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The Implications of Digital School Quality Information for Neighborhood and School Segregation: Evidence from a Natural Experiment in Los Angeles

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ABSTRACT

A digital information explosion has transformed cities' residential and educational markets in ways that are still being uncovered. Although urban stratification scholars have increasingly scrutinized whether emerging digital platforms disrupt or reproduce longstanding segregation patterns, direct links between one theoretically important form of digital information– school quality data– and neighborhood and school segregation are rarely drawn. To clarify these dynamics, we leverage an exogenous digital information shock, in which the *Los Angeles Times*' website revealed measures of a particularly important school quality proxy– schools' value-added effectiveness– for nearly all elementary schools in the Los Angeles Unified School District. Results suggest that although the information shock had no detectable effects on residential sorting or neighborhood racial segregation, it did exert modest effects on school sorting—particularly for Latino and Asian students— albeit not in ways that materially diminished school racial segregation because the racial compositions of high- and low value-added schools were broadly similar both before and after the information shock. We conclude that the urban stratification implications of digital information may be more nuanced than often appreciated, with effects shaped by racial heterogeneity in both constraints and preferences vis-à-vis specific types of information and operating through mechanisms beyond residential segregation.

Keywords: Digital information, neighborhood and school segregation, racial achievement gaps

Tectonic shifts in the U.S. during the twentieth century, including the Great Migration, the post-war immigration boom, the decline of industrialization, and the rise of the knowledge economy, reshaped households' residential preferences and constraints in ways that profoundly shaped race- and class-based segregation patterns. Twenty-first century America has been marked by new macro shocks: the simultaneous digital information explosion and choice-based policy expansion. Digital platforms like Zillow, Redfin, and GreatSchools.org have largely supplanted traditional sources of neighborhood and school information (Besbris et al., 2021; Schachner and Sampson, 2020). Meanwhile, housing and school vouchers, alongside a growing charter school sector and liberalizing school enrollment regime, have empowered families to more readily act on digital information to make residential and educational decisions. The degree to which these novel shifts have reshaped segregation patterns is the subject of ongoing debates within urban research.

In the early days of digitalization, optimists predicted that the "democratization" of neighborhood and school quality information via digital platforms and the expansion of choice-based policies could level the playing field (Lane, 2019; Sawicki and Craig, 1996) and potentially reduce race- and class-based segregation. Digital resources might broaden access to higher-quality neighborhood and school information and partially disintermediate discriminatory real estate brokers and social networks– both of which historically dominated contextual sorting processes in the U.S. (Besbris, 2020; Korver-Glenn, 2021). If true, then the strong, persistent links between household, school, and neighborhood demographics might attenuate.

Yet ecological analyses are incongruent with this story. School and neighborhood racial segregation among families in U.S. metropolitan areas have stagnated in the twenty-first century, and by some measures have actually increased (Logan, 2013; Owens, 2017; Reardon and Owens, 2014), at the same time as choice-based public policies and digitalization have become entrenched. A plausible direct link between digitalization and *increased* segregation has emerged from recent studies that scrape and analyze Craigslist rental ads. This research suggests that: the quantity and quality of Craigslist ads is sharply higher in affluent White neighborhoods; ads for market-rate, rather than affordable, subsidized units predominate; and racially coded ad language may constitute a new, digitalized form of racial steering (Besbris et al., 2021; Boeing et al., 2021; Kennedy et al., 2021).

Yet it may be premature to infer that digitalization typically fuels urban inequities. Craigslist-based studies have not scrutinized the patterns and drivers of contemporary contextual sorting processes among the subset of households that has exhibited the steepest rise in residential segregation during the digital age: those with children (Owens, 2016, 2017). For these households, school information is likely a key driver of residential and educational decisions (Schachner and Sampson, 2020), and this information is increasingly procured for families through digital platforms beyond Craigslist (e.g., GreatSchools.org). Despite school quality information's theoretical importance, research examining the effects of its digital dissemination on neighborhood and school sorting and segregation remains scarce. Instead, scholars typically examine the effects of this information on other outcomes more tangentially related to segregation, including housing prices (Figlio and Lucas, 2004; Imberman and Lovenheim, 2016). Vanishingly few studies of digital school quality information "shocks" examine their neighborhood and school sorting and segregation effects simultaneously, even though the effects may meaningfully diverge across outcomes and contexts, especially in cities where exercising school choice is common.

