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

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

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Abstract

In this paper, I investigate how publicizing school social climate information is capitalized into the housing market and how it affects the sorting of homebuyers from different economic backgrounds. I first provide descriptive evidence on the novelty of school climate relative to other school characteristics. Next, using a plausibly exogenous shock of school climate information in Chicago, I employ a border discontinuity design with event studies and a difference-in-differences framework. I find that providing this information publicly leads to price increases for homes assigned to better climate ratings and find suggestive evidence that more advantaged families sort into these homes. The initial impacts dissipate within a year as the information becomes less salient and the search costs increase. The second round of school climate ratings received much less news coverage, leading to muted capitalization. However, higher income families had a significant reaction to the updated ratings, suggesting differences in access to infor-mation. My work provides revealed preference evidence that households value school climate quality.

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1 Introduction

School social climate refers to the social, learning, and working conditions experienced by students, families, and teachers in schools. Educators and researchers argue that this school characteristic provides a measure of students' social wellbeing that is lacking from more traditional measures of school quality, such as test scores (Bryk et al., 2010; Darling-Hammond, 2004; Gagnon and Schneider, 2019; Jackson et al., 2020a; Thapa et al., 2013). Students' exposure to worse social and learning conditions, based on disruptive peers, has been linked to worse academic performance and labor market outcomes (Carrell et al., 2018; Carrell and Hoekstra, 2010). Furthermore, better school climate may foster students' socioemotional development, which can, in turn, positively influence students' educational attainment and criminal involvement (Jackson et al., 2023, 2020b; Porter et al., 2023; Sorrenti et al., 2024).

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

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

In this paper, I provide the first causal evidence of how publicized school climate information is capitalized into the housing market and how it affects sorting of homebuyers from different economic backgrounds across neighborhoods. I leverage a plausibly-exogenous shock of new information that increased the salience of school climate quality across the Chicago Public Schools (CPS) district in fall of 2011. Prior to 2011, biennial reports were privately provided to school administrators for internal use but were not released to the public (Levenstein, 2016). By only changing the salience of school climate quality but not other school characteristics, I isolate parental preferences for school climate from preferences for other school characteristics.

The climate information in this study was based on surveys administered to students and teachers in the spring of 2011, which were then summarized into school climate reports. The reports provided information to consistently compare schools based on five dimensions of school climate.[1] Each school in the district was assigned an overall composite school climate quality rating based on a five-rating color-coded scale.

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 borders. Additionally, the high frequency of the data allows me to explore immediate and dynamic reactions in the housing market over time. Furthermore, I link the transactions data with home mortgage data that contain information on homebuyers' demographics. The breadth and depth of these two datasets combined allow me to investigate differential effects of school climate information on incoming homebuyers by economic 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. Compared to proficiency rates, school climate ratings exhibit a weaker relationship with school poverty levels. Additionally, climate ratings were difficult to predict based on these and other already public information.

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 September 2011, before they were updated in September 2012, in order to use the cleanest information shock. I leverage the suddenly public 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 embedded into a border discontinuity design.

[1] The five dimensions are: (1) supportive environments, (2) ambitious instruction, (3) parental involvement, (4) teacher collaboration, and (5) effective leadership.

My event studies show no differential pre-trend in the relationship between school climate and housing market outcomes, suggesting that the information was not correlated with pre-release secular trends in home prices. The information shock led to a 9% to 21% price premium for homes assigned to better climate ratings relative to the worst rating in the first post-shock quarter, but these effects begin to dissipate after the second quarter. This dissipating effect is similar to those found by other relevant information campaign studies using school ratings based on student performance (Bogin and Nguyen-Hoang, 2014; Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011; Haisken-DeNew et al., 2018).

Additionally, I show suggestive evidence that there was an immediate 6% to 16% increase in the incomes of homebuyers purchasing homes in neighborhoods assigned to better climate ratings, compared to the incomes of those buying in the worst climate rating school zones. In heterogeneity analysis, I find suggestive evidence that families with children have stronger and more sustained capitalization and buyer income effects.

Overall, my results indicate that releasing school climate ratings has short-term positive impacts on property values and that better ratings attract more advantaged homebuyers. I explore two potential mechanisms that can help explain the short-lived nature of these effects: (1) the information shock may have led to an immediate increase in demand, and then a delayed response in the supply of available homes on the market or a decline in demand over time; and (2) homebuyers may be able to value school climate information only when it is highly salient and easily accessible (low search costs).

The first potential mechanism could be based on the short- and long-run demand for homes and the changing supply of houses available on the market. In the short-run, the information shock may have led to an increased demand for homes in better climate school zones. The supply of homes may not be able to react immediately to the increased demand, which would lead to an immediate increase in sales prices for in-demand properties that were already on the market. As time goes on, the initial price premium may lead to an increase in supply of available homes in in-demand school zones to meet the increased demand for homes, bringing sales prices back down at the higher supply quantity. I test this mechanism using changes in the number of transactions, but do not find significant evidence for the long-run supply channel, suggesting that demand returns to pre-shock levels over time.

A second potential mechanism for the short-term effects could be that homebuyers value school climate information when it is highly salient and search costs are low. Thus, as CPS's information campaign ends and news coverage stops, the cost of obtaining school climate information increases, even though it is still publicly available. 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 (Bogin and Nguyen-Hoang, 2014; Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011; Haisken-DeNew et al., 2018; Zahirovic-Herbert and Turnbull, 2008), supporting this hypothesis. Further evidence for this hypothesis can be seen in online search patterns over time. Google Trends data show a spike in searches for school climate-related terms during the months of the information campaign, which return to pre-shock levels soon thereafter.

The second release of the climate reports was complicated by climate rating variability and a dampened information campaign, which led to weaker capitalization effects in the second year. However, the impacts on homebuyer incomes were sustained, suggesting that higher income families were better able to seek out the information.

Relationship to the literature. My paper makes several important contributions to various strands of research. First, my work contributes to a large and growing literature on parental preferences for school quality. Most recently, this literature has focused on utilizing families' ranked lists of schools to infer preferences without explicitly providing households with school quality information (Abdulkadiroğlu et al., 2020; Beuermann et al., 2023) or employing randomized experiments to examine how information changes families' ranking of schools (Ainsworth et al., 2023; Bergman et al., 2020; Campos, 2024; Hastings and Weinstein, 2008). Much of the literature has focused on preferences for schools' academic levels and value-added. However, studies are beginning to explore households' preferences for schools' non-test-score-based traits, such as schools' causal impacts on arrests and employment, student satisfaction with the school's curricular specialization, or perceived school impacts on college attendance and earnings (Ainsworth et al., 2023; Beuermann et al., 2023).[2] I contribute to this literature by exploring families' preferences for school climate, an increasingly accessible non-test-score-based measure of school quality for which revealed preference research is limited.

I most directly contribute to a literature that focuses on parental revealed preferences for social-learning environments. Generally, this literature has relied on selection on observables to estimate preferences for singular aspects of school social conditions. 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,

[2] Beuermann et al. (2023) find that families in Trinidad and Tobago choose schools that causally have positive impacts on high-stakes tests and also those that causally reduce arrests and increase employment. The authors suggest that parents may be able to infer school effectiveness even when information is imperfect. On the other hand, using a randomized information experiment, Ainsworth et al. (2023) find that families in Romania report having a strong preference for non-test-based school traits (i.e. student satisfaction with the program's curricular specialization). This preference is so strong that families forego substantial test-based value-added, even when provided with accurate value-added information.

controlling for other school characteristics. On the other hand, Gibbons and Silva (2011) find that in England, families do not actually pay more for homes assigned to schools with higher rates of student-reported happiness, controlling for test-based factors. Relative to this literature, I provide the first causal evidence of how families value school social factors by using a plausibly exogenous shock of new school climate information.[3]

My empirical approach follows a line of research using quasi-random information or policy shocks to study the capitalization of various school characteristics on the housing market. The majority of this literature has focused on how school academic levels and value-added impact house prices (Bogin and Nguyen-Hoang, 2014; Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011; Haisken-DeNew et al., 2018; Hussain, 2023; Imberman and Lovenheim, 2016; Zahirovic-Herbert and Turnbull, 2008). Studies have also used similar approaches to study the capitalization of academic and non-academic school expenditures, such as teacher salaries, infrastructure improvements, and athletic facilities (Bayer et al., 2021; Biasi et al., 2024; Cellini et al., 2010; Lafortune and Schönholzer, 2022), as well as the capitalization of the racial and economic composition of schools (Collins and Kaplan, 2022; Mothorpe, 2018; Turnbull et al., 2018; Wada and Zahirovic-Herbert, 2013; Zahirovic-Herbert and Turnbull, 2008).[4] To my knowledge, I am the first to examine how school climate information impacts house prices and the sorting of homebuyers from different economic backgrounds.[5]

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.

[3]Additionally, this is some of the first evidence of revealed preferences for school climate using a publicly accessible multidimensional measure of social conditions derived from extensive research and comprehensive surveys. 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 schools having at least 10 students responding to a single survey question. However, Hailey (2020) uses publicly available survey-based measures of school safety, but does not leverage plausibly exogenous variation.

[4]Clapp et al. (2008) and Clapp and Ross (2004) provide early evidence of how changes in school district demographic composition impact house prices.

[5]Gibbons and Silva (2011) examine the cross-sectional relationship between schools' average student happiness and house prices, however their approach lacks quasi-random variation for causal identification.

2 Institutional Background

2.1 What is school climate and does it matter?

For the past decade, the US Department of Education, and many states and school districts across the country have increasingly begun to focus on measuring, improving, and promoting the social, learning, and working conditions experienced by school stakeholders. 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; Jordan and Hamilton, 2019; Thapa et al., 2013).

The National School Climate Council (2007) broadly suggests that this concept represents *patterns of school life experiences that reflect norms, goals, values, interpersonal relationships, teaching, learning and leadership practices, and organizational structures*. Educational institutions typically measure these conditions by surveying different stakeholders about their experiences and perceptions of conditions at their school (Gruenert, 2008; Jordan and Hamilton, 2019; Zullig and Matthews, 2014).

While, school climate is a nebulous term, a growing line of research suggests that the social conditions commonly captured in measures of school climate matter for teacher and student outcomes. First, a large literature in education suggests that the day-to-day social environments in schools (e.g. collegial relationships and principal leadership) can support effective instruction, help teachers develop their skills, and increase teacher satisfaction and retention (Jackson and Bruegmann, 2009; Simon and Johnson, 2015).[6]

Second, school climate (as measured by student and teacher surveys) is a very strong and positive predictor of school effectiveness in improving students' skills and behaviors (Bryk et al., 2010; Hart et al., 2020; Porter et al., 2023).[7] Additionally, climate is a better predictor of school effectiveness than other publicly available information about schools, such as demographics, average test scores, or commonly used school ratings (Porter et al., 2023). Given this relationship between school climate and school effectiveness, climate is an especially relevant proxy for school quality, which many states and school districts have started using or piloting for accountability or public transparency purposes.

[6] See Kraft and Falken (2020) for a review of the literature on the impacts of school climate on teachers.

[7] A growing literature emphasizes schools' value-added to a combination of students' test scores, socioemotional skills, and observed behaviors in school (Jackson et al., 2023, 2020b; Porter et al., 2023; Sorrenti et al., 2024). Those studies suggest that the short- and long-run impacts of fostering socioemotional development matters as much or more than fostering test score growth.

2.2 Measuring school climate in CPS

In this study, I use school climate measures based on the *Five Essential Supports Framework* that was developed by the University of Chicago Consortium on School Research (CCSR) through more than a decade of research. These measures are based on the *Five Essentials* survey administered to students in grades 6–12 and to all teachers across CPS, which are summarized in five school climate components: (1) supportive environment, (2) ambitious instruction, (3) involved families, (4) collaborative teachers, and (5) effective leadership.[8] This framework and *Five Essentials* survey has now been used by and administered in over 6,000 schools across many school districts in 22 states (UChicago Impact, 2021).[9]

Each of the five climate components is based on multiple survey questions of students' and teachers' perceptions about the school social conditions.[10] 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).[11] 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.[12] 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,

[8] Studies suggest that schools that perform well in the *Five Essentials* framework contribute positively to student academic and non-academic outcomes (Bryk et al., 2010; Hart et al., 2020; Porter et al., 2023).

[9] See https://consortium.uchicago.edu/surveys for details about the *Five Essentials* Survey.

[10] Refer to Appendix C.1 for details about how survey questions are combined to create each component.

[11] 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.

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

the overall climate ratings were labeled as "not yet organized" (red), "partially organized" (orange), "moderately organized" (yellow), "organized" (lime), or "well-organized" (green), which, for ease of presentation, I refer to as ratings "F", "D", "C", "B", and "A", respectively.

2.3 The release of school climate information in Chicago

Since the early 1990s, CCSR administered school climate surveys in CPS every two years in the spring through 2011. After processing the surveys, CCSR privately provided climate reports to principals and district administrators in the late summer to early fall, without requiring them to share the information with staff or parents (Levenstein, 2016).[13]

In September 2011, CPS and CCSR publicly released easily digestible school climate reports, allowing stakeholders, including parents and the community, to access them for the first time.[14] The reports were presented through an online database and could be accessed without charge or registration.[15] Figure 1 shows a sample school climate report from the website. The database was searchable by school name, address, and zip code, allowing anyone to access the report for any school in the district. No other information about school performance or characteristics was included in these reports. Since 2011, the climate surveys have been conducted annually, with updated reports made publicly available.

Then in November 2011, CPS families received physical school progress reports during student report card pickup days.[16] The front of these school reports contained measures of the school's academic performance, which in some form were already publicly released annually before 2011.[17] The back of the school reports included color-coded climate component ratings from the original climate reports website.

Additionally, Chicago news outlets covered the initial online database release in September and the physical school progress reports distribution in November. These included large media outlets in the city, such as the Chicago Sun-Times and CBS Chicago.[18]

[13] Appendix C.2 provides more details about the privately provided pre-2011 climate reports.

[14] Appendix C.3 describes potential reasons for the sudden release of information.

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

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

[17] The Illinois State Board of Education published annual academic performance reports since 2001, which are regularly reported on by local news media.

[18] This data release was less controversial and received less media coverage than the 2011 value-added data release in the Los Angeles Unified School District (LAUSD) that was used by Imberman and Lovenheim (2016). However, the validity of the climate ratings was not publicly questioned the way value-added data was questioned in Los Angeles.

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's attendance boundaries and their 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. Fourth, I must have information about the neighborhoods where each property is sold. I therefore construct a dataset from multiple sources. The following subsections describe each data source in detail.

3.1 School Characteristics

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

Next, 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.[19] Thus, 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), weakening the link between high schools and residential choice. In the robustness section, I show that my results are consistent even when including high school climate effects.

Additionally, I obtain school-level performance and demographic information from CPS and the Illinois State Board of Education (ISBE). ISBE's school report card data contain school-level information on the percentage of students meeting or exceeding profi-

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

ciency levels on the Illinois Standards Achievement Test; the number of students enrolled; the racial/ethnic composition of students; and 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). Some form of school proficiency rates have been available since 2001, when No Child Left Behind required publishing such information. The CPS school progress reports dataset also includes school-level value-added measures, which have been publicly released by CPS since the fall of 2008 (Myers, 2008, 2009).

