. In Goyette, K. and Lareau, A., editors, *Choosing Homes, Choosing Schools*, pages 1–24. Russell Sage Foundation.

Gruenert, S. (2008). School Culture, School Climate: They are not They are not the same thing. Technical report, National Association of Elementary School Principals.

Hailey, C. (2020). *Choosing Schools, Choosing Safety: The Role of School Safety in School Choice*. PhD thesis, New York University, New York, NY.

Hart, H., Young, C., Chen, A., Zou, A., and Allensworth, E. M. (2020). Supporting School Improvement: Early Findings from a Reexamination of the 5Essentials Survey. Technical report, University of Chicago Consortium on School Research, Chicago, IL.

Harte, J. (2021). Cuomo's successor vows no toxic work climate in New York government. *Reuters*.

Hassan, M. and Geys, B. (2016). What Do We Value Most in Schools? A Study of Preference Rankings of School Attributes. *Social Science Quarterly*, 98(5):1313–1327.

Hastings, J. S. and Weinstein, J. M. (2008). Information, School Choice, and Academic Achievement: Evidence from Two Experiments. *The Quarterly Journal of Economics*, 123(4):1373–1414.

Hayes, K. J. and Taylor, L. L. (1996). Neighborhood School Characteristics: What Signals Quality to Homebuyers? *Federal Reserve Bank of Dallas Economic Review*, page 8.

HMDA (2018). Home Mortgage Disclosure Act (HMDA) Data.

Imberman, S. A. and Lovenheim, M. F. (2016). Does the market value value-added? Evidence from housing prices after a public release of school and teacher value-added. *Journal of Urban Economics*, 91:104–121.

Isaac, M. (2017). Inside Uber's Aggressive, Unrestrained Workplace Culture. *The New York Times*.

Jacob, B. A. and Lefgren, L. (2007). What Do Parents Value in Education? An Empirical Investigation of Parents' Revealed Preferences for Teachers. *The Quarterly Journal of Economics*, 122(4):1603–1637.

Jennings, K. (2011). Welcome to the Safe and Supportive Schools Website.

Jordan, P. and Hamilton, L. (2019). Walking a Fine Line: School Climate Surveys in State ESSA Plans. Technical report, FutureEd - Georgetown University.

Kahneman, D. (2003). Maps of Bounded Rationality: Psychology for Behavioral Economics. *American Economic Review*, 93(5):1449–1475.

Klugman, J., Gordon, M. F., Sebring, P. B., and Sporte, S. E. (2015). A First Look at the 5Essentials in Illinois Schools. page 52.

Kostyo, S., Cardichon, J., and Darling-Hammond, L. (2018). Building a Positive School Climate. Technical report.

Levenstein, R. (2016). 2014 My Voice, My School Survey Quality Profile. Technical Report, UChicago Consortium on School Research, Chicago, IL.

Mahoney, A. (2021). Sierra Club and Sunrise Movement react to criticism for toxic workplace cultures. *Grist*.

Meyer, R. (2013). Value-Added. Technical report, Value-Added Research Center, University of Wisconsin - Madison.

Myers, J. (2008). District 'adds value' to performance policy. *Chicago Reporter*. Section: Catalyst Chicago.

Myers, J. (2009). Value-added scores give mixed view of Chicago school turnarounds. Section: Catalyst Chicago.

National School Climate Council (2007). The School Climate Challenge: Narrowing the Gap Between School Climate Research and School Climate Policy, Practice Guidelines and teacher Education Policy. Technical report.

Parker, J. A. and Souleles, N. S. (2017). Reported Effects vs. Revealed-Preference Estimates: Evidence from the propensity to spend tax rebates. Working Paper 23920, National Bureau of Economic Research. Series: Working Paper Series.

Pope, N. G. (2019). The effect of teacher ratings on teacher performance. *Journal of Public Economics*, 172:84–110.

Public Affairs (2021). Berkeley survey: Campus climate overall is positive, but marginalized still feel excluded. *Berkeley News*.

Rhodes-Conway, S. (2020). Mayor Calls for Action after Survey Results on City Work Culture. *City of Madison, Wisconsin*.

Rich, P. M. and Jennings, J. L. (2015). Choice, Information, and Constrained Options: School Transfers in a Stratified Educational System. *American Sociological Review*, 80(8):1069–1098.

Ries, J. and Somerville, T. (2010). School Quality and Residential Property Values: Evidence from Vancouver Rezoning. *The Review of Economics and Statistics*, 92(4):928–944.

Thapa, A., Cohen, J., Guffey, S., and Higgins-D'Alessandro, A. (2013). A Review of School Climate Research. *Review of Educational Research*, 83(3):357–385.

The Aspen Institute (2021). Creating Conditions for Student Success: A Policymakers' School Climate Playbook. Technical report, The Aspen Institute.

UChicago Impact (2021). 5Essentials.

U.S. Department of Education (2013). Topics & Research: Topics and Research.

U.S. Department of Education (2018). Quick Guide on Making School Climate Improvements. Technical report, Office of Safe and Healthy Students, Washington, DC.

Weininger, E. B. (2014). School Choice in an Urban Setting. In Lareau, A. and Goyette, K., editors, *Choosing Homes, Choosing Schools*, pages 268–294. Russell Sage Foundation.

Wilensky, J. (2018). Presidential Task Force on Campus Climate to survey Ithaca campus. *Cornell Chronicle*.

Yinger, J. (2015). Hedonic markets and sorting equilibria: Bid-function envelopes for public services and neighborhood amenities. *Journal of Urban Economics*, 86:9–25.

Zotti, E. (2020). Confidence in Chicago's public schools is up on the North Side, elsewhere not so much. *Chicago Sun-Times*.

ZTRAX (2020). Zillow's Transaction and Assessment Database (ZTRAX).

Zullig, K. and Matthews, M. R. (2014). School Climate. In Michalos, A. C., editor, *Encyclopedia of Quality of Life and Well-Being Research*, pages 5687–5692. Springer Netherlands, Dordrecht.

Figures

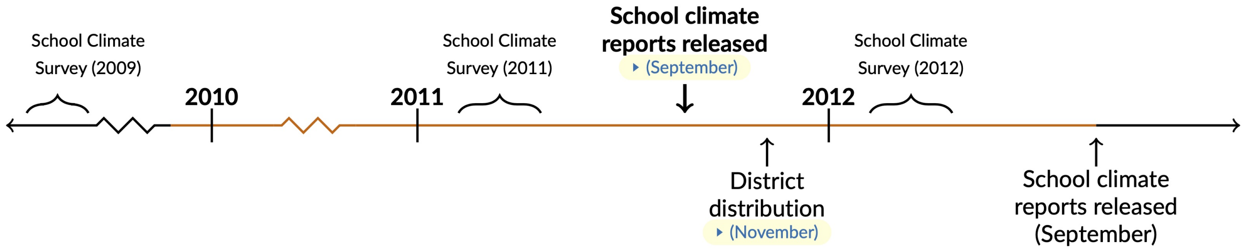

School Climate Survey (2009)
2010
2011
School Climate Survey (2011)
School climate reports released
(September)
2012
School Climate Survey (2012)
District distribution
(November)
School climate reports released (September)