To clarify these ambiguities, we ask: Does the digital provision of publicly-accessible information on schools' value-added quality (i.e., their estimated causal effects on student learning) increase or decrease race-based segregation in both neighborhoods and schools? To answer this question, we exploit a natural experiment in which the *Los Angeles Times* (*LAT*) calculated and digitally disseminated value-added measures for over 400 residentially-zoned, Los Angeles Unified School District (LAUSD) elementary schools on their free online platform in 2010 and 2011. We link these measures to geospatial boundaries of school catchment zones and census tracts, enabling us to gauge whether the rankings drove tract-level sociodemographic shifts after the information shock, based on American Community Survey (ACS) data. We also track school-level enrollment patterns and sociodemographic shifts pre- and post-shock, using annual data from the California Department of Education (CDE: 2000-01 through 2012-13).

Whereas prior studies suggest information shocks revealing schools' average test scores likely increase segregation, our results tell a more nuanced story. We find the digital dissemination of information on schools' value-added quality has null effects on neighborhood sorting and segregation by race in Los Angeles. We do find detectable, if modest, effects on school enrollment patterns, particularly among Latino and Asian families, but the information-induced shifts do not appear to meaningfully change school segregation because the racial compositions of high- and low value-added schools were broadly similar. These patterns suggest the urban stratification implications of digital information may be even more nuanced than previously assumed.

How New Digital Sources of Information Reshape or Reproduce Segregation Processes

For over a century, a vibrant strand of urban inequality research has examined how household-level preferences and constraints interact with macroeconomic shifts and evolving normative, institutional, and informational conditions to produce race-based residential segregation (Galster, 2020). Much less is known about how information technology— specifically, the digitalization of residential and educational markets—is impacting segregation in contemporary cities. The lack of resolution on how digital information interacts with households' preferences and constraints to reshape urban inequities reflects theoretical ambiguities and thorny methodological challenges.

Theoretical Expectations and Emerging Findings from Craigslist Studies

In the digital revolution's early days, some scholars and policymakers optimistically predicted that the "democratization of data" through online platforms could mitigate race- and class-based informational divides (Lane, 2019; Sawicki and Craig, 1996). This view held that unequal social networks and institutional gatekeepers in the housing market could be bypassed and that higher-quality information could be accessed online, yielding enhanced residential options for disadvantaged households. However, several decades into the digital age, most evidence suggests racial segregation of neighborhoods and schools in the U.S. has not materially declined (Krysan and Crowder, 2017; Logan, 2013; Owens, 2017; Reardon and Owens, 2014). Thus, the expansion of digital information may not only have failed to arrest these patterns; it may have exacerbated them.

There are theoretical reasons to believe the latter proposition is true. The well-documented digital divide along race and class lines (Fairlie, 2004) may have meant that more advantaged households disproportionately accessed, and acted on, expanding digital information.

Further, the content of the newly-available digital information may have explicitly and implicitly stoked class- and race-based antipathies (Benjamin, 2019), further supporting advantaged households' ability to identify– and fueling their desire to access– privileged bastions. In contrast to the democratization of data view, a fast-growing body of urban research supports this less sanguine perspective.

For example, several studies that scrape Craigslist rental ads find that digital information expansion in the housing market may have exacerbated residential segregation through multiple mechanisms. Craigslist's informational benefits appear largely confined to more affluent households; households reliant on affordable/subsidized housing— disproportionately low-income— are much less likely to access relevant listings (Boeing and Waddell, 2017). Further, Whiter, more affluent communities exhibit a marked advantage vis-à-vis the quantity and quality of Craigslist unit listings (Boeing, 2020; Boeing et al., 2021). One study argues that Craigslist ads may employ a coded "racialized discourse," generating new forms of residential steering (Kennedy et al., 2021).

However, this emerging body of Craiglist-based studies provides only a partial view of digital information's segregative effects for two key reasons. First, most of the studies probe the discursive content of the digital information and its spatial patterns, rather than its actual sorting effects. Although it is possible that biases in the provision and interpretation of rental ad information have material effects on residential sorting, this possibility has rarely been tested (cf. Besbris et al., 2022). More direct, causal tests exploiting exogeneity are needed.

Second, aggregate analyses suggest segregation is higher, and has grown more sharply during the digital age, among households with children compared to those without them (Owens, 2016, 2017). Given that family structure shapes residential preferences and constraints, aggregate estimates may obscure varying effects of digitization on different populations. The studies reviewed above may thus elide the informational sources and mechanisms shaping decisions of the group that is disproportionately driving residential segregation's growth.

A Strategic Case: School Quality Information Shocks' Effects on Segregation

Examining the causal effects of school quality information's digital dissemination constitutes a theoretically strategic case that helps mitigate the limitations described above. Since the late 1990s, the systematic collection and online dissemination of information on various school characteristics by state and local government agencies in the U.S. (Lareau and Goyette, 2014; Schachner and Sampson, 2020) and across the Global North (Ladd and Fiske, 2001) has rapidly expanded. Such dissemination has racial segregation implications only if it causes families (of at least one racial group) to sort themselves into schools or neighborhoods that demographically diverge from their counterfactual (origin) school or neighborhood.