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, covering two years before the information shock and one year after, to capture the cleanest information change before ratings were updated in September 2012. These data include sales prices and dates, geographic location, mortgage details, homeowner occupancy, and physical house characteristics, including the number of bedrooms and bathrooms, square footage, and year built. Following Billings et al. (2018), I focus on mortgage deeds, which identify home purchases that were acquired with a mortgage. These transactions can be linked to home mortgage applications data that provide socioeconomic and demographic information about homebuyers. I describe this process in the following subsection.

For my analysis, I select the 44,099 transactions geocoded as being located within one of the 2011–2012 elementary school attendance boundaries in CPS. I limit the sample to single-family residences, townhouses, condominiums, and rowhouses, which includes 35,324 transactions. I exclude intrafamily, dissolution, non-arm's length, and re-recorded deed transactions. Furthermore, I exclude transactions with missing sales price and those with a price of zero. These limitations bring the sample size to 29,950. I identify and exclude 1,584 duplicate records for the same transactions. To limit potential outliers, I winsorize sales prices lower than $38,500 (1st percentile) and higher than $1,500,000 (99th percentile). Lastly, I limit the sample to the 24,618 homeowner-occupied transactions for which the borrower mailing address matches the property address.

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

3.3 Homebuyer Self-Reported Income

Homebuyer income 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. 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 through a procedure outlined by Billings (2019).

To link the data, I first obtain the full sample of home sales transactions with concurrent mortgages that had a positive loan amount and for which the Census tract can be identified based on the property location. I use three rounds of linking, each round being fuzzier than the prior. First, I link transactions that are uniquely identified in each of the two datasets based on sale year, loan amount, and Census tract. Second, I link those that remain unmatched based on sale year, loan amount, Census tract, and lender's name. 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.[20]

3.4 Neighborhood Characteristics

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

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

weapon-involved crime rate, and a property crime rate.[21] 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 climate information, demographics, or performance; 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. Lastly, I keep only transactions for properties within 0.2 miles from the nearest school attendance boundary, leaving me with a final sample of 13,586 transactions.

3.5 Summary Statistics

I present summary statistics of some key variables in Table 1. The table displays averages and standard deviations for the overall sample, and separately for each of the five climate ratings. Overall, the average home in Chicago sold for $287,510. The average homebuyer income was $101,218. Furthermore, the average sold home was zoned to an above average proficiency school and about average value-added. These schools are majority non-White and majority FRPL-eligible. Homes in the overall sample were located in neighborhoods with an average median household income of $65,406.

The second through last columns show that the school climate ratings were not completely uncorrelated with school and neighborhood demographics. The second and last columns break down these statistics for the best and worst climate ratings, respectively. The best climate school zones tend to have higher sales prices and homebuyer incomes than the worst climate school zones. On average, homes in the best climate school zones sold for about $119,000 more than homes in the worst climate school zones, but the difference in homebuyer income was only about $37,000. The best climate schools also had higher proficiency and value-added rates, a larger composition of white students, and fewer FRPL-eligible students. Additionally, on average, properties in the best climate school zones were in neighborhoods with higher median household incomes. Homes in the best climate school zones were slightly bigger by about 200 sqft and more likely to be condominiums.

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

4 Did Climate Ratings Provide New Information?

In this section, I present suggestive evidence that school climate ratings revealed new information that was unlikely to have been easily anticipated by the public prior to their release. The initial publicly available school climate ratings were not strongly correlated with traditionally measured school characteristics that are generally available to the public.

Using data from the academic year before the initial information release, I find that school poverty rates were much less correlated with school climate ratings than with school proficiency rates. In Chicago, school proficiency rates were strongly negatively correlated with the share of students eligible for free or reduced-price lunch (FRPL), with a correlation of –0.7, which is consistent with well-established patterns in the education literature. In contrast, school climate ratings were only moderately correlated with FRPL rates ($\rho = -0.3$) and proficiency rates ($\rho = 0.4$). These findings suggest that climate ratings may offer additional insight beyond academic metrics, rather than reinforcing socioeconomic disparities.[22]

Figure 2 presents these correlations graphically. The polygons in the background represent elementary school attendance zones across CPS. Purple zones represent schools where more than 90% of students in those schools are FRPL-eligible.[23] The dots represent the location of each neighborhood school in the district. The dots' colors in the left map represent proficiency rates relative to the average elementary school. Blue circles are schools with the highest proficiency rates in the city, while red circles represent the least-proficient schools in the city.[24] This map makes it visually clear that there is a strong relationship between school poverty rates and school proficiency rates, as is widely documented in the education literature. Schools with higher proficiency rates almost always serve fewer poor students.

On the other hand, the map on the right side of figure 2 shows that the best climate schools can be found all across the district. Schools can have excellent school climate and yet have higher- or lower-FRPL rates, and so can schools with some of the worst climate ratings. This relationship leads to the weak correlation coefficient of -0.3.

To further quantify these findings, I use regression models to predict various school characteristics based on easily accessible school data. These prediction models allow me to examine how easily savvy parents would have been able to predict school quality and how new some of this information may have been to them. Table 2 shows the estimated R^2 from linear regression models.[25] Columns (1) and (2) show that school proficiency rates and

[22] These patterns align with evidence from a recent pilot study (Gagnon and Schneider, 2019).

[23] 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.

[24] I replace greens with blues in order to present color-blind friendly displays.

[25] Ordered and multinomial logit models show similar patterns (available upon request).

FRPL-rates are highly predictable. The models estimate that 70% to 77% of the variation in school proficiency rates and FRPL-eligibility rates, respectively, can be explained by other school characteristics. Column (3) shows that school value-added is much less predictable, with only about 24% of the school value-added variation being explained by the model, which is similar to the percentage found by Imberman and Lovenheim (2016). Columns (4)–(6) show that school climate ratings are slightly less predictable than school value-added, and substantially less predictable than school proficiency rates or FRPL-rates. Only about 7% to 21% of the variation in school climate can be explained by these models.[26]

5 Identification Strategy

In this section, I turn to the causal effects of providing school climate information. To obtain more credible estimates, I compare neighborhoods with differing school climate ratings before and after the information shock in order to account for confounding spatial and temporal factors. To do this, I specifically study the effects of publicly releasing school climate ratings on the housing market using a dynamic difference-in-differences (DID) framework embedded into a border discontinuity design, based on regressions of the following form:

$$\begin{aligned} Y_{ist} = \alpha_0 + \sum_{q=1}^{4}\Big(\sum_{r=D}^{A}(\alpha_{r,q} Climate_{r,s} * 1(Qtr_t = q))\Big) \\ + \Gamma \mathbf{X}_{it} + \theta_t + \nu_{s_j,s_k} + \mu_s + \varepsilon_{ist}, \end{aligned} \tag{1}$$

where Y_{ist} is the outcome of interest for property i in school zone s in month-year t. The key variable of interest, $Climate_{r,s}$, represents an indicator for each climate rating, r, from "A" to "D", which are only activated for the corresponding rating that will be assigned to school s starting in September 2011. Climate rating "F" is excluded to serve as the reference.

The model allows for semi-parametric school climate effects in each quarter of the post-shock school year by interacting the climate ratings with each of the four post-shock quarter indicators.[27] It is important to study information shock effects dynamically because related studies find dissipating effects within months after school quality information is released (Bogin and Nguyen-Hoang, 2014; Fiva and Kirkebøen, 2011; Haisken-DeNew et al., 2018). The initial post-shock quarter (September–November 2011) encapsulates the main school climate information campaign that included news media coverage, although the climate reports remained publicly available online afterward. To my knowledge, CPS and local

[26] Appendix Table B1 provides all coefficients.

[27] I exclude main climate effects because these would be time-invariant and captured by school fixed effects.

news media did not actively promote climate information during the rest of the school-year after November. Although the administration of the spring 2012 climate surveys could have indirectly nudged parents to seek out the information in the second and third quarters after the original information shock. For the main analysis, I focus on the initial climate ratings, before they were updated in September 2012, providing the cleanest information shock.

In this model, I include month-by-year fixed effects, θ_t, to control for any time-varying changes in house prices that are experienced across the school district, including seasonal changes. I also include boundary fixed effects, ν_{s_j,s_k}, which represent streets that separate houses in very close proximity to each other, where one side of the street is served by school s_j and the other side of the street is served by a different school, s_k.[28] The boundary fixed effects ensure the comparison of properties sharing similar neighborhood amenities, which also captures time-invariant differences between different boundaries, such as the reputation or other unobservable aspects of specific streets. Additionally, I include school fixed effects, μ_s, which control for time-invariant school quality and zone differences, such as the school's prestige or perceived quality. The inclusion of both month-year and boundary fixed effects means the estimates are identified off of changes in the difference in outcomes between properties across a given boundary line before and after the information shock.

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

I also include a vector of property-specific characteristics, $\mathbf{X}_{it}$, to compare properties with similar features, such as number of bedrooms and bathrooms, square footage, age, distance to downtown, and an indicator for condominiums. As detailed in Section 3, I imputed the property characteristics for condominiums. Therefore, I interact property characteristics with a condominium indicator in the regressions to allow for different slopes for each property characteristic between condominiums and non-condominiums.[29]

Two main assumptions underlie this DID approach. The first is that there are no differential pre-release trends in outcomes that vary by school climate. The close proximity of the properties being compared in my model makes this assumption more likely to hold, as the outcomes for properties so close to each other are likely to trend similarly. I test this

[28] I follow the literature and link property transactions to their nearest boundary within 0.2 miles (Bayer et al., 2007; Black, 1999; Zheng, 2022).

[29] In Section 6.4, I show that my estimates are qualitatively similar with and without including the condominium transactions, as well as when including school and neighborhood controls.

assumption by conducting event study analyses that explore the school climate effect on the housing market in each of the eight quarters before the information release and in the four quarters after. These models are based on regressions of the following form:

$$Y_{ist} = \kappa_0 + \sum_{\tau}^{T} \Big(\sum_{r=D}^{A} (\gamma_{r,t} Climate_{r,s} * 1(t=\tau)) \Big) \\ + \Gamma \mathbf{X}_{it} + \theta_t + \nu_{s_j,s_k} + \mu_s + \varepsilon_{ist}, \tag{2}$$

where the variables are the same as in equation 1, except that the $\gamma_{r,t}$ coefficients represent the difference in the outcome of interest between climate rating r and climate rating "F" in relative period t. To minimize the sensitivity of these estimates to the choice of reference period, I use constrained regressions to estimate these models, where pre-shock coefficients average to zero. Thus, each $\gamma_{r,t}$ represents the school climate effect in period t, relative to the average relationship in the pre-shock period (Miller, 2023).[30] Moreover, constrained regressions allow my coefficients to be more directly comparable to the DID estimates.

The DID approach also assumes that there are no contemporaneous unobservable shocks that are correlated with the initial school climate ratings and the outcomes of interest. Again, the close proximity of the properties being compared in my model makes this assumption more likely to hold, since contemporaneous shocks would likely affect properties on both sides of the street similarly due to their proximity. Although this assumption is not directly testable, I note that the district did not begin using school climate ratings for accountability until the 2013-14 school year, and were initially only used for informational purposes (Levenstein, 2016). This suggests that there were no other intentional concurrent changes attached to the release of this information that may affect the housing market.

6 Results

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

6.1 School climate information effects on housing values

Figure 3 presents the quarterly dynamics of log house prices for each school climate rating relative to the worst rating two years before and one year after the information shock. All

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

four panels are estimated in the same regression through equation 2. The dots represent the estimated coefficients from the event study model in each relative quarter, while the error bars represent the 95% confidence interval for each estimate.

Across all four climate rating event studies, house prices are relatively flat as a function of future school climate ratings before the information is publicly released. Thus, the figures show supporting evidence for the parallel trends assumption. Each panel shows that there is a visually clear and significant positive price change in the initial post-shock quarter relative to the pre-shock average estimates.

Table 3 summarizes estimated coefficients based on DID models from equation 1. In the interest of brevity, this table only reports coefficients from the first post-shock quarter that would capture reactions from the active information campaign.[31] The first column of panel A shows that the information shock led to a 21% price premium for homes assigned to climate rating "A" relative to rating "F" in the first post-shock period, which is statistically significant at the 1% level. For climate ratings "B", "C", and "D", there were also immediate price premiums between 9% and 13% relative to rating "F", all of which are statistically significant at the 5% level.[32]

Figure A4 presents a forest plot showing that my estimates are generally consistent with studies estimating capitalization from releasing novel school quality ratings that were based on test performance.[33] My estimates are about half the size of those presented by Figlio and Lucas (2004), who study the initial release of school grades in Florida, but still within their confidence intervals. I estimate a very similar information impact to that by Bogin and Nguyen-Hoang (2014), who examine the failing school designation in Mecklenburg County, North Carolina. However, I estimate larger rating effects than Haisken-DeNew et al. (2018), who investigate the impact of nationally releasing school ratings in Victoria, Australia.[34]

Table 3 further shows that the coefficient for climate rating "A" is statistically significantly larger than the coefficients of the other three ratings, based on F-tests of the null hypothesis that the differences are zero. On the other hand, the estimated effects for climate ratings "B", "C", and "D" are not statistically different from each other. This suggests that homebuyers react distinctly for the best climate rating compared to the other ratings, but respond similarly between climate ratings that are around average. These differential effects

[31] I show the full set of quarterly coefficients graphically in Figure A3 and describe them below.

[32] These estimates may be a lower bound, since families may still access better climate schools through Chicago's school choice program, without having to live in a specific school zone.

[33] For each paper, I focus on the most immediate (short-term) estimated impact available.

[34] The bottom half of the forest plot in figure A5 includes smaller coefficients from studies that use information shocks not directly comparable to the climate ratings release, such as rating updates or continuous/numeric school quality measures. Stakeholders may not appreciate or understand continuous/numeric measures as easily as discrete measures based on color-coding or letter-grading (Glazerman et al., 2020).

are consistent with studies that find non-linear impacts of school quality on property values (Bibler and Billings, 2019; Ries and Somerville, 2010). However, this is in contrast to Figlio and Lucas (2004) who estimate more linear, although imprecise, reactions between ratings "A"-"B" and ratings "B"-"C".

For ease of comparison over time, Figure A3 presents semi-parametric quarterly estimates based on DID models from equation 1. The figure shows that the effects begin to dissipate by the second quarter, at which point only the best climate rating effect remains statistically significant at the 10% level, with an estimated impact of 13%, which is about half the impact in the initial post-shock quarter. By the third and fourth post-shock quarters all estimates return to pre-shock levels. Almost all studies using a similar information shock approach find that capitalization effects dissipate over time and return to pre-publication levels within months after the information shock (Bogin and Nguyen-Hoang, 2014; Fiva and Kirkebøen, 2011; Haisken-DeNew et al., 2018).[35] I discuss potential fade out mechanisms in Section 7.

6.2 School climate information effects on homebuyer incomes

A growing literature shows socioeconomic differences in parental preferences for different school qualities (Hastings et al., 2009; Jacob and Lefgren, 2007), as well as differences in likelihood to link residential decisions to school options (Barrow, 2002; Billings et al., 2018). In this subsection, I examine the impacts of school climate information on the sorting of homebuyers from different socioeconomic backgrounds.