Figure 1: Example of school climate reports website

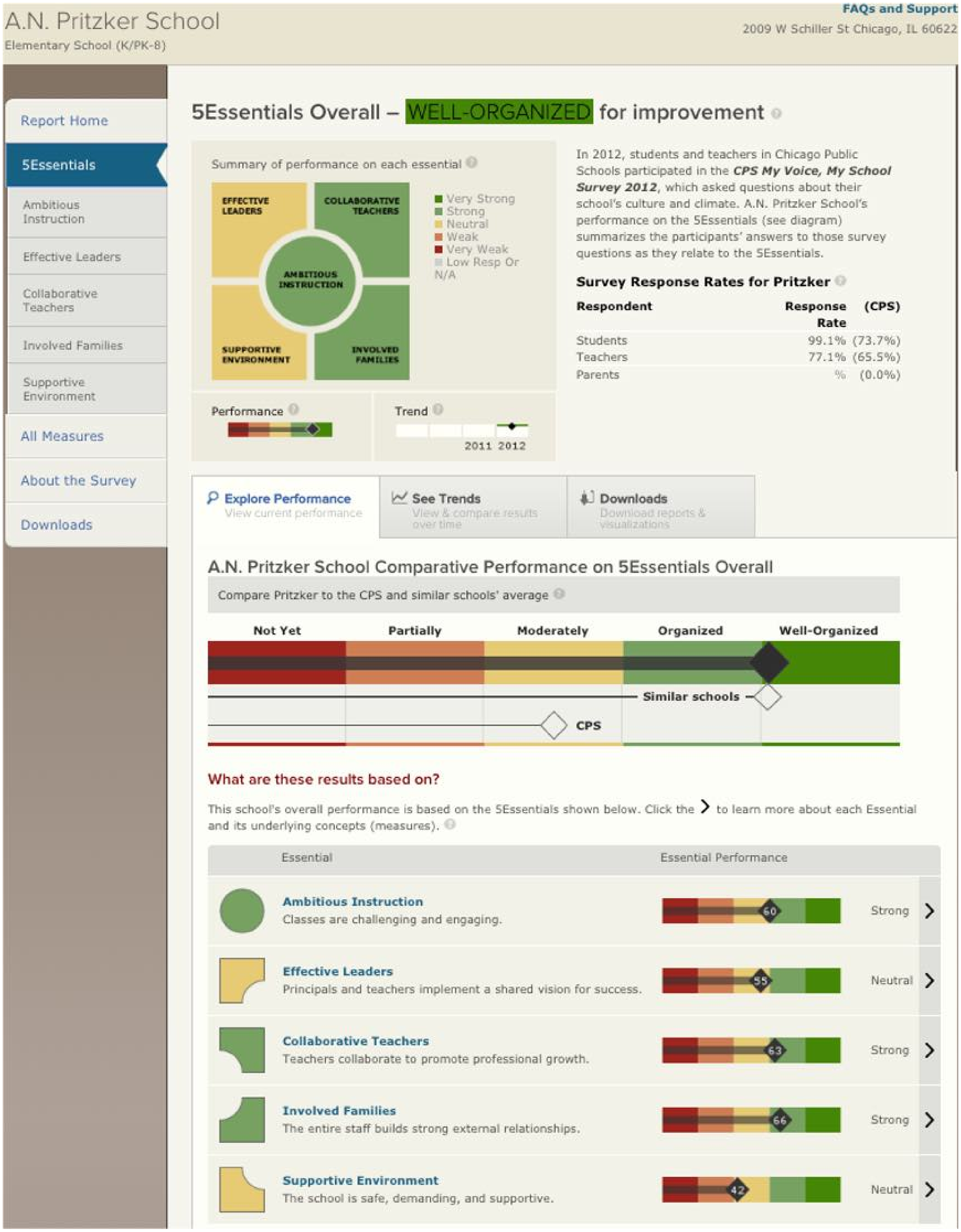
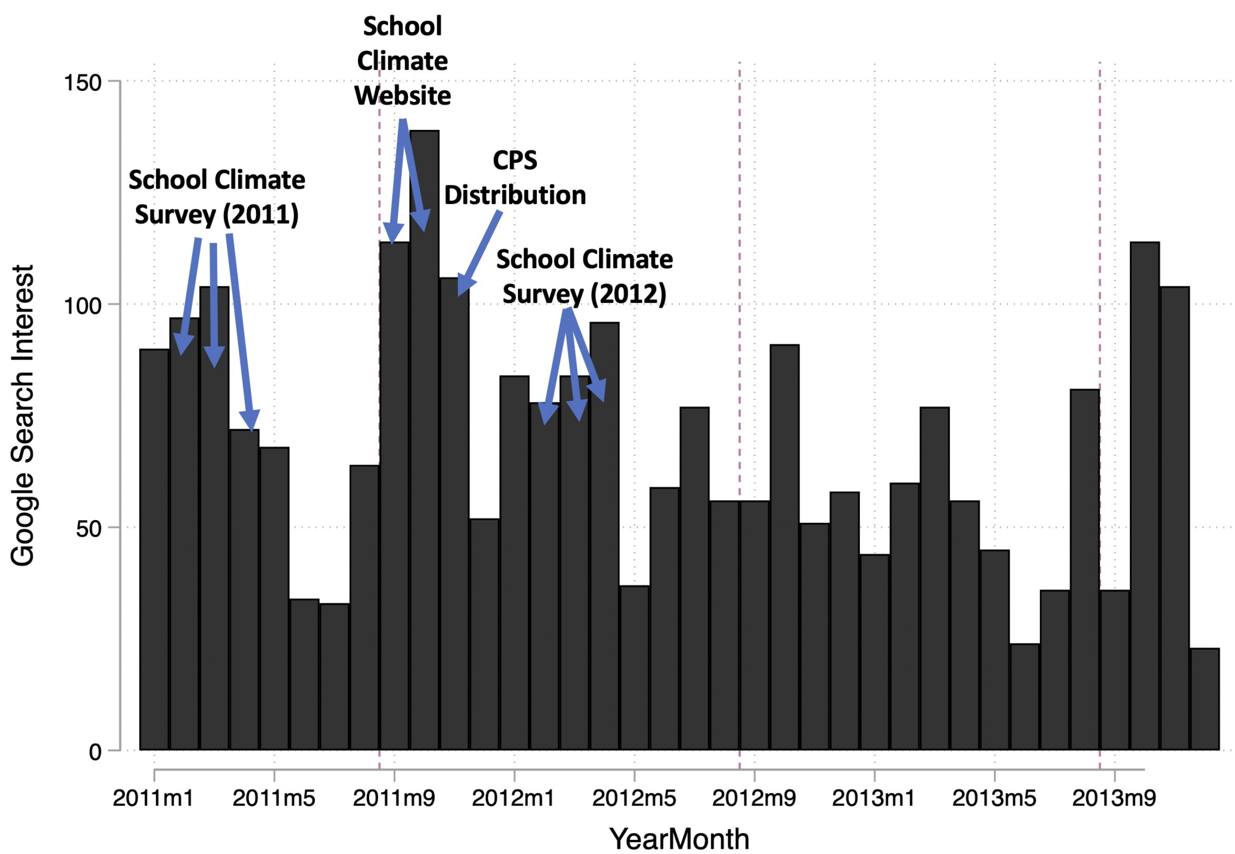
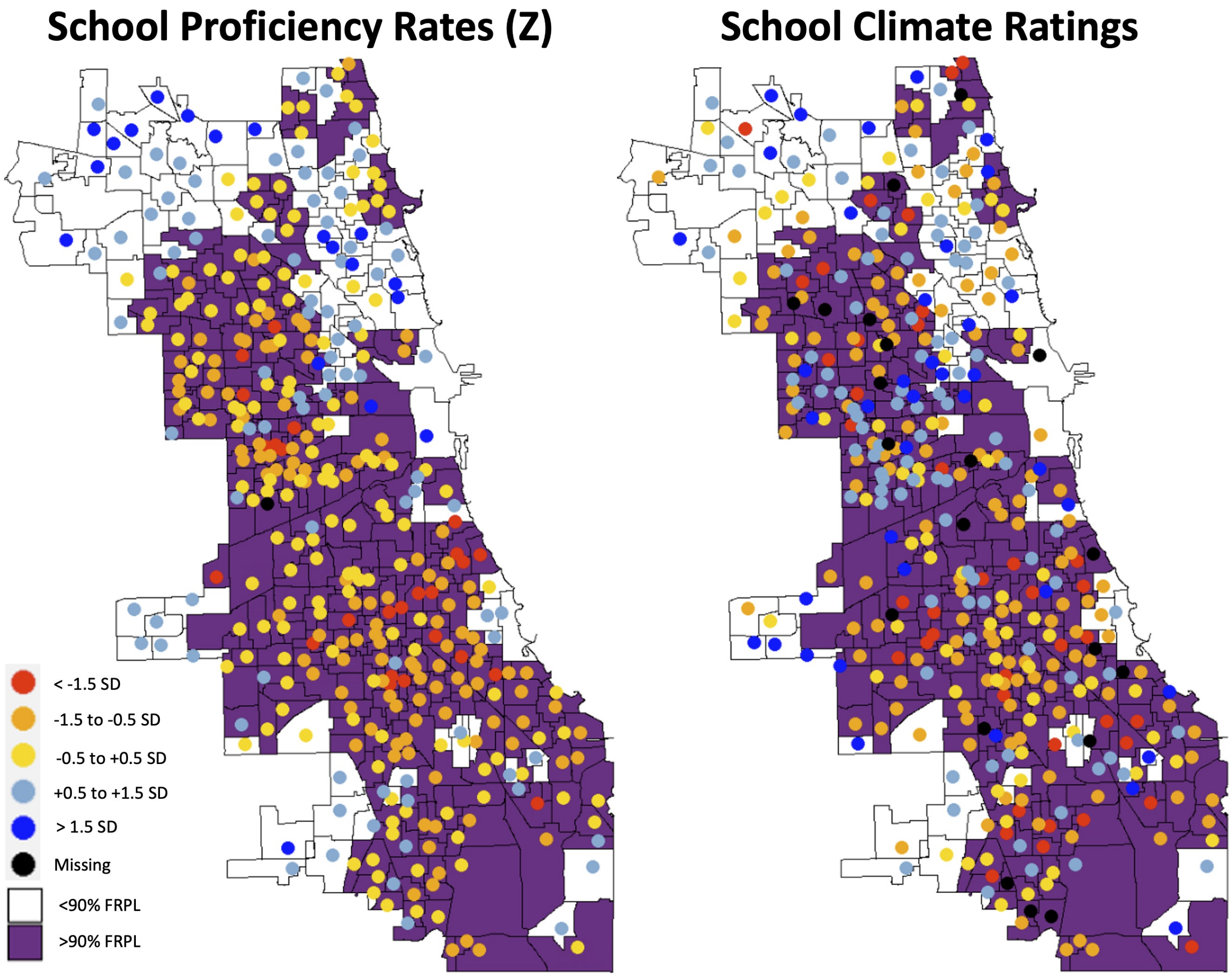


Figure 2: Google Search Trends for School Climate Related Keywords: school climate, school culture, and school environment



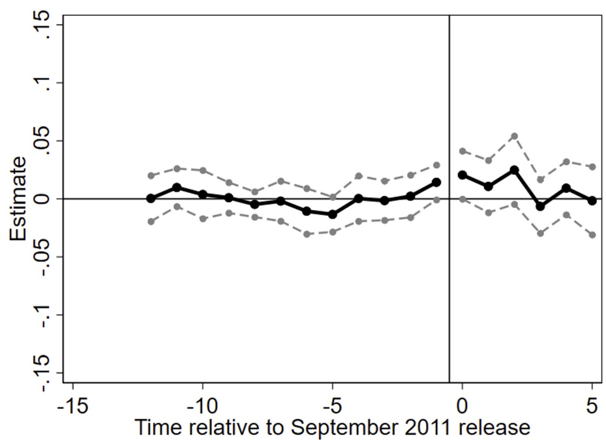
Notes: Google Trends search results based on keywords *school climate*, *school culture*, and *school environment*, for the Chicago, Illinois area between January 1, 2011 and August 1, 2016. The Google Trends website changed geographic definitions in January 1, 2011, making it difficult to compare before 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 3: School proficiency rates (left) and School Climate ratings (right) overlayed on school FRPL rates by school attendance zones

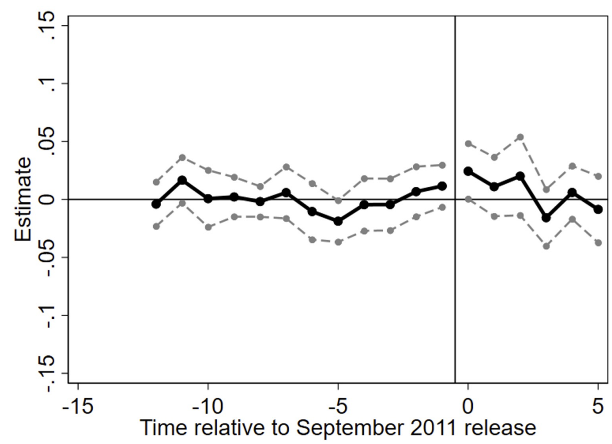


Notes: The purple polygons represent the attendance boundaries for schools serving a population of students that is more than 90% eligible for free-or-reduced-price lunch (FRPL), a measure of student income. The white polygons represent neighborhood schools serving higher-income students. I choose a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

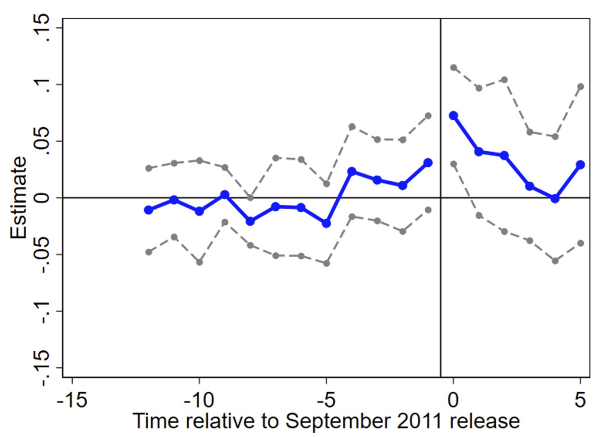
Figure 4: Bi-monthly event study estimates: Log Housing Prices



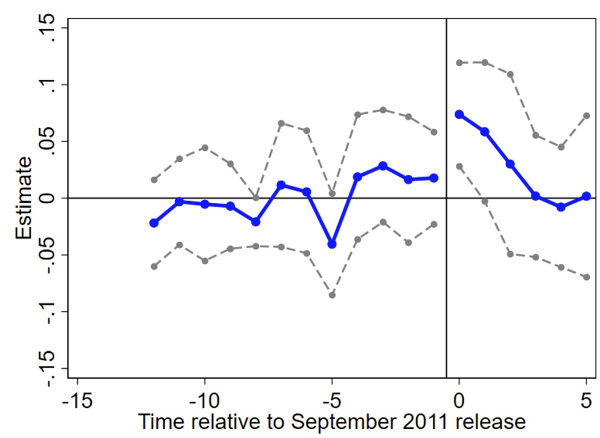
(a) School Zone FE Model, Ratings: All



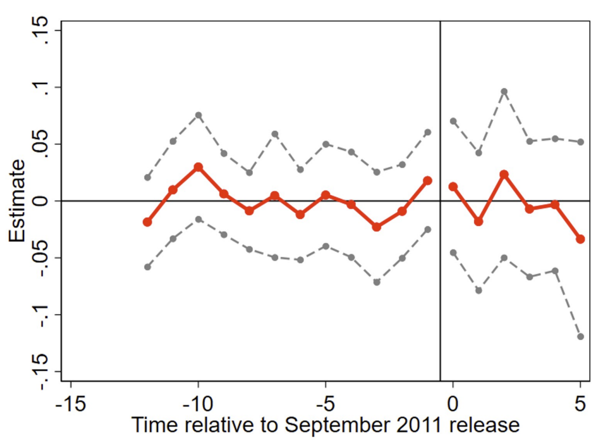
(b) Boundary FE Model, Ratings: All



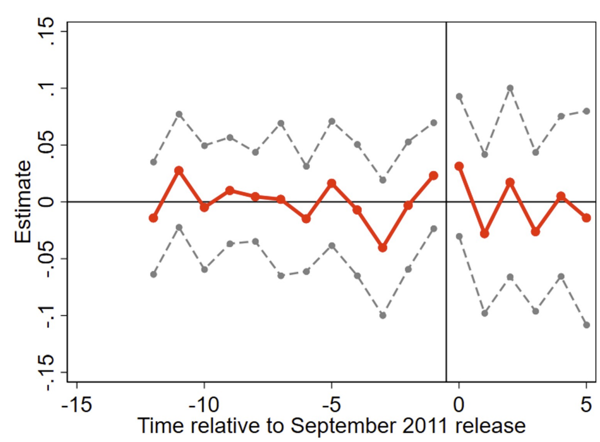
(c) School Zone FE Model, Ratings: 3,4,5