Prior research suggests these criteria might be met, at least when the disseminated school quality information captures average test scores. Schools' test score levels closely proxy the race and class composition of their students and accessing the "bundle" of high-scoring, highly advantaged schools appears particularly desirable to White (Schachner, 2022b) and affluent (Rich and Jennings, 2015) families. Enrolling in these high-status schools historically required residentially relocating to their catchment zones, and affluent White families enjoyed a significant edge in pursing this school access strategy, given their well-documented advantages in navigating housing markets—particularly cost-prohibitive ones.

But contemporary dynamics of neighborhood and school sorting are more complex, generating ambiguous expectations regarding the effect of digital school information on residential segregation. On one hand, the expansion of school choice options and liberalized enrollment policies in many high-cost metros could reduce racial disparities in school-based residential decision-making, since neighborhood residence and school access are no longer tightly linked. On the other hand, school-based residential decision-making may persist in ways that exacerbate segregation, if advantaged parents are disproportionately willing and able to pay a premium for geographic proximity to a high-scoring school close to their home or if they evaluate the prospects for home value appreciation based, in part, on how high-scoring the local public schools are.

Empirical evidence provides some support for the latter possibilities. Schachner and Sampson (2020) show that even in school choice-dominated Los Angeles, dissemination of schools' average test scores may increase residential segregation, in part, because highly-educated, highly-skilled families, who are disproportionately White, tend to sort into neighborhoods on the basis of them. Hasan and Kumar (2018) extends beyond Los Angeles, using the staggered roll-out of the widely-used GreatSchools.org platform to assess the causal effects of the site's school quality metrics—which rely heavily on average test scores— on zip code-based segregation. The platform's expansion coincided with increased racial segregation.

Although these studies suggest that digitally supplying average test score information exacerbates neighborhood and perhaps school segregation, average test score measures are only one type of information, and they are weakly correlated with schools' causal effects on student learning (Deming, 2014). It would thus be premature to conclude that digitally providing school data increases segregation; the effects may depend on the specific type of school quality data provided.

The Present Study: Segregation Effects of Digitally-Disseminated School Value-Added Quality Information

Recent studies have attempted to clarify this possibility by assessing the effects of digitally disseminating data on school *value-added* in place of, or in addition to, the traditional average test score measures. The typical approach to measuring schools' value-added quality entails estimating how much better or worse a school's students performed on spring standardized tests (typically in Math and/or English/Language Arts–ELA) compared to the scores that would be predicted based on its students' baseline skill levels (i.e., test scores in the spring of year *t*–1), sociodemographic characteristics and special education status (Jennings et al., 2015; Lloyd and Schachner, 2021). Importantly, value-added measures of school quality tend to be much less strongly correlated with schools' student sociodemographics and much more predictive of their causal effects on students' short- and long-term outcomes than are average test score-based measures of school quality (Deming, 2014).

In the early 2010s, a natural experiment occurred, whereby *LAT* calculated and digitally disseminated measures capturing the value-added quality of teachers and schools for over 400 public elementary school campuses in LAUSD; the data were first released in late August 2010, and they were updated in April 2011. Scholars have subsequently leveraged this exogenous shock to gauge the effects of digital value-added information on housing prices and intra-school classroom sorting. One such study found that neighborhood housing prices did not measurably shift in accordance with their catchment schools' value-added ratings (Imberman and Lovenheim, 2016). Another study scrutinized within-school classroom sorting effects, finding that students who were already high-achieving became more likely to access classrooms of teachers with high value-added ratings (Bergman and Hill, 2018). These two studies address important questions, but they do not directly tie digital school value-added quality information to neighborhood and school segregation, as this study does.

The effect of digital school value-added quality information on neighborhood and school segregation are more theoretically ambiguous in twenty-first century Los Angeles than in other cities, during earlier time periods, because its core-city school district has seen the link between neighborhood residence and school enrollment substantially attenuate over the past two decades. The expansion of charter schools, magnet schools, and inter- and intradistrict choice regimes have enabled LAUSD students to access a much larger school choice set than they had before. Overall, LAUSD could be characterized as evolving from an "enforced catchment area system" during the twentieth century to a hybrid system, somewhere between "open" and "restricted" choice during the twenty-first (Boterman et al., 2019). More detail on LAUSD's hybrid choice system is provided in the Online Supplement—Methodological Appendix. It is important to note that by the 2000s, only about half of LAUSD students attended their local school (Schachner, 2022b). It follows that digital information effects on neighborhood sorting could be different than those on school sorting in Los Angeles and in the many other major cities across the Global North that have seen similar shifts in the school-neighborhood link.