Figure 4 presents event study estimates comparing log homebuyer incomes in neighborhoods with each climate rating relative to those with the worst climate rating over time. The new homebuyer incomes are relatively flat as a function of future school climate ratings before the information is publicly released–again supporting the assumption of no differential pre-trends. The top left panel shows that there is an immediate and statistically significant effect on homebuyer incomes in response to the best climate rating, but the rest of the panels show that for other climate ratings the immediate reaction was more muted.

In Column (1) in panel B of Table 3, I present the DID estimates for the first post-shock quarter. There was a 16% increase in the incomes of buyers purchasing homes in neighborhoods assigned to the best climate rating, compared to the incomes of those buying in the worst climate rating school zones (p-value$<$0.05). The other climate ratings experienced positive change, but their coefficients lack precision. These positive estimates are in line with past research suggesting that higher-income families strongly value teachers' ability to promote student satisfaction (Jacob and Lefgren, 2007).[36]

[35]See Table B2 for a list of related papers that explore dynamic changes over time.

[36]Relatedly, Figlio and Lucas (2004) find that a school grade information shock differentially attracted

Appendix Figure A6 summarizes the DID estimates for all four post-shock quarters and shows that the best climate rating impact quickly dissipates by the second post-shock quarter. Overall, only one of the 16 point estimates is statistically significant at the 10% level, so the main effects on income are suggestive.[37]

6.3 Heterogeneous Effects

The previous two subsections demonstrate that school climate information impacts the housing market, especially in the initial post-shock quarter when the information is first released. The extent of these effects could vary among different types of homebuyers and among different types of schools. I now turn to several potential sources of variation in reactions.

Homebuyers that are more likely to engage with the school system may care more about the quality of the neighborhood school (Zahirovic-Herbert and Turnbull, 2008). In column (2) in panel A of Table 3, I find slightly larger initial rating impacts on the price of homes intended for families with kids, as proxied by homes with three or more bedrooms that were not condominiums. This suggests that homebuyers with children care about school climate, or that childless homebuyers may be willing to pay more for better climate ratings because they believe future families with kids will value the amenity (Brunner and Balsdon, 2004; Harris et al., 2001; Hilber and Mayer, 2009).[38] Additionally, column (2) of panel B shows that higher-income buyers have a strong and significant preference for any of the climate ratings over the worst rating—further suggesting that homebuyers with children may be leading the housing market reaction to climate ratings.[39]

A second proxy for families is whether the home was purchased by two buyers (potentially married) as opposed to a single-buyer (potentially single). Column (2) in Table B3 includes only those transactions with co-borrowers, while column (3) includes only those with single-borrowers. The standard errors for these estimates are larger and sometimes double those

higher income students (as proxied by FRPL-eligibility) differentially into "B" schools relative to "C", but find no difference between "A" and "B" schools.

[37]However, I show additional evidence of income effects in Sections 6.3 and 7.2, especially for homes that are likely for families with children and in the longer-term during the second information release.

[38]The school climate information campaign takes place after the moving season, when school is already in session. Therefore, any reactions to the information would be from whoever is entering or is already in the market to purchase a home during each relative quarter, even if it is not the peak of moving season. While families with school-age children may be less likely to move during the school year, those responding to the information campaign could include families with younger children, families planning to have children, and buyers without children. Therefore, my estimates may be a lower bound of parental preferences for school climate. Related studies using academic-based school quality have similarly timed information shocks, and still find immediate capitalization impacts–within the first quarter (Bogin and Nguyen-Hoang, 2014; Fiva and Kirkebøen, 2011; Haisken-DeNew et al., 2018).

[39]Similar to the main sample, Figure A7 shows that the immediate positive impacts quickly dissipate for the sample of larger homes.

from the main estimates in column (1). Given these large standard errors, there are no statistically significant differences in estimates between co-borrowers and single-borrowers during the first post-shock period. However, Figure A8 suggests a more sustained price impact for co-borrower transactions (panel a) than for single-borrower transactions (panel b), which dissipates by the fourth post-shock quarter. Figure A9 suggests a similar pattern for buyer incomes, however, only the third post-shock quarter co-borrower (panel a) estimates are statistically significantly different from zero at the 5% level. These differences between co-borrowers and single-borrowers are noisy and indistinguishable from statistical noise so they are suggestive at best. As in the main sample, the housing price results are stronger and more robust than the income effects.

Families face trade-offs between various school characteristics when deciding where to send their children to school. Therefore, I explore heterogenous climate information effects on properties with varying levels of zoned school characteristics (proficiency, value-added, FRPL, and racial composition). In the interest of brevity, Table B4 presents the estimated impacts in the first post-shock quarter for the top quartile and bottom quartile of each school characteristic separately along each column. Although the precision varies, estimates for the top and bottom quartiles are typically in the same direction and their differences are not significantly different from each other.[40] This suggests the reaction to school climate information was similar across other school characteristics.

6.4 Robustness Checks

I now test the sensitivity of my main findings by conducting a series of robustness checks. Appendix Table B5 shows the results from various specifications for the effects of releasing school climate ratings on house prices (panel a) and homebuyers' incomes (panel b). Column (1) shows my main results for comparison. The estimates are very similar if I exclude the school fixed effects in column (2) or if I exclude the border fixed effects in column (3). Robustness to these two alternative specifications suggests that there are no unobservable differences in housing market trends (even if there are level differences) that correlate with school climate either across schools or across boundaries.[41]

[40] In order to increase statistical power, I combine ratings "A" and "B" to a single rating (best climate), and do the same for ratings "C" and "D" (medium climate). In the second and third to last rows of each panel, I present the p-values associated with the F-test of the null hypothesis that the coefficient on the interaction term for the top quartile equals the coefficient on the interaction term for the bottom quartile, separately for each climate rating.

[41] This pattern is consistent with findings by Clapp and Ross (2004), who find that even though the racial composition of schools changed over time in response to labor market area demographic shocks, those shocks did not create local differences in housing prices and all prices within a given labor market area tended to move up together based on market wide housing demand.

Since school climate may be correlated with neighborhood and school conditions, I next account for the existing information set available. Appendix Table B6 shows very similar estimates when I replicate the approach by Dhar and Ross (2012), where I include boundary side fixed effects and boundary fixed effect trends (column 2),[42] time-varying school controls (column 3),[43] and the combination of these two specifications (column 4). Column (5) shows that the estimates are also very similar when I include both neighborhood and school controls. Furthermore, as described in Section 3, transactions for condominiums required to have property characteristics imputed, but column (6) shows that the climate rating capitalization remains consistent even when excluding condominiums.

In Table B7, I test the robustness of the main price and income effects to specifications that vary how I incorporate the boundary fixed effects. Column (1) replicates the main estimates. In column (2), I show that the first post-shock quarter price and income estimates are robust to interacting the boundary FEs with an indicator for the post shock period. While column (3) shows qualitatively similar patterns when interacting the boundary FEs by post by quarter. The estimated impacts are larger and remain statistically significant.

As detailed in Section 2, CPS distributed additional school quality information through physical report cards starting in November 2011 (two months after the climate reports). These additional pieces of information may affect how the school climate ratings affected the housing market, since school climate is positively correlated with school proficiency and value-added rates. To formally test the impacts of the school progress report cards, I run models that include proficiency and value-added information shocks that are initiated in November 2011. Column (2) of Appendix Table B8 shows consistent price and income effects. This makes sense since the school climate ratings were separately released about two months before the school report cards that contained proficiency and value-added information.

The analysis in this study has focused on the school climate ratings effects for elementary school zones. CPS also administered and publicly released school climate survey results for almost all high schools in the district. Therefore, each property received school climate information for both the neighborhood elementary school and the neighborhood high school. To test whether the high school climate rating shocks drive my main results, I conduct models that include quarterly effects for the high school climate ratings in my main models. In column (3) of Appendix Table B8, I show that the climate rating effects for the neighborhood elementary schools are consistent but noisier to those in my main models. This suggests that the neighborhood elementary schools climate rating effects were not driven by the climate

[42] Boundary fixed effect trends are based on the interaction between the boundary fixed effect and the continuous school year measure.

[43] The school controls include two years of lagged proficiency rates, as well as racial/ethnic, LEP, IEP, and FRPL enrollment shares.

ratings assigned to neighborhood high schools.

To ensure that I am comparing houses in adjacent neighborhoods that have access to the same amenities, I also conduct my analysis using various distances to the nearest boundary. In appendix Table B9, I show that the choice of distance from the border does not greatly affect the estimates, but these become noisier as the distance and sample become smaller. Lastly, although the main analysis focuses on mortgage-based transactions to examine both prices and income, Appendix Table B10 shows that price capitalization estimates remain consistent when cash transactions are included, with nearly double the sample.

7 Potential Mechanisms

In this section, I investigate potential mechanisms behind the immediate and then dissipating school climate impacts on the housing market. Most prior research shows similar short-term capitalization impacts from academic-based school quality information shocks (see Appendix Table B2 for more details).[44] I consider two main channels: impacts on the demand and supply of housing in Section 7.1 and information salience and search costs in Section 7.2.

7.1 Supply and demand mechanism

Changes to public goods may lead to neighborhood demand shocks that may impact house prices (Banzhaf and Walsh, 2008; Tiebout, 1956), while the extent of these impacts depends on the local supply of available housing (Hilber and Mayer, 2009; Paciorek, 2013).

The climate information effect on house prices and its ensuing fadeout could potentially be explained by the short- and long-run supply and demand of houses available on the market. In the short-run, the information shock may lead to an immediate increased demand for homes assigned to better climate schools. The supply of available homes may not be able to react immediately to the increased demand, which would lead to an immediate increase in sales prices for in-demand properties that were already on the market. As time goes on, the initial price premium may lead to an increased supply of available homes assigned to in-demand schools to meet the increased demand for homes with access to better climate ratings, bringing sales prices back down at the higher supply quantity.

To explore this potential channel, I examine the climate information shock effects on the

[44] While research shows that homebuyers react to information based on academic performance levels (Bogin and Nguyen-Hoang, 2014; Figlio and Lucas, 2004; Haisken-DeNew et al., 2018), they do not react to information based on value-added (Imberman and Lovenheim, 2016; Kane et al., 2003), which is in line with other research on parental school preferences (Abdulkadiroğlu et al., 2020; Ainsworth et al., 2023).

housing supply, as proxied by the number of executed sales transactions.[45] Figure A10 shows event studies of the difference in the number of transactions between each respective rating and the worst rating in each quarter around the information shock.

While the estimates are quite noisy, there is no evidence of differential pre-trends, or a break in trend once the information takes place. This suggests that the immediate price effects in this study were driven by an increase in housing demand without a change in available houses on the market. Furthermore, since the number of transactions does not significantly change when house prices return to pre-shock levels across all ratings, the longer-run housing supply channel cannot fully explain the dissipating price premiums. This pattern suggests that demand returns to pre-shock levels over time.

7.2 Information salience and search costs mechanism

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

Therefore, a second potential mechanism for the immediate—and then dissipating—effects could be that homebuyers value school climate, but only pay for it when they can observe the information. This would suggest that as the information campaign ends and news coverage stops, the cost of obtaining school climate information increases, even though the reports are still publicly available. Homebuyers who enter the market after the information campaign may not be aware of the climate reports, making it costlier to access the information.

Evidence for this mechanism can be seen in online search patterns over time. Google Search Trends data in Figure 5 shows how Chicagoans searched for school climate related terms over the course of three years.[46] The dashed red lines identify the yearly school climate report releases. The largest jump in search interest occurred in the months following the initial school climate information release. This reaction dissipates by the end of the first post-shock quarter, which is in line with the quarterly school climate capitalization.

Further evidence for this channel can be seen from the second release of school climate reports in September 2012, however this release was complicated by concurrent events that

[45] Appendix C.4 provides details on this process.

[46] I calculate Google Search Interest by adding the hit rates in each month for the terms: "school climate," "school culture," "school organization," and "school environment." My Google Search Trends time series starts in January 2011 because at that point Google changed how it defined geographies, making it difficult to compare search patterns before and after January 1, 2011.

dampened the prominence of the information. The updated 2012 climate reports were released three school days before the Chicago Teachers Union went on a week-long strike, the longest in the district's history, which overtook local news media coverage. Therefore, even though the climate ratings were publicly released and accessible, the information shock would have been more muted, potentially leading to higher search costs for the ratings. This is corroborated by the muted Google searches for related terms in the last quarter of 2012.

Tables 4 and 5 allow for multiple climate rating information shocks on sales prices and on buyer incomes, respectively. In column (1), I present the initial year-level school climate rating impacts, which only includes the original climate ratings from September 2011.[47] Then in column (2) I extend the data through SY 2012-13 and continue to estimate the impact from the September 2011 climate ratings through time. Column (3) allows for the initial (2011) climate ratings to have separate impacts starting in September 2011 and an additional impact starting in September 2012. Lastly, in column (4) I also allow there to be a separate impact for the second (2012) climate rating updates starting in September 2012.

Column (1) in Table 4 shows that better climate ratings were positively capitalized into house prices relative to the worst climate rating during the first year. However, column (2) shows no additional impacts from the first climate ratings starting in September 2012. Furthermore, columns (3) and (4) provide evidence of null capitalization on house prices from the initial (2011) and updated (2012) climate ratings during the second information release. These muted capitalization effects may be due to the increased search costs due to a reduction in salience or, as suggested by Figlio and Lucas (2004), the climate rating variability—the correlation in ratings across 2011 and 2012 is only about 0.49, and 67% of schools change rating assignment.[48] Another reason may be that most families were not aware of the climate information updates due to the teacher strikes taking over news media coverage the same week of the climate ratings release.[49]

On the other hand, columns (2) and (3) in Table 5 suggest that the initial ratings had slightly more sustained, although noisy, impacts in attracting higher income families to better climate school zones. Importantly, column (4) shows that the second (2012) climate ratings also had their own impacts attracting higher income families, even though these updated

[47] These point estimates are smaller than the main first post-shock quarter point estimates from Table 3, because the year-level estimates encapsulate post-shock quarters with full and dissipated impacts.

[48] The 2012 climate ratings were calculated relative to the 2011 average. This means that the 2012 ratings were not meant to compare schools in 2012, but rather compare them to previous year's distribution of school climate performance. Facing potential pressure from local families to improve their climate, 42% of schools improve their rating from 2011 to 2012 and only 24% are assigned a worse rating.

[49] I find that the muted capitalization does not seem to be due to changes in preferences by incoming homebuyers for school proficiency as opposed to school climate. In Appendix Table B11, I show that controlling for contemporaneous, yearly-updated school proficiency rates does not significantly change the year-level estimates by much.

ratings did not capitalize into prices. This suggests that higher-income families value school climate, and that they have the resources and social networks needed to seek out and act on the information, even when it is not actively promoted (Sattin-Bajaj and Roda, 2018).

8 Conclusion and Discussion

A growing body of research emphasizes the crucial role of school social climate on student outcomes. Over the past decade, efforts to measure and improve school climate have increased across the US. If families value this quality, making this information available can influence school choice, residential decisions, and equitable access to good schools. However, there is limited causal research on whether stakeholders value school climate.