(d) Boundary FE Model, Ratings: 3,4,5



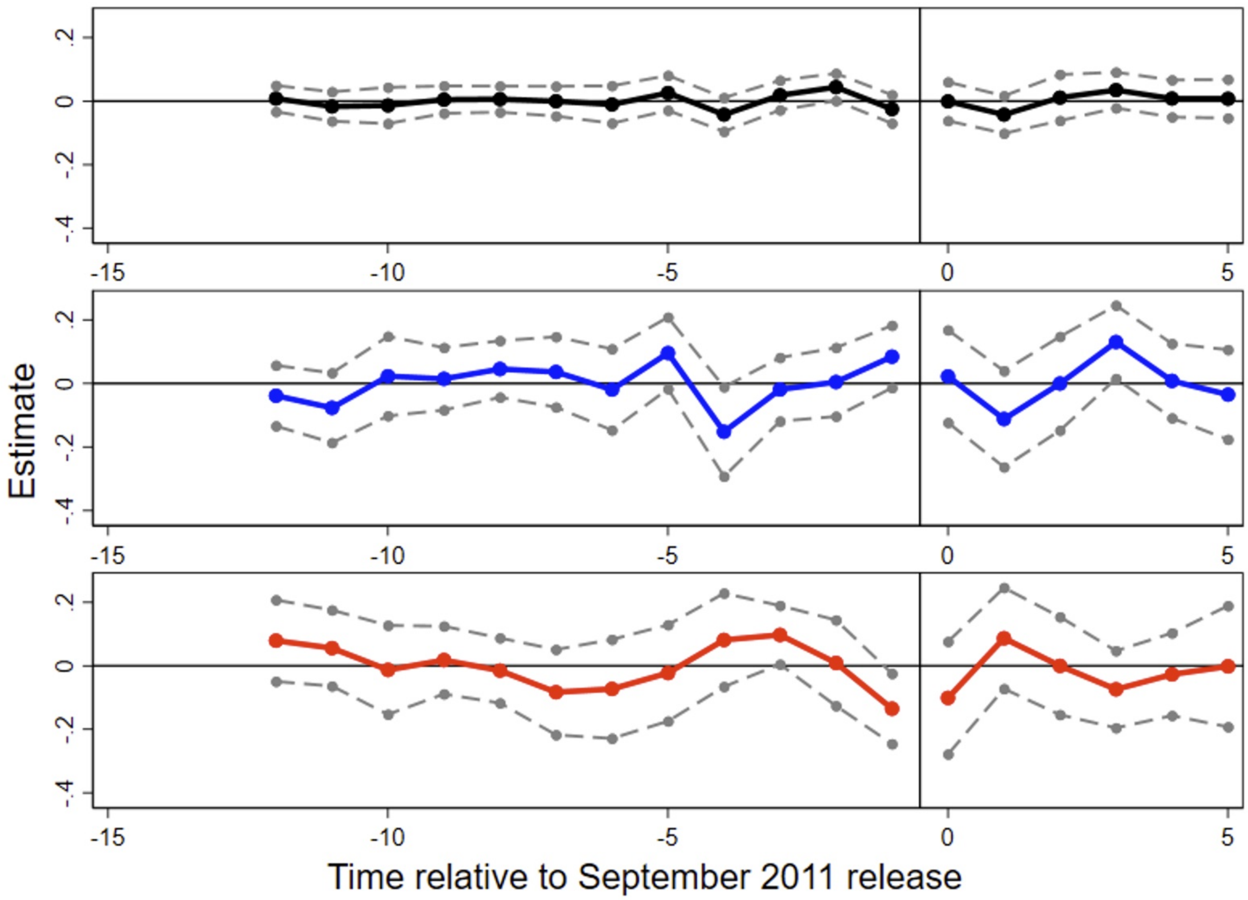
(e) School Zone FE Model, Ratings: 3,4,5



(f) Boundary FE Model, Ratings: 3,4,5

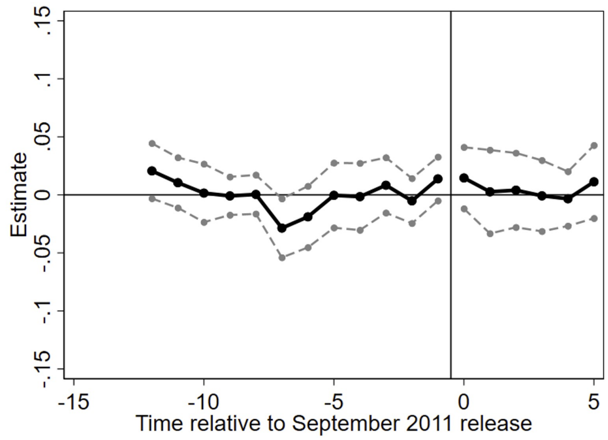
Notes: These event studies are based constrained regressions where the pre-shock coefficients average to zero (refer to equation 2 for details). Constrained regressions allow coefficients to be more directly comparable to DID estimates. Each event study figure is based on a separate regression estimation.

Figure 5: Bi-monthly-level event study estimates: Number of Transactions (using Poisson model)

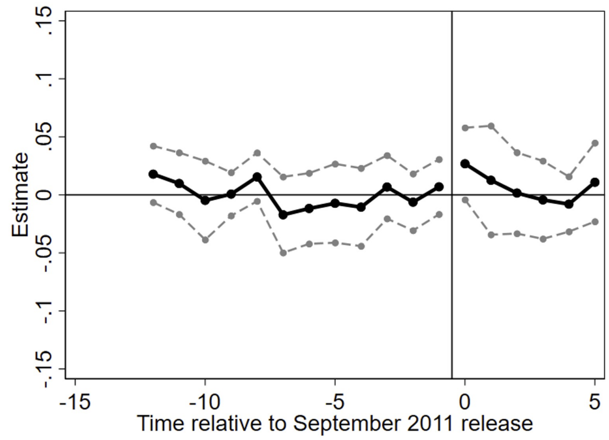


Notes: Estimation is based on Poisson regression models based on equation 1, where the outcome of interest is the number of transactions. Models are based on data at the school-by-year level for the number of transactions. Each figure is a separate regression. Each model includes month-by-year and school 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.

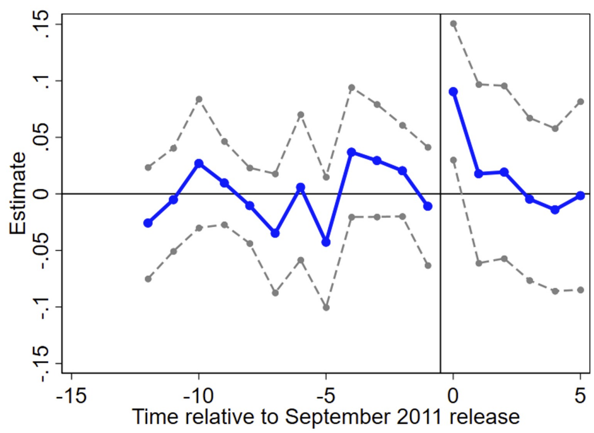
Figure 6: Bi-monthly event study estimates: Log Homebuyer Incomes



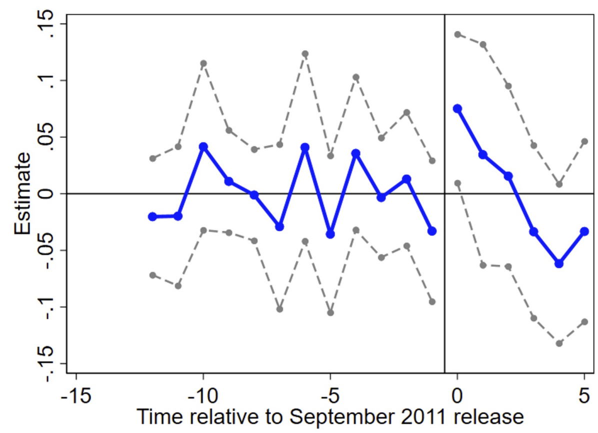
(a) School Zone FE Model, Ratings: All



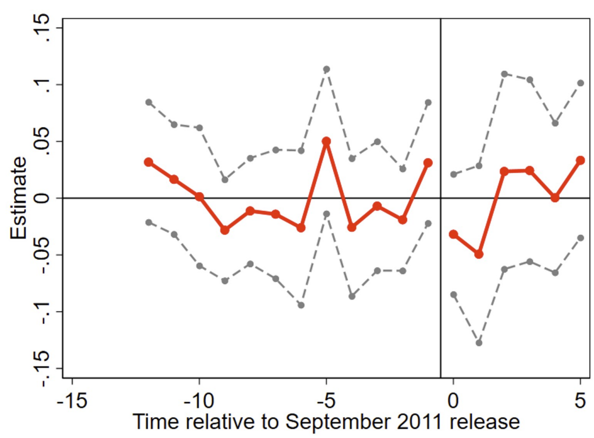
(b) Boundary FE Model, Ratings: All



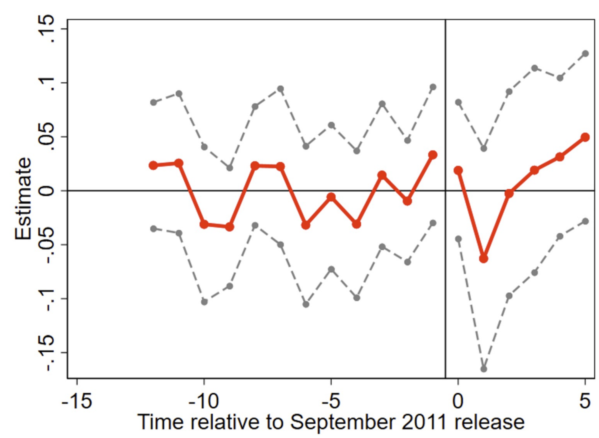
(c) School Zone FE Model, Ratings: 3,4,5



(d) Boundary FE Model, Ratings: 3,4,5



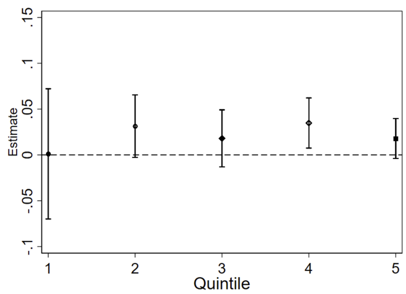
(e) School Zone FE Model, Ratings: 3,4,5



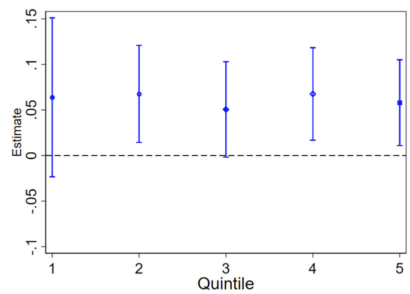
(f) Boundary FE Model, Ratings: 3,4,5

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. Each event study figure is based on a separate regression estimation.