Concretely, digital value-added information could generate shifts in neighborhood sorting and segregation if LAUSD families residentially relocate to the attendance zones of more highly-rated schools. Another, rarely-tested pattern, is also plausible: value-added information could shape school sorting and segregation but not neighborhood-related outcomes if, for example, Angelenos take advantage of the new information and increased school choice options to place their children in different schools than they otherwise would have, without residentially relocating. This stationary variant of choice has received scrutiny in recent school segregation studies (Boterman, 2021; Oberti, 2020). However, most U.S. studies examining exogenous school information shocks' effects elide it.

This study employs the strategic case of LAUSD and the *LAT* information shock to clarify the complex digital information and segregation links in a choice-rich urban context. By estimating the effects of the same shock on both neighborhood and school outcomes, using two different datasets, we clarify the potentially distinct effects of digital school quality information on multiple important domains of inequality. Moreover, by disaggregating analyses by race in a remarkably racially diverse context like Los Angeles, we illuminate how racial heterogeneity in informational preferences and constraints may operate. These unique features of our study help lay the groundwork for a richer theoretical model of digital information's effects on urban stratification.

DATA & METHODS

Key Variables and Analytic Sample

To predict neighborhood and school sorting and segregation shifts, our key independent variable is the estimate of public elementary schools' value-added quality that was published online by *LAT* in April 2011 and still accessible at https://projects.latimes.com/value-added/. The previous value-added estimates from late August 2010 were highly correlated with the April 2011 estimates but covered fewer schools and were likely published too close to the fall 2010 semester to affect enrollment patterns during the 2010-2011 school year.

The 2011 value-added measures are based on longitudinal, student-level test score data for 2nd-5th graders who were enrolled in LAUSD elementary schools between 2004-05 and 2009-

10. The *LAT* value-added models generated a Math-specific, ELA-specific, and overall score (combining Math and ELA) for each school. Each of the three scores was converted into quintile-based rankings, with schools labeled as Least, Less, Average, More, and Most effective vis-à-vis Math, ELA, or overall– relative to the other ranked schools. All quintile measures are time invariant, since schools were only ranked once, using student-level data pooled across six school years. For details on *LAT*'s value-added model specification, which generated estimates of both school- and teacher-level quality, see Buddin (2011).

This five-category classification scheme was easily interpretable by parents and freely accessible to anyone with internet access. The information was only disseminated online, not in the newspaper's print edition, but the print edition did reference the online rankings in multiple articles. Visitors to the *LAT* website could easily organize all ranked schools by value-added quintile or could search for specific schools' rankings. Prior studies document that the information shock was widely-publicized in both English- and Spanish-language print publications and radio stations. It thus provides a valuable test of digital information's effects on neighborhood and school sorting.

Accounting for Pre-Shock School Quality Information: The Academic Performance Index

These value-added measures were not the only school quality proxies available to Angelenos during the timeframe in question. Between the 1998-99 and the 2012-13 school years, CDE calculated a standardized, widely-disseminated measure of the average test scores (the type of measure most prior work on school information effects employs) of nearly every public school in California, including all *LAT*-ranked schools. This measure, known as the *Academic Performance Index (API)*, aggregates students' performance on specific standardized test modules into one school-level API score for every school year. Although the precise methodology is obscure, the score itself– which ranges from 300 to 800– is easily interpreted (see CDE, 2012 for more details on the API methodology). API scores were published both in print and online by *LAT* on an annual basis for LAUSD schools. Countless news stories covered the API scores, which were also available for free on CDE's website.

One might intuit that parents could closely approximate schools' value-added rankings based on the API information that pre-dated the rankings' release. However, this is not the case. Although both sets of metrics were intended to capture differences in school quality, schools with high average *levels* of test scores do not consistently exhibit higher rates of sociodemographically-adjusted (i.e., value-added) *growth* in test scores. Indeed, Imberman and Lovenheim (2016) show that API and *LAT* value-added rankings are not strongly correlated.