In this paper, I present evidence that school climate ratings provide valuable insights that are not easily observable without public information. I then provide the first causal evidence that publicizing school climate information affects housing market dynamics. By linking home transaction data with home loan applications and leveraging a 2011 Chicago Public Schools information shock, I find an immediate, significant increase in home prices for properties assigned to better climate schools, which quickly dissipates. Similarly, I find suggestive evidence that the information attracted higher-income homebuyers to these neighborhoods.

The immediate and significant effects, which dissipate soon after, can be due to different mechanisms. First, I find evidence that the immediate price increase was likely due to increased demand without a change in housing supply. This channel cannot fully explain the dissipating impacts over time. Second, I find evidence suggesting the information campaign increased the salience of school climate information, which in turn decreased the cost of finding the information. On the other hand, as the salience of the information declined, the cost of knowing about the data and finding it increased, especially for homebuyers entering the housing market without an active climate information campaign.

The second release of the climate reports was complicated by climate rating variability and a dampened information campaign, which led to weaker capitalization effects in the second year. However, the impacts on homebuyer incomes were sustained, suggesting that higher income families were better able to seek out the information.

My findings offer evidence that families value school climate quality when this information is 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 climate information to help form their decisions for school choice, then they should make the information clear, easily accessible, and salient. However, because climate ratings can affect house prices and attract more advantaged families, districts may want to balance promoting climate quality to attract families and ensuring all students have access to good school climates. I leave these important considerations for future work.

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Figures

Figure 1: Example of school climate reports website

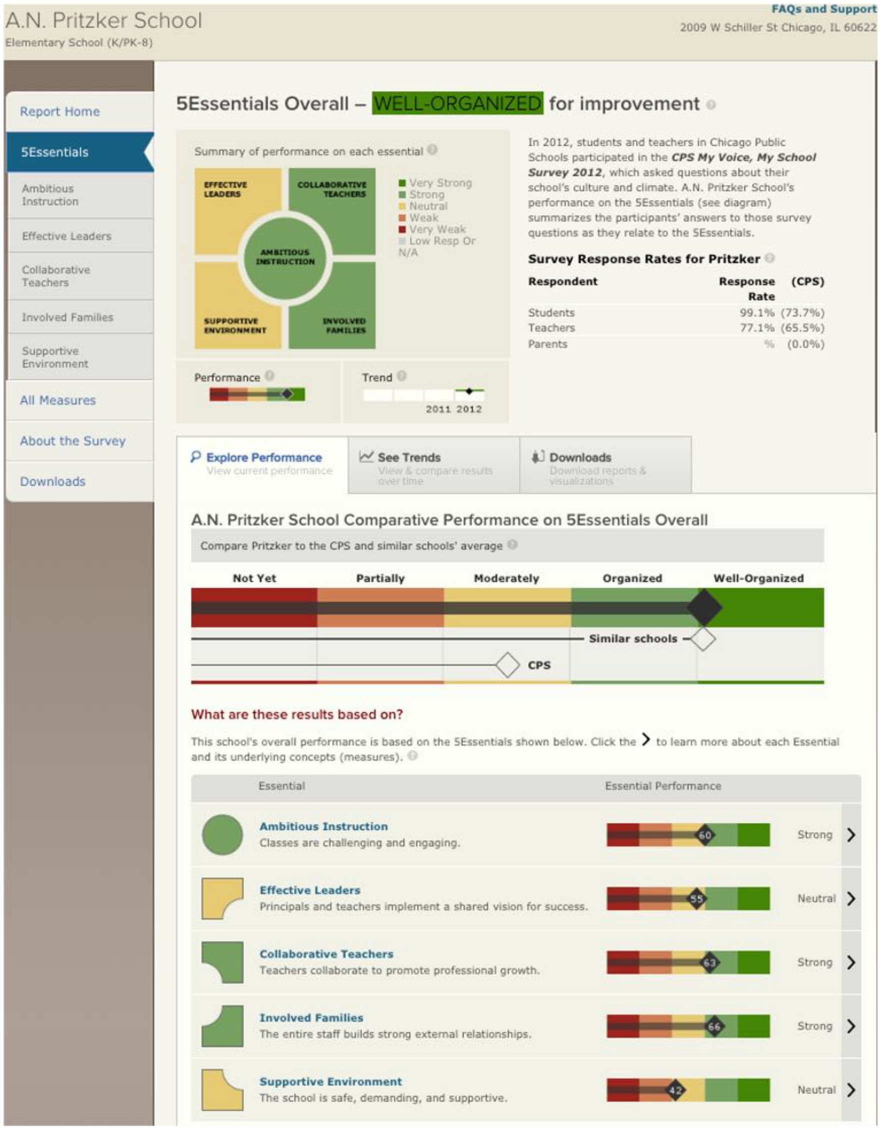
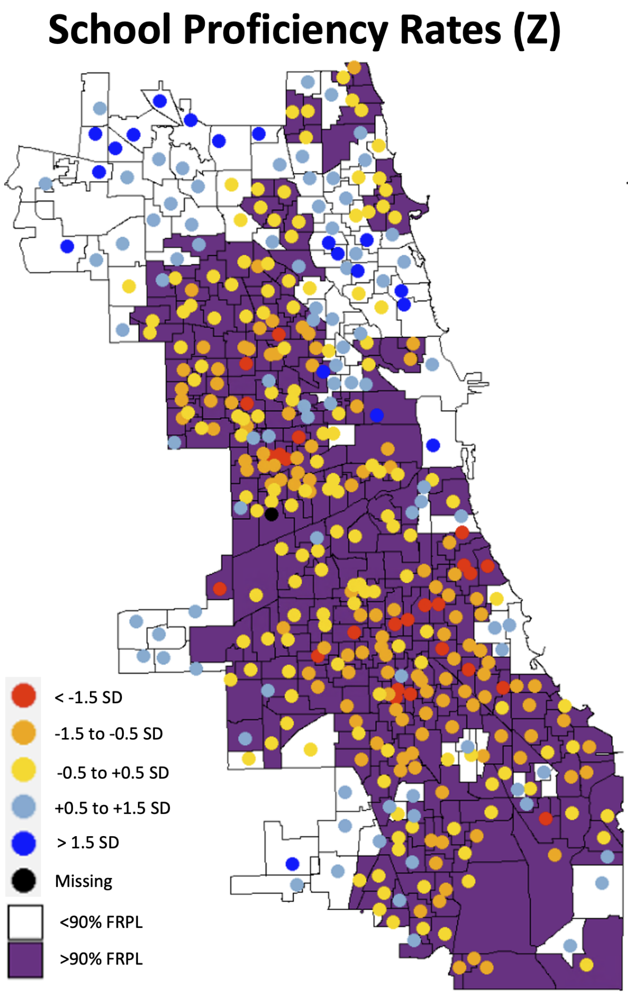
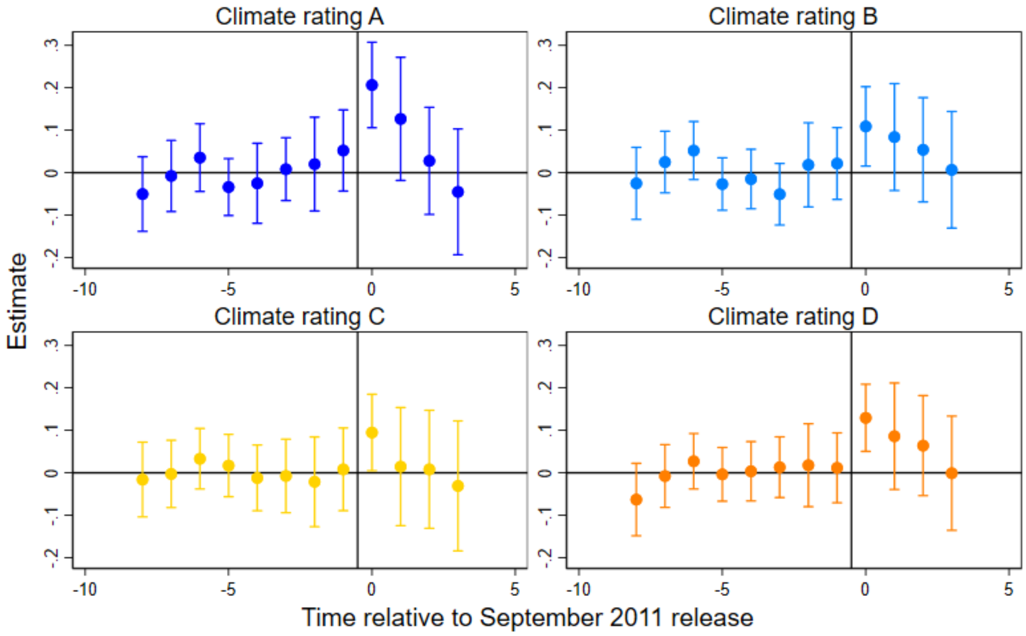


Figure 2: School proficiency rates (left) and School Climate ratings (right) overlayed on school FRPL rates by school attendance zones



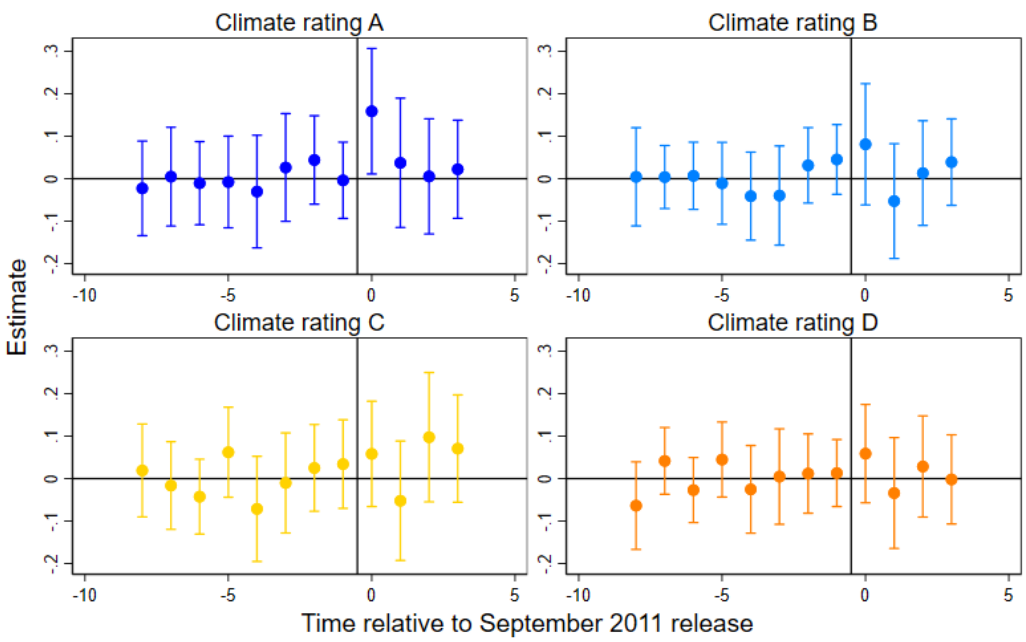
Notes: The purple polygons represent the attendance boundaries for schools serving a population of students that is more than 90% eligible for free-or-reduced-price lunch (FRPL), a measure of student income. The white polygons represent neighborhood schools serving higher-income students. I choose a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

Figure 3: Quarterly event study estimates: Log Home Sales Price



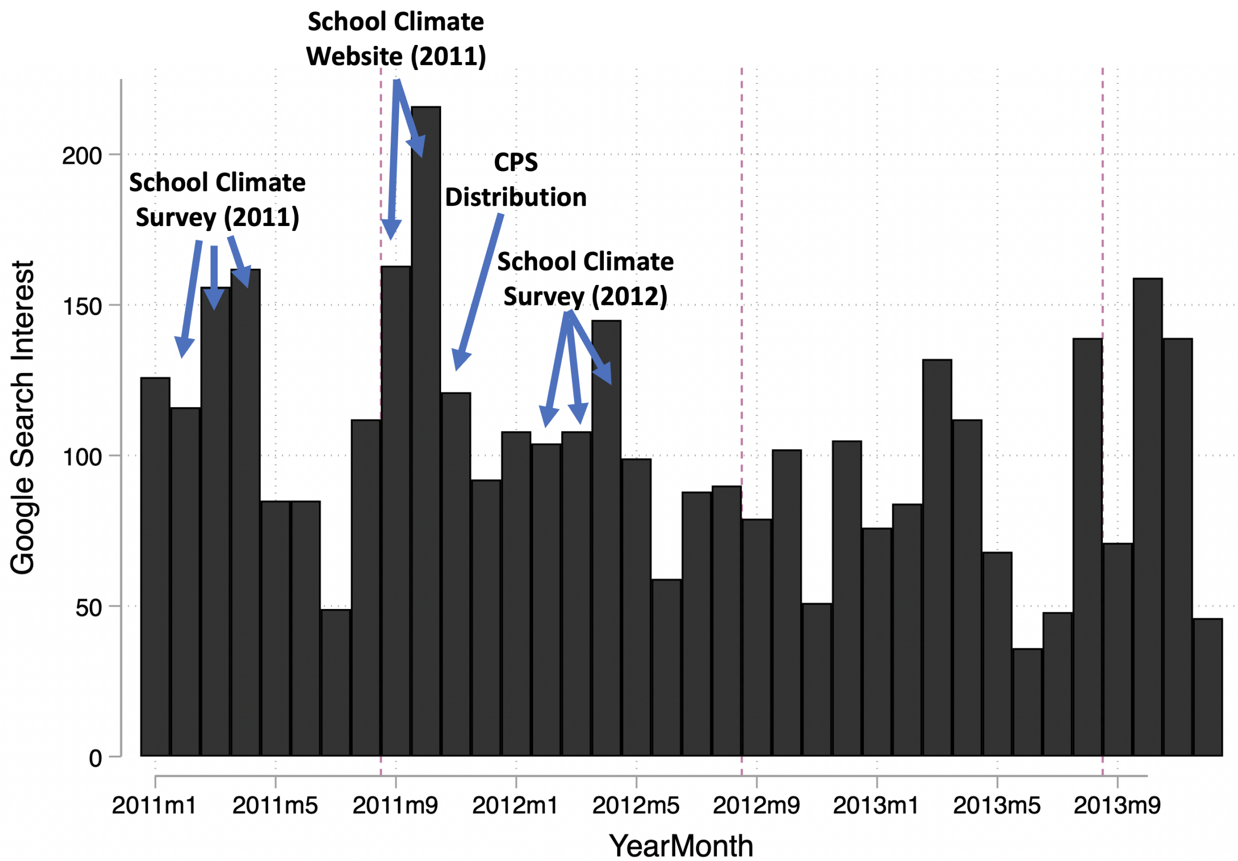
Notes: Sample is based on transactions that took place between 09/2009 through 08/2012. These event studies are based constrained regressions as described for equation 2.

Figure 4: Quarterly event study estimates: Log Homebuyer Income



Notes: Sample is based on transactions that took place between 09/2009 through 08/2012. These event studies are based constrained regressions as described for equation 2.