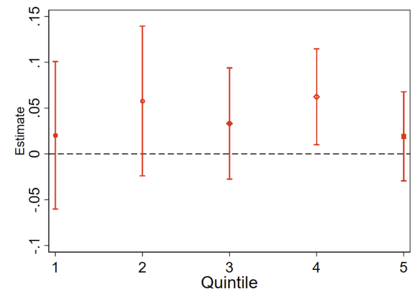
Figure 7: Heterogeneity in estimated effect during first post-shock period: Log Sales Prices



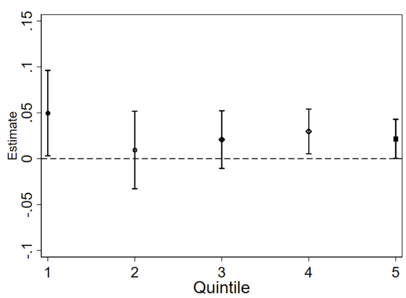
(a) By non-FRPL quintile



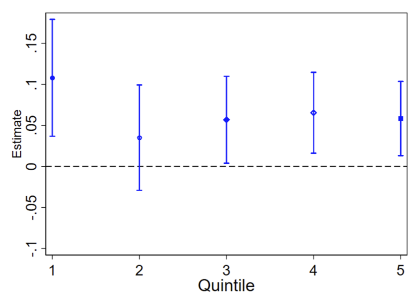
(b) By non-FRPL quintile



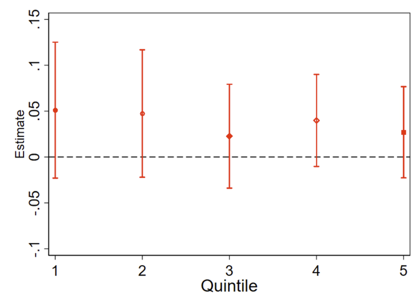
(c) By non-FRPL quintile



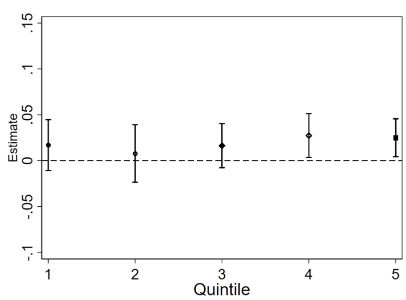
(d) By proficiency quintile



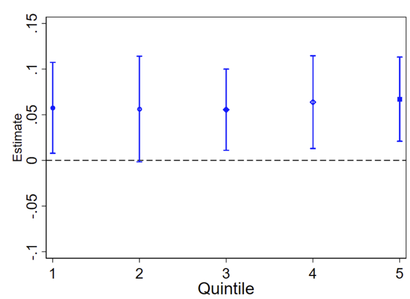
(e) By proficiency quintile



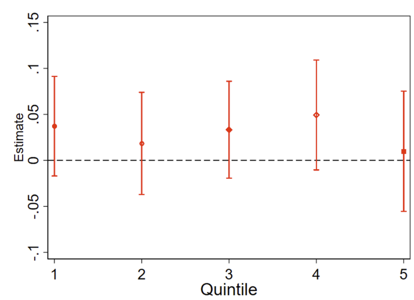
(f) By proficiency quintile



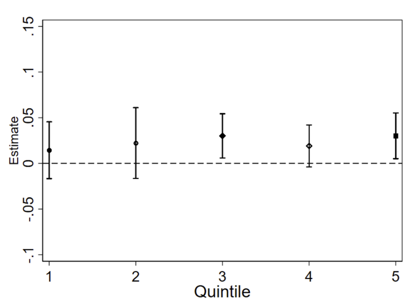
(g) By value-added quintile



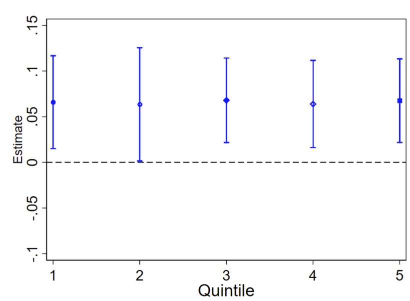
(h) By value-added quintile



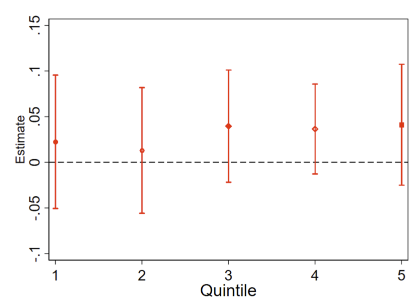
(i) By value-added quintile



(j) By pre-release price quintile



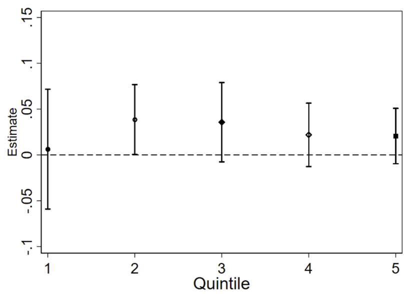
(k) By pre-release price quintile



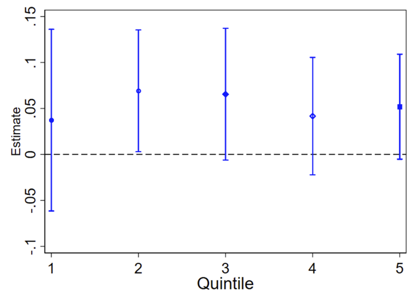
(l) By pre-release price quintile

Notes: These figures are based on estimation of a modified version of equation 2, which includes separate effects for school zones with different levels of student affluence, proficiency, or value-added. This is done bye interacting each post-shock climate score with an indicator for each quintile of the school characteristic of interest. The first column uses the full sample of climate ratings, the second column focuses on school zones with climate ratings 3, 4, and 5, while the third column focuses on school zones with climate ratings 1, 2, and 3. For brevity, only effects for the first post-shock quarter are presented.

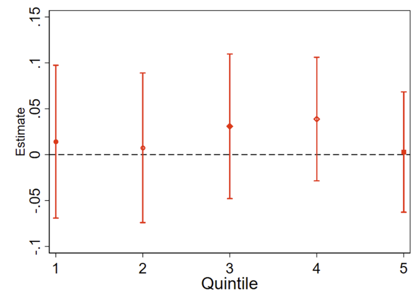
Figure 8: Heterogeneity in estimated effect during first post-shock period: Log Income



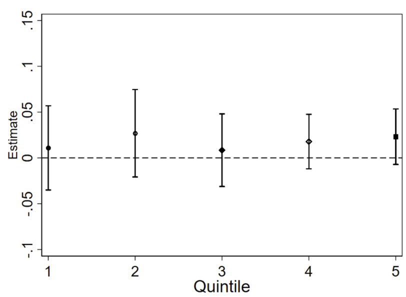
(a) By non-FRPL quintile



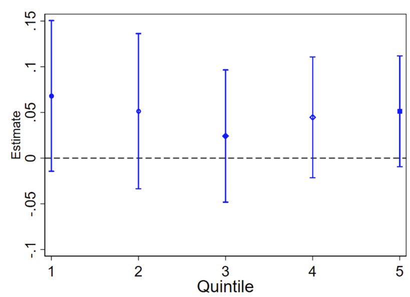
(b) By non-FRPL quintile



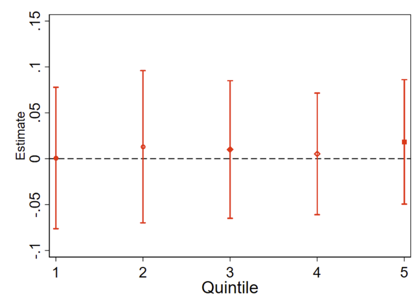
(c) By non-FRPL quintile



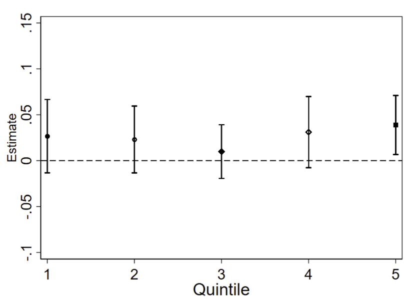
(d) By proficiency quintile



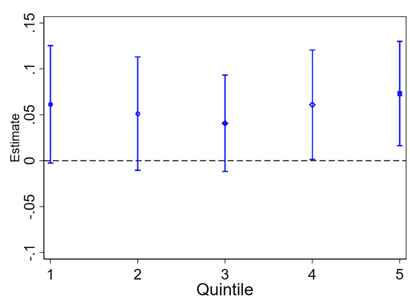
(e) By proficiency quintile



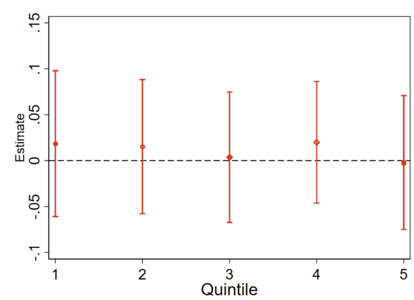
(f) By proficiency quintile



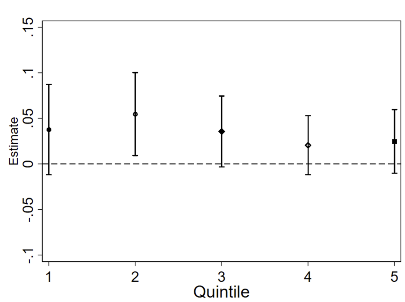
(g) By value-added quintile



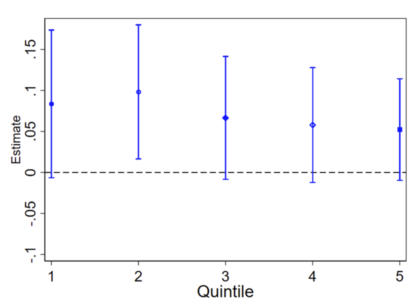
(h) By value-added quintile



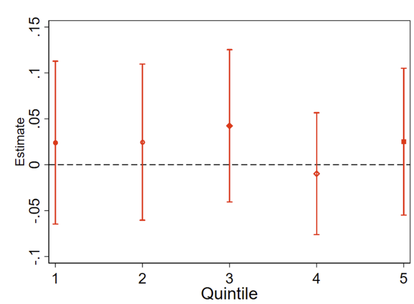
(i) By value-added quintile



(j) By pre-release price quintile



(k) By pre-release price quintile



(l) By pre-release price quintile

Notes: These figures are based on estimation of a modified version of equation 2, which includes separate effects for school zones with different levels of student affluence, proficiency, or value-added. This is done bye interacting each post-shock climate score with an indicator for each quintile of the school characteristic of interest. The first column uses the full sample of climate ratings, the second column focuses on school zones with climate ratings 3, 4, and 5, while the third column focuses on school zones with climate ratings 1, 2, and 3. For brevity, only effects for the first post-shock quarter are presented.