Despite this weak correlation, our multivariate models—described below— account for schools' API rankings in predicting neighborhood and school sorting outcomes for several reasons. First, prior work suggests that many Los Angeles parents were aware of the API rankings and a subset made neighborhood and school decisions based on them during the 2000s and 2010s (Schachner and Sampson 2020); excluding API-based controls could thus induce modest bias in our estimated effects of *LAT* rankings, particularly for certain groups. Relatedly, although our focus is primarily on the effects of the *LAT* value-added rankings, it is instructive to benchmark the magnitude of these effects to those generated by the ubiquitous API school quality rankings, which pre-dated the *LAT* rankings by over a decade. Lastly, the inclusion of both sets of rankings enables us to examine potential interaction effects between them that mimic the complex, multidimensional nature of contemporary school decision-making. The informational ecosystem changed considerably after the 2012-2013 school year, when the CDE discontinued its calculation and use of API scores, so we opt to end the present study's timeframe at that point.

To generate API effect estimates that can be easily interpreted and directly benchmarked with the *LAT* value-added rankings' effect estimates we include API-based control variables operationalized in a manner that parallels the time-invariant, quintile-based construction of the *LAT* rankings. To this end, we first average schools' annual API scores across the 2000-01 through 2010-11 school years (i.e., before the *LAT* information shock plausibly shaped sorting patterns) and then convert these mean scores into time-invariant quintile rankings. In addition to facilitating interpretation and benchmarking against the *LAT* rankings' effects, the quintile-based construction also enables nonlinear effects of API rankings to be captured; prior research on contextual sorting suggests neighborhood and school features often exhibit highly nonlinear effects on residential and educational selection (Galster 2020). Although a key tradeoff of this decision is the inability to control for time-varying (i.e., lagged) measures of school API, the measure is very highly correlated from year-to-year, reflecting the strong link between student sociodemographics and average (rather than value-added) test scores. Thus, creating a pooled average across a full decade rather than using time-varying API scores obscures very little information about schools' test score rank. Robustness check models, described below, that incorporate lagged, continuous operationalizations of API generate substantively similar inferences regarding *LAT* rankings' effects on school and neighborhood sorting, as do models that exclude any measure of API.

We link the *LAT* and API rankings, which exhibit a ~0.10 correlation in our analytic sample (see transition matrix showing the joint distribution of value-added and API quintiles in Online Supplement—Table A1) to CDE annual school enrollment data from school years 2000-

01 through 2012-13. We then use multivariate models (described below) that assess quintile-based stratification in schools' annual K-5 enrollment change both before (2000-01 through 2010-11) and after (2011-12 and 2012-13) the spring 2011 *LAT* information shock.

Our core school-level outcomes are total, and race-disaggregated, *K-5 school enrollment*. Including these enrollment measures helps us assess, first, whether schools' total enrollment levels shift with value-added rankings and then, whether there is racial heterogeneity in enrollment shifts, with potentially important school segregation implications. We also examine the information shock's impact on neighborhood sorting. Specifically, we assign every census tract (in 2010 boundaries) within LAUSD to the elementary school whose catchment boundaries capture the largest portion of the tract's elementary school-aged population (ages 5-9), and then characterize the tract by the school's value-added quintile, if available. We examine the total, and race-disaggregated, *number of children under age 10,* within each tract pre- and post-information shock, using ACS 2007-11 and 2012-16 five-year average data, respectively. In robustness checks, we estimate the value-added rankings' effects on all neighborhood outcomes measured during later periods of time (i.e., ACS 2013-17 and 2014-18), in case the effects exhibit a temporal lag given the considerable time required to consider, prepare for, and complete a residential move.

We also run robustness check models that switch our outcomes from total and race-disaggregated school enrollment and neighborhood child population *levels* to racial *shares* of our analytic sample schools' K-5 enrollment and neighborhoods' child population. Our primary focus on enrollment and population levels (versus racial shares) maximizes the study's policy relevance at a time when large urban districts like LAUSD are suffering widely-publicized enrollment woes and are considering whether certain informational interventions could partially mitigate them. However, we report results of analyses predicting both levels and racial shares below.

Of the 470 *LAT*-ranked elementary schools, our core analytic sample consists of the 419 LAUSD schools that were matched with CDE's official enrollment data for some portion of the study timeframe and enrolled at least one student across grades K-5 for every school year during the timeframe (see more detailed sample specification information in the Online Supplement–Methodological Appendix). These 419 schools have: uninterrupted annual enrollment K-5 for all thirteen years; school-level value-added quintile rankings on the *LAT* website; and valid measures of all control variables below (School-Year *N*=5,447). In robustness checks below, we relax the uninterrupted annual enrollment restriction, bringing in LAT-ranked schools that opened after the 1999-2000 school year or had an unexplained gap in their enrollment data. Results remain substantively unchanged.