Figure 5: Google Search Trends for School Climate Related Keywords



Notes: Google Trends search results based on keywords *school climate*, *school culture*, *school organization*, 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 terms together in each month.

Tables

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

Characteristics	All schools	Climate Rating A	Climate Rating B	Climate Rating C	Climate Rating D	Climate Rating F
Key regression variables						
Sale price	287,510	314,464	334,729	226,992	288,872	195,336
	(227,302)	(241,647)	(255,378)	(160,231)	(229,508)	(129,080)
Mortgage Income	101,218	108,798	115,950	82,515	101,962	72,080
	(92,878)	(99,962)	(102,412)	(69,600)	(95,349)	(53,988)
Avg. School Performance						
Proficiency rates (Z)	0.13	0.64	0.41	-0.11	-0.02	-0.56
	(0.80)	(0.55)	(0.80)	(0.74)	(0.73)	(0.76)
Value-Added (Z)	0.03	0.45	0.31	0.10	-0.29	-0.25
	(0.86)	(1.00)	(0.69)	(0.77)	(0.82)	(0.75)
Avg. School Characteristics						
% White	22.4	30.6	30.1	17.0	19.3	8.4
	(23.3)	(21.0)	(25.7)	(18.7)	(22.3)	(17.4)
% FRPL	73.8	66.2	61.1	81.7	78.5	91.3
	(26.8)	(27.7)	(30.2)	(19.3)	(23.6)	(17.0)
Parcels' Census Block-Group Characteristics						
% White	51.3	60.6	59.9	45.5	49.7	25.6
	(30.6)	(23.2)	(30.1)	(30.4)	(30.7)	(24.9)
Median HH income	65,406	70,162	72,616	58,071	64,994	49,468
	(27,465)	(27,787)	(27,741)	(23,751)	(28,270)	(17,670)
Avg. Property Characteristics						
Square Feet	1,638	1,666	1,757	1,524	1,635	1,433
	(675)	(640)	(741)	(622)	(669)	(528)
% Condo	39.8	42.1	41.3	35.4	42.6	25.9
	(48.9)	(49.4)	(49.3)	(47.8)	(49.5)	(43.8)
N-Observations	13,586	1,876	3,539	2,065	5,026	1,080
N-Schools	335	35	83	62	120	35

Notes: Summary statistics are based on sample described in section 3, which includes transactions that took place between 09/2009 through 08/2012. Standard deviations are shown in parentheses.

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

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

Notes: Sample includes schools serving properties in main sample (described in Section 3) during pre-shock period, which includes properties that were transacted between 09/2009 through 08/2011. Refer to appendix Table B1 for full table with coefficients. These regressions also include: school standardized proficiency rate (except in column 1); % Asian, % Black, % Hispanic, % Native American, % Multi-Race; % FRPL (except in column 2); % LEP, % IEP; enrollment; average yearly school crimes (based on 2007 through 2011 FY); parent perceived school safety; and block-group education levels (HS, some college, college, and graduate). All models except for proficiency rates outcome model control for profiency rates. All models except for % FRPL outcome model control for % FRPL. To make fair comparisons, columns (1) through (3) use versions of the outcome variables that have five levels that are comparable to the climate levels (estimates are very similar whether I use the 5-level outcome or the continuous measures). These levels are created by grouping the following standardized values into five ratings: rating of 1 if less than -1.5 SD; rating of 2 if between -1.5 SD and -0.5 SD; rating of 3 if between -0.5 SD and +0.5 SD; rating of 4 if between +0.5 SD and +1.5 SD; rating of 5 if greater than +1 SD. Columns (1) through (4) include all school zones in the sample, while column (5) only includes yellow or better climate school zones, and column (6) includes the sample of yellow or worse climate school zones.

Table 3: Effect of school climate rating information on log sale prices and log buyer income (during first post-shock quarter)

	(1)	(2)
Panel A: Dependent Variable is Log Sale Price		
Climate Rating A x PostQ0	0.209***	0.219***
	(0.051)	(0.064)
Climate Rating B x PostQ0	0.107**	0.108
	(0.047)	(0.073)
Climate Rating C x PostQ0	0.093**	0.120*
	(0.045)	(0.068)
Climate Rating D x PostQ0	0.133***	0.155***
	(0.039)	(0.057)
Observations	13586	6237
Panel B: Dependent Variable is Log Homebuyer Income		
Climate Rating A x PostQ0	0.162**	0.228***
	(0.075)	(0.079)
Climate Rating B x PostQ0	0.078	0.133*
	(0.072)	(0.068)
Climate Rating C x PostQ0	0.055	0.226***
	(0.063)	(0.072)
Climate Rating D x PostQ0	0.064	0.104*
	(0.059)	(0.058)
Observations	13586	6237
Bigger Homes		Y

Notes: Estimation is based on equation 1. In the interest of brevity, these only present the estimated impacts in the first post-shock quarter (Q0). The model includes month-by-year fixed-effects, school fixed-effects, and boundary fixed-effects, as described in section 5. Sample is based on transactions that took place between 09/2009 through 08/2012. Bigger houses are those that have at least three bedrooms and are not condominiums. Standard errors are clustered at the school zone level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Table 4: Impacts of school climate rating information on **log sales price**, through 2011-12 or 2012-13

	Through SY2011-12	Through SY2012-13		
	(1)	(2)	(3)	(4)
1st Rating A x Post Sept 2011	0.075*	0.075**	0.073*	0.073*
	(0.043)	(0.032)	(0.042)	(0.042)
1st Rating B x Post Sept 2011	0.062*	0.060**	0.056	0.056
	(0.037)	(0.029)	(0.036)	(0.036)
1st Rating C x Post Sept 2011	0.023	0.012	0.020	0.020
	(0.042)	(0.032)	(0.041)	(0.041)
1st Rating D x Post Sept 2011	0.074**	0.060**	0.068*	0.068*
	(0.036)	(0.029)	(0.035)	(0.035)
1st Rating A x Post Sept **2012**			0.002	0.000
			(0.045)	(0.047)
1st Rating B x Post Sept **2012**			0.006	0.002
			(0.040)	(0.042)
1st Rating C x Post Sept **2012**			-0.015	-0.018
			(0.043)	(0.045)
1st Rating D x Post Sept **2012**			-0.015	-0.017
			(0.038)	(0.039)
2nd Rating A x Post Sept 2012				0.003
				(0.033)
2nd Rating B x Post Sept 2012				0.001
				(0.034)
2nd Rating C x Post Sept 2012				0.019
				(0.034)
2nd Rating D x Post Sept 2012				-0.003
				(0.036)
Observations	13582	18063	18063	18063

Notes: Estimation is based on a modified version of equation 1 that aggregates information impact(s) through the post period(s). Sample is based on transactions that took place between 09/2009 through 08/2012 (column 1) or between 09/2009 through 08/2013 (columns 2, 3, and 4). As described in Section 7.2, column (3) allows the initial (2011) climate ratings to have separate impacts starting in September 2011 and an additional impact starting in September 2012. Column (4) also allows for the second (2012) climate ratings to have their own impacts that start in September 2012. The model includes month-by-year fixed-effects, school fixed-effects, and boundary fixed-effects, as described in section 5. I exclude observations that are affected by attendance boundary changes between 2011-12 and 2012-13. Standard errors are clustered at the school zone level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

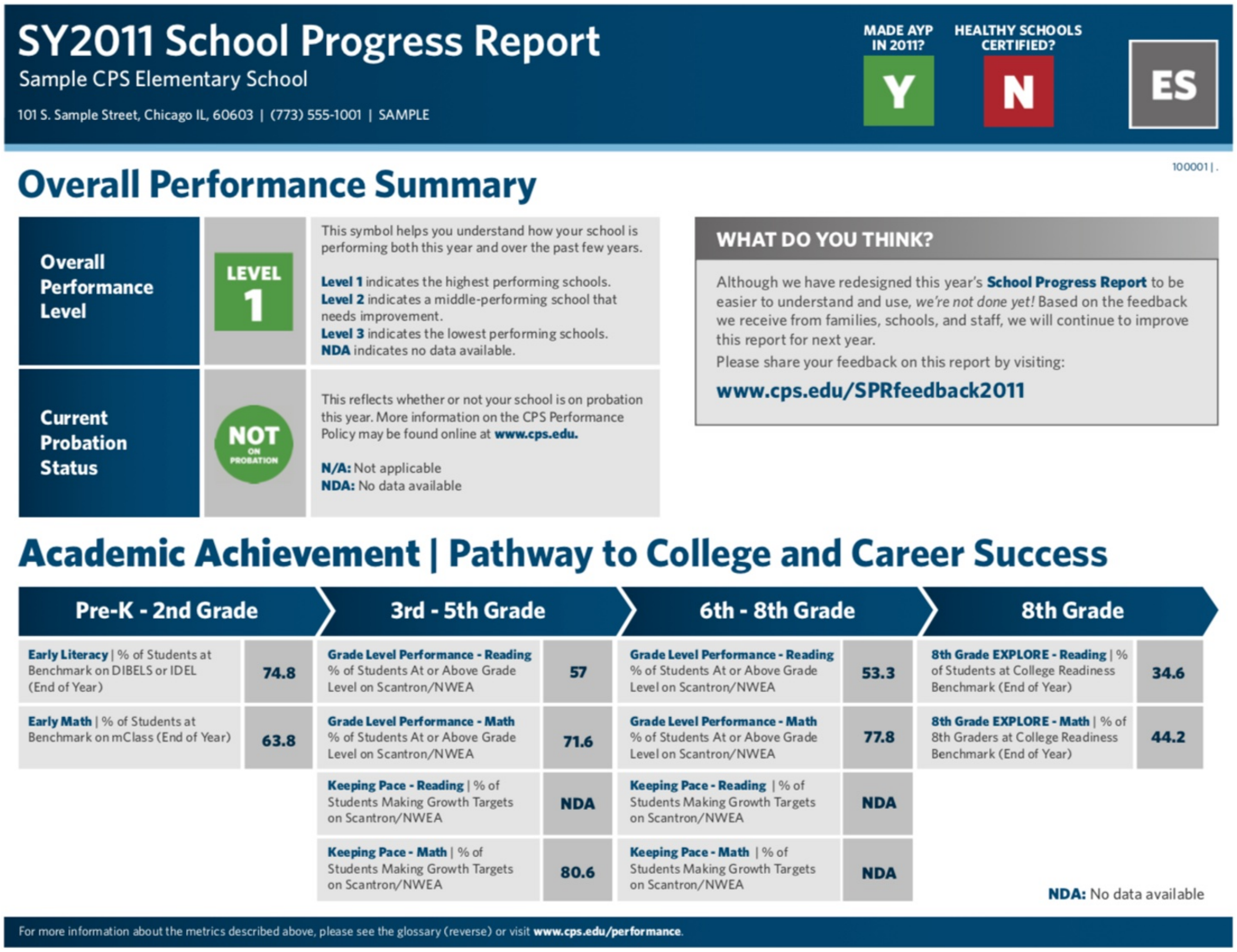
Table 5: Impacts of school climate rating information on **log buyer income**, through 2011-12 or 2012-13

	Through SY2011-12	Through SY2012-13		
	(1)	(2)	(3)	(4)
1st Rating A x Post Sept 2011	0.057	0.071**	0.055	0.055
	(0.040)	(0.031)	(0.040)	(0.041)
1st Rating B x Post Sept 2011	0.023	0.034	0.020	0.020
	(0.033)	(0.022)	(0.032)	(0.033)
1st Rating C x Post Sept 2011	0.052	0.038*	0.045	0.045
	(0.035)	(0.021)	(0.034)	(0.035)
1st Rating D x Post Sept 2011	0.022	0.040**	0.014	0.015
	(0.030)	(0.020)	(0.029)	(0.030)
1st Rating A x Post Sept **2012**			0.035	0.025
			(0.043)	(0.045)
1st Rating B x Post Sept **2012**			0.031	0.014
			(0.044)	(0.044)
1st Rating C x Post Sept **2012**			-0.007	-0.022
			(0.047)	(0.047)
1st Rating D x Post Sept **2012**			0.052	0.043
			(0.042)	(0.042)
2nd Rating A x Post Sept 2012				0.093**
				(0.037)
2nd Rating B x Post Sept 2012				0.115***
				(0.039)
2nd Rating C x Post Sept 2012				0.148***
				(0.040)
2nd Rating D x Post Sept 2012				0.089**
				(0.039)
Observations	13582	18063	18063	18063

Notes: Estimation is based on a modified version of equation 1 that aggregates information impact(s) through the post period(s). Sample is based on transactions that took place between 09/2009 through 08/2012 (column 1) or between 09/2009 through 08/2013 (columns 2, 3, and 4). As described in Section 7.2, column (3) allows the initial (2011) climate ratings to have separate impacts starting in September 2011 and an additional impact starting in September 2012. Column (4) also allows for the second (2012) climate ratings to have their own impacts that start in September 2012. The model includes month-by-year fixed-effects, school fixed-effects, and boundary fixed-effects, as described in section 5. I exclude observations that are affected by attendance boundary changes between 2011-12 and 2012-13. Standard errors are clustered at the school zone level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Appendix A Figures

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



SY2011 School Progress Report

Sample CPS Elementary School

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

MADE AYP IN 2011? Y

HEALTHY SCHOOLS CERTIFIED? N

ES

100001 | .

Overall Performance Summary

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

WHAT DO YOU THINK?