Tables

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

Characteristics	All	Red to Yellow Climate	Yellow to Green Climate
Key regression variables			
Sale price	200,118	183,691	211,265
	(115,627)	(98,617)	(123,566)
Mortgage Income	73.69	68.76	76.24
	(40.60)	(36.28)	(41.80)
Mortgage Both White	0.309	0.262	0.341
	(0.339)	(0.328)	(0.345)
Avg. School Performance			
Proficiency rates (Z)	-0.0567	-0.282	0.190
	(0.942)	(0.873)	(0.915)
Value-Added (Z)	0.00818	-0.146	0.239
	(0.958)	(0.927)	(0.974)
Avg. School Characteristics			
% White	9.302	6.429	12.23
	(17.68)	(14.21)	(20.10)
% FRPL	87.93	91.77	84.08
	(19.73)	(14.14)	(23.32)
Avg 5-yr school crime rate (Z)	-0.015	0.099	-0.099
	(0.855)	(0.897)	(0.838)
Parcels' Census Block-Group Characteristics			
Median HH income	48,102	45,149	50,594
	(20,346)	(17,687)	(21,763)
Avg 5yr property crime rate (Z)	0.026	0.043	0.019
	(0.354)	(0.347)	(0.368)
Avg. Property Characteristics			
Square Feet	1,472	1,423	1,492
	(390)	(397)	(354)
Condo	0.228	0.205	0.236
	(0.325)	(0.316)	(0.332)
N-Observations (pre & post)	16,952	10,352	9,176
N-Schools	335	217	180

Summary statistics are based on pre-shock data (between September 2009 and August 2011). The first column includes the full sample, the second column only includes the sample with average or worse climate ratings (red to yellow ratings), while the third column includes the sample with average or better climate ratings (yellow to green ratings). 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) % FRP-Lunch (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: Robust errors in parentheses. These regressions also include: school standardized proficiency rate (except in column 1); % Asian, % Black, % Hispanic, % White, % 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. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

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

	(1)	(2)	(3)	(4)
Panel A: Include School Zones with All Climate Ratings **1, 2, 3, 4, 5**				
Proficiency Rates (Z)	0.242***	0.042***	0.064***	0.066***
	(0.020)	(0.013)	(0.014)	(0.014)
Value-Added (Z)			-0.041***	-0.039***
			(0.010)	(0.010)
Climate Rating				-0.005
				(0.007)
Observations	12237	12237	12237	12237
Panel B: Properties in School Zones with Climate Ratings ***Yellow to Green***				
Proficiency Rates (Z)	0.258***	0.071***	0.088***	0.091***
	(0.026)	(0.016)	(0.015)	(0.016)
Value-Added (Z)			-0.039***	-0.039***
			(0.013)	(0.013)
Climate Rating				-0.007
				(0.015)
Observations	6605	6605	6605	6605
Panel C: Properties in School Zones with Climate Ratings ***Red to Yellow***				
Proficiency Rates (Z)	0.230***	0.035**	0.053***	0.053***
	(0.025)	(0.016)	(0.017)	(0.017)
Value-Added (Z)			-0.039***	-0.036***
			(0.012)	(0.012)
Climate Rating				-0.017
				(0.017)
Observations	7513	7513	7513	7513
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: School attendance boundary fixed-effect estimates of school climate relationship with log sales price during prerelease period ($\leq$0.2 miles from border)

	(1)	(2)	(3)	(4)
Panel A: Include School Zones with All Climate Ratings ***1, 2, 3, 4, 5***				
Proficiency Rates (Z)	0.033***	0.026***	0.048***	0.058***
	(0.010)	(0.010)	(0.011)	(0.011)
Value-Added (Z)			-0.039***	-0.034***
			(0.007)	(0.007)
Climate Rating				-0.018***
				(0.006)
Observations	9721	9721	9721	9721
Panel B: Properties in School Zones with Climate Ratings ***Yellow to Green***				
Proficiency Rates (Z)	0.040***	0.030**	0.043**	0.043**
	(0.014)	(0.015)	(0.017)	(0.017)
Value-Added (Z)			-0.018	-0.018
			(0.012)	(0.012)
Climate Rating				0.001
				(0.013)
Observations	5305	5305	5305	5305
Panel C: Properties in School Zones with Climate Ratings ***Red to Yellow***				
Proficiency Rates (Z)	0.089***	0.092***	0.098***	0.101***
	(0.024)	(0.025)	(0.025)	(0.025)
Value-Added (Z)			-0.020	-0.014
			(0.014)	(0.013)
Climate Rating				-0.028
				(0.018)
Observations	5847	5847	5847	5847
Housing Characteristics	Y	Y	Y	Y
Block-Group characteristics		Y	Y	Y

Notes: Estimates are based on simple school attendance boundary discontinuity 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 and nearest school boundary FE. Standard errors are clustered at the school level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Table 5: Effect of school climate rating information on log sale prices

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
	All Climate Ratings		Better Climate Ratings		Worse Climate Ratings	
	Zone FE	Border FE	Zone FE	Border FE	Zone FE	Border FE
Climate Rating x PostQ1	0.018**	0.022**	0.058***	0.060***	0.012	0.031
	(0.009)	(0.010)	(0.020)	(0.023)	(0.023)	(0.025)
Climate Rating x PostQ2	0.019*	0.014	0.046*	0.055*	0.001	-0.018
	(0.011)	(0.013)	(0.026)	(0.031)	(0.030)	(0.034)
Climate Rating x PostQ3	-0.002	-0.004	0.010	0.008	-0.006	-0.008
	(0.009)	(0.010)	(0.020)	(0.023)	(0.029)	(0.035)
Climate Rating x PostQ4	0.003	-0.008	0.015	-0.010	-0.020	-0.013
	(0.014)	(0.011)	(0.036)	(0.028)	(0.033)	(0.038)
Observations	16952	13586	9176	7480	10352	8171

Notes: Estimation is based on equations 1 for the odd numbered column models and 3 for the even numbered columns. All models include 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. Standard errors are clustered at the school zone level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table 6: Effect of school climate rating information on number of transactions (based on Poisson model)

Independent variable	(1)	(2)	(3)
	All Climate Ratings	Better Climate Ratings	Worse Climate Ratings
Climate Rating x PostQ1	-0.020	0.005	-0.079
	(0.028)	(0.067)	(0.074)
Climate Rating x PostQ2	-0.005	-0.077	0.078
	(0.030)	(0.070)	(0.075)
Climate Rating x PostQ3	0.022	0.089*	-0.063
	(0.026)	(0.050)	(0.057)
Climate Rating x PostQ4	0.009	-0.031	-0.008
	(0.026)	(0.056)	(0.069)
Observations	12420	6588	8064

Estimates based on poisson regression models at the school-by-year level for the number of transactions. Each column is a separate regression. Each model includes month-by-year and school zone fixed-effects. Standard errors clustered at school zone level.

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-by-year level for the number of transactions. Each column is a separate regression. Each model includes month-by-year and school zone fixed-effects. Standard errors are clustered at the school zone level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table 7: Effect of school climate rating information on log homebuyer incomes

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
	All Climate Ratings		Better Climate Ratings		Worse Climate Ratings	
	Zone FE	Border FE	Zone FE	Border FE	Zone FE	Border FE
Climate Rating x PostQ1	0.012	0.023	0.063**	0.051*	-0.029	0.011
	(0.012)	(0.015)	(0.029)	(0.031)	(0.027)	(0.032)
Climate Rating x PostQ2	-0.001	0.001	0.028	0.041	-0.015	-0.046
	(0.013)	(0.015)	(0.032)	(0.034)	(0.032)	(0.035)
Climate Rating x PostQ3	-0.007	-0.010	-0.015	-0.051	0.013	0.031
	(0.013)	(0.014)	(0.035)	(0.037)	(0.037)	(0.041)
Climate Rating x PostQ4	0.009	0.004	0.004	-0.033	0.022	0.032
	(0.013)	(0.012)	(0.039)	(0.030)	(0.032)	(0.035)
Observations	16952	13586	9176	7480	10352	8171

Notes: Estimation is based on equation 1 for the odd numbered column models and on equation 3 for the even numbered columns. All models include 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. Standard errors are clustered at the school zone level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Appendix A: Further institutional background

School climate reports before September 2011

From 1992 through 2007, CCSR delivered hard copies to principals whose school achieved at least 50% student or 50% teacher response rates.[33] In 2009, CCSR began electronically delivering these same school reports privately to principals. Then in 2011, CCSR changed the format of the reports to be more user-friendly for school leaders and parents. This included substantial changes to the names of the school climate factors, the score calculations, and the amount of information in each page (Levenstein, 2016). Historically, principals had the option but were not obligated to share these reports with their teachers, staff, parents, and/or communities (Chicago Tribune, 2011; Levenstein, 2016).[34]

Response rate requirements to generate school climate ratings

Schools must have at least eight teachers or 10 students to receive a report. They must also achieve a 50% response rate from students and/or 50% response rate from instructional staff to quality for the report. Furthermore, teacher or student data is only used to generate each climate factor if more than 50% of that group responded. This means that if, for example, more than 50% of students responded but less than 50% of teachers responded then four out of the five components in Ambitious Instruction will have scores because they only rely on student responses. But the one component in this climate factor that relies on teacher responses will not be generated due low response. For more information about the components that make up each climate factor, as well as the survey questions used for each component please refer to `https://cps.5-essentials.org/`.

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

[34]Each report included an agreement that if shared with individuals who were not the principal, they would not release the report to others without the principal's permission.

Combining climate component scores to generate an overall school climate rating

The school climate rating is calculated by adding up the school's performance on each individual climate and culture measure. Being strong or very strong on a measure counts as +1, each neutral or missing measure counts as 0, while being weak or very weak counts as -1. The sum of these scores decides how organized the school was deemed to be. Well-organized schools scored +3, +4, or +5; organized schools scored +1 or +2; moderately organized schools scored 0; partially organized schools scored -1 or -2; and not yet organized schools scored -3, -4, or -5.

More information about school report cards in 2011 and in previous years

The School Progress Report Cards also contained measures of the school's overall performance level, probation status, Annual Yearly Progress (AYP) status, healthy schools certification, test score averages and improvements, the percent of students meeting/exceeding grade level on test and growth targets for elementary schools, and high school test score averages, improvements and graduation rates, as well as teacher/student attendance rates, parent satisfaction, and student safety scores. The majority of this non-climate information was already publicly available from the district through School Scorecards. The main difference is that starting in 2011, the school reports integrated school climate information.

The majority of non-climate school information in the 2011 school report cards was mostly already available before the fall of 2011. The format changed somewhat between 2006 and 2010, but in general they contained information on the school's demographics, test performance and improvement, graduation and attendance rates, as well as the percent of students in the school/district who felt safe at school and the percent of parents who reported being satisfied with their school. To clarify, the percent of parents reporting being satisfied with the school is not a part of the original school climate reports created by CCSR, furthermore, the percent of students reporting feeling safe at school is a question within a component that is used to generate some of the school climate factors, but the question does not entail as much information as the full factors. This information sounds similar but is not as detailed as the school climate information that was released in September 2011. It is unclear how these School Scorecards were distributed, but it seems that the earliest

Scorecards were also available during report card pick up days, but I have not been able to find a definitive answer for this.

Furthermore, CPS released an interactive and comprehensive online map providing details and links to the full progress report cards for each school in the city for easier spatial comparison (refer to Figure 4). The online version contained more school information than the physical school report cards had. This included school value-added scores (only for elementary/middle schools), IEP compliance rates, and number of misconducts. It also provided college eligibility rates and freshmen on-track rates for high schools.

Appendix B: Discrete school climate information effects models

Multiple suburban school zone control groups

My first approach is to compare school zones with each of the five climate ratings to suburban school zones that would receive that same climate rating three years later, but did not receive it in September 2011.[35] I estimate semi-parametric regressions of the following form:

$$
\begin{aligned}
Y_{ist} = \beta_0 &+ \sum_{r=1}^{5}\Big(\sum_{q=1}^{4}\beta_{q,r}1(Climate_s = r) * 1(PostQuarter_t = q) * Treat\Big) \\
&+ \sum_{r=1,\neq 3}^{5}\Big(\sum_{q=1}^{4}\Pi_{q,r}1(Climate_s = r) * 1(PostQuarter_t = q)\Big) \\
&+ \sum_{r=1}^{5}\Big(\Lambda Climate_s * (t-5.5) * 1(t<0)\Big) \\
&+ \Gamma\mathbf{X}_{it} + \theta_t + \mu_s + \varepsilon_{ist} \qquad (4)
\end{aligned}
$$

where variables are defined as in equation 1. In this model, I include separate indicators, $1(Climate_s = r)$, for which of the five climate ratings, r, a school would first receive. I also include treatment indicator, $Treat$, for whether the corresponding school zone actually received a climate rating in September 2011. Therefore, the coefficient $\beta_{q,r}$ represents the DID estimate of the net change in the outcome during post-shock quarter q relative to before the information campaign, between properties zoned to schools with climate rating r that received the information treatment and suburban schools that did not receive the treatment but would receive that same rating three years later.

