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The GreatSchools Rating Change

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THE GREATSCHOOLS RATING CHANGE

BY

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ACCEPTANCE

This dissertation was prepared under the direction of the *HUONG NGUYEN* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

THE GREATSCHOOLS RATING CHANGE

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GreatSchools (GS) rating is the most visible school quality measure available to homebuyers. In 2017, GS changed its rating system, by incorporating other rating components in its measure and shifting away from focusing exclusively on test scores (TS). Using this abrupt rating change event, I examine the market response to the GS rating change via home prices by comparing homes in school districts that received GS rating changes to similar ones in districts with no rating changes before and after the event. Home price coefficients after the GS rating change are lower than those before the change, reflecting a sensitivity reduction in market response to the new GS rating due to the redistribution of schools across GS rating categories that led to a disconnection between the new rating and socio-demographics. Prices in districts that received GS rating increases were not significantly impacted, while prices in districts where GS ratings were downgraded significantly increase by 3.6%. Homebuyer locality drives such market response. In districts with the highest proportions of non-local in-migration, the direction of the GS rating change, net of TS change, is dominant, consistent with the reliance on availability heuristics that the GS ratings system provides. Whereas in districts comprised heavily of local homebuyers, the direction of TS change is dominant as local homebuyers appear to disregard the GS reference point.

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The GreatSchools Rating Change

GreatSchools (GS) rating is the most visible school quality measure available to homebuyers. In 2017, GS changed its rating system, by incorporating other rating components in its measure and shifting away from focusing exclusively on test scores (TS). Using this abrupt rating change event, I examine the market response to the GS rating change via home prices by comparing homes in school districts that received GS rating changes to similar ones in districts with no rating changes before and after the event. Home price coefficients after the GS rating change are lower than those before the change, reflecting a sensitivity reduction in market response to the new GS rating due to the redistribution of schools across GS rating categories that led to a disconnection between the new rating and socio-demographics. Prices in districts that received GS rating increases were not significantly impacted, while prices in districts where GS ratings were downgraded significantly increase by 3.6%. Homebuyer locality drives such market response. In districts with the highest proportions of non-local in-migration, the direction of the GS rating change, net of TS change, is dominant, consistent with the reliance on availability heuristics that the GS ratings system provides. Whereas in districts comprised heavily of local homebuyers, the direction of TS change is dominant as local homebuyers appear to disregard the GS reference point.

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I. Introduction

This paper studies the impact of the GS rating change on home prices. The GS rating change is a novel implementation, whereby GS – the most popular school rating organization, applied a major change in its nationwide rating system in November of 2017 (hereafter: YE2017). The change steers GS rating away from focusing exclusively on TS by incorporating other rating components that measure equity and student progress. Millions of current and prospective homeowners use GS rating since it is the only third-party rating publicly displayed by the largest real estate listing brokers in the U.S., such as Zillow, Trulia, Realtor, Redfin, etc.

[**Figure 1**]

The GS rating change aims to "help uncover the strengths of schools successfully serving Black, Latinx, Native American and low-income students", according to GS' statement explaining the purpose of the rating change.[1] The GS rating change aiming to reward schools that better support underserved student population is likely to increase GS ratings for schools in low-income neighborhoods with a higher share of minority groups. This rating change is unique in that it yields a quasi-exogenous shock that does not impact the schools' fundamentals or the properties' characteristics. This shock only pertains to the event of GS repackaging the weights that make up its rating.

The linkage between home location and school attendance assignment in the U.S. makes household's locational choice important. A home is also the largest asset in an average household's balance sheet, implying home purchase being one of the most essential decisions by households. For that reason, I use home prices to capture the market outcome due to the GS rating change. I

[1] For more information about the rating change, see https://www.greatschools.org/gk/ratings/.

utilize a sample of ZTRAX single-family transactions in the Atlanta-CBSA. Matched samples are constructed for transactions assigned to schools that experience no GS changes to compare with similar assets in schools that undergo rating changes, before and after YE2017. The difference in home prices post- versus pre-implementation for closely matched transactions reflects the impact of the GS rating change.

The first part of this paper provides evidence that some schools benefit from the GS rating change more than the others. The evidence from the school-level analyses reflects GS' social mission in "creating a more equitable future for all children" and suggests that the GS rating change aims to align the rating system with this mission.[2] As an overview, schools that are more likely to get a rating boost following the GS rating change comprise more economically disadvantaged students with lower academic performance, while newly downgraded schools tend to be located in affluent neighborhoods with a smaller share of minority groups.

The second research section investigates the market response to the GS rating change. Comparing home prices before versus after the GS rating change, the lower price coefficients indicate that the new GS rating became less relevant to the market. This is the consequence of the reduction in correlation between the new GS rating and neighborhood socio-demographics, as TS is no longer a major component after the rating change. In addition, based on the change, home prices are statistically unchanged in attendance zones that contain schools with positive GS rating changes, but prices significantly increase in areas of negative GS rating changes. Via placebo and heterogeneity tests, the results show that the market outcomes are no longer driven by TS, as they used to be historically.

[2] For more information about GreatSchools' vision and values, see https://www.greatschools.org/gk/about/.

I further explore how different parts of the market respond to the GS rating change in the third segment of the paper. By exploiting the divergent signals of school quality that emerge when the revised GS ratings move in the opposite directions in various subsamples, I find that home prices purchased by out-of-city buyers (hereafter: nonlocal buyers) move in the same direction as GS rating. These are uninformed buyers who are most likely dependent on heuristics, such as readily accessible third-party GS ratings. In contrast, the local buyers, whose established knowledge about the local schools has been passed down through generations in their towns, pay more attention to TS performance. Thus, home prices purchased by the locals move in the same direction as TS.

The remainder of this study is organized as follows. The next section reviews the literature and draws on the contributions of this study. Section III elaborates GS as an organization and details the GS rating change. Section IV describes the data and outlines the main matched sample methodology. Section V presents the empirical methodology. The results are discussed in section VI, within which subsections 1-3 respectively entail validation, the market response, and the channel for such response. The final section provides concluding remarks.

II. Literature Review

This study naturally belongs to the literature on household preferences in location choice. Most empirical studies use house prices to infer the value placed on school quality. A rich literature has documented significant home price premium in areas of higher school quality (Black, 1999; Bayer et al., 2007; Kane et al., 2006). In this line of research, the definition of school quality has mostly been directly associated with standardized TS, which is often criticized for its high correlation with neighborhood socio-demographics (Downes and Zabel, 2002). My study contributes to the literature in investigating household preference when school quality is a measure of both standardized test score and equity rating.

School reputation is sometimes preferable to school quality by households. The definition of reputation in the economics literature forms on the basis of past actions and correlates positively to the organization's performance or ability to produce quality products (Roberts and Dowling, 2002; Clark and Montgomery, 1998; Shapiro, 1983). Meanwhile, the literature in Industrial Organization (IO) defines reputation as a result of influential third parties' evaluations on the organization (Rao, 1994; Rindova and Fombrun, 1999; Stuart, 2000). Rindova et al. (2005) finds that media rankings have the largest significant effect on school prominence, while school prominence has the largest significant effect on price premium of students' starting salary. In other words, being known or famous (evaluated via the third parties) surpasses being good (signaled by the organization's performance). The study of Jacob and Lefgren (2007) specifies that only higher-income school parents seek out teachers of good reputation, while low-income school parents choose teachers based on their perceived ability.

My study resonates with the previous economics studies, as it documents evidence of long-standing reputational effect as a mechanism through which local homebuyers evaluate school quality. That is, school reputation for the informed, local investors connotates prolonged past performance. Meanwhile, the finding that uninformed investors, such as nonlocal buyers, following influential third-party (i.e., GS) rating resonates with the IO literature. Different from other studies, my focus on GS rating provides insights into households' preference of reputation in earlier-stage education (i.e., K-12) within the public school system in the U.S.

Finally, this work pertains to the literature in behavioral finance that examines the tendency of retail investors to succumb to availability heuristic and herding mentality. A series of seminal work by Tversky and Kahnerman (1973, 1974, 1979) has set the stage for researchers to further investigate how people's judgements often rely on shortcuts and rules of thumb, or so-called heuristics (Benartzi and Thaler, 2007; Thakor, 2015; Kliger and Kudryavtsev, 2010; Stango and Zinman, 2009). In essence, GS rating is the free shortcut to school ranking with immediate availability, while obtaining TS requires costly and tedious search. Consistent with the theory of availability heuristic, this paper finds that informationally disadvantaged homebuyers, like the nonlocals, tend to rely on GS rating. However, local households prefer to use TS as the signal of school quality, a choice consistent with households' knowledge of the local schools' long-standing reputation.

This study also teases out an information channel that has an implication on herding behavior. More than two decades of studies have documented that retail investors do tend to herd when making financial decisions (Shiller, 1984; Amihud et al., 2003; Chen, 2008; Avery and Zemsky, 1998; Cipriani and Guarino, 2014). Following the literature, one expects homebuyers to succumb to the herd mentality and base their location decisions on the popular GS rating. Instead, this paper finds some resiliency in local homebuyers, who are considered informed investors and not passive followers of GS rating.

III. GS Organization and GS Rating Change

Since school performance like TS often involves time-consuming search and varies widely across states, GS standardizes K-12 public school quality ratings to inform families and education stakeholders of how schools are serving all students. The organization reduces thousands of TS across subjects and grades into a natural number rating system between 1 and 10 (highest) for each school. It is by far the most visible source of school rating, attracting more than 49 million users to its website each year. With a nationwide coverage of schools in the U.S., GS is the only third-party school rating displayed by the seven largest real estate listing platforms in the U.S.

By YE2017, GS launched a new rating to reflect school quality that "prioritizes equitable outcomes", aligning with its social mission of "creating a more equitable future for all children".[3] Before this change, GS rating consisted of 100% TS. Post-YE2017, in general, the rating contains only 19% TS, while the remaining weights are distributed to equity component (26%), student progress (36%), and college readiness (20%). However, for elementary schools, which are the focus of this study, college readiness is not relevant. Thus, the component weightings in the new GS rating for elementary schools are as follows: 30% TS, 31% equity, and 39% student progress. Since GS is an independent non-profit organization, the YE2017 event of rating change is arguably an exogenous implementation free of political bias.

[**Figure 2**]

The component weightings can vary, depending on school level and data availability. At the end of each school year, GS takes the weighted average of the components to form the final summary rating (i.e., GS rating). According to GS' classification, a rating of 7-10 is "above average", 5-6 is "average", and 1-4 is "below average". GS rating is ubiquitously displayed under the section for schools on national brokerage websites, where users can click on the ratings of

[3] For more information about the GS rating change, see https://www.greatschools.org/gk/ratings-methodology/ and https://www.prnewswire.com/news-releases/greatschoolsorg-launches-nationwide-ratings-update-for-public-schools-301137183.html.

schools associated with the listed property to be directed to the details on the GreatSchools.org website.

[**Figure 3**]

The following segment describes the construction of GS component ratings.[4] As a general rule, each component is assigned a 1-10 GS value, basing upon the school's average percentile performance relative to others in a state. Specifically, the 1st to 9th percentiles receives a "1", while the 90th to 99th get a "10". The "test score" component is computed as a weighted average percentile of a school's proficiency rate in state standardized exams across grades and subjects. "Student progress" is the year-over-year academic performance growth, evaluated via state standardized assessments (TS) across grades and subjects. This measure captures student improvement regardless of academic starting points. Since the data in this paper is limited to the overall school-level TS rather than assessment ratings for specific grades and subjects, I use the year-over-year change in average TS as proxy for the "student progress" measure, which is called "percentage change in TS", or $\%\Delta TS$. "College readiness" is measured by graduation rate and SAT performance, indicating the degree to which high schools prepare their students for colleges.

The remaining component, "equity", is important in this paper. It reflects how well schools serve disadvantaged students, defined by the racial and socioeconomic backgrounds that historically show persistent gaps. It is the ranked performance in proficiency tests, student progress, and college readiness of a school's disadvantaged group compared to all other students in the state. By including TS and percentage change in TS in my regressions, I control for the TS

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[4] The description in this section was obtained from GreatSchools.org in 2021, reflecting the relevant methodology applied to the GS ratings within the sample periods of this study. In 2022, the GS website updated its methodology displays that show nuanced differences from the previous computations of the components.

and student progress components within the summary GS rating and effectively identify the effect of the GS rating change via the equity component.

IV. Data and Matching Methodology

GS organization displays the most updated cross-sectional ratings but does not keep a time-series record. As a result, I obtain proprietary GS data over the years from a national homebuilder, of which the Atlanta office has the most comprehensive archive. For that reason, my sample focuses primarily on the Atlanta-CBSA. The analysis in this paper centers on elementary schools, since it is the smallest unit of division for school attendance assignment.

[**Figure 4**]

Essentially, each property is fixed to only one elementary school. In the end, I collect and analyze GS ratings for 435 elementary schools, representing 100% coverage within the Atlanta-CBSA, during 2015-2018.

[**Figure 5**]

Residential home price is the main dependent variable of interest. Price data, housing characteristics, and buyer information are provided by Zillow Transaction and Assessment Database (ZTRAX). Since yearly updated GS ratings are distributed to homebuilders and listing platforms on December 31st of each year, homebuyers rely on the previous-year ratings to make location decisions. For example, 2017 sales are affected by 2016 GS rating. Overall, I collect 2017-2019 data of 103,207 single-family, arm's length transactions within GS-available districts.

For the same years and schools, I obtain TS data from the Georgia Governor's Office of Student Achievement. This is the one and only source of Georgia state standardized TS used by all institutions. TS is a continuous rating system from 0 to 100, accompanied with the discrete letter grade ranking system from A (above or equal to 90) to F (below 60). The combination of directions of change in GS rating and TS produces four social phenomena, illustrated in Panel A of Figure 6. I map the locations of schools that experience these phenomena in Panel B.

[**Figure 6**]

In the next step, I collect shapefile-format data of school attendance boundaries from the National Center for Education Statistics and Census block group boundaries from the U.S. Census Bureau. In ArcGIS, I joint these boundaries and housing coordinates to identify 1:1 matching of a residential property to its assigned elementary school and unique block group. Data of neighborhood demographics is also measured at the Census block group level and collected from the American Community Survey (ACS). For the analysis of 'local' versus 'nonlocal' homebuyers, I utilize transaction-level mailing addresses of the buyers, where 'local' is defined as within-city in-migration.