Our neighborhood-level analytic sample begins with the 419 LAUSD public elementary schools in our core analytic sample and uses geospatial data on all of these schools' catchment boundaries (as of the 2017-18 school year)[1] to assign census tracts that are fully or partially subsumed by the catchment boundaries of the 419 campuses to one of these schools. 1,000 Los Angeles County tracts fit these parameters and contain values on all tract-level variables below.

Analytic Strategy

School Sorting Models

To estimate the causal effect of *LAT*'s value-added school quality rankings on neighborhood and school composition, we estimate the rankings' effects on temporal shifts in key outcomes at both the neighborhood (i.e., tract) and school levels. Our analytical approach for the *school* sorting models can be written as a three-level hierarchical linear model (HLM), with random intercepts and fixed slopes:

(Equation 1)

Level-1: (Total K-5 enrollment)$_{ijt}$=β_{0ijt} +β_1(Total K-5 enrollment, lagged)$_{ijt}$+β_1(Total K-5 enrollment, lagged)$^2_{ijt}$ +e_{ijt}

Level-2: β_{0jt}=γ_{00t} + γ_{01}(Less Effective VA Ranking)$_j$ X Post-Shock$_t$+
γ_{02}(Average VA)$_j$ X Post-Shock$_t$+
γ_{03}(More Effective VA)$_j$ X Post-Shock$_t$+
γ_{04}(Most Effective VA)$_j$ X Post-Shock$_t$+
γ_{05}(Low API)$_j$+γ_{06}(Average API)$_j$+ γ_{07}(High API)$_j$+
γ_{08}(Highest API)$_j$+r_{0j}

Level-3: γ_{00t}=δ_{000}+v_{00j}

The outcome is total K-5 enrollment in school year *t* (level-1), nested within school *i* (level-2), which is located within Los Angeles community area *j* (level-3; community area operationalization is described in more detail below). In this model, δ_{000} represents the fixed component of the community-level intercept, and v_{00j} is the random error component of the community-level intercept. γ_{00t} represents the fixed component of the school-level intercept, r_{0j} is the random error component of the school-level intercept, and e_{ijt} is the school year-specific error term. This model and all that follow assume the random components of the community-and school-level intercepts and the tract-level residual are normally distributed with means of zero and variances of τ_3^2, τ_2^2 , σ^2, respectively.

The key parameters of interest are the four level-2 coefficients on schools' value-added quintile rankings (γ_{01} , γ_{02} , γ_{03} , γ_{04}). Note, too, that these coefficients capture the enrollment effects of the value-added rankings interacted with a binary variable ("Post-Shock" above) indicating whether the school year is *after* the information shock occurs. The indicator equals 1 for school years 2011-12 and 2012-13 and 0 for 2000-01 through 2010-11 because the rankings were not publicized in this earlier period. Given that a one-year lagged measure of total K-5 enrollment is included in the models, a significant and positive coefficient on the value-added ranking X Post-shock interactions estimates the causal enrollment effect of a school receiving a given *LAT* quintile ranking *compared to the lowest ranking*– pending several assumptions. One key assumption is that there are no detectable pre-shock trends in the focal coefficients. Substantively, if temporal trends in school enrollment and population patterns diverged by value-added quintile ranking *before* these rankings were ever published, it would indicate the information shock was, in fact, not an exogenous event or did not provide new information. We consider whether this "parallel" trends assumption holds below.

To further mitigate potential internal validity threats, we include several control variables beyond API that could confound *LAT* value-added ranking effects on school enrollment. These controls include: *academic year fixed effects*; the calendar *year the school opened*; whether the school was a *charter* or had an *on-site magnet school*; and a *parental education index* (lagged one year), which is a time-varying measure calculated by CDE tracking the average educational attainment level of the parents of all students attending a given public school. The index ranges from 1 (within the school, the average student's parents were not high school graduates) to 5 (the average student's parents received graduate school training).

For models that predict total K-5 enrollment, we also control for *schools' racial composition* (i.e.,% Black, % Latino, % Asian; lagged one year) in case some families' enrollment decisions reflect minority avoidance considerations. Models that predict race-disaggregated K-5 enrollment or racial shares do not include all of these racial composition controls, though robustness check models confirm the same substantive results regardless of whether or not they are all included. Lastly, we include fixed effects capturing the *Los Angeles community area* in which the schools are located. These community areas, described in Online Supplement—Methodological Appendix, are larger than census tracts and reflect socially-meaningful community boundaries. Including the area fixed effects helps adjust for difficult-to-measure spatial dynamics, including geographically-accessible school choice sets.