Single suburban school zone control group

Second, I compare housing outcomes in school zones in CPS that were assigned one of the five school climate ratings to the housing outcomes across suburban school zones, which did

[35] The Illinois State Board of Education began to publicly release school climate ratings for the majority of public school systems across the state in November 2014. Only about half of public schools received school climate ratings for the 2014-2015 school year, while about 80% received climate ratings for the 2015-2016 school year. I use suburban schools' first publicly available school climate ratings in this subanalysis.

not receive school climate ratings information, before and after the information campaign. This approach does not differentiate between school zones in the control group. For this, I estimate semi-parametric regressions that control for differential pre-trends:

$$
\begin{aligned}
Y_{ist} = \beta_0 + \sum_{r=1}^{5} \Big(\sum_{q=1}^{4} \beta_{q,r} 1(Climate_s = r) * 1(PostQuarter_t = q) \Big) \\
+ \sum_{r=1}^{5} \Big(\Lambda Climate_s * (t - 5.5) * 1(t < 0) \Big) \\
+ \Gamma \mathbf{X}_{it} + \theta_t + \mu_s + \varepsilon_{ist}
\end{aligned}
\qquad (5)
$$

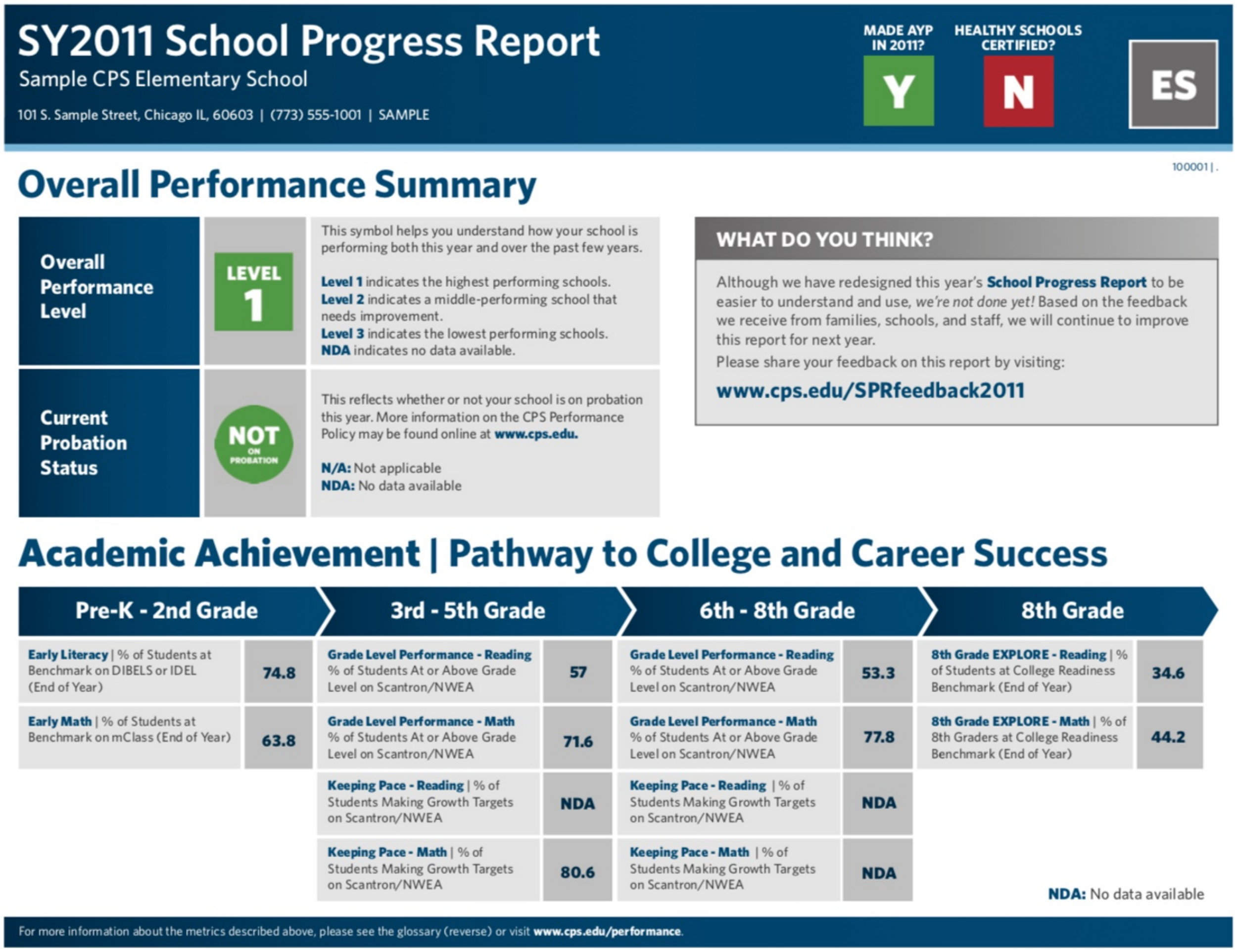
where the variables are defined as in equation 1. In this model, I use suburban school zones as the omitted/reference group. Therefore, the coefficient $\beta_{q,r}$ represents the DID estimate of the net change in the outcome between properties zoned to schools with climate rating r and those zoned to suburban schools during post-shock quarter q, relative to before the information campaign.

Average climate rating school zones as reference group

As a third approach, I modify equation 5 to compare housing outcomes in school zones that were assigned the yellow (average) climate rating, to the housing outcomes in school zones with each of the other climate ratings (blue, light blue, orange, and red), before and after the information campaign (the excluded reference group in the equation is now the average climate rating). This is similar to the approach used by Figlio and Lucas (2004) to study the effects of school performance grades on the housing market.

Appendix 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

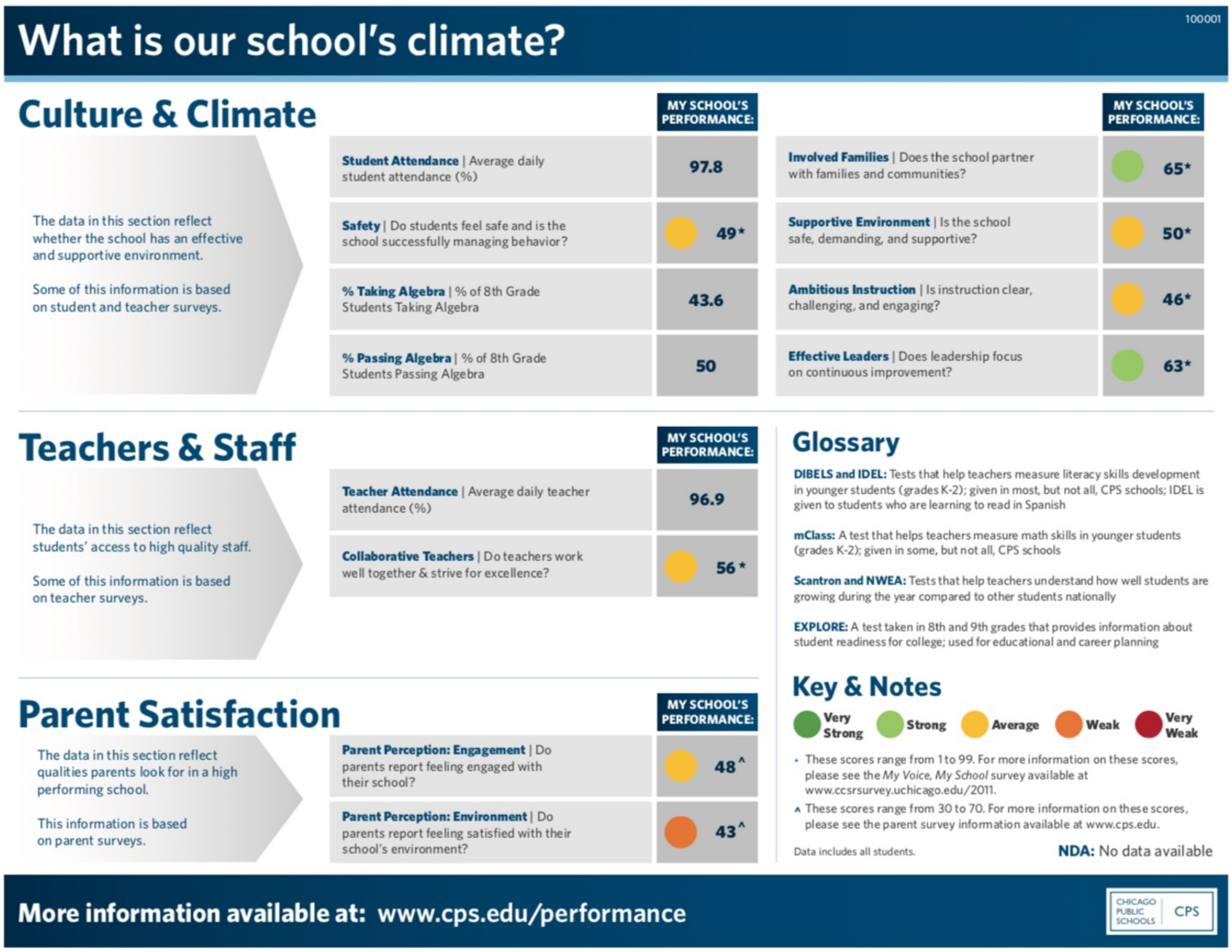
Academic Achievement | Pathway to College and Career Success

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



100001

What is our school's climate?

Culture & Climate

The data in this section reflect whether the school has an effective and supportive environment.

Some of this information is based on student and teacher surveys.

	MY SCHOOL'S PERFORMANCE:
Student Attendance | Average daily student attendance (%)	97.8
Safety | Do students feel safe and is the school successfully managing behavior?	49*
% Taking Algebra | % of 8th Grade Students Taking Algebra	43.6
% Passing Algebra | % of 8th Grade Students Passing Algebra	50

	MY SCHOOL'S PERFORMANCE:
Involved Families | Does the school partner with families and communities?	65*
Supportive Environment | Is the school safe, demanding, and supportive?	50*
Ambitious Instruction | Is instruction clear, challenging, and engaging?	46*
Effective Leaders | Does leadership focus on continuous improvement?	63*

Teachers & Staff

The data in this section reflect students' access to high quality staff.

Some of this information is based on teacher surveys.

	MY SCHOOL'S PERFORMANCE:
Teacher Attendance | Average daily teacher attendance (%)	96.9
Collaborative Teachers | Do teachers work well together & strive for excellence?	56*

Parent Satisfaction

The data in this section reflect qualities parents look for in a high performing school.

This information is based on parent surveys.

	MY SCHOOL'S PERFORMANCE:
Parent Perception: Engagement | Do parents report feeling engaged with their school?	48^
Parent Perception: Environment | Do parents report feeling satisfied with their school's environment?	43^

Glossary

DIBELS and IDEL: Tests that help teachers measure literacy skills development in younger students (grades K-2); given in most, but not all, CPS schools; IDEL is given to students who are learning to read in Spanish

mClass: A test that helps teachers measure math skills in younger students (grades K-2); given in some, but not all, CPS schools

Scantron and NWEA: Tests that help teachers understand how well students are growing during the year compared to other students nationally

EXPLORE: A test taken in 8th and 9th grades that provides information about student readiness for college; used for educational and career planning

Key & Notes

Very Strong · Strong · Average · Weak · Very Weak

* These scores range from 1 to 99. For more information on these scores, please see the *My Voice, My School* survey available at www.ccsrsurvey.uchicago.edu/2011.

^ These scores range from 30 to 70. For more information on these scores, please see the parent survey information available at www.cps.edu.