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

Please share your feedback on this report by visiting:

www.cps.edu/SPRfeedback2011

Academic Achievement | Pathway to College and Career Success

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

NDA: No data available

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

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

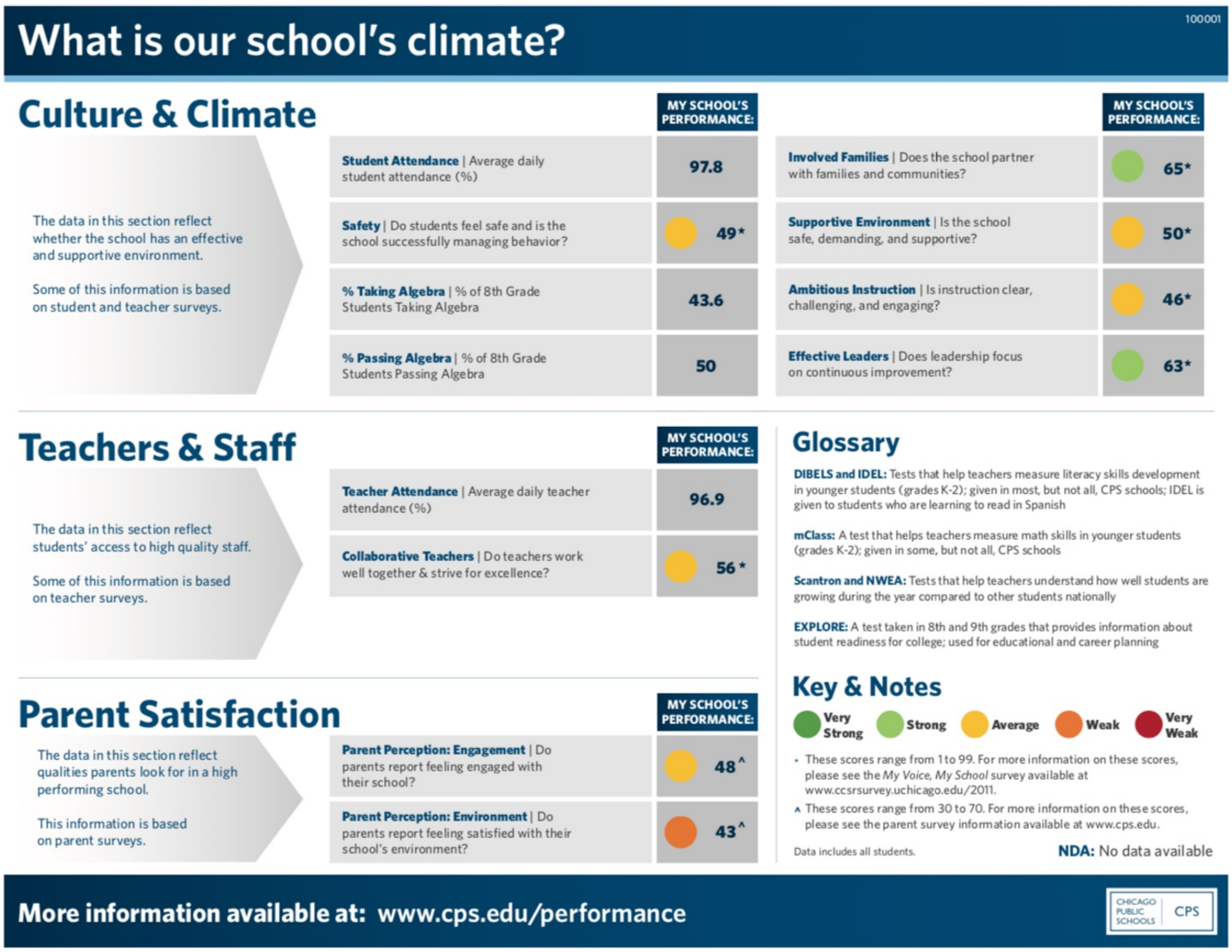
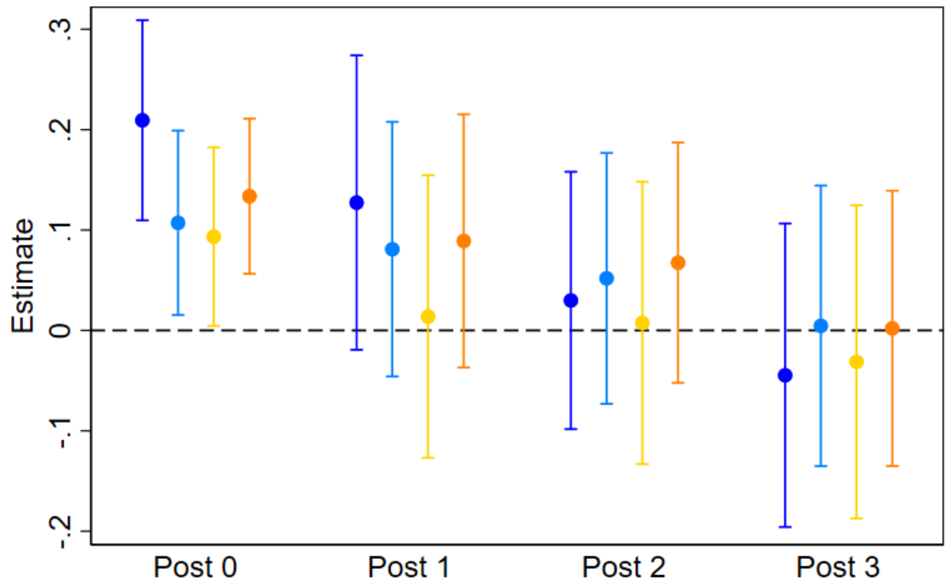
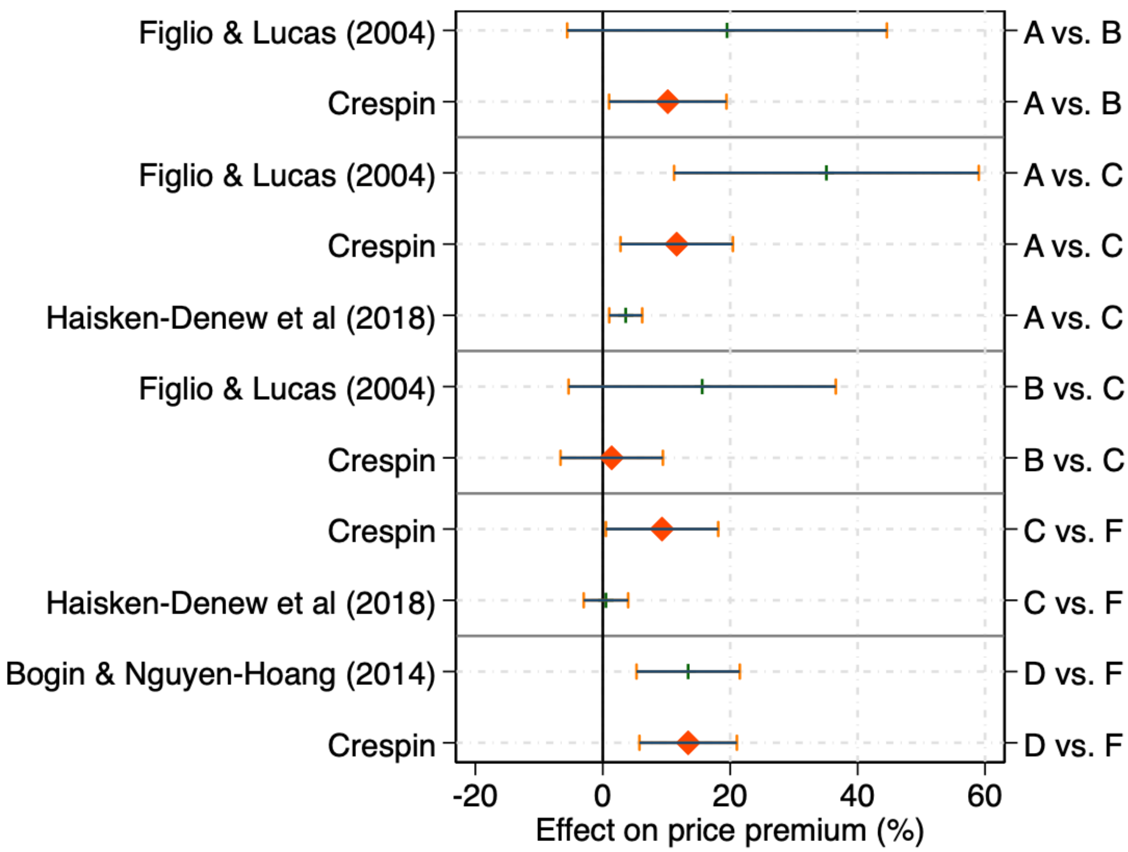


Figure A3: Quarterly DID estimates: Log Sales Price



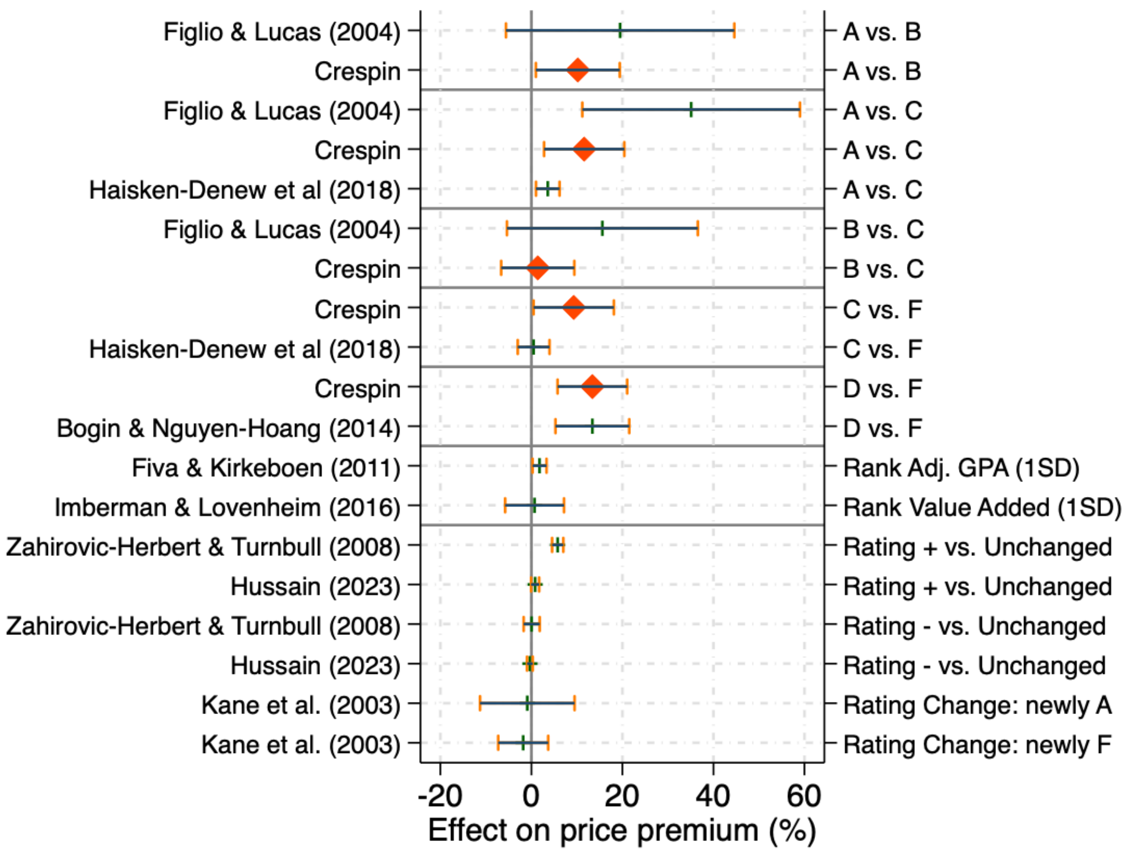
Notes: These estimates are based on equation 1. Sample is based on transactions that took place between 09/2009 through 08/2012.

Figure A4: Forest Plot – Only new information shock strategy (DID approach)



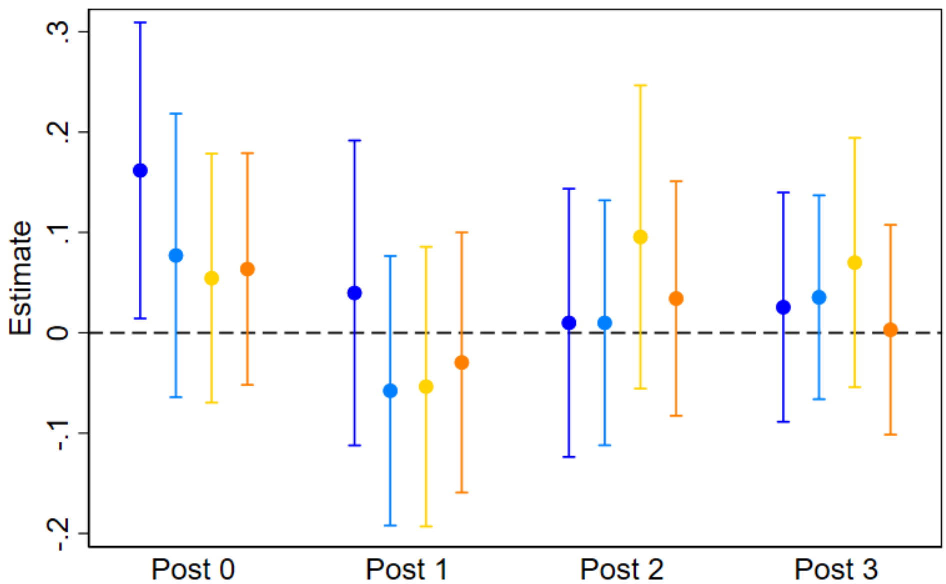
Notes: Each estimate represents the information impact on house prices in terms of the comparison on the right-side y-axis. For example, the top estimate is interpreted as the information shock effect on the difference between rating "A" and rating "B" on home sales prices. The error bars represent the 95% confidence interval for each estimate. I focus on the most immediate (short-term) estimated impact available in each paper.

Figure A5: Forest Plot – New and Updated info shocks (various approaches)



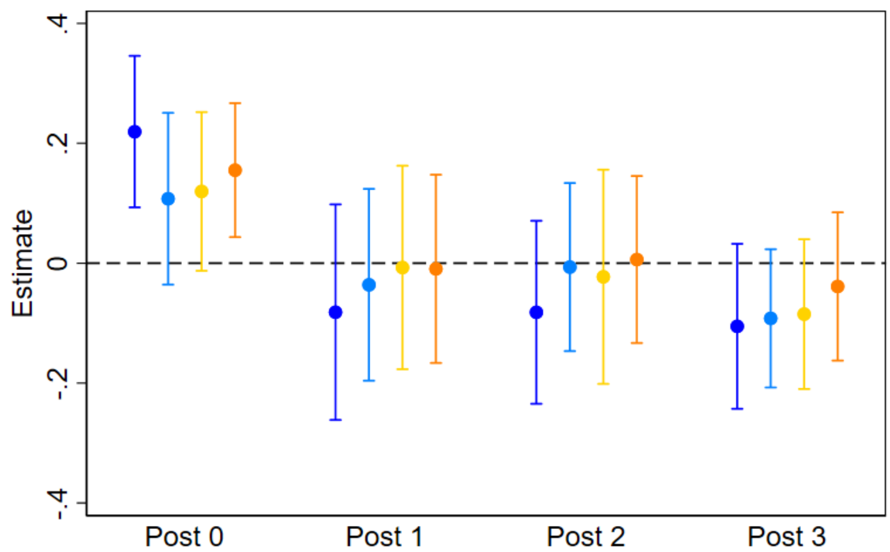
Notes: Each estimate represents the information impact on house prices in terms of the comparison on the right-side y-axis. For example, the top estimate is interpreted as the information shock effect on the difference between rating "A" and rating "B" on home sales prices. The error bars represent the 95% confidence interval for each estimate. I focus on the most immediate (short-term) estimated impact available in each paper.