***Full Sample*:**

Table 1 displays summary statistics for school performance by GS rating and TS, property characteristics, and neighborhood demographics. The first column of Table 1 describes the full sample, of which 44% of homes are assigned to schools that experience GS rating change (i.e., $\triangle$GS = 1), hereafter called the treatment group, as opposed to the control group that sees no change in GS rating (i.e., $\triangle$GS = 0). Properties sold post-implementation at YE2017 (i.e., post = 1) are subject to the new GS rating that incorporates rating components other than TS.

[**Table 1**]

In the full sample, the average GS rating is 6, consistent with the "average" classification by GS, while the mean TS is 80, comparable to a B in letter grade. The average sale price is $127 per SF and the average property structure is about 2,500 SF. A typical home in this sample is a 4-bed, 3-bath structure in 22,000-SF lot, constructed 28 years before the transaction date (prop age). These households reside in neighborhoods of the following average statistics: $86,500 median income, 69% employed, and 2% growth in population annually.

Separating into pre-implementation (2017) versus post-implementation (2018-2019) periods respectively, the second and third columns of Table 1 display summary statistics from transactions in the control groups, along with the fourth and fifth columns for the treatment ones. The final columns of Table 1 summarize the transactions in the split treatment group, within which positive GS change (i.e., △GS+) and negative GS change (i.e., △GS-) show considerable heterogeneity in neighborhood characteristics. As a result, I carefully construct matched samples in an effort to draw a meaningful comparison between the treatment and the control, before versus after the GS rating change.

There are questions regarding the necessity of matching – why go through the matching process if one can control for observable variables? Ho et al. (2007) pointed out that matching allows parametric models to work better as the process reduces imbalance, model dependence, researcher discretion, and bias. Essentially, matching is like pruning, which is useful to drop non-matching control observations and to make the data more comparable, thereby reducing the dispersion of the estimated parameters. In short, matching makes controls matter less. Figure 4 in Ho et al. (2007) illustrates the reduction in variability of matched data as compared to the raw data.

Matched Sample:

There are four empirical matching methods that alleviate selection bias and heterogeneity: (1) repeat sales price indices, (2) spatial regression discontinuity design (RDD), (3) manual characteristic match, and (4) propensity-score matching (PSM). This paper adopts the manual characteristic sampling as the main matching methodology, because other alternatives can be logically excluded using the following reasonings: First, due to the limited number of years in my sample, the total repeat sales are insufficient to apply method (1). Specifically, 77% of properties in the sample are sold once during 2017-2019. However, this method is used to establish a result benchmark as I extend the sample of repeat sales to the start of 2012. Second, the geographical focus on the Atlanta-CBSA prevents the use of boundary discontinuity design - a type of spatial RDD often used in the residential real estate literature - because the total number of similar properties within a 5-mile-spatial-buffer across school attendance boundaries makes up only 1% of the full sample. Third, PSM is not ideal because the factors that affect assignments to treatment (GS rating change) or control (no GS rating change) are at the school level, or roughly neighborhood level, but not at the property level. In itself, PSM is traditionally thought to alleviate potential endogeneity due to confounding variables, but it has increasingly been criticized for its limitations such as discarding potentially useful data and introducing bias (King and Nielsen, 2018; Garrido et al., 2014). As a result, PSM might perform relatively well in matching characteristics of Census block groups, but it is expected to perform inadequately in identifying comparable transactions that have similar physical and transactional characteristics.

I apply the manual characteristic matching as the main methodological approach to measure the change in home prices relative to closely comparable transactions. The treatment is separated into positive treatment group, denoted as $\triangle$GS (+), and negative treatment group, denoted as $\triangle$GS (-). Following McMillen (2012), who demonstrates that a matching estimator produces similar results to repeat sales in the context of constructing housing price indices, I create a 4-way match, whereby one transaction from the control pre-implementation is matched with one treatment pre-implementation, one control post-implementation, and one treatment post-implementation. Specifically, I apply a matching procedure that follows the order of importance of USPAP criteria, which are the most recognized appraisal standards in the U.S.

For each subject, matched transactions must be assigned to schools that share a similar starting baseline in academic performance, particularly within ±2 GS ratings and ±15% TS in 2016. The transactions must occur in the same zip code within ±4 calendar quarters of the treatment transaction sale date. These criteria facilitate comparable locations and market conditions. To be included in the matched group, the transaction must be a single-family home like the subject property, has the same number of bedrooms, house size is within ±50% of the subject size, and the structure is constructed within ±20 years of the property age. I then conduct the nearest-neighbor PSM matching by median income and apply the geodesic method by Karney (2013) to select the properties closest in distance to the subject and narrow down to exactly four transactions per matched sample as per the illustration below.

	Control	**Treatment**
Before YE2017	1 observation	1 observation
After YE2017	1 observation	1 observation

Based on the matching process above, there are 4 matches per sample multiplied by 2,115 matched samples for the positive treatment group (i.e., 8,460 observations), and 4 matches multiplied by 5,509 matched samples for the negative treatment group (i.e., 22,036 observations). Each of the sample with 4 closely matched transactions is called a cohort hereafter. Table 2 provides summary statistics of the matched samples and displays within-cohort means for the treatment and control groups, of which the treatment are split into positive and negative groupings, within the pre-implementation versus post-implementation periods.

[**Table 2**]

Across several variables, the insignificant sample means indicate adequate comparability between the matched treatment and control transactions. In the positive treatment groupings, the average price per SF is $115 for the treatment transactions and $110 for control transactions before YE2017. Applying the same process to the post-implementation period, the treatment transaction prices are $118 per SF on average, which is significantly different from the control average of $114 per SF at the 10% level. A similar story obtains for the negative treatment group. These summary statistics validate that the matched sample procedure alleviates sample heterogeneity. In the next section, I further apply the difference-in-differences framework to estimate home prices as a result of the GS rating change.

V. Empirical Methodology

For property transaction i assigned to school s and located in Census block group b at time t, the difference-in-differences framework is as follows:

$$\ln\left(price_{i,s,b,t}\right) = \kappa \times treated_{i,s,b} + \xi \times post_t + \beta \times treated_{i,s,b} \times post_t + \epsilon_{i,s,b,t} \qquad (1)$$

where the dependent variable is the natural log of transaction price $\ln\left(price_{i,s,b,t}\right)$. Housing transactions within an attendance boundary of a school that receives GS rating change from one year to another is indicated by $treated_{i,s,b} = 1$. The control group, $treated_{i,s,b} = 0$, includes households attending schools that experience no GS rating change. These transactions take place either prior to the YE2017 GS rating change ($post_t = 0$), or after the change ($post_t = 1$). For the control group pre-implementation, I construct matched sample counterparts, the characteristics of which are highly comparable. Finally, $\epsilon_{i,s,b,t}$ is the error term.

With two periods $post_t \in \{0,1\}$, the coefficient of interest is a double difference in means:

$$\beta = \left(\mathbb{E}\left[price_{i,s,b,\mathbf{1}} | treated_{i,s,b} = \mathbf{1}\right] - \mathbb{E}\left[price_{i,s,b,\mathbf{0}} | treated_{i,s,b} = \mathbf{1}\right]\right) -$$
$$\left(\mathbb{E}\left[price_{i,s,b,\mathbf{1}} | treated_{i,s,b} = \mathbf{0}\right] - \mathbb{E}\left[price_{i,s,b,\mathbf{0}} | treated_{i,s,b} = \mathbf{0}\right]\right),$$

where β is the average treatment effect (ATE). One can only observe $price_{i,s,b,\mathbf{1}}$ if the property is in the treatment group, or $price_{i,s,b,\mathbf{0}}$ otherwise. Since the counterfactual of what would have been in the case of absent treatment cannot be observed, the average treatment effect β is our coefficient of interest. The ATE assumes that both treatment and control groups share similar characteristics. To alleviate potential violations in this parallel trend assumption, I follow Abadie (2005) to include a series of covariates. Accordingly, the main empirical analyses in this study apply the following regression:

$$\ln\left(price_{i,s,b,t}\right) = \beta \times treated_{i,s,b} \times post_t + \boldsymbol{X}'_{i,t}\boldsymbol{\gamma} + \boldsymbol{Z}'_{b,t}\boldsymbol{\delta} + \lambda_t + \alpha_s + \sigma_b + \epsilon_{i,s,b,t} \quad (2)$$

where the coefficient of interest, β, captures the degree of pricing effect on the school rating deviation between the historic GS rating and the YE2017 GS rating, compared to the pricing of schools with no GS rating change. β essentially reflects home price differences between the treatment and the control before versus after the GS rating change. $\boldsymbol{X}_{i,t}$ is a vector of control variables for property characteristics, while $\boldsymbol{Z}_{b,t}$ controls for the neighborhood demographics that vary through time, including academic performance such as TS and percentage change in TS. Quarter-year fixed effects, λ_t, account for economic conditions and cycles. School fixed effects, α_s, control for time-invariant school features that may affect the prices of homes assigned to the schools. Both the λ_t and α_s fixed effects absorb the individual $post_t$ and $treated_{i,s,b}$ terms, respectively.

The school level is larger than block group level, since multiple block groups are assigned to one school attendance zone. Thus, Census block group fixed effects, σ_b, are important to account for time-invariant neighborhood characteristics, which are some determining factors of household locational decisions. I also include fixed effects at the broader level of zip code and the most granular level of cohort. As elaborated in the previous section, each cohort includes four closely matched properties from the 4-way match construction.

VI. Results

1) Validation

First, I provide evidence that there are schools benefiting from the GS rating change more than others. Via the following logistic functions, I examine the characteristics of the student population whose schools' likelihood of getting GS rating change is as follows:

$$\mathbb{I}_{\Delta GS>0} = \frac{1}{1+e^{-\left(X'_{i,b,t}\gamma+\gamma_0\right)}} + \epsilon_{i,b,t} \tag{3}$$

$$\mathbb{I}_{\Delta GS<0} = \frac{1}{1+e^{-\left(X'_{i,b,t}\gamma+\gamma_0\right)}} + \epsilon_{i,b,t} \tag{4}$$

where $\mathbb{I}_{\Delta GS>0}$ and $\mathbb{I}_{\Delta GS<0}$ take the value of 1 if the school receives a GS rating upgrade and downgrade, respectively. $\boldsymbol{X}_{i,b,t}$ is a vector of school-level characteristics, including percentage change in TS, percentage of Black students, percentage of White students, percentage of families receiving SNAP, percentage of students with disability, log of median income, percentage of employment in the neighborhood in which the school is located, and population growth of the neighborhood.

[**Table 3**]

Table 3 shows evidence that in the new GS rating change, schools that are more likely to get a GS rating boost comprise more Black students, more children in families receiving SNAP food stamp, lower income families, and they tend to perform worse in academic performance, as reflected in the TS change. The opposite is true in the case of downgraded GS in the new implementation.

It is possible that the prominent characteristics above are confounded by changes in TS performances. Figure 7 examines the differences between the distribution of GS rating in Panel A and that of TS in Panel B.

[**Figure 7**]

In Panel A, comparing the GS rating distribution from before the change (in green) versus after (in red), there are a lot fewer 1's, 2's, and 10's. In order words, since the GS rating change event, schools that used to have extremely low ratings got upgraded, while those previously with high ratings got downgraded. This action of the GS rating change is consistent with the universal definition of equity, where the most economically disadvantaged students get boosted the most, while assistance to the most advantaged students is taken away. Meanwhile, Panel B shows almost no change in TS distribution before versus after the implementation. This graphical illustration thus alleviates the concern that TS and GS change concurrently in the same manner.

Figure 8 presents GS rating categories and characteristics. Top-rating schools, or those classified as "above average" with 7-to-10 GS ratings, are located in economically more advantaged neighborhoods as opposed to bottom-rating schools called "below average" with 1-to-4 GS ratings: higher median income ($93,384 vs. $56,907), more Whites (65% vs. 11%), and more educated (49% vs. 29% with at least college education). Importantly, top-rating schools are more likely to be downgraded (65% vs. 15%), and bottom-rating schools have much higher chance to get upgraded (64% vs. 11%).

[**Figure 8**]

While the section above analyzes the characteristics of schools in the new GS rating system and provides evidence that some schools are benefiting from the GS rating change, it is helpful to understand the relative differences in school features between the historic GS rating (before GSΔ) and the YE2017 GS rating (after GSΔ). Figure 9 serves this purpose.

[**Figure 9**]

Historically (before YE2017), GS rating was perfectly corresponded with TS. Therefore, the largest category of positive GS rating change, ∆GS (+), before YE2017, represented by the grey bars in Panel A, took place in predominantly white areas. In the period after the GS rating change, the positive GS rating change concentrated in non-white areas, as shown by the black bars in Panel A. On the other hand, Panel B shows the concentration in non-white areas for schools that received negative GS rating change, ∆GS (-), historically. If the schools were in mostly white areas, they were more likely to get downgraded after YE2017. The relative comparison in Figure 9 confirms the redistribution of the proportion of schools that receive GS rating change basing on socio-demographics.

2) Market response

Was there a market response to the GS rating change? I examine this question using home prices as the measure of market's reaction. In Figure 10, I graph the coefficient plots of home price against GS rating categories in Panel A and against TS in Panel B. Panel A shows that the market still responds to the new GS rating but not as much as before. Households' sensitivity to the new GS rating decreases. In other words, when GS incorporates other components into its rating, it makes the rating less relevant to households. Panel B plots home price against TS, measured in discrete letter grade categories. The market responds to TS similarly before and after. The graph of Panel B is purposefully designed to be on a similar scale to Panel A to emphasize the resemblance between all price coefficients in Panel B and the price coefficient of GS rating before YE2017 in Panel A. Such a resemblance is explained by these GS coefficients' complete correspondence to TS.