Neighborhood Sorting Models

To assess *LAT* ranking effects on neighborhood, rather than school, sorting patterns, we switch to a two-level HLM predicting tract total population under age 10 of tract *i* (level-1) in 2012-16 nested within community area j (level-2). We incorporate this two-level nesting structure since error terms of geographically-contiguous tracts are likely correlated. Note that a third level is unnecessary for tract-level models because, unlike the school model that contained thirteen annual enrollment measures, we only have two measures of tract population under age 10 (one measure tracked before the shock, i.e., ACS 2007-11, and one measure tracked after it—either ACS 2012-16, ACS 2013-17 or ACS 2014-18). The key coefficients are the main effects of *LAT* value-added quintile rankings for tracts' assigned catchment schools; Post-Shock-quintile ranking interaction terms are unnecessary because the tract-level models only predict the outcome at one time point, post-shock. For these models, we include several tract-level control variables measured in the pre-shock period (ACS 2007-11) capturing housing market and sociodemographic factors revealed by prior research to shape residential decision-making among Angelenos with children (Schachner and Sampson, 2020) and U.S. tracts' sociodemographic trajectories (Schachner, 2022a). The most important control is the lagged measure of the outcome variable. Other control variables are listed in Online Supplement—Methodological Appendix.

RESULTS

The descriptive statistics presented in Online Supplement Table A2 and A3 reveal overall and racially-disaggregated means of child population and student enrollment levels, as well as racial shares of neighborhood children and elementary school populations, stratified by school value-added ranking. They also show *changes* in these variables from the pre- to post-shock period across value-added rankings. The descriptive patterns of change reveal a detectable gradient emerging that corresponds to the digital information, at least for some groups. Neighborhoods with schools ranked as most effective see larger gains in White child population from pre- to post-shock periods compared to neighborhoods with less effective schools. Similarly, the most effective schools are the only LAUSD schools in the analytic sample to realize year-on-year total K-5 enrollment gains.

Figure 1 provides a descriptive portrait of how analytic sample schools' annual enrollment changes vary by whether they were ranked in the top or bottom value-added ranking.

Prior to the information shock, there is no clear evidence of a value added-based difference in yearly enrollment change, which supports our parallel trends assumption. However, after the shock, the highest value-added schools see a moderation in enrollment declines, while the lowest ranked schools see continued enrollment loss. The descriptive patterns are thus congruent with the digital dissemination of value-added information spurring shifts in school enrollment decisions among a modest number of students. Some families who, in the absence of value-added information, would have sent their children to LAUSD schools with lower value-added rankings— or private, charter, or non-district schools— may have instead managed to enroll them in LAUSD schools ranked as "Most Effective."[2]

Please insert Figure 1 here

Tract-level Multivariate Models

Table 1 presents our first set of multivariate models, gauging whether school value-added rankings stratified shifts in tracts' populations of children under age 10. The key coefficients (in the bottom panel) indicate schools' value-added rankings did not change the overall size of the child population residing in surrounding census tracts (Model 1). Models 2-5 predict population changes separately by child race/ethnicity. Again, no clear differences in population trends across value-added rankings emerge.

However, the middle panel shows that the more commonly-scrutinized school test score level-based quality proxies may matter for some groups, in a nonlinear manner; neighborhoods with local schools in the highest API quintiles gain more young White and Asian children over time, which we tentatively interpret as evidence that the former groups exhibit disproportionate preferences for, and capacity to access, neighborhoods in close proximity to advantaged, high-scoring schools. These types of neighborhoods appear to lose larger numbers of Latino children over time, perhaps due to residential displacement.

Note that value-added rankings do not appear to shape these neighborhood outcomes in subsequent timeframes, either (results based on ACS 2013-17 and 2014-18 are presented in Table A4). The rankings also do not exhibit significant effects when the API control is operationalized as a continuous, rather than categorical variable (Table A5), or when the outcome switches from race-disaggregated population levels to racial shares of children under 10 (see Tables A6 and A7).

Please insert Table 1 here

School-level Multivariate Models

Different patterns emerge when examining school, rather than neighborhood, outcomes (Table 2). After confirming that total K-5 enrollment and school racial composition in one year strongly predicts total K-5 enrollment in the next (Models 1-2), we gauge the independent effects of school quality rankings on enrollment levels. Starting with the longstanding test score level-based measure, API, we do not see significant effects of our API quintile measures for the total enrollment outcome (Model 3). Model 4 directly tests whether the focal value-added rankings independently shape elementary school enrollment patterns. Accounting for all controls, including the school's API rankings, top *LAT* quintile-ranked elementary schools see a small but significant annual K-5 enrollment boost (estimated at ~13 students) in the post-publication period, compared to otherwise similar schools ranked in the bottom quintile. When it comes to school enrollment, if not neighborhood sorting, digitally-disseminated value-added rankings do appear to matter, if modestly.