Figure A6: Quarterly DID estimates: Log Homebuyer Income

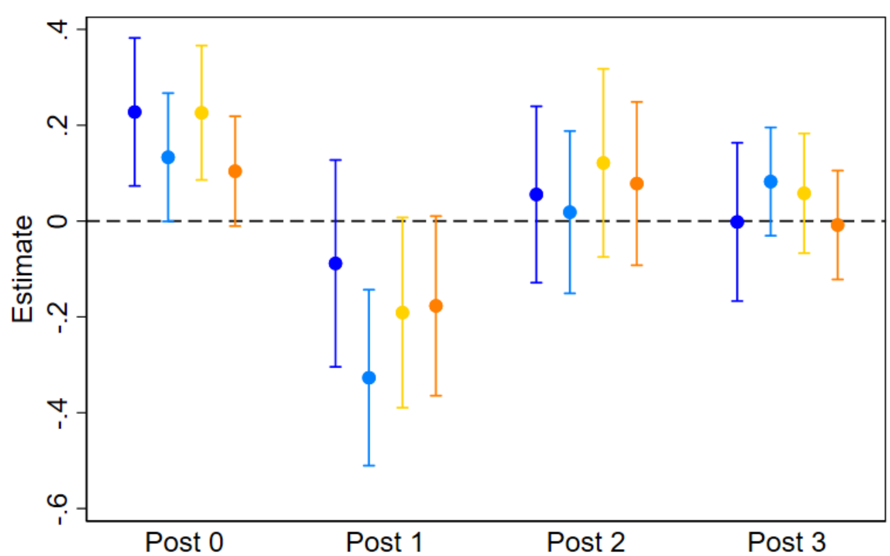


Notes: These estimates are based on equation 1. Sample is based on transactions that took place between 09/2009 through 08/2012.

Figure A7: Quarterly DID estimates for larger homes



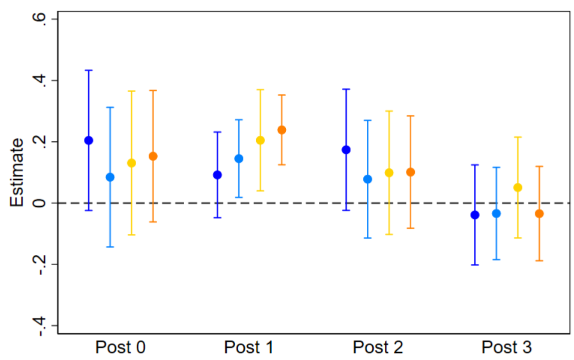
(a) Log Sales Price



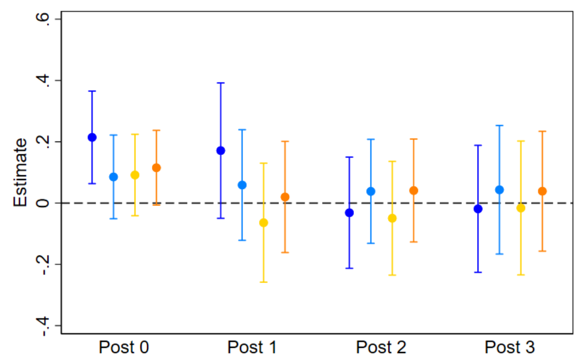
(b) Log Buyer Income

Notes: These estimates are based on equation 1. Sample is based on transactions that took place between 09/2009 through 08/2012. Bigger houses are those that have at least three bedrooms and are not condominiums.

Figure A8: Quarterly DID estimates: **Log Sales Price**, with or without co-borrower



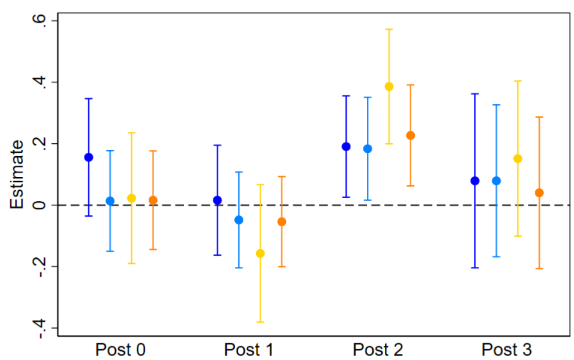
(a) Only co-borrowers



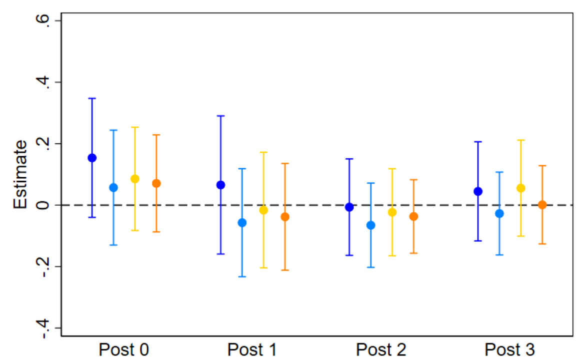
(b) Only single-borrowers

Notes: These estimates are based on equation 1. Sample is based on transactions that took place between 09/2009 through 08/2012.

Figure A9: Quarterly DID estimates: **Log Buyer Income**, with or without co-borrower



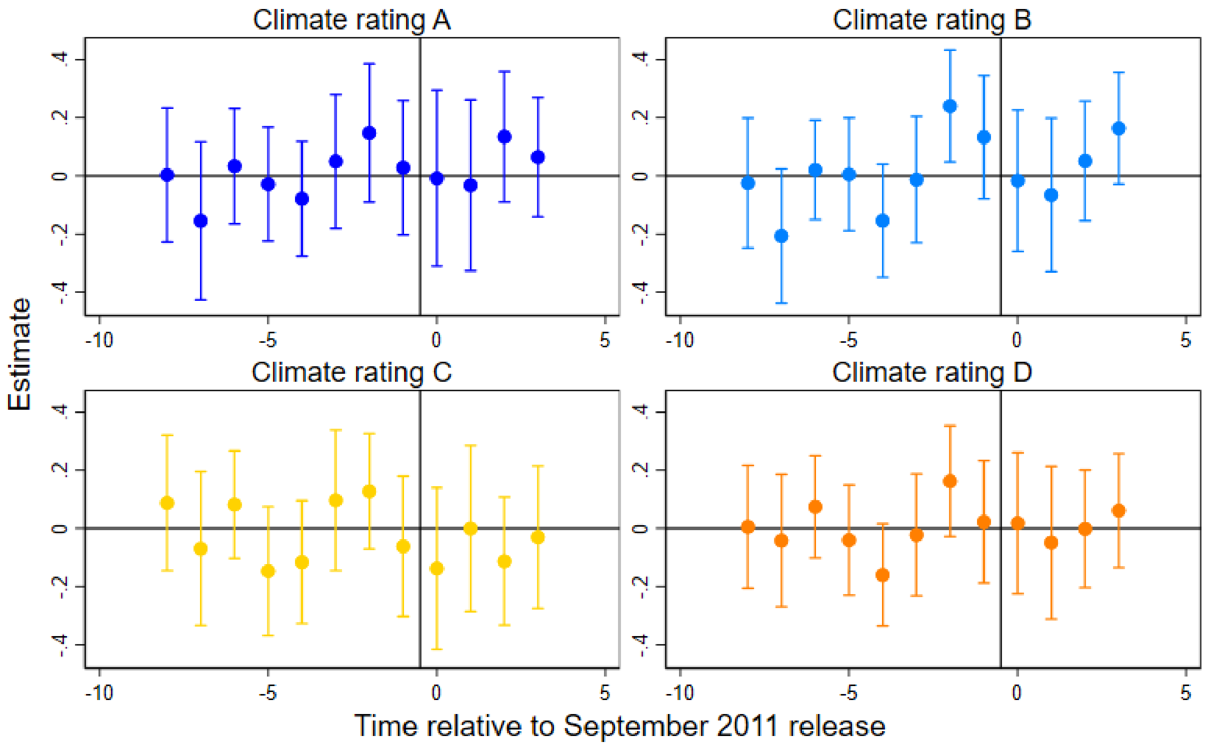
(a) Only co-borrowers



(b) Only single-borrowers

Notes: These estimates are based on equation 1. Sample is based on transactions that took place between 09/2009 through 08/2012.

Figure A10: Quarterly event study estimates: Number of Transactions (based on school zone fixed effects Poisson model)



Notes: Sample is based on transactions that took place between 09/2009 through 08/2012. Estimation is based on Poisson regression models based on equation 1, where the outcome of interest is the number of transactions. Models are based on data at the school zone-by-month level for the number of transactions. Each figure is a separate regression. Each model includes month-by-year and school zone fixed-effects. These event studies are based constrained regressions where the pre-shock coefficients average to zero (refer to section 7 for details). Constrained regressions allow coefficients to be more directly comparable to DID estimates.

Appendix B Tables

Table B1: Predictability of various school characteristics (pre-info shock)

	(1) Proficiency Rates (Z)	(2) FRPL Rate (Z)	(3) Value-Added (Z)	(4) Overall Climate	(5) Best Climate	(6) Worst Climate
% FRPL	-0.012**		0.006	-0.007	0.008	-0.005
	(0.005)		(0.008)	(0.010)	(0.010)	(0.007)
Enrollment	-0.000	-0.000	-0.000	-0.001**	-0.001*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Attendance Rate	0.190***	-0.019	-0.007	0.081	0.045	0.029
	(0.025)	(0.019)	(0.039)	(0.049)	(0.042)	(0.033)
% Asian	0.007	0.025***	-0.005	0.006	0.004	0.004
	(0.007)	(0.005)	(0.011)	(0.016)	(0.017)	(0.008)
% Black	-0.009*	0.024***	0.011	0.006	-0.006	0.005
	(0.004)	(0.002)	(0.008)	(0.010)	(0.010)	(0.006)
% Hispanic	0.000	0.022***	-0.003	0.004	0.000	0.002
	(0.005)	(0.002)	(0.008)	(0.010)	(0.011)	(0.006)
% Native	-0.041	0.017	-0.235	-0.283*	-0.052	-0.054
	(0.076)	(0.054)	(0.125)	(0.137)	(0.167)	(0.095)
% Multi-race	0.004	-0.118***	-0.023	0.031	0.008	0.005
	(0.033)	(0.024)	(0.045)	(0.052)	(0.047)	(0.053)
% LEP	-0.019***	0.003	0.019*	-0.001	-0.013	0.001
	(0.005)	(0.003)	(0.008)	(0.010)	(0.009)	(0.007)
% IEP	-0.002	-0.012	-0.002	-0.002	0.007	-0.016
	(0.009)	(0.007)	(0.013)	(0.016)	(0.013)	(0.012)
Nbhd HS Education	2.314***	-1.031*	-0.553	-0.833	-0.156	-0.002
	(0.636)	(0.415)	(1.101)	(1.172)	(1.061)	(0.866)
Nbhd Some Coll. Educ.	0.621	-1.595***	-2.023*	-0.777	-0.375	-0.183
	(0.556)	(0.369)	(0.932)	(1.011)	(0.773)	(0.670)
Nbhd College Educ.	1.204	-0.179	-0.351	0.543	-0.294	0.334
	(0.707)	(0.399)	(0.934)	(1.114)	(1.087)	(0.760)
Nbhd Graduate Educ.	1.363	-2.330***	-1.160	-2.954*	-0.028	-1.043
	(0.865)	(0.498)	(1.203)	(1.292)	(1.221)	(0.924)
Avg yearly school crimes	-0.026***	0.001	0.022**	0.000	-0.010	0.007
	(0.006)	(0.004)	(0.008)	(0.010)	(0.009)	(0.007)
Proficiency Rates (Z)		-0.128**	0.836***	0.473***	0.169	0.180
		(0.046)	(0.095)	(0.130)	(0.111)	(0.094)
Observations	335	335	335	335	180	217
R-squared	0.712	0.770	0.235	0.211	0.172	0.074
Adjusted R-squared	0.699	0.759	0.196	0.171	0.091	-0.001

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

Table B2: Summary of existing school quality information shocks on house prices, with and without dissipating effects

Study	**Location**	**Year(s) Shocked**	**Information**	**Fadeout begins:**
Panel A: Finds dissipating effects				
Figlio and Lucas (2004)	Florida	1999	School Grade designations based on test scores	By end of 1st year (higher frequency not shown)
Fiva & Kirkeboen (2011)	Oslo, Norway	2005	School-level adjusted GPAs	By second quarter
Bogin & Nguyen-Hoang (2014)	Mecklenburg County, NC	2004	AYP Failure Designation	By second month
Haisken-DeNew et al (2018)	Victoria, Australia	2010	School Grade designations re-released online	After 1st quarter
Panel B: Does not find dissipating effects				
Hussain (2023)	England	2006-2008	Changes in Quality inspection ratings	Not across years (higher frequency not shown)

Notes: This table includes all known published papers that study school quality capitalization by using an information shock approach. Only includes studies that find an effect on house prices from school quality information, in order to show how frequently these effects fade out. Furthermore, I only include studies that show dynamic effects, otherwise one cannot tell if there were dissipating effects.

Table B3: Effect of school climate rating information on log sale prices and log buyer income (during first post-shock quarter)

	(1)	(2)	(3)
Panel A: Dependent Variable is Log Sale Price			
Climate Rating 5 x PostQ0	0.209***	0.204*	0.214***
	(0.051)	(0.117)	(0.077)
Climate Rating 4 x PostQ0	0.107**	0.085	0.085
	(0.047)	(0.116)	(0.070)
Climate Rating 3 x PostQ0	0.093**	0.131	0.092
	(0.045)	(0.120)	(0.068)
Climate Rating 2 x PostQ0	0.133***	0.153	0.115*
	(0.039)	(0.109)	(0.062)
Observations	13586	4964	8622
Panel B: Dependent Variable is Log Homebuyer Income			
Climate Rating 5 x PostQ0	0.162**	0.156	0.154
	(0.075)	(0.098)	(0.099)
Climate Rating 4 x PostQ0	0.078	0.014	0.057
	(0.072)	(0.084)	(0.095)
Climate Rating 3 x PostQ0	0.055	0.023	0.086
	(0.063)	(0.108)	(0.086)
Climate Rating 2 x PostQ0	0.064	0.016	0.071
	(0.059)	(0.082)	(0.081)
Observations	13586	4964	8622
Only Co-Borrowers		Y	
Only Single-Borrower			Y

Notes: Estimation is based on equation 1. In the interest of brevity, these only present the estimated impacts in the first post-shock quarter (Q0). The model includes month-by-year fixed-effects, school fixed-effects, and boundary fixed-effects, as described in section 5. Sample is based on transactions that took place between 09/2009 through 08/2012. Standard errors are clustered at the school zone level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Table B4: Heterogeneity in estimated effect of school climate rating on house prices and homebuyer income