[**Figure 10**]

a) Analyses via repeat sales

Case and Shiller (1989) developed the Case-Shiller home price index (HPI) that uses repeat sales of single-family homes to estimate the national trend in home price. Repeat sales control for within-individual variation, since observed as well as unobserved property characteristics between a pair of transactions for the same property remain constant. In this section, I collect ZTRAX data dating back to the beginning of 2012 to build the Atlanta-CBSA Case-Shiller HPI. To minimize the problem of outliers, I trim the data such that the total returns across holding periods do not exceed 250% and -100%. Table 4 provides the descriptive statistics for the repeat sales sample.

[Table 4]

There are 85,690 pairs of repeat sales from 2012Q1 to 2019Q4, within which 21,648 (25%) belongs to the control group, 29,954 (35%) to the positive treatment group, and 34,088 (40%) to the negative treatment group. Each group classification is based on the GS rating change of the school that is assigned to a property by YE2017. Even though the GS rating change took place by

YE2017, there is no change in property fundamentals, school performance, or neighborhood quality of life. As a result, the one-time GS rating change in 2017 is appropriate to be used to classify a property over the entire period of study.

The equations below demonstrate how the property characteristics in the repeat sales sample are differenced out in the process of estimating price appreciation for property i between time t and $t + k$:

$$\ln(price_{i,t}) = \boldsymbol{C}_i{}'\boldsymbol{\beta} + \alpha_t + \epsilon_{i,t} \tag{5}$$

$$\ln(price_{i,t+k}) = \boldsymbol{C}_i{}'\boldsymbol{\beta} + \alpha_{t+k} + \epsilon_{i,t+k} \tag{6}$$

$$\Rightarrow \ln\left(\frac{price_{i,t+k}}{price_{i,t}}\right) = (\alpha_{t+k} - \alpha_t) + (\epsilon_{i,t+k} - \epsilon_{i,t}) \tag{7}$$

$$\Rightarrow \ln\left(\frac{price_{i,t+k}}{price_{i,t}}\right) = \sum_{j=1}^{32} \alpha_j S_{i,j} + (\epsilon_{i,t+k} - \epsilon_{i,t}) \tag{8}$$

where equation (5) shows that the price of property i at time t, or $price_{i,t}$, is a function of all characteristics C of property i and the concurrent market level of home price appreciation, α_t. Equation (6) expresses similarly for the same property, except at time $t + k$. Equation (7) is essentially the rate of price appreciation being a function of a change in market price level between t and $t + k$, resulting from the subtraction of equation (5) from equation (6). Thus, the terms that express property characteristics, $\boldsymbol{C}_i{}'\boldsymbol{\beta}$, in both equations are differenced out, as it is acceptable to assume that the locational and physical characteristics of a property is unchanged from time t to $t + k$.

My model specification is equation (8), where S is a matrix of dummies indicating buy/sale dates within quarter $j = 1$ (2012Q1) and $j = 32$ (2019Q4). I then implement an OLS estimation of equation (8) to create the Atlanta-CBSA-focused HPI, adding school fixed effects, county clustering, and quarter dummies to exclude seasonal variation. The coefficients, α_j, are the rate of price appreciation over the 32 quarters. Thus, to convert the coefficients into meaningful price-level index, I take the exponential and index them to the base quarter of the event of GS rating change, which is 2017Q4. Figure 11 compares this study's replication of the Case-Shiller HPI for the Atlanta-CBSA to the quarterly S&P Case-Shiller GA-Atlanta HPI (ATXRNSA).[5]

[Figure 11]

The two HPI are mostly aligned, with some divergence at the beginning due to limited observations from my sample of repeat sales, resulting in an HPI that is less representative in the first five quarters. In Figure 12, I graph the changes in average home prices for the control, negative treatment, and positive treatment groups over time. Parallel trend among the groups is visible up until the event of the major GS rating change in 2017Q4.

[Figure 12]

Immediately after the event, the price indices among the three groups diverge significantly. Negative treatment continues to diverge from the control group per each passing quarter, while the positive treatment starts to converge towards the control group by the third quarter post event. In order to investigate the statistical differences of coefficients from two different regressions, one for the treatment and one for the control, I set up the two equations as a system of Zellner (1962)'s seemingly unrelated equations and estimate them jointly by stacking the pair group of interest into the following form:

[5] Reported by the St. Louis Fed: https://fred.stlouisfed.org/series/ATXRNSA.

$$\begin{bmatrix} \ln\left(\frac{price_{i,t+k}}{price_{i,t}}\right)_{treated} \\ \ln\left(\frac{price_{i,t+k}}{price_{i,t}}\right)_{control} \end{bmatrix} = \begin{bmatrix} \sum_{j=1}^{32} S_{i,j}^{treated} & 0 \\ 0 & \sum_{j=1}^{32} S_{i,j}^{control} \end{bmatrix} \begin{bmatrix} \alpha_j^{treated} \\ \alpha_j^{control} \end{bmatrix} + \begin{bmatrix} (\epsilon_{i,t+k} - \epsilon_{i,t})^{treated} \\ (\epsilon_{i,t+k} - \epsilon_{i,t})^{control} \end{bmatrix} \quad (9)$$

While the setup leads to a variance-covariance matrix that allows to test for equality of coefficients from the two groups, the distributions of the error terms are unknown and not independent due to the nonlinear transformation (i.e., exponential) required to convert the rate of price appreciation into the price-level index. As a result, I apply the Wald test for nonlinear restrictions on model parameters. The Wald test uses the delta method to derive the standard errors and confidence intervals for the nonlinear (transformed) parameters. Figure 13 presents the results of the value differences between the coefficients of the treatment and the control for each quarter relative to the event of GS rating change.

[Figure 13]

Panel A of Figure 13, the HPI differences between the negative treatment and the control, shows that the two groups are not statistically different before the event. However, after the event, the group with GS rating decreases sees significantly higher home price in comparison to the group with no GS rating change. Similarly, the HPI differences between the positive treatment and the control are not statistically significant at the 95% level for all quarters leading up to the event in 2017Q4. The group that experiences GS rating increases see significantly lower home prices in comparison to the control group immediately after the event of major GS rating change. However, by the third passing quarter, the differences diminish and are no longer significant.

While these results establish some guiding estimates, they are not sufficient due to the lack of TS data associated with property transactions that occurred prior to 2016. Because controlling for TS and percentage change in TS is essential to identify the effect of the GS rating change on home price, I now use the characteristic matched sample, where TS and percentage change in TS are known, to find home price estimates. Consequently, the results in this section are the motivation for the next part of this study – main regression analyses of home price estimates via characteristic matched sample.

b) Baseline analyses via characteristic matched sample

Using the characteristic matched sample, I conduct difference-in-differences regressions in Table 5 to explore the market response to the GS rating change. The dependent variable is log of home price. There are specifications in each group with different fixed effects and added controls. The preferred specification is the final column, in which the fixed effects are the most restrictive and in which TS and percentage change in TS (%TS change) are included as controls. These controls effectively account for the 'test score' and 'student progress' components in the new GS rating.

[**Table 5**]

In Panel B of Table 5, I separate the treatment into positive and negative GS rating groupings. The positive treatment group in Panel B of Table 5 shows negative coefficients ranging from -2.1% to -2.3%, not statistically different from zero. However, prices of homes in schools with negative GS rating changes increase significantly, by 3.1% to 3.6%, which are statistically different from their control counterparts at the 1% level. TS and percentage change in TS are included in the regressions to control for academic performance, and cohort fixed effects are included to compare the differences between the treatment and the control, before and after, within cohorts of transactions with similar characteristics.

To confirm that the GS rating change is indeed the driver of the results in Table 5, I carry out a couple of robustness tests. The first is a placebo test: I create a counterfactual group that represents the hypothetical case in which GS never changed its rating system. In this placebo test, the new 2017 and 2018 GS ratings are based on the older rating system, where 100% of the component is TS. Figure 14 demonstrates the comparison between the actual versus the counterfactual data.

[**Figure 14**]

Since the 2016 data is in-sample, the actual and counterfactual ratings align perfectly at 45 degrees. Because 2017 is the first year of the new GS rating, the counterfactual rating does not align perfectly with the actual rating. In fact, the actual 2017 GS rating overrated scores at the lower end, and underrated scores at the higher end. For example, a "1" counterfactual GS rating, which consists of 100% TS, is actually rated as a "2" in the new rating with added equity component.

In Table 6, using the repeat sales sample, I perform the difference-in-differences regression as specified in equation (2) to ensure robustness as compared to the baseline results from Table 5. Even though the results in Figure 14 and 15 come from regressions on the repeat sales at the property level, where property characteristics are conveniently cancelled out in between each paired transaction across time as shown in equation (8), the robustness repeat sales regression is at the transaction level, where each property is associated with more than one transaction.

[**Table 6**]

Since the regression compares two groups of fairly different characteristics (i.e., control versus treatment), and the transaction-level regression does not allow for a cancellation of the vector of property characteristics, I perform a manual characteristic match between the control and treatment groups. The matching criteria require matched transactions of both groups to be in the same zip code, to have the same number of bedrooms and full bathrooms. In the regression, I control for log of property square footage, age and age square. In addition, the regression includes year-quarter fixed effects, zip code fixed effects, school fixed effects, block group fixed effects, and property fixed effects. The regression results are displayed in Table 6.

Consistent with the baseline results, home prices are inversely proportional to GS rating change. After the event of major GS rating change in 2017Q4, prices of homes in the positive treatment group, compared to those in the matched control group, are 3.2% lower – a number not statistically different from zero. However, prices of homes in the negative treatment group, compared to property prices in the matched control counterparts, are 7.1% higher, which is statistically significant at the 1% level. Overall, our estimates are robust in both the falsification exercise and the repeat sales regressions.

3) The channel of market response

In this section, the paper investigates the segment of market that responds to the GS rating change. I utilize transaction-level mailing addresses of the buyers, where ‘local’ is the reference group, defined as migration within the same city of the property for sale. Table 7 displays the regression results of the four heterogeneity groupings that represent the four combinations of direction of changes for GS rating and TS in columns (1) through (4).

[Table 7]

The difference between columns (2) and (1) represents a significant 16.5% price premium for the local when buying houses in schools that performed well academically and received positive TS changes, but the net GS rating decreases due to component ratings other than TS. Yet, one observes a 10.8% price discount, statistically significant at the 1% level, when the nonlocals buy houses associated with schools whose net GS rating decreases. These numbers reverse signs in the last column, reflecting the difference between specifications (4) and (3). Table 7 displays the regression results that reflect the signaling effect: nonlocal buyers rely on the heuristic GS rating, while local buyers follow the school quality signaled by TS. The different reactions between the locals and nonlocals are due to the information channel via which they use to judge school quality.

Overall, the direction of the GS rating change is dominant in the case of nonlocal in-migration, consistent with the reliance on availability heuristics that the GS rating system provides to those who are new to the neighborhoods. Whereas in the case of local homebuyers, the direction of TS change is dominant, as local homebuyers appear to disregard the convenient third-party school-quality ratings. Simply put, the locals are knowledgeable about the quality of the local schools, thereby forgoing the signals provided by the new GS reference point.

VII. Conclusion

GS is the most popular school quality rating that provides free and convenient access to the public in the US. This paper first studies the market response to the GS rating change in YE2017, where GS organization incorporates rating components other than TS to its school quality measure. The GS rating change is essentially a redistribution of the number of schools from the extreme low or high GS rating categories to the middle groupings, even though the distribution of TS across categories before versus after YE2017 are unchanged. After the GS rating change in YE2017, schools that receive positive GS rating change are likely to comprise more Blacks, more

SNAP students, and more children from lower income families. These schools perform worse academically, as justified by TS, and are located in neighborhoods with lower employment. The opposite characteristics are reflected in the case of schools that receive negative GS change in the new rating system.

The rating redistribution reflected in the GS rating change is also evident in the analysis comparing historical GS rating change and the YE2017 change. Historically, when GS rating was perfectly corresponded with TS, the largest category of positive GS rating change took place in predominantly White areas. Meanwhile, after the GS rating change event, positive GS rating change are seen in mostly non-White areas. This consequence is consistent with the definition of equity, in which the most economically disadvantaged students get upgraded the most, while the most advantaged ones are often downgraded.

The main analysis of this paper investigates the response of market participants to the GS rating change via home prices. I find that the GS rating change made the overall GS rating less relevant to the market, since home prices are less responsive to changes in the rating index. When conducting a heterogeneity analysis that exploits the cases when GS rating and TS move in opposite directions, I find that home premiums move in the same direction as GS rating changes in markets that are heavily comprised of nonlocal homebuyers. Markets with high proportions of local homebuyers see home premiums move in the same direction as TS, irrespective of the third-party school rating changes. This finding suggests that the pricing premiums evident in this study are closely linked to the value of availability heuristic associated with informationally disadvantaged homebuyers.