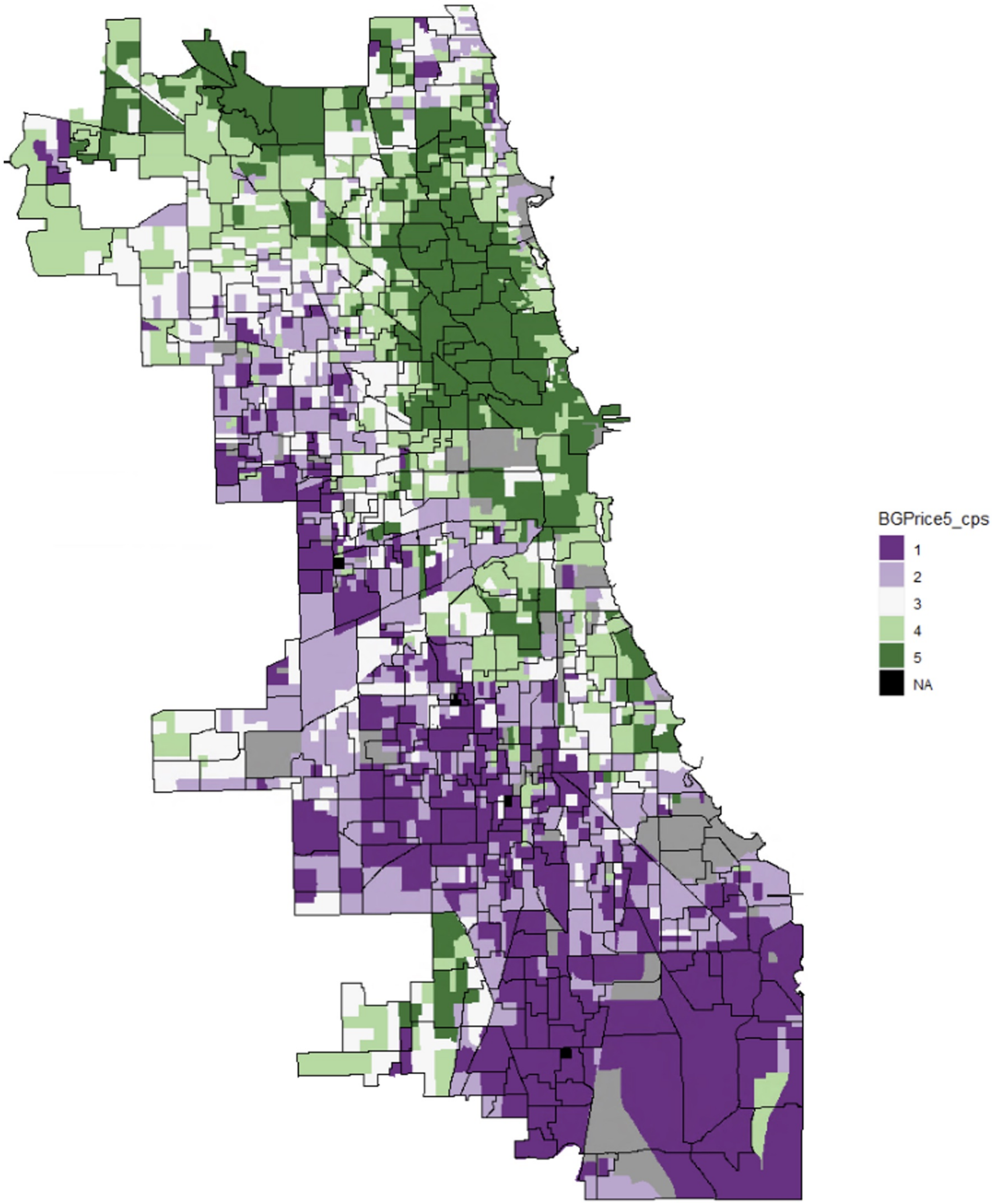
Data includes all students.

NDA: No data available

More information available at: www.cps.edu/performance

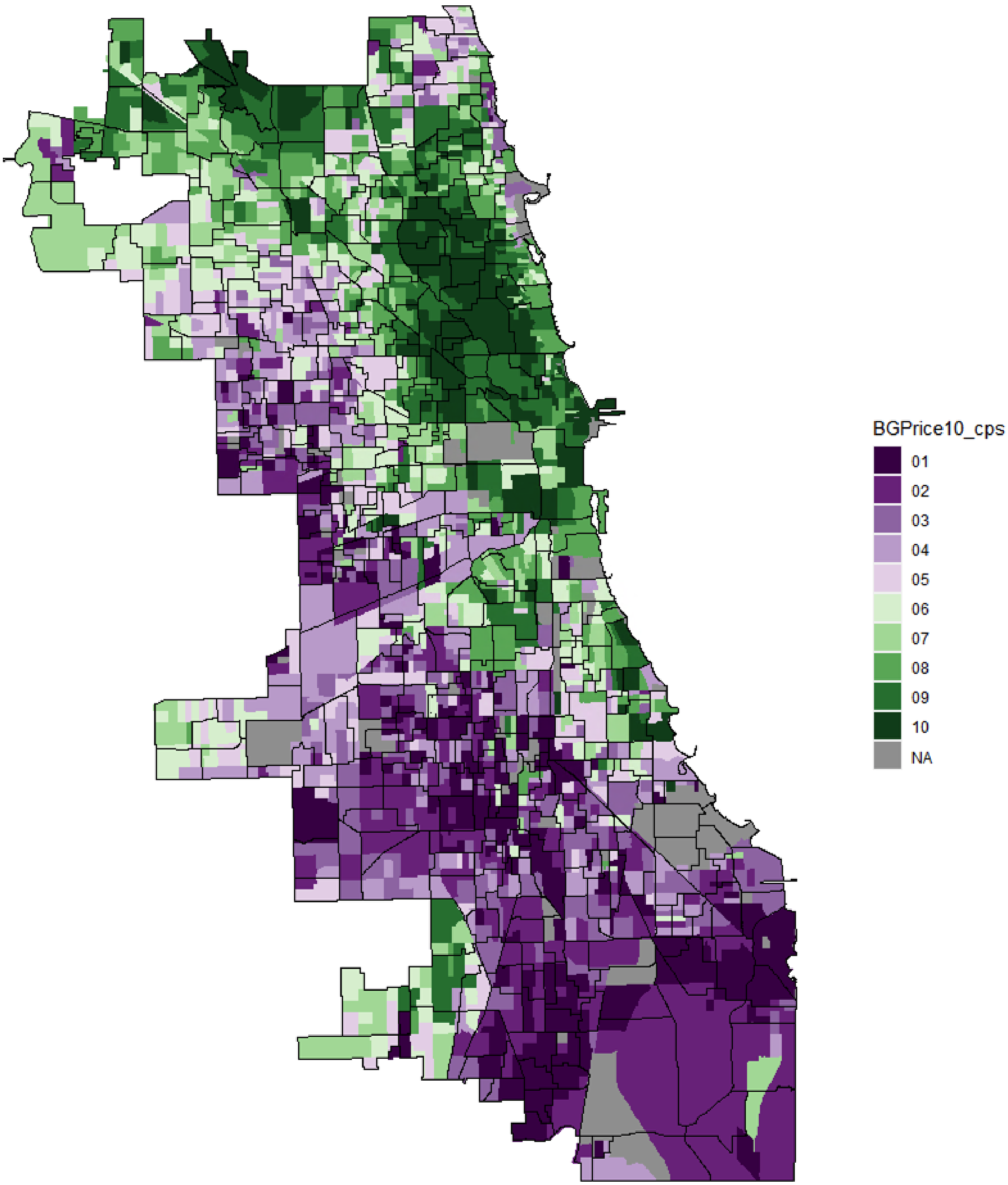
CHICAGO PUBLIC SCHOOLS CPS

Figure A3: Historical neighborhood prices by quintiles (based on 2006-2007 through 2010-2011 SY transactions)



Notes: Neighborhood price quintiles are ordered from 1 (least expensive) to 5 (most expensive) Census block-groups. I use home sales transactions from the 2006-2007 SY through the 2010-2011 SY to calculate historical neighborhood sales prices. Gray areas represent areas without enough transactions to produce estimates.

Figure A4: Historical neighborhood prices by deciles (based on 2006-2007 through 2010-2011 SY sales)



Notes: Neighborhood price deciles are ordered from 1 (least expensive) to 10 (most expensive) Census block-groups. I use home sales transactions from the 2006-2007 SY through the 2010-2011 SY to calculate historical neighborhood sales prices. Gray areas represent areas without enough transactions to produce estimates.

Appendix Tables

Table A1: Robustness tests of DID estimates of school climate rating information on log sale prices

Independent variable	(1)	(2)	(3)	(4)	(5)
Panel A: Climate Ratings 1, 2, 3, 4, 5					
Climate Rating x Post1	0.103***	0.030***	0.023**	0.027**	0.027**
	(0.028)	(0.011)	(0.010)	(0.011)	(0.011)
Climate Rating x Post2	0.085***	0.014	0.008	0.004	0.004
	(0.028)	(0.011)	(0.011)	(0.012)	(0.012)
Climate Rating x Post3	0.046	-0.008	-0.007	-0.012	-0.013
	(0.028)	(0.012)	(0.011)	(0.011)	(0.012)
Climate Rating x Post4	0.083***	0.008	-0.004	-0.007	-0.007
	(0.028)	(0.013)	(0.012)	(0.012)	(0.012)
Observations	20079	20078	20078	16152	16152
Panel B: Climate Ratings 3, 4, 5					
Climate Rating x Post1	0.189***	0.057**	0.056***	0.047**	0.052**
	(0.060)	(0.023)	(0.021)	(0.023)	(0.023)
Climate Rating x Post2	0.176***	0.058**	0.042*	0.056**	0.053*
	(0.057)	(0.025)	(0.024)	(0.026)	(0.027)
Climate Rating x Post3	0.081	0.011	0.010	0.007	0.006
	(0.065)	(0.030)	(0.026)	(0.028)	(0.028)
Climate Rating x Post4	0.110	-0.004	-0.012	-0.009	-0.008
	(0.071)	(0.030)	(0.026)	(0.027)	(0.028)
Observations	10858	10858	10858	8889	8889
Panel C: Climate Ratings 1, 2, 3					
Climate Rating x Post1	0.051	0.031	0.024	0.031	0.036
	(0.059)	(0.027)	(0.024)	(0.027)	(0.027)
Climate Rating x Post2	-0.023	-0.024	-0.016	-0.044	-0.041
	(0.062)	(0.034)	(0.031)	(0.034)	(0.035)
Climate Rating x Post3	-0.011	-0.038	-0.029	-0.041	-0.044
	(0.063)	(0.031)	(0.030)	(0.030)	(0.031)
Climate Rating x Post4	0.083	0.026	0.013	0.001	0.004
	(0.064)	(0.036)	(0.035)	(0.035)	(0.035)
Observations	12237	12236	12236	9685	9685
Main climate effects	Y	Y		Y	
Controls (Property, CBG)		Y	Y	Y	Y
Controls (CBG latent price trend)		Y	Y	Y	Y
Controls (School)		Y		Y	
School FE			Y		Y
Boundary FE (<0.2mi)				Y	Y

Table A2: Robustness tests of DID estimates of school climate rating information on log buyer income