	Proficiency (1)	VA (2)	FRPL (3)	Black (4)	Latino (5)	White (6)
Panel A: Outcome is Log Sales Prices						
Rating A/B x PostQ0 x Top Quartile	0.029***	0.032***	0.010	0.040***	0.023**	0.032***
	(0.009)	(0.010)	(0.021)	(0.015)	(0.011)	(0.009)
Rating A/B x PostQ0 x Bottom Quartile	0.049**	0.017	0.030***	0.020*	0.031**	0.050***
	(0.019)	(0.013)	(0.009)	(0.010)	(0.014)	(0.014)
Rating C/D x PostQ0 x Top Quartile	0.037***	0.041**	0.062*	0.055*	0.039***	0.039***
	(0.014)	(0.018)	(0.032)	(0.031)	(0.015)	(0.013)
Rating C/D x PostQ0 x Bottom Quartile	0.048**	0.029*	0.035**	0.034**	0.042	0.064**
	(0.024)	(0.015)	(0.014)	(0.013)	(0.027)	(0.031)
Rating A/B p-value (Top = Bottom)	0.29	0.25	0.35	0.18	0.58	0.15
Rating C/D p-value (Top = Bottom)	0.62	0.44	0.39	0.46	0.89	0.38
Observations	13,586	13,586	13,586	13,586	13,586	13,586
Panel B: Outcome is Log Homebuyer Income						
Rating A/B x PostQ0 x Top Quartile	0.024	0.033**	0.055*	0.019	0.010	0.024*
	(0.015)	(0.015)	(0.031)	(0.016)	(0.022)	(0.014)
Rating A/B x PostQ0 x Bottom Quartile	0.014	0.015	0.023	0.013	0.025	0.035**
	(0.014)	(0.021)	(0.015)	(0.015)	(0.017)	(0.018)
Rating C/D x PostQ0 x Top Quartile	0.032	0.022	0.028	0.013	0.023	0.024
	(0.020)	(0.026)	(0.032)	(0.032)	(0.021)	(0.020)
Rating C/D x PostQ0 x Bottom Quartile	-0.001	0.021	0.020	0.031	0.023	0.025
	(0.026)	(0.022)	(0.020)	(0.020)	(0.026)	(0.033)
Rating A/B p-value (Top = Bottom)	0.47	0.38	0.30	0.68	0.51	0.50
Rating C/D p-value (Top = Bottom)	0.11	0.96	0.78	0.52	0.97	0.97
Observations	13,586	13,586	13,586	13,586	13,586	13,586

Notes: Sample is based on transactions that took place between 09/2009 through 08/2012. Estimation is based on a modified version of equation 1 that includes separate effects for schools with different school characteristics, which is done by interacting the post-shock climate rating with an indicator for the school characteristic quartile of interest. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Table B5: Robustness tests of dynamic DID estimates of climate rating information impacts, varying fixed effects (during first post-shock quarter)

Independent variable	(1)	(2)	(3)
Panel A: Outcome is Log Price			
Climate Rating A x PostQ0	0.209***	0.180***	0.186***
	(0.051)	(0.050)	(0.048)
Climate Rating B x PostQ0	0.107**	0.087*	0.088**
	(0.047)	(0.045)	(0.043)
Climate Rating C x PostQ0	0.093**	0.077*	0.073*
	(0.045)	(0.044)	(0.043)
Climate Rating D x PostQ0	0.133***	0.100***	0.117***
	(0.039)	(0.038)	(0.036)
Observations	13586	13586	13586
Panel B: Outcome is Log Income			
Climate Rating A x PostQ0	0.162**	0.139*	0.140*
	(0.075)	(0.072)	(0.073)
Climate Rating B x PostQ0	0.078	0.067	0.069
	(0.072)	(0.068)	(0.067)
Climate Rating C x PostQ0	0.055	0.053	0.025
	(0.063)	(0.060)	(0.059)
Climate Rating D x PostQ0	0.064	0.042	0.058
	(0.059)	(0.055)	(0.056)
Observations	13586	13586	13586
Boundary FE	Y	Y	
School FE	Y		Y
Main climate effects		Y	

Notes: Refer to notes from Table 3. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table B6: Robustness tests of dynamic DID estimates of climate rating information impacts, varying neighborhood, school, and family proxy controls included (during first post-shock quarter)

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Outcome is Log Sale Price						
Climate Rating A x PostQ0	0.209***	0.200***	0.195***	0.219***	0.204***	0.171***
	(0.051)	(0.061)	(0.051)	(0.057)	(0.053)	(0.056)
Climate Rating B x PostQ0	0.107**	0.110*	0.089*	0.127**	0.096**	0.084
	(0.047)	(0.062)	(0.047)	(0.061)	(0.048)	(0.056)
Climate Rating C x PostQ0	0.093**	0.105*	0.085*	0.129**	0.086*	0.109**
	(0.045)	(0.058)	(0.048)	(0.055)	(0.049)	(0.051)
Climate Rating D x PostQ0	0.133***	0.106*	0.122***	0.114**	0.129***	0.137***
	(0.039)	(0.056)	(0.040)	(0.053)	(0.042)	(0.044)
Observations	13586	13586	13586	13586	13586	8183
Panel B: Outcome is Log Homebuyer Income						
Climate Rating A x PostQ0	0.162**	0.164**	0.139*	0.174**	0.144*	0.172**
	(0.075)	(0.074)	(0.073)	(0.076)	(0.074)	(0.073)
Climate Rating B x PostQ0	0.078	0.071	0.054	0.094	0.054	0.140**
	(0.072)	(0.079)	(0.072)	(0.082)	(0.071)	(0.060)
Climate Rating C x PostQ0	0.055	0.094	0.043	0.099	0.043	0.201***
	(0.063)	(0.072)	(0.064)	(0.073)	(0.065)	(0.059)
Climate Rating D x PostQ0	0.064	0.065	0.050	0.066	0.054	0.133**
	(0.059)	(0.066)	(0.059)	(0.066)	(0.060)	(0.054)
Observations	13586	13586	13586	13586	13586	8183
School FE	Y	Y	Y	Y	Y	Y
Boundary FE	Y	Y	Y	Y	Y	Y
≤0.2mi from boundary	Y	Y	Y	Y	Y	Y
Boundary side FE		Y		Y		
Boundary FE * Time Trend		Y		Y		
Time-varying school controls			Y	Y	Y	
Neighborhood controls					Y	
Exclude condominiums						Y

Notes: Refer to notes from Table 3. The school controls include two years of lagged proficiency rates, as well as racial/ethnic, LEP, IEP, and FRPL enrollment shares. Neighborhood controls are described in Section 3. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$

Table B7: Robustness tests of dynamic DID estimates of climate rating information impacts, varying border by time interactions (during first post-shock quarter)

	(1)	(2)	(3)
Panel A: Outcome is Log Sales Prices			
Climate Rating A * PostQ0	0.209***	0.320***	0.545***
	(0.051)	(0.064)	(0.102)
Climate Rating B * PostQ0	0.107**	0.181***	0.387***
	(0.047)	(0.062)	(0.088)
Climate Rating C * PostQ0	0.093**	0.193***	0.370***
	(0.045)	(0.061)	(0.096)
Climate Rating D * PostQ0	0.133***	0.170***	0.318***
	(0.039)	(0.059)	(0.096)
Observations	13586	13586	13586
Panel B: Outcome is Log Income			
Climate Rating A * PostQ0	0.162**	0.163**	0.369***
	(0.075)	(0.078)	(0.142)
Climate Rating B * PostQ0	0.078	0.083	0.231*
	(0.072)	(0.076)	(0.131)
Climate Rating C * PostQ0	0.055	0.121*	0.272*
	(0.063)	(0.073)	(0.140)
Climate Rating D * PostQ0	0.064	0.017	0.083
	(0.059)	(0.067)	(0.141)
Observations	13586	13586	13586
School FEs	Y	Y	Y
Boundary FEs	Y		
Boundary FEs × Post		Y	
Boundary FEs × Post × Quarter			Y

Notes: Refer to notes from Table 3. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table B8: Robustness tests of dynamic DID estimates of climate rating information impacts, varying additional information shocks (during first post-shock quarter)

Independent variable	(1)	(2)	(3)
Panel A: Outcome is Log Price			
Climate Rating A x PostQ0	0.209***	0.204***	0.187***
	(0.051)	(0.051)	(0.052)
Climate Rating B x PostQ0	0.107**	0.103**	0.088*
	(0.047)	(0.047)	(0.049)
Climate Rating C x PostQ0	0.093**	0.091**	0.076
	(0.045)	(0.046)	(0.049)
Climate Rating D x PostQ0	0.133***	0.134***	0.115***
	(0.039)	(0.039)	(0.043)
Observations	13,586	13,586	12,940
Panel B: Outcome is Log Income			
Climate Rating A x PostQ0	0.162**	0.151**	0.144*
	(0.075)	(0.075)	(0.081)
Climate Rating B x PostQ0	0.078	0.068	0.062
	(0.072)	(0.072)	(0.074)
Climate Rating C x PostQ0	0.055	0.052	0.036
	(0.063)	(0.063)	(0.069)
Climate Rating D x PostQ0	0.064	0.061	0.063
	(0.059)	(0.059)	(0.069)
Observations	13,586	13,586	12,940
School FE	Y	Y	Y
Boundary FE	Y	Y	Y
Proficiency and VA Info. Impacts		Y	
HS Climate effects			Y

Notes: Refer to notes from Table 3. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table B9: Robustness tests of dynamic DID estimates of climate rating information impacts, varying distance from nearest border (during first post-shock quarter)

Independent variable	(1)	(2)	(3)	(4)
Panel A: Dependent Variable is Log Sale Price				
Climate Rating A x PostQ0	0.188***	0.217***	0.209***	0.185***
	(0.046)	(0.046)	(0.051)	(0.058)
Climate Rating B x PostQ0	0.102**	0.112***	0.107**	0.057
	(0.042)	(0.042)	(0.047)	(0.051)
Climate Rating C x PostQ0	0.072*	0.074*	0.093**	0.048
	(0.042)	(0.042)	(0.045)	(0.049)
Climate Rating D x PostQ0	0.138***	0.138***	0.133***	0.100**
	(0.036)	(0.035)	(0.039)	(0.043)
Observations	16,273	15,167	13,586	11,434
Panel B: Dependent Variable is Log Homebuyer Income				
Climate Rating A x PostQ0	0.128*	0.169**	0.162**	0.118
	(0.071)	(0.072)	(0.075)	(0.092)
Climate Rating B x PostQ0	0.055	0.080	0.078	0.005
	(0.064)	(0.067)	(0.072)	(0.077)
Climate Rating C x PostQ0	0.005	0.029	0.055	-0.006
	(0.058)	(0.062)	(0.063)	(0.073)
Climate Rating D x PostQ0	0.066	0.063	0.064	0.033
	(0.054)	(0.058)	(0.059)	(0.067)
Observations	16,273	15,167	13,586	11,434
≤0.35mi from border	Y			
≤0.25mi from border		Y		
≤0.20mi from border			Y	
≤0.15mi from border				Y

Notes: Refer to notes from Table 3. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table B10: Robustness tests of dynamic DID estimates of climate rating information impacts on Log Sales Prices, including transactions with and without mortgages (during first post-shock quarter)

	(1)	(2)
Climate Rating A x PostQ0	0.209***	0.210***
	(0.051)	(0.066)
Climate Rating B x PostQ0	0.107**	0.153**
	(0.047)	(0.066)
Climate Rating C x PostQ0	0.093**	0.115*
	(0.045)	(0.065)
Climate Rating D x PostQ0	0.133***	0.158**
	(0.039)	(0.063)
Observations	13586	23509
Mortgage-based transactions	Y	Y
Cash transactions		Y

Notes: Refer to notes from Table 3. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Table B11: Impacts of school climate rating information on **log sales price**, controlling for school proficiency rates, through 2011-12 or 2012-13

	Through SY2011-12	Through SY2012-13		
	(1)	(2)	(3)	(4)
1st Rating A x Post Sept 2011	0.069	0.069**	0.067	0.067
	(0.043)	(0.032)	(0.043)	(0.043)
1st Rating B x Post Sept 2011	0.059	0.057*	0.053	0.053
	(0.037)	(0.030)	(0.036)	(0.036)
1st Rating C x Post Sept 2011	0.020	0.009	0.016	0.017
	(0.042)	(0.033)	(0.041)	(0.041)
1st Rating D x Post Sept 2011	0.071*	0.056*	0.065*	0.065*
	(0.036)	(0.029)	(0.035)	(0.035)
1st Rating A x Post Sept **2012**			0.002	0.007
			(0.045)	(0.047)
1st Rating B x Post Sept **2012**			0.007	0.007
			(0.040)	(0.042)
1st Rating C x Post Sept **2012**			-0.015	-0.014
			(0.043)	(0.045)
1st Rating D x Post Sept **2012**			-0.018	-0.018
			(0.038)	(0.039)
2nd Rating A x Post Sept 2012				-0.008
				(0.033)
2nd Rating B x Post Sept 2012				-0.004
				(0.034)
2nd Rating C x Post Sept 2012				0.008
				(0.033)
2nd Rating D x Post Sept 2012				-0.005
				(0.035)
Observations	13582	18063	18063	18063

Notes: Estimation is based on a modified version of equation 1 that estimates a year-level information impact(s). Sample is based on transactions that took place between 09/2009 through 08/2012 (column 1) or between 09/2009 through 08/2013 (columns 2, 3, and 4). As described in Section 7.2, column (3) allows the initial (2011) climate ratings to have separate impacts starting in September 2011 and an additional impact starting in September 2012. Column (4) also allows for the second (2012) climate ratings to have their own impacts that start in September 2012. The model includes month-by-year fixed-effects, school fixed-effects, and boundary fixed-effects, as described in section 5. I also control for lagged school proficiency rates. I exclude observations that are affected by attendance boundary changes between 2011-12 and 2012-13. Standard errors are clustered at the school zone level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

Appendix C Additional details

C.1 Details of how school climate components were generated by CCSR

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

The process is then repeated for each of the other four school climate components. The ambitious instruction component is made up of subcomponents that measure students' perceived course clarity, course instruction, and quality of student discussions. The measure for involved families is based on students' perceived human and social resources in the community as well as teachers' perceived quality of interactions with parents. The collaborative teachers component measures teachers' trust and collaboration with each other. Lastly, the effective leadership component is based on teachers' perceived influence in the school and their trust in their principal's effectiveness. Klugman et al. (2015) provides a more complete description of each of the school climate components measured in this framework.

C.2 Pre-2011 school climate reports

CCSR privately provided climate reports to principals and district administrator since before 2011. Some principals simply stored the reports, while others shared them with their teachers and the local school council (Vevea, 2011). Even though principals could have shared these reports with the public, these may still have not been easily accessible since the pre-2011 version of the climate reports was quite complex and had privacy requirements.

The pre-2011 reports were not easily digestible. For example, a report would present 20 to 40 separate color-coded climate ratings, without providing an overall summative rating. Also, from the 1990s through 2007, CCSR privately delivered paper copies of the reports to principals (Levenstein, 2016). In 2009, CCSR transitioned to online delivery, but these still remained private, requiring a principal-specific username and password. Additionally, the reports explicitly stated not to distribute without the school's permission.

C.3 Potential reasons for publicly releasing school climate reports

One potential reason for the sudden release of long-withheld school information is that Rahm Emanuel became Mayor of Chicago in early 2011, after working in the Obama administration, which promoted the measurement and improvement of schools' social environments (U.S. Department of Education, 2010). A second potential reason for publicly releasing the information is that Mayor Emanuel's education transition team included Tim Knowles, who was director for the UChicago Urban Education Institute, which houses CCSR (Vevea, 2011).

C.4 Estimating impacts on housing supply/demand

Although I cannot directly observe changes in the supply of or demand for houses, the number of home sales transactions may represent the quantity of transactions where supply meets demand at different points in time. For this analysis, I create a balanced monthly panel of the number of transactions in each school zone and in each school zone by nearest border area during my sample period. I do not require homebuyer income information nor homeowner occupancy for these transactions in order to account for relevant and available properties. Furthermore, I limit the sample to units within 0.2 miles from the nearest border. The results are consistent across these sample selection rules. I use Poisson model versions of equation 2, where the outcome of interest is the number of nearest border-by-school zone-by-month level transactions.