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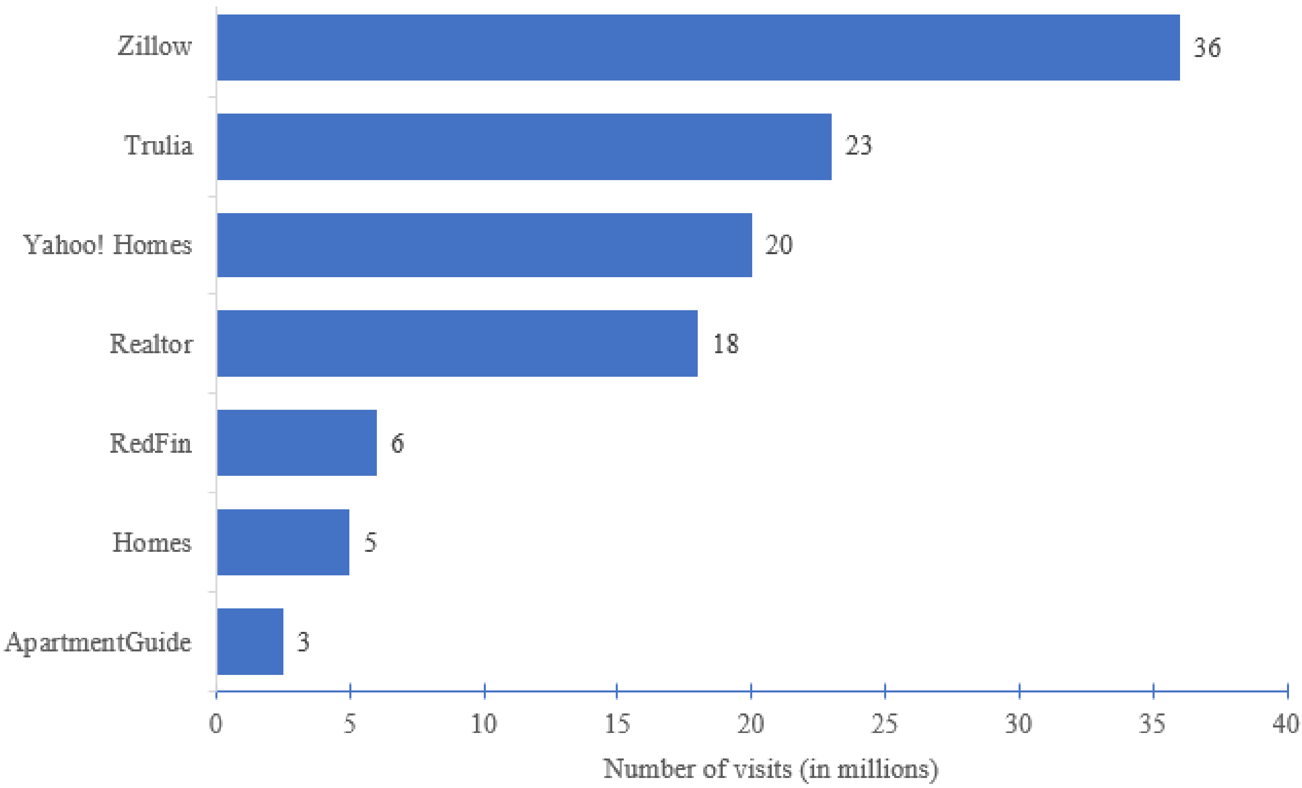
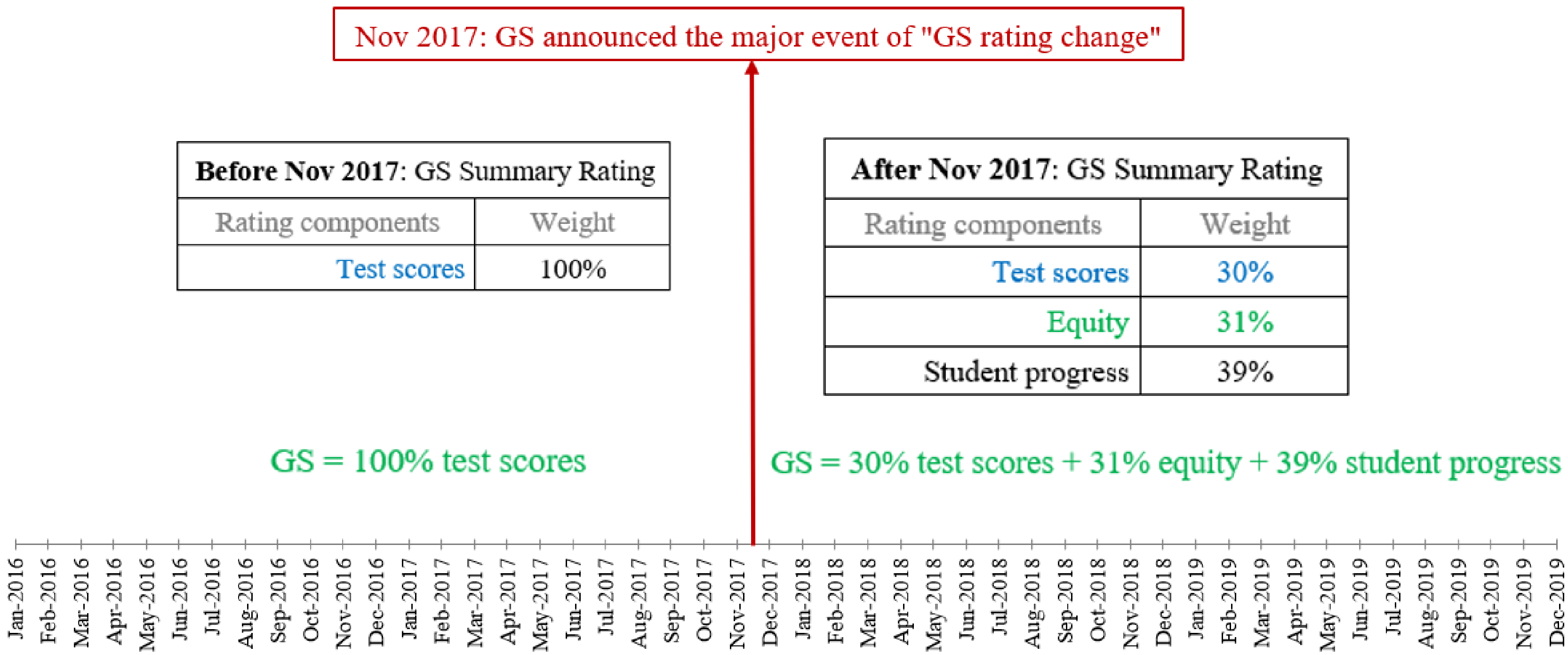
Figure 1. The list of major real estate listing platforms in the U.S. based on monthly visits



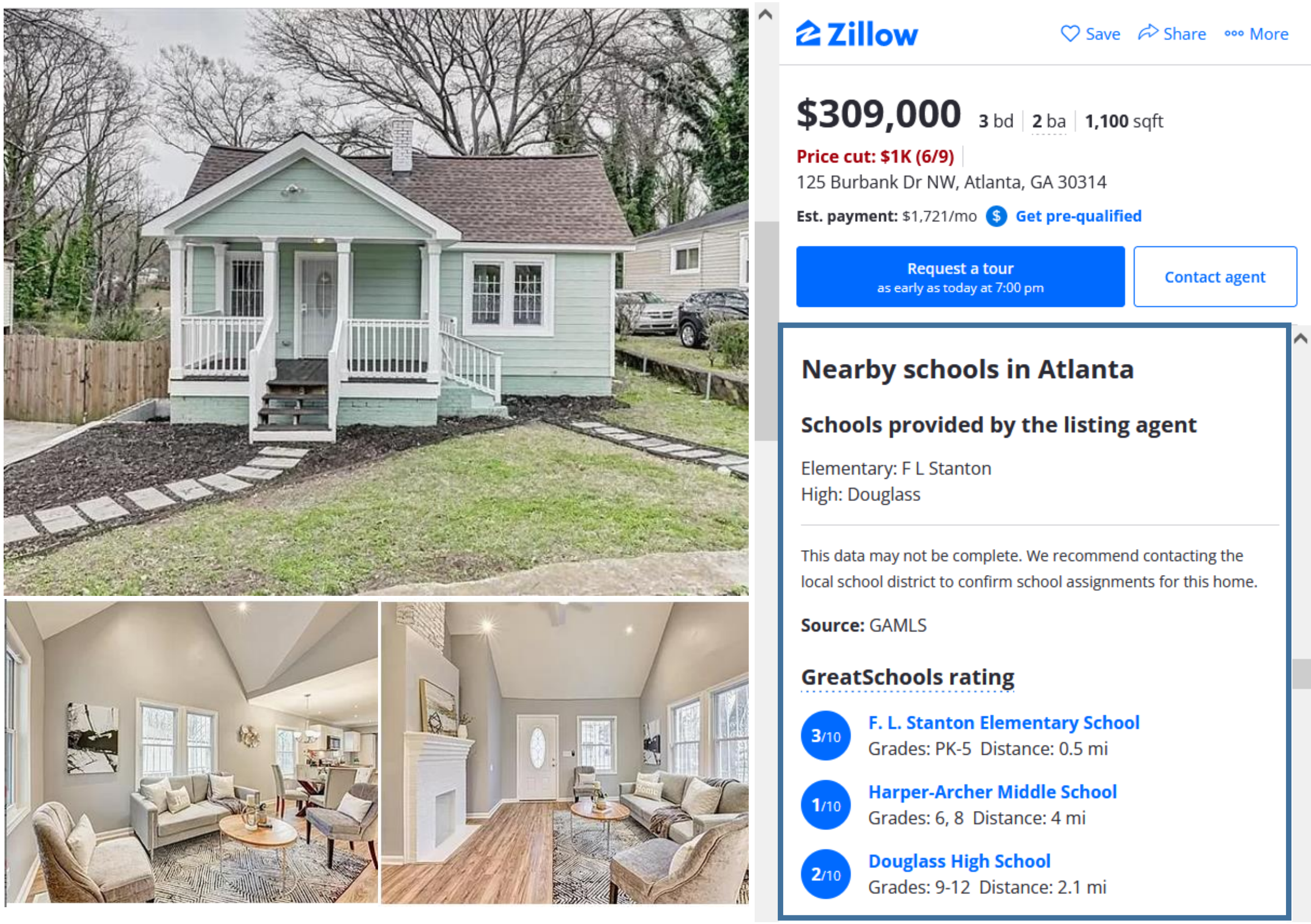
Notes: This figure shows the seven largest real estate listing platforms in the U.S., ranked by the end of 2021 based on the number of monthly website visits. All of these platforms use GreatSchools as the only third-party partner to display school-quality rating of the public schools relevant to each listing.

Figure 2. GreatSchools rating change event in the case applied to elementary schools



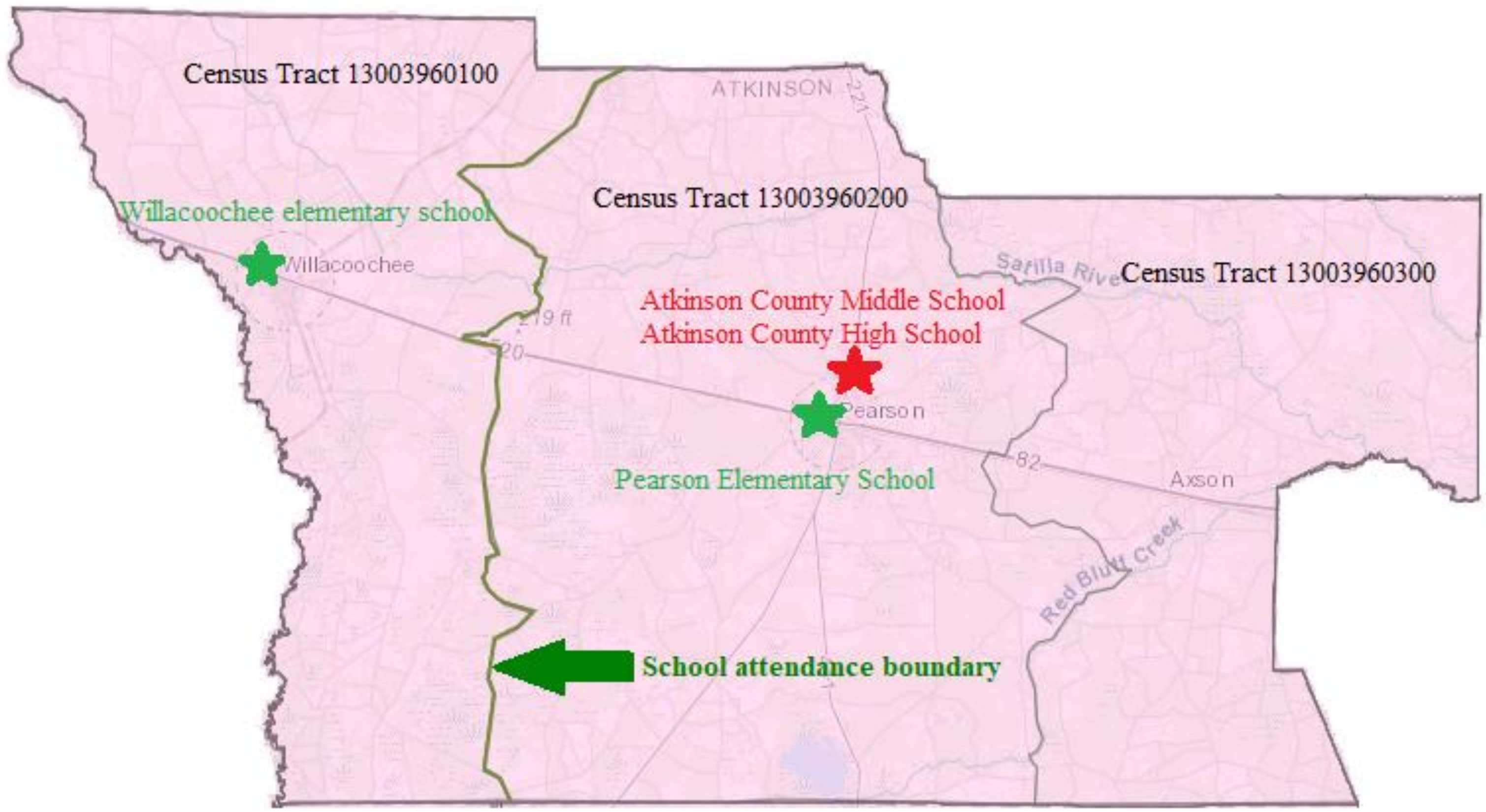
Notes: Figure 2 illustrates the timeline of the event of GS policy change and specifies the components that make up the historic vs. the current GS rating for elementary schools. GS rating is released in December 31st of each year. As a result, the third-party real estate listing platforms and homebuyers rely on GS ratings of the previous year. For example, 2017 home sales are affected by the 2016 GS ratings.

Figure 3. An example of GreatSchools rating in Zillow



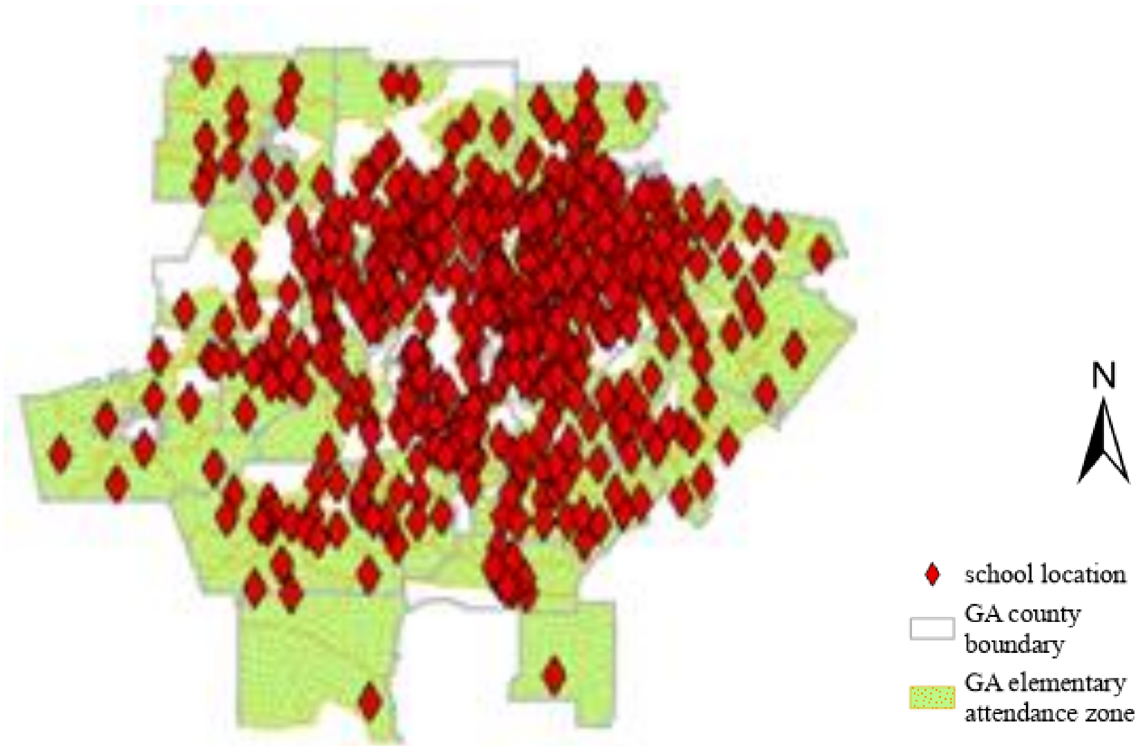
Notes: This figure shows a typical listing for sale on Zillow. GreatSchools rating is under the "Nearby schools" section. Each K-12 public school within the school attendance boundary associated with the listing is assigned a GreatSchools rating. Each school's GS summary rating is displayed as a clickable link that directly leads prospective buyers to GreatSchools website, within which specific breakdowns of the rating components are specified. This section in Zillow also includes a disclaimer and a brief description about GreatSchools.

Figure 4: An example school attendance assignment



Notes: This figure demonstrates school attendance assignment in the U.S., using Atkinson County as an example. Atkinson County happens to be the school district as well - Atkinson County School District. The county is divided into 3 Census Tracts and 2 separate school attendance zones. Within the school district, all children of 11-14 years old go to the one and only Atkinson County Middle School. Those of 15-18 ages attend the one and only Atkinson County High School. However, there are 2 elementary schools in the county, between which the school attendance boundary lies. 6-to-10-year-old children whose households belong to Census Tract 13003960100 attend Willacoochee Elementary, while those reside in Tracts 13003960200 and 13003960300 can only go to Pearson Elementary.

Figure 5. GS data coverage in metro Atlanta-CBSA



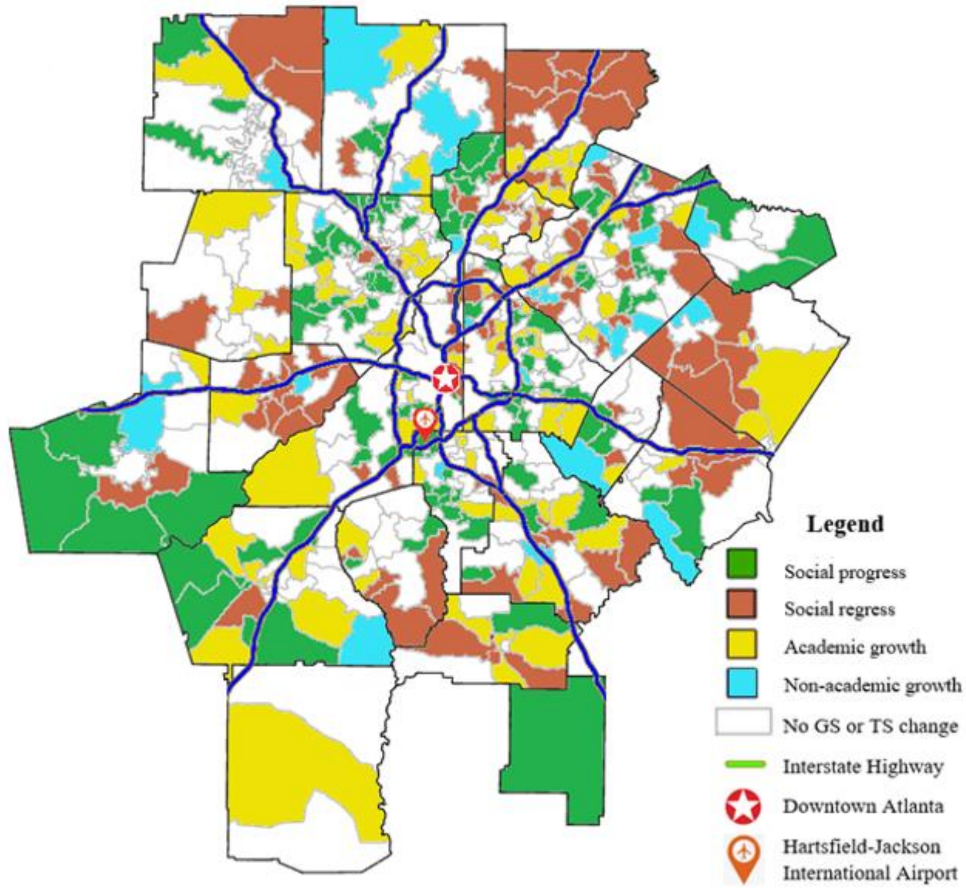
Notes: This map illustrates the locations of 435 elementary schools in the research sample, representing 100% coverage within Atlanta-CBSA. School attendance zone is a smaller unit than school district and country. The specific school to which a child attend is associated with the attendance boundary within which the child's house is located.

Figure 6. Social phenomena and hypotheses

Panel A. Social phenomena based on GS and TS changes

Social progress GS↑ & TS↑	Social regress GS↓ & TS↓
Academic growth GS↓ & TS↑	Non-academic growth GS↑ & TS↓

Panel B. Locations of schools experiencing the four social phenomena

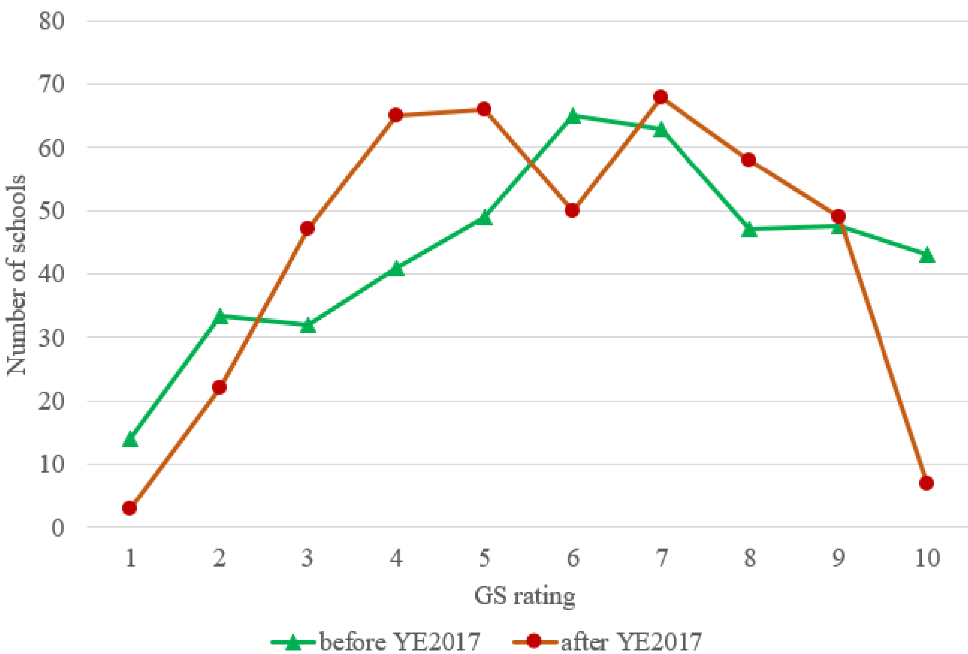


Notes: Figure 6 is divided into three panels. Panel A represents the four social phenomena divided by the change in direction of GS rating and test score. Social progress is the phenomenon in which both GS rating and test score improve over the academic year. Social regress is the opposite, where both GS rating and test score perform worse than the previous year. DEI decline phenomenon occurs when GS rating is decreasing but academic component like test score improves. This shows that the school does well academically, but still receive a negative GS rating change due to lower DEI performance. DEI growth is a phenomenon that take place when GS rating improves but test score regresses. Since GS rating includes both academic and DEI performance, the difference shows that only DEI performance has grown. Both bottom quadrants represent the deviation between test score and GS rating, reflecting the DEI component, or equitable growth/decline of the school.

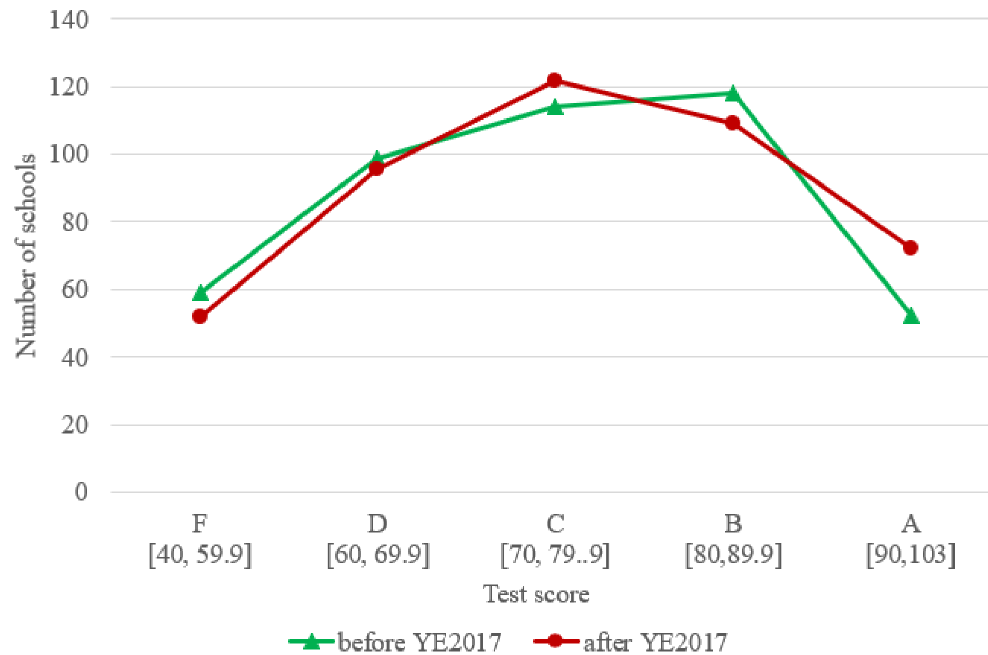
Panel B is a map of the locations of schools experiencing the four phenomena. The schools in the sample are bounded by Atlanta-CBSA. The map of Interstate 285, Atlanta downtown, and Hartsfield-Jackson International Airport visualize the relative locations between the city of Atlanta and its metropolitan areas.

Figure 7. Rating distribution

Panel A. GS rating distribution



Panel B. TS distribution



Notes: Figure 7 displays the distributions of ratings by the number of schools. Panel A represents GS rating distribution, which shows the number of schools in each of the 1-10 categories of GS rating. Panel B shows TS distribution, in which TS is classified by the discrete letter grades F-A. For each graph, the green line demonstrates the distribution before YE2017, and the red line is for the period after the GS rating change by YE2017.

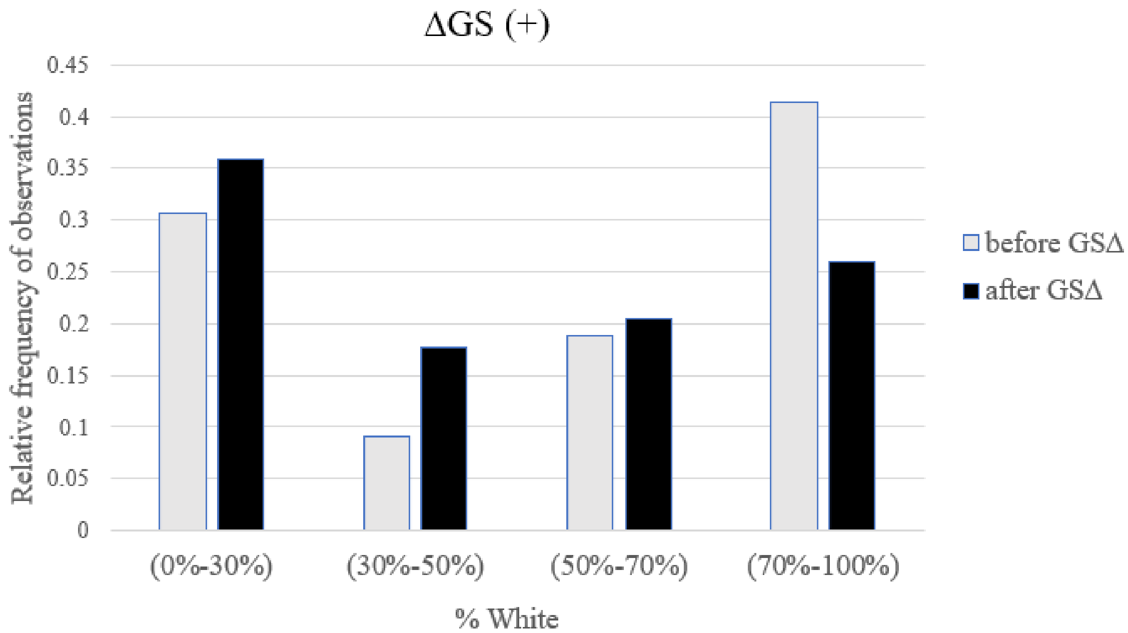
Figure 8. GS rating categories

<table>
<tr><th>GS</th><th>number of schools</th><th>median income</th><th>median % white</th><th>median college</th><th>% GS ↑</th><th>% GS ↓</th></tr>
<tr><td>10</td><td rowspan="4">202</td><td rowspan="4">$93,384</td><td rowspan="4">65%</td><td rowspan="4">49%</td><td rowspan="4">11%</td><td rowspan="4">65%</td></tr>
<tr><td>9</td></tr>
<tr><td>8</td></tr>
<tr><td>7</td></tr>
<tr><td>6</td><td rowspan="2">104</td><td rowspan="2">$71,528</td><td rowspan="2">45%</td><td rowspan="2">35%</td><td rowspan="2">34%</td><td rowspan="2">42%</td></tr>
<tr><td>5</td></tr>
<tr><td>4</td><td rowspan="4">129</td><td rowspan="4">$56,907</td><td rowspan="4">11%</td><td rowspan="4">29%</td><td rowspan="4">64%</td><td rowspan="4">15%</td></tr>
<tr><td>3</td></tr>
<tr><td>2</td></tr>
<tr><td>1</td></tr>
</table>

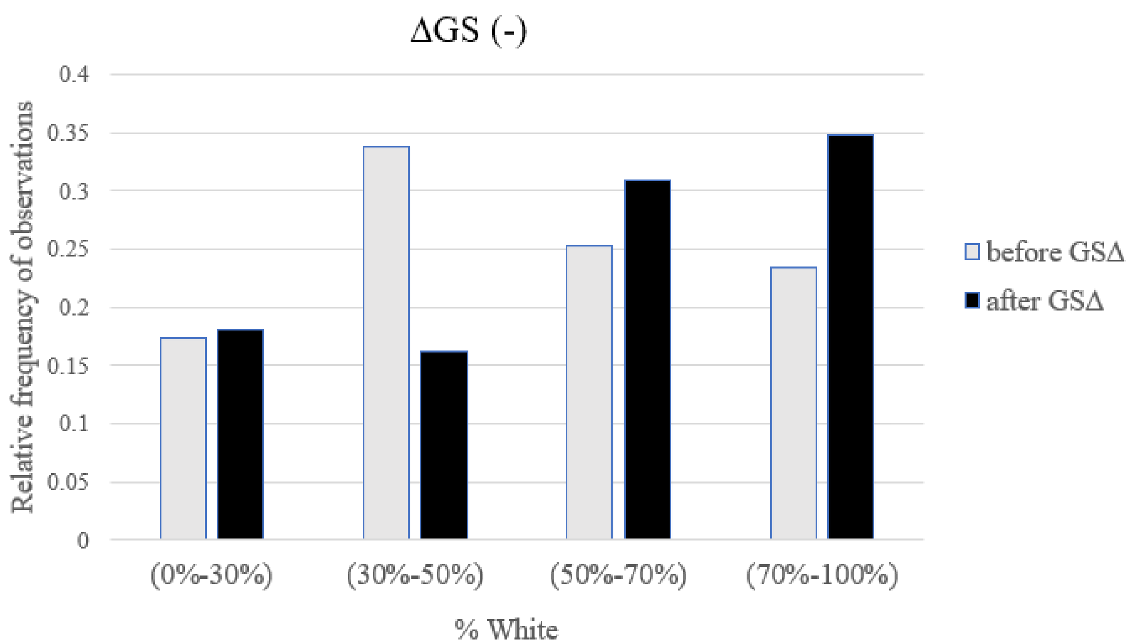
Notes: Figure 8 presents the characteristics of GS rating categories. The first column shows GS rating categories from 10 to 1. According to GS' classification, 10-7 is "above average", 6-5 is "average", and 4-1 is "below average". Figure 10 is thus divided accordingly, into three groups. The second column is the number of schools in each classification. The third column represents the median income of neighborhoods in which schools in each classification are located. The fourth column is the median percentage of White population. The fifth column show the median percentage of population within the neighborhoods that obtains at least a college education. The last two columns are the percentages of schools with GS rating increases, and those with GS rating decreases.

Figure 9. Historic GS rating change vs. YE2017 GS rating change

Panel A. Distribution of schools that got positive GS rating change, ΔGS (+), before vs. after YE2017



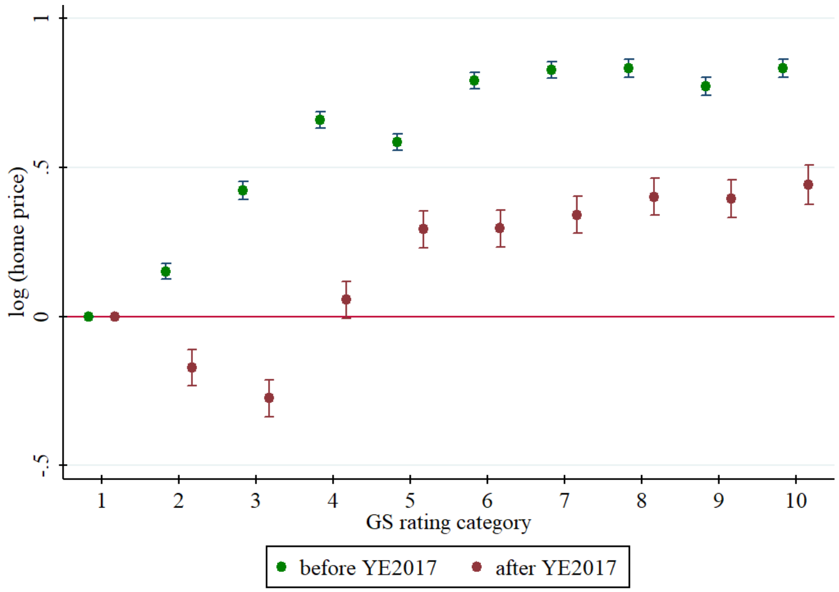
Panel B. Distribution of schools that got positive GS rating change, ΔGS (-), before vs. after YE2017



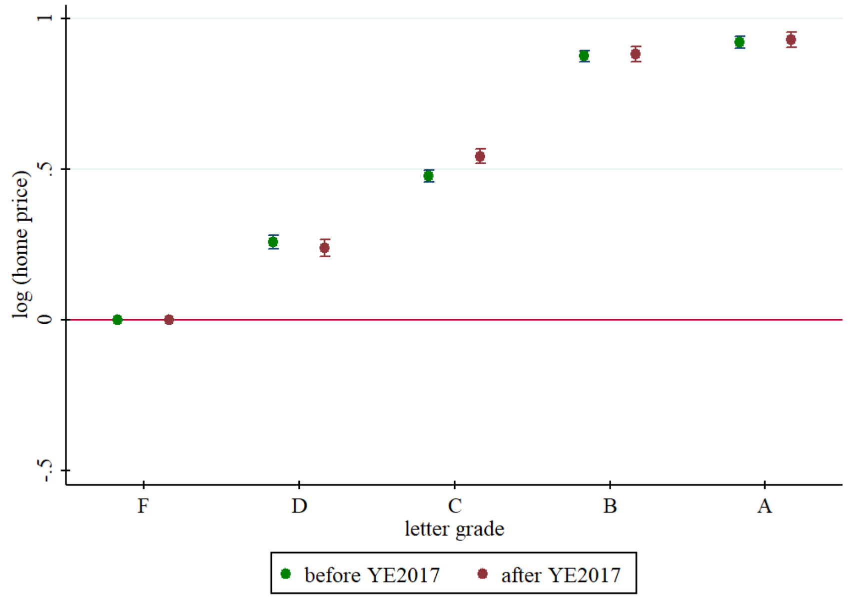
Notes: Figure 9 shows which schools receive positive GS rating changes in Panel A and negative GS rating changes in Panel B, before versus after YE2017. The grey bars represent the relative frequency of school observations by percentage of Whites (% White) historically, or before the GS rating change. The black bars show similar content for the period after YE2017, when GS incorporated other components including a DEI measure for school quality.

Figure 10. Home price and rating coefficients

Panel A. Home price against GS rating categories

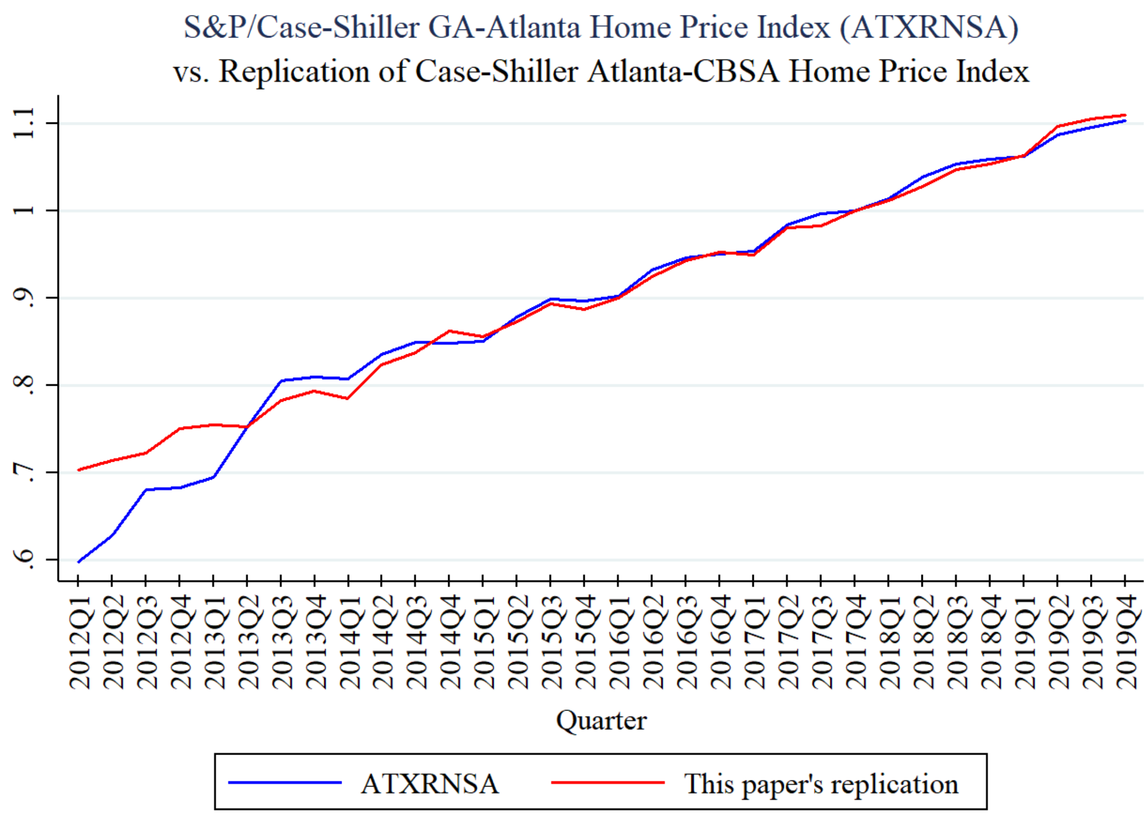


Panel B. Home price against TS categories



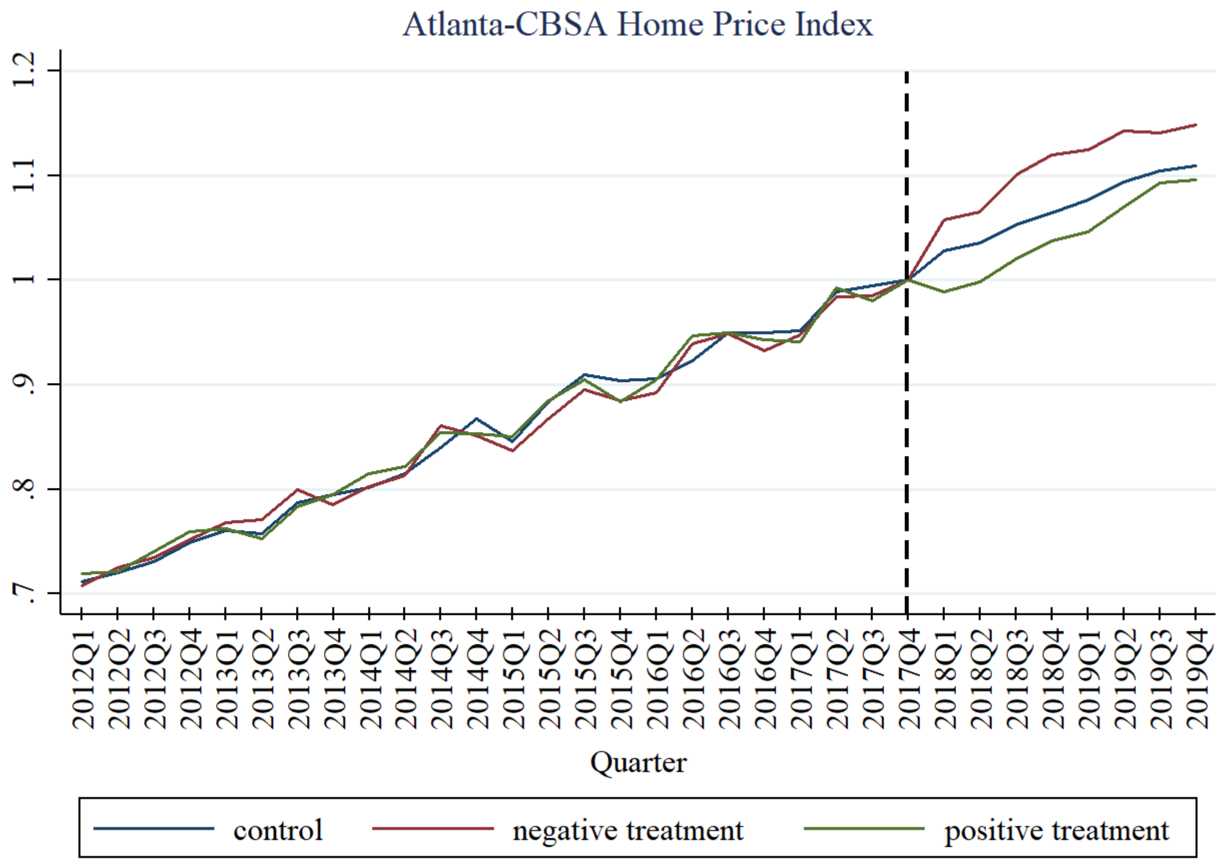
Notes: Figure 10 plots transaction prices estimated for each rating category, controlling for property-level characteristics, neighborhood, and year fixed effects. Panel A is for GS rating categories, ranging from 1 to 10, with GS=1 being the base case. Panel B is estimated price for TS, which is divided by the letter grade categories from F to A, with F being the base case. The red reference line is set at the price coefficient of zero. The green dots represent price coefficient for ratings before YE2017, while the red dots show those after YE2017. The bar across each dot displays 95% confidence band for the estimated home price.

Figure 11. Comparing to S&P/Case-Shiller GA-Atlanta home price index (ATXRNSA)



Notes: Figure 11 graphs the S&P/Case-Shiller GA-Atlanta home price index (ATXRNSA) and this paper's replication of the Case-Shiller home price index for the Atlanta-CBSA area. Represented by the blue line, the ATXRNSA is created by S&P Global CoreLogic as the average of repeat sales prices quarterly. For comparison purpose, I standardize the data such that the base quarter is 2017Q4. Represented by the red line, my replication of the Case-Shiller index is created from the sample of ZTRAX repeat sales that focuses on Atlanta-CBSA area from 2012Q1 to 2019Q4, the results of which is obtained from equation (8) regression and transformed using exponential.

Figure 12. Replication of the Case-Shiller home price index for Atlanta-CBSA

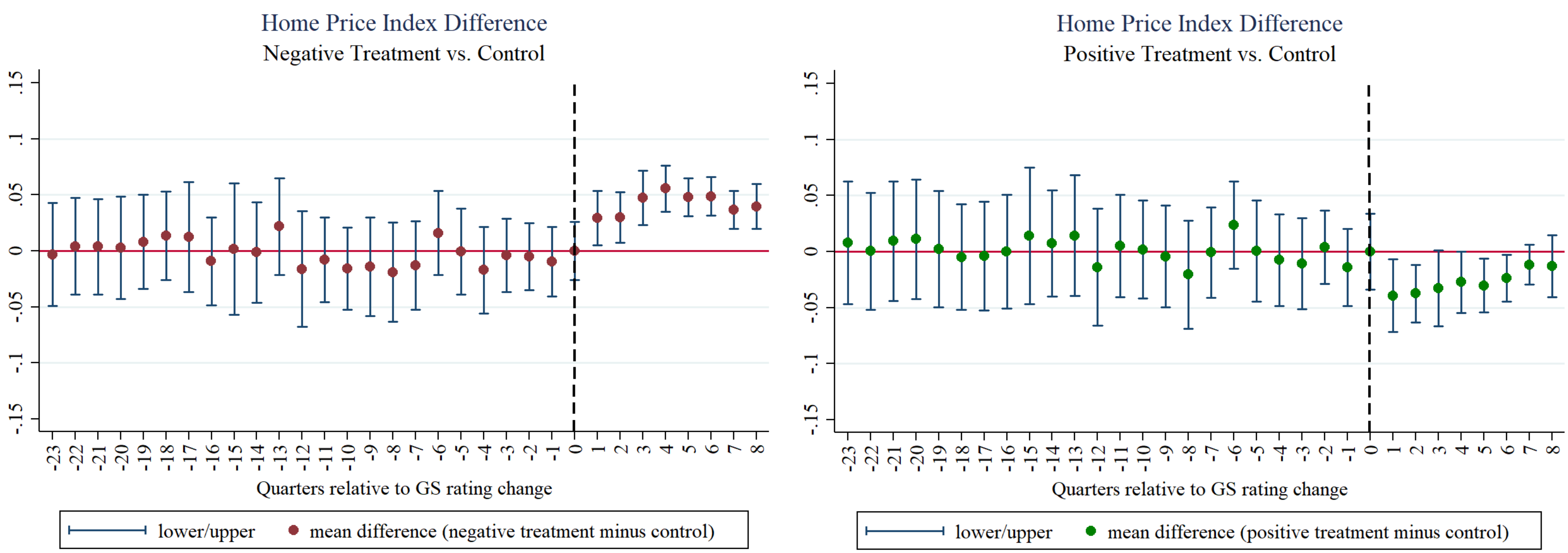


Notes: Figure 14 displays the home price index (HPI) created from the sample of repeat sales that focuses on Atlanta-CBSA area from 2012Q1 to 2019Q4. The indices are the exponential transformations of the results of equation (8) regressions. The blue line represents the HPI for the control group, including properties of which schools in the neighborhood do not experience GS rating change in 2017Q4 – the quarter that GS implements a major change in its school rating system – signified by the black dotted vertical on the timeline. The red line is the HPI for the negative treatment group, which includes properties in districts that receive GS rating decreases. The green line demonstrates the HPI for the positive treatment group, or repeat transactions of properties that are assigned to schools that experience GS rating increases. In this chart, 2017Q4 is the base quarter, where the three lines of HPI meet at one.

Figure 13. Dynamic event charts

Panel A. Dynamic chart between negative treatment and control

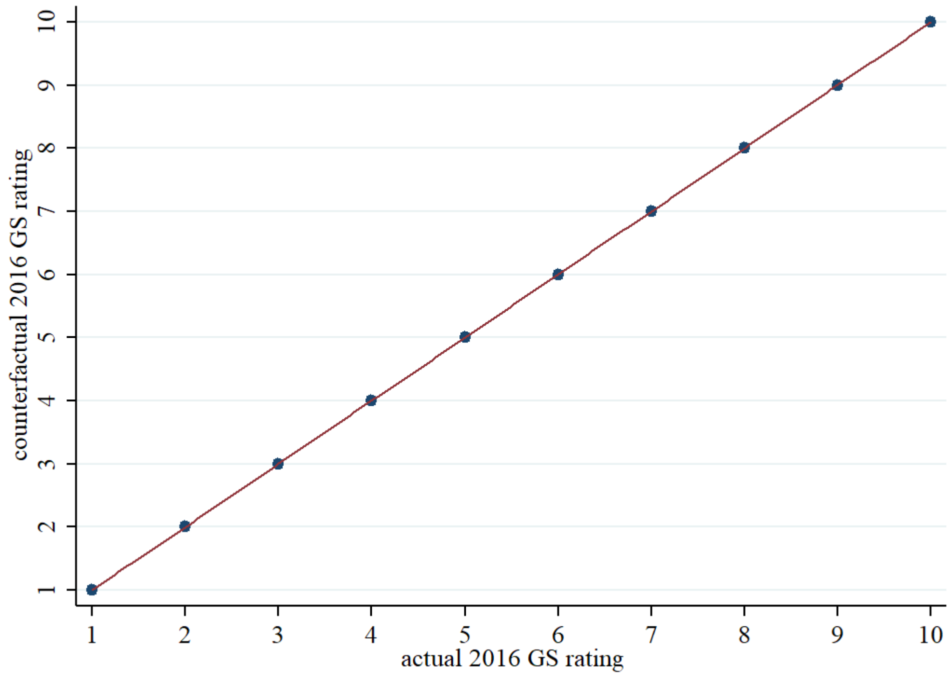
Panel B. Dynamic chart between positive treatment and control



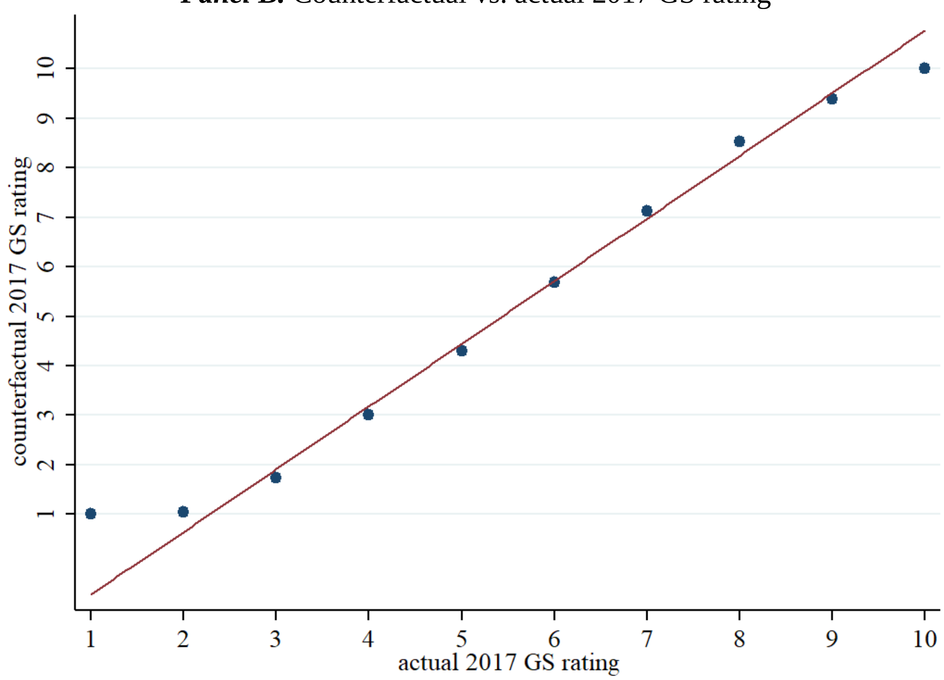
Notes: Figure 13 includes two panels of the dynamic event-study charts. Panel A graphs the differences in the HPI coefficients of the negative treatment and those of the control group. Panel B graphs the differences in the HPI coefficients of the positive treatment and those of the control group. These graphs are the results of the differences in the transformed (exponential) coefficients from equation (8) regressions, after applying non-linear Wald test to the seemingly unrelated equation setup (9) to find the standard errors and confidence intervals. The red reference line is set at the price coefficient difference of zero. The blue dots represent the mean differences of price coefficients between the treatment and the control group for each of the quarters, from 23 quarters before the event leading up to 8 quarters after the event of GS rating change in 2017Q4. 2017Q4 – the quarter that GS implements a major change in its school rating system, denoted as 0 in the dynamic timeline – is signified by the black dotted vertical on the timeline. The bar across each blue dot displays 95% confidence interval for the estimated difference in HPI coefficients.

Figure 14. Counterfactual ratings in placebo design

Panel A. Counterfactual vs. actual 2016 GS rating



Panel B. Counterfactual vs. actual 2017 GS rating



Notes: Figure 14 compares counterfactual GS rating that uses 100% TS to the actual rating that GS organization adopts during a particular year. Panel A is for 2016, the year immediately before the event of

GS rating change. Panel B is for 2017, the first year that the actual GS rating incorporates a DEI measure from focusing exclusively on test scores. The red line is a reference line of 45 degrees.

Table 1. Summary statistics: unmatched sample

		Full sample	Full sample				Treatment sample			
	sample:	Combined control & treatment	Control △GS=0		Treatment △GS=1		△GS+		△GS-	
	period:	2017, 2018, 2019	pre	post	pre	post	pre	post	pre	post
	stat:	mean	mean	mean	mean	mean	mean	mean	mean	mean
variable	unit	(stdev)	(stdev)	(stdev)	(stdev)	(stdev)	(stdev)	(stdev)	(stdev)	(stdev)
△GS	0,1	0.44	0	0	1	1	1	1	1	1
post	0,1	0.66	0	1	0	1	0	1	0	1
GS	score	6	7	6	6	6	6	6	6	6
		(2)	(3)	(2)	(2)	(2)	(2)	(2)	(2)	(2)
TS	score	80	81	82	78	78	77	77	79	80
		(13)	(14)	(12)	(13)	(13)	(15)	(14)	(12)	(12)
price	per SF	$127	$118	$131	$118	$131	$141	$114	$103	$146
		($186)	($135)	($121)	($140)	($300)	($203)	($173)	($73)	($374)
house size	SF	2,509	2,645	2,511	2,462	2,467	2,486	2,452	2,447	2,479
		(1,120)	(1,133)	(1,118)	(1,092)	(1,133)	(1,238)	(1,187)	(987)	(1,085)
lot size	SF	22,208	21,527	22,588	21,623	22,436	25,183	23,625	20,049	21,475
		(72,454)	(52,783)	(92,442)	(42,034)	(62,284)	(56,404)	(65,179)	(33,668)	(59,827)
bedrooms	count	4	4	4	4	4	4	4	4	4
		(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)
bathrooms	count	3	3	3	3	3	3	3	3	3
		(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)
prop age	yrs	28	25	29	28	29	33	28	25	31
		(21)	(21)	(21)	(21)	(22)	(24)	(21)	(19)	(24)
median income	$	86,523	84,938	90,154	81,348	85,538	88,924	83,204	76,405	87,554
		(38,891)	(34,100)	(40,093)	(38,038)	(39,515)	(48,355)	(41,092)	(28,350)	(37,988)
employment	%	0.69	0.69	0.69	0.68	0.68	0.68	0.68	0.68	0.69
		(0.08)	(0.08)	(0.08)	(0.09)	(0.08)	(0.10)	(0.09)	(0.08)	(0.08)
population growth	%	0.02	0.02	0.02	0.02	0.03	0.02	0.03	0.03	0.02
		(0.11)	(0.11)	(0.11)	(0.12)	(0.12)	(0.11)	(0.13)	(0.12)	(0.11)
	obs	102,206	14,392	42,409	20,200	25,205	7,855	11,584	12,345	13,621

Notes: Table 1 provides summary statistics, including the mean and standard deviation (stdev) for the sample of residential transactions from ZTRAX during 2017 to 2019, prior to applying any matched sample process. The first column displays the full sample, including transactions in the control group, positive treatment group, and negative treatment group. The second to third columns summarize transactions assigned to schools that experience no GS rating change, before (2017) and after (2018-2019) the GS rating change policy. The fourth to fifth columns deliver similar summary statistics for transactions assigned to schools that experience any GS rating change, either positive or negative. The final four columns summarize transactions in split treatment groups of positive GS change only and negative GS change only, before and after GS policy. △GS is an indicator for transactions in schools that were ultimately receive GS rating change (△GS =1). Post is an indicator for transactions occurring after 2017 (post=1), when GS rating system change took effect. GS is the GS rating in natural number from 1 to 10, and TS is the continuous test score from 0 to 100. Price is the transaction price, displayed on a per square foot (SF) basis. House size is the rentable building area of the structure, displayed in SF. Lot size equals the land area. Bedrooms is the number of bedrooms. Bathrooms equal the total number of full and half baths. Prop age equals the year of the transaction date minus the year built, displayed in years (yrs). Median income is the median dollar amount earn yearly at the Census block group level. Employment is the rate calculated by the number of employed people divided by the total labor force in the neighborhood. Population growth is the change in population in percentage term from one year to another. Obs is the number of transaction observations in each subsample.

Table 2. Within-cohort summary statistics: matched sample via characteristic matching method

	match process:	△GS (+)						△GS (-)					
	period:	before			after			before			after		
	variable △GS	0	1	difference	0	1	difference	0	1	difference	0	1	difference
PROPERTY	price per SF	$110	$115	5	$114	$118	4*	$105	$103	(2)	$111	$109	(2)
	test score	79.2	79.3	0	76.7	76.9	0	85.7	83.0	(3)	83.8	83.7	0
	house size	2,527	2,544	17	2,436	2,469	33	2,497	2,598	102**	2,525	2,473	(53)
	bedrooms	4	4	0	4	4	0	4	4	0	4	4	0
	bathrooms	3	3	0	3	3	0	3	3	0	3	3	0
	prop age	27	26	(1)	27	27	0	20	19	(1)	20	20	1
DEMOGRAPHIC	median income	89,694	88,760	(935)	88,326	90,685	2,359*	82,383	82,477	93	85,569	80,746	(4,823)***
	employment	0.67	0.68	0	0.68	0.68	0	0.69	0.70	0	0.70	0.68	0
	population growth	0.02	0.02	0	0.02	0.01	0	0.04	0.03	0	0.05	0.06	0
	obs	2,108	2,108		2,108	2,108		5,506	5,506		5,506	5,506	

Notes: Table 2 displays within-cohort summary statistics based on the matching procedure used to generate the matched sample. Based on the matching process, a matched sample must contain one control transaction pre-policy, one control transaction post-policy, one treatment transaction pre-policy, one treatment transaction post-policy – a total of four transactions that satisfy the following restrictions: ±2 GS ratings and ±15% test score in 2016, ±4 calendar quarters, same zip code, same number of bedrooms, ±50% of the subject's house size, ±20 years of the property age, arm's length transaction and single family only. The first column lists the variable names, defined in the notes for Table 1. The second to seven columns are matched samples of the positive-only treatment group (△GS (+)). Specifically, the second column designates the subsample means for the control (△GS=0) observations, while the third column contains those for the treatment (△GS=1). The fourth column equals the difference, along with ***, **, and * denoting statistical significance for the *t*-test of difference in means between △GS=1 and △GS=0 subsamples at the 1%, 5%, and 10% levels, respectively. For each match group of positive and negative GS rating change, the subsamples are divided into observations pre-policy (before) and post-policy (after). Columns eighth to thirteenth provide similar statistics for the negative-only treatment group (△GS (-)).

Table 3. Characteristics of schools with high likelihood of GS rating change

Panel A. Characteristics of schools with high likelihood of increased GS rating

Dependent variable	$\mathbb{1}_{\triangle GS>0}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
△% test score	-1.978***								-2.247***
	(0.08)								(0.08)
% Black		0.736***							0.798 ***
		(0.03)							(0.03)
% White			-0.557***						
			(0.03)						
% SNAP families				1.199***					
				(0.04)					
% disability					-0.261				-0.015
					(0.30)				(0.31)
log(median income)						-0.169***			
						(0.02)			
% employment							-1.565***		-1.393***
							(0.11)		(0.11)
population growth								-0.064	-0.071
								(0.08)	(0.08)
Observations	17,493	17,493	17,493	17,493	17,493	17,493	17,493	17,493	17,493
Pseudo R-squared	1%	1%	1%	0%	0%	0%	0%	0%	2%
AIC	73,725	73,683	73,291	73,458	74,342	74,276	74,139	74,342	72,752

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B. Characteristics of schools with high likelihood of decreased GS rating

Dependent variable	$\mathbb{1}_{\triangle GS<0}$								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
△% test score	1.468***								1.913***
	(0.07)								(0.07)
% Black		-0.928***							-1.042 ***
		(0.03)							(0.03)
% White			0.701***						
			(0.03)						
% SNAP families				-0.547***					
				(0.04)					
% disability					0.775***				0.404
					(0.28)				(0.28)
log(median income)						0.049**			
						(0.02)			
% employment							0.296***		0.005
							(0.10)		(0.10)
population growth								0.223	0.239***
								(0.07)	(0.07)
Observations	23,385	23,385	23,385	23,385	23,385	23,385	23,385	23,385	23,385
Pseudo R-squared	1%	1%	1%	0%	0%	0%	0%	0%	2%
AIC	82,547	81,859	82,421	82,775	82,970	82,972	82,970	82,969	81,185

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Table 3 reports results from the logistic estimation of the characteristics of the student bodies in schools with high likelihood of GS rating change. Panel A displays results from the estimation of equation (3), with the indicator variable, $\mathbb{I}_{\Delta GS>0}$, equaling one for schools getting GS rating upgrades. Panel B displays results from the estimation of equation (4), with the indicator variable, $\mathbb{I}_{\Delta GS>0}$, equaling one for schools getting GS rating downgrades. Δ% test score is the annual percentage change of the school-level test score. % Black is the portion of students identified as African Americans in the student body. % White is the proportion of students whose race is Caucasian. % SNAP families is the percentage of students whose families are so economically disadvantaged that they are eligible to receive food stamps. % disability is the percentage of students with disability within the school population. Log(median income) is the log of median income of the neighborhoods in which the according schools are located. % employment is the employment rate of the neighborhood. Population growth is the percentage change in neighborhood's population. Standard errors are displayed in parentheses. ***, **, and * denote statistical significance for the estimated coefficient at the 1%, 5%, and 10% levels, respectively. Pseudo R-squared is an analogue to R-squared for logistic regressions. AIC is the Akaike information criterion that estimates the prediction error of the statistical models.

Table 4. Descriptive statistics for the repeat sales sample

	full sample	control ΔGS=0	treatment ΔGS (+)	treatment ΔGS (-)
number of repeat sales pairs	85,690	21,648	29,954	34,088
% of total	100	25	35	40
purchase price ($)	178,853	180,434	165,383	189,686
sale price ($)	231,053	228,134	213,738	248,122
holding period (quarters)	9	10	9	9
holding period return total	46%	42%	46%	49%
holding period return per quarter	9.1%	7.8%	9.4%	9.7%
number of unique properties	69,198	17,510	23,760	27,928
Percentage of properties with one or more repeat sales				
1	79.84	79.83	78.28	81.18
2	16.99	17.12	18.07	16.00
3	2.72	2.71	3.05	2.45
4	0.38	0.29	0.51	0.33
5	0.06	0.06	0.08	0.04
6	0.00	0.00	0.00	0.00

Notes: This table displays the descriptive statistics of the sample of repeat sales, which focuses on single families in the Atlanta-CBSA area from 2012Q1 to 2019Q4. The first column displays the full sample, including transactions in the control group, positive treatment group, and negative treatment group. The second column describes the control group, defined as properties in areas that see no GS rating changes. The third to fourth columns, ΔGS (+) and ΔGS (-), present descriptive statistics for transactions that are located in areas that experience positive GS rating change and negative GS rating change, respectively. Number of repeat sales pairs is the count of pairs of transactions (i.e., purchase transaction and sale transaction). % of total is the proportion of the number of repeat sales for each group in comparison to the full sample. Purchase price is the average price of the properties in the sample when being bought. Sale price is the average price of the properties in the sample when being sold. Holding period is the average number of quarters in between a purchase transaction and a sale transaction. Holding period return total is the average percentage of capital gain for the property across all quarters starting from the quarter of purchase and ending in the quarter of sale. Holding period return per quarter is the holding period return total divided by the number of holding quarters. Number of unique properties is the count of unique addresses of the properties in the sample. Since these repeat sales are at the property level and each property is associated with more than one transaction, the bottom of Table 16 tabulates the percentage of properties within each category of number of paired transactions.

Table 5. Estimated premiums using characteristic matched sample:
Home prices in schools with GS rating changes

	△GS+			△GS-		
Dependent var: log(price)	(1)	(2)	(3)	(4)	(5)	(6)
treated*post	-0.024	-0.037	-0.038	0.030***	0.038***	0.036***
	(0.024)	(0.030)	(0.029)	(0.010)	(0.011)	(0.011)
hedonic controls	X	X	X	X	X	X
% TS change	X	X	X	X	X	X
TS control	X	X	X	X	X	X
quarter FE	X	X	X	X	X	X
zip code FE	X	X	X	X	X	X
school FE	X	X	X	X	X	X
block group FE		X	X		X	X
cohort FE			X			X
Observations	8,460	8,460	8,460	22,036	22,036	22,036
Match samples	2,115	2,115	2,115	5,509	5,509	5,509
Adj R-squared	0.677	0.698	0.706	0.542	0.580	0.589

Notes: Table 5 studies home price estimations using equation (2). The sample is constructed from the manual characteristic matching process, as described in the notes to Table 2. Observations are at the property-year level. This table displays results for separate treatment groups: positive treatment on the left-hand side, and negative treatment on the right-hand side. Hedonic controls include the house size, property age and its square, median income, employment rate, TS and percentage change in TS (% TS change) to control for academic performance, along with indicator variables for quarter-year fixed effects, zip code fixed effects, school fixed effects, block group fixed effects, and matched cohort fixed effects. In each model, the dependent variable is the housing transaction price, log(price), and indicator variables are included for post, treated, along with the interaction term treated*post, which measures the price impact of the new GS rating implemented in YE2017. All variables are defined in the notes to Table 1. Standard errors displayed in parentheses are heteroskedasticity robust and clustered at the school level. ***, **, and * denote statistical significance for the estimated coefficient at the 1%, 5%, and 10% levels, respectively.

Table 6. Robustness test

Dependent var: log(price)	△GS+	△GS-
treated*post	-0.032	0.071***
	(0.060)	(0.007)
hedonic controls	Yes	Yes
% TS change	No	No
TS control	No	No
quarter FE	Yes	Yes
zip code FE	Yes	Yes
school FE	Yes	Yes
block group FE	Yes	Yes
Property FE	Yes	Yes
Observations	78,063	80,310
Adj R-squared	0.757	0.755

Notes: Table 6 reports home price estimations on the repeat sales sample using equation (2). The sample is additionally constructed from a manual characteristic matching process: a matched group must contain at least one transaction from the control and one transaction from the treatment group that are located in the same zip code, have the same number of bedrooms and the same number of full bathrooms. Observations are at the transaction-level. Column (1) displays results for the positive treatment, as compared to the control group. Column (2) shows coefficients for the negative treatment group in comparison to the control one. Hedonic controls include the house size, property age and its square, median income, employment rate, along with indicator variables for quarter-year fixed effects, zip code fixed effects, school fixed effects, block group fixed effects, and property fixed effects for each repeat sales pair. There are no controls for % TS change or TS level, due to the lack of TS data before 2016 from the Georgia Governor's Office of Student Achievement. In each regression, the dependent variable is the log of housing transaction price, log(price). The main coefficient of interest is the interaction term treated*post, which measures the difference between the treatment and control groups after the event – essentially the price impact of the new GS rating implemented in YE2017.
All variables are defined in the notes to Table 1. Standard errors displayed in parentheses are heteroskedasticity robust and clustered at the school level. ***, **, and * denote statistical significance for the estimated coefficient at the 1%, 5%, and 10% levels, respectively.

Table 7. Heterogeneity test by migration type

Dependent Var	Log(price)					
	(1) △GS+ & △TS+	(2) △GS- & △TS+	Difference (2) – (1)	(3) △GS- & △TS-	(4) △GS+ & △TS-	Difference (4) – (3)
treated*post	0.005	0.170***	0.165***	-0.012	-0.146**	-0.134***
	(0.043)	(0.020)	(0.031)	(0.017)	(0.073)	(0.033)
treated*post*nonlocal	0.005	-0.103***	-0.108***	-0.150***	0.078*	0.228***
	(0.045)	(0.020)	(0.032)	(0.030)	(0.044)	(0.033)
hedonic controls	X	X		X	X	
% TS change	X	X		X	X	
TS control	X	X		X	X	
quarter FE	X	X		X	X	
zip code FE	X	X		X	X	
school FE	X	X		X	X	
block group FE	X	X		X	X	
cohort FE	X	X		X	X	
Observations	6,098	10,301		11,676	2,299	
Match samples	1,529	2,585		2,922	579	
Adj R-squared	0.628	0.650		0.562	0.757	

Notes: This table reports the effect of home buyers' locality on home prices in areas with schools that experience GS rating change after YE2017. Columns (1) to (4) are for the mutually exclusive groupings of property transactions in school districts that experience (1) positive GS rating change and positive TS change (**△GS+ & △TS+**), (2) negative GS rating change and positive TS change (**△GS- & △TS+**), (3) negative GS rating change and negative TS change (**△GS- & △TS**), and (4) positive GS rating change and negative TS change (**△GS+ & △TS-**), respectively. The difference between column (2) and (1) represents home price estimates in school districts that experience net GS rating reduction due to measures other than TS. The difference between column (4) and (3) represents home price estimates in school districts that experience net GS rating increase due to measures other than TS. The dependent variable is log of home price. The key independent variable is the interaction between treated*post and nonlocal, where nonlocal equals the proportion (%) of the population of homebuyers that come from a city different from the city where the transacted property is located. All regressions control for characteristics and fixed effects that are defined in Table 5. Standard errors displayed in parentheses are heteroskedasticity robust and clustered at the school level. ***, **, and * denote statistical significance for the estimated coefficient at the 1%, 5%, and 10% levels, respectively.