Please insert Table 2 here

We run several additional models to clarify whether the estimated value-added ranking effects on school enrollment growth in the 2011-12 and 2012-13 school years has a plausibly causal interpretation. First, we lift our analytic sample restriction pertaining to continuous K-5 enrollment, enabling us to add in 31 previously-excluded LAUSD schools with value-added rankings (Model 5). In this larger analytic sample, the same patterns hold, though the focal coefficient on the most effective value-added ranking variable attenuates slightly. Finally, Model 6 preserves this larger analytic sample and adds in school-level fixed effects, which controls for all time-invariant features of schools that could confound the effects of the value-added rankings on post-2011-12 enrollment patterns. The focal coefficient is nearly identical to that generated in Model 4: the highest value-added schools are estimated to gain approximately 13 students more than they otherwise would have been expected to enroll in pre-shock years.

Table A8 presents a series of robustness check models for the core analytic sample. Model 1 excludes the API control entirely. Models 2 and 3 restore it but use a lagged, continuous operationalization rather than a categorical, time invariant one, with the latter model adding in school fixed effects. Models 4 and 5 preserve the continuous API control but remove the school racial composition controls, with the latter model adding in school fixed effects. Across all five robustness check models, the focal coefficient on the highest value-added ranking variable remains significant, with a magnitude remaining in a narrow range, of approximately 12-14 students.

Having increased confidence in our core results, we revisit the parallel trends assumption (see Table A9 models). Results suggest that the assumption holds; K-5 total and race-disaggregated enrollment growth is not significantly stratified by schools' *LAT* value-added rankings in the period *before* the rankings were published, but it is afterward. The same table suggests value-added ranking effects on total K-5 enrollment were stronger in the 2012-13 school year than in 2011-12. This pattern may reflect a temporal lag in parents and students adjusting their enrollment decisions based on value-added rankings.

Understanding Mechanisms and Implications for School Segregation

We now shift to clarifying the mechanisms underlying the effects described above and, most crucially for this study's objectives, the implications of the effects and mechanisms for school racial segregation. Starting with mechanisms, one might assume that value-added effects on enrollment are concentrated within schools of choice– i.e., magnet and charter schools– given the greater ease with which parents can access them. If true, LAUSD charter and magnet schools that achieved higher value-added rankings may have seen the largest enrollment boosts.

However, multivariate models suggest otherwise. Table A10's models show that within the traditional public sector, a top quintile ranking predicts an 18 student annual enrollment increase. Magnet/charter schools do not see significant value-added-associated enrollment gains. Pooled models with interaction terms reinforce this heterogeneity pattern, but the interaction terms' coefficients do not reach conventional significance thresholds.

Another possible moderator of value-added rankings' effects is perceptions of the school's quality based on pre-existing rankings (i.e., API). One might expect schools with the lowest API rankings that were subsequently rated as the highest value-added schools would see the biggest enrollment boosts associated with the value-added rankings' publication. Table A11, which stratifies our analytic sample of schools by time-invariant API rankings, reveals a slightly more complicated pattern. Schools in the middle of the API distribution that were subsequently ranked as the highest value-added schools see the largest enrollment boosts (~22 students). Models 5 and 6 provide additional nuance, with the latter revealing that among traditional public schools, average-API schools see significantly higher enrollment boosts associated with receiving the highest value-added ranking than otherwise similar schools with higher or lower API rankings. Table A12 suggests that schools' average sociodemographic characteristics do not moderate the value-added rankings' effects on total K-5 enrollment.

Overall, these school heterogeneity analyses indicate that traditional public schools with average test score levels see the largest enrollment gains associated with a high value-added ranking. Magnet/charter schools and the highest and lowest API schools do not exhibit clear value-added ranking impact on enrollment perhaps because parents' selection of them reflects strong preferences for other school features (e.g., for specialized programs/curricula, extracurricular offerings, school reputation, or more sociodemographically homogenous student populations).

We next shift to examining heterogeneity in the value-added rankings' effects on enrollment by student characteristics– first by age and then most importantly by ethnic identity. Starting with the former, Table A13 reveals significant value-added ranking effects on enrollment in Grades 1-5 but not Kindergarten. We infer that intra- or interdistrict transfers across traditional public schools among non-Kindergarteners— that do not necessarily coincide with residential relocations— may be the key mechanism by which value-added rankings shape school enrollment. Next, we assess value-added rankings' effects on both trajectories in *race-specific* student enrollment levels, as well as shifts in schools' racial shares (Tables A14-A19).

Prior research on school segregation and opportunity hoarding often scrutinizes White families' decisions. Although one might expect Whites to disproportionately