Independent variable	(1)	(2)	(3)	(4)	(5)
Panel A: Climate Ratings 1, 2, 3, 4, 5					
Climate Rating x Post1	0.086***	0.022	0.018	0.022	0.022
	(0.030)	(0.015)	(0.015)	(0.017)	(0.018)
Climate Rating x Post2	0.058*	0.006	-0.001	0.002	0.002
	(0.031)	(0.016)	(0.015)	(0.017)	(0.017)
Climate Rating x Post3	0.047*	0.003	0.006	0.007	0.007
	(0.026)	(0.015)	(0.015)	(0.016)	(0.017)
Climate Rating x Post4	0.075***	0.013	0.004	0.004	0.006
	(0.027)	(0.015)	(0.014)	(0.014)	(0.014)
Observations	16445	16444	16444	13243	13243
Panel B: Climate Ratings 3, 4, 5					
Climate Rating x Post1	0.205***	0.081**	0.076**	0.029	0.041
	(0.067)	(0.032)	(0.031)	(0.035)	(0.035)
Climate Rating x Post2	0.131**	0.031	0.008	0.021	0.020
	(0.065)	(0.036)	(0.034)	(0.038)	(0.037)
Climate Rating x Post3	0.033	-0.031	-0.026	-0.043	-0.047
	(0.059)	(0.036)	(0.036)	(0.039)	(0.041)
Climate Rating x Post4	0.092	-0.018	-0.030	-0.057	-0.054
	(0.070)	(0.035)	(0.033)	(0.034)	(0.035)
Observations	8946	8946	8946	7327	7327
Panel C: Climate Ratings 1, 2, 3					
Climate Rating x Post1	-0.016	-0.027	-0.014	0.030	0.033
	(0.065)	(0.035)	(0.035)	(0.044)	(0.046)
Climate Rating x Post2	-0.026	-0.005	0.008	-0.031	-0.023
	(0.067)	(0.039)	(0.035)	(0.040)	(0.041)
Climate Rating x Post3	0.048	0.034	0.048	0.076*	0.069
	(0.056)	(0.039)	(0.041)	(0.045)	(0.046)
Climate Rating x Post4	0.062	0.049	0.040	0.040	0.041
	(0.064)	(0.034)	(0.031)	(0.035)	(0.036)
Observations	10016	10015	10015	7936	7936
Main climate effects	Y	Y		Y	
Controls (Property, CBG)		Y	Y	Y	Y
Controls (CBG latent price trend)		Y	Y	Y	Y
Controls (School)		Y		Y	
School FE			Y		Y
Boundary FE (<0.2mi)				Y	Y

Table A3: Effect of school climate rating information on log sale prices and on log buyer income, controlling for pre-trends

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
	Climate ratings: 1,2,3,4,5		Climate ratings: 3, 4, 5		Climate ratings: 1, 2, 3	
	Log Price	Log Income	Log Price	Log Income	Log Price	Log Income
Climate Rating x Post1	0.020	0.012	0.045*	0.060**	0.024	0.002
	(0.013)	(0.017)	(0.026)	(0.030)	(0.024)	(0.040)
Climate Rating x Post2	0.005	-0.007	0.032	-0.008	-0.016	0.023
	(0.012)	(0.017)	(0.026)	(0.037)	(0.031)	(0.041)
Climate Rating x Post3	-0.010	-0.001	-0.001	-0.041	-0.029	0.064
	(0.013)	(0.019)	(0.028)	(0.042)	(0.030)	(0.051)
Climate Rating x Post4	-0.007	-0.002	-0.023	-0.046	0.013	0.055
	(0.013)	(0.017)	(0.027)	(0.036)	(0.035)	(0.038)
Pre-trend	0.000	0.000	0.001	0.001	-0.000	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	20078	16444	10858	8946	12236	10015

Table A4: Effect of school climate rating information on log sale prices and on log buyer income, excluding condonimiums

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
	Climate ratings: 1,2,3,4,5		Climate ratings: 3, 4, 5		Climate ratings: 1, 2, 3	
	Log Price	Log Income	Log Price	Log Income	Log Price	Log Income
Climate Rating x Post1	0.017	0.009	0.028	0.036	0.054**	0.032
	(0.011)	(0.016)	(0.022)	(0.038)	(0.024)	(0.036)
Climate Rating x Post2	0.002	-0.019	0.037	-0.030	-0.015	0.016
	(0.011)	(0.017)	(0.030)	(0.041)	(0.034)	(0.036)
Climate Rating x Post3	-0.001	0.001	0.013	-0.027	-0.020	0.047
	(0.012)	(0.017)	(0.027)	(0.035)	(0.029)	(0.045)
Climate Rating x Post4	-0.011	-0.003	-0.024	-0.033	0.017	0.018
	(0.014)	(0.015)	(0.028)	(0.037)	(0.034)	(0.032)
Observations	12532	10265	6855	5618	7710	6341

Table A5: Effect of school climate rating information on log sale prices, focusing on transactions for 3+ bedroom properties, excluding condonimiums

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
	All Climate Ratings		Better Climate Ratings		Worse Climate Ratings	
	Zone FE	Border FE	Zone FE	Border FE	Zone FE	Border FE
Climate Rating x PostQ1	0.014	0.023	0.038*	0.057**	0.034	0.046
	(0.011)	(0.014)	(0.021)	(0.026)	(0.029)	(0.036)
Climate Rating x PostQ2	-0.008	-0.014	-0.013	-0.022	0.006	-0.016
	(0.013)	(0.017)	(0.028)	(0.037)	(0.034)	(0.047)
Climate Rating x PostQ3	-0.012	-0.016	-0.010	-0.028	-0.015	-0.013
	(0.012)	(0.014)	(0.025)	(0.038)	(0.034)	(0.046)
Climate Rating x PostQ4	-0.010	-0.022	-0.003	-0.003	-0.019	-0.037
	(0.013)	(0.017)	(0.027)	(0.035)	(0.029)	(0.036)
Observations	7857	6237	4389	3503	4747	3751

Table A6: Effect of school climate rating information on log homebuyer income, focusing on transactions for 3+ bedroom properties, excluding condonimiums

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
	All Climate Ratings		Better Climate Ratings		Worse Climate Ratings	
	Zone FE	Border FE	Zone FE	Border FE	Zone FE	Border FE
Climate Rating x PostQ1	0.011	0.035**	0.018	-0.012	0.016	0.108***
	(0.014)	(0.017)	(0.034)	(0.040)	(0.034)	(0.038)
Climate Rating x PostQ2	-0.023	-0.037	0.026	0.046	-0.049	-0.106*
	(0.020)	(0.023)	(0.039)	(0.047)	(0.047)	(0.055)
Climate Rating x PostQ3	-0.008	-0.010	0.002	-0.044	0.011	0.049
	(0.017)	(0.019)	(0.040)	(0.044)	(0.044)	(0.052)
Climate Rating x PostQ4	0.007	0.009	-0.032	-0.037	0.024	0.032
	(0.015)	(0.019)	(0.036)	(0.041)	(0.030)	(0.034)
Observations	7857	6237	4389	3503	4747	3751

Table A7: Effect of school climate rating information on log sale prices, focusing on transactions for 3+ bedroom properties, excluding condonimiums

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
	All Climate Ratings		Better Climate Ratings		Worse Climate Ratings	
	Zone FE	Border FE	Zone FE	Border FE	Zone FE	Border FE
Climate Rating x PostQ1	0.017*	0.021**	0.058***	0.060***	0.010	0.029
	(0.009)	(0.010)	(0.020)	(0.022)	(0.023)	(0.025)
Climate Rating x PostQ2	0.014	0.010	0.042*	0.056*	-0.004	-0.024
	(0.011)	(0.014)	(0.025)	(0.030)	(0.030)	(0.034)
Climate Rating x PostQ3	-0.007	-0.008	0.006	0.008	-0.011	-0.015
	(0.009)	(0.011)	(0.021)	(0.025)	(0.029)	(0.034)
Climate Rating x PostQ4	-0.002	-0.012	0.011	-0.010	-0.025	-0.019
	(0.014)	(0.013)	(0.032)	(0.027)	(0.035)	(0.040)
Observations	16952	13586	9176	7480	10352	8171

Table A8: Effect of school climate rating information on log homebuyer income, focusing on transactions for 3+ bedroom properties, excluding condonimiums

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
	All Climate Ratings		Better Climate Ratings		Worse Climate Ratings	
	Zone FE	Border FE	Zone FE	Border FE	Zone FE	Border FE
Climate Rating x PostQ1	0.016	0.021	0.062**	0.051*	-0.030	0.009
	(0.015)	(0.015)	(0.029)	(0.030)	(0.027)	(0.032)
Climate Rating x PostQ2	-0.002	-0.006	0.022	0.040	-0.022	-0.054
	(0.016)	(0.015)	(0.030)	(0.032)	(0.033)	(0.035)
Climate Rating x PostQ3	-0.008	-0.016	-0.020	-0.050	0.007	0.023
	(0.016)	(0.015)	(0.034)	(0.037)	(0.036)	(0.039)
Climate Rating x PostQ4	0.008	-0.002	-0.001	-0.034	0.016	0.025
	(0.016)	(0.013)	(0.038)	(0.030)	(0.034)	(0.036)
Observations	16952	13586	9176	7480	10352	8171

Table A9: Effect of school climate rating information on log sale prices, fcontrolling for high school climate ratings effects

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
	All Climate Ratings		Better Climate Ratings		Worse Climate Ratings	
	Zone FE	Border FE	Zone FE	Border FE	Zone FE	Border FE
Climate Rating x PostQ1	0.016*	0.020*	0.056***	0.056**	0.005	0.024
	(0.009)	(0.011)	(0.019)	(0.022)	(0.025)	(0.026)
Climate Rating x PostQ2	0.015	0.011	0.046*	0.060*	-0.021	-0.042
	(0.011)	(0.014)	(0.026)	(0.031)	(0.031)	(0.035)
Climate Rating x PostQ3	-0.001	-0.000	0.009	0.011	-0.009	-0.005
	(0.009)	(0.010)	(0.020)	(0.023)	(0.031)	(0.036)
Climate Rating x PostQ4	0.001	-0.007	0.003	-0.011	-0.025	-0.015
	(0.013)	(0.012)	(0.028)	(0.028)	(0.035)	(0.039)
Observations	16188	12940	8777	7130	9811	7728

Table A10: Effect of school climate rating information on log sale prices and on log buyer income, using specifications where suburban or yellow climate school zones are the reference group, controlling for pre-trends

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
	Same Climate Suburban Zones Reference		Suburban Zones Reference		Yellow Zones Reference	
	Log Price	Log Income	Log Price	Log Income	Log Price	Log Income
Climate Rating 5 x Post1	0.057	0.109**	0.071*	0.099**	0.092*	0.120**
	(0.043)	(0.054)	(0.042)	(0.049)	(0.053)	(0.060)
Climate Rating 4 x Post1	0.022	-0.042	-0.003	-0.081*	0.021	-0.051
	(0.039)	(0.058)	(0.035)	(0.047)	(0.049)	(0.058)
Climate Rating 3 x Post1	-0.014	-0.058	-0.030	-0.034		
	(0.042)	(0.053)	(0.039)	(0.044)		
Climate Rating 2 x Post1	0.003	-0.051	0.005	-0.022	0.033	0.009
	(0.033)	(0.047)	(0.028)	(0.040)	(0.045)	(0.053)
Climate Rating 1 x Post1	-0.161**	-0.107	-0.099*	-0.034	-0.073	-0.009
	(0.071)	(0.091)	(0.053)	(0.079)	(0.063)	(0.087)
Climate Rating 5 x Post2	0.020	0.081	0.029	0.044	0.066	-0.000
	(0.037)	(0.066)	(0.032)	(0.059)	(0.050)	(0.073)
Climate Rating 4 x Post2	0.064*	-0.055	0.007	-0.068	0.043	-0.111*
	(0.038)	(0.058)	(0.032)	(0.046)	(0.049)	(0.063)
Climate Rating 3 x Post2	-0.107**	-0.029	-0.044	0.040		
	(0.049)	(0.064)	(0.043)	(0.054)		
Climate Rating 2 x Post2	-0.007	-0.002	0.007	0.012	0.049	-0.028
	(0.039)	(0.060)	(0.033)	(0.042)	(0.050)	(0.060)
Climate Rating 1 x Post2	0.010	0.031	-0.034	-0.006	0.006	-0.049
	(0.075)	(0.100)	(0.058)	(0.075)	(0.070)	(0.086)
Observations	43427	35714	43733	35976	20084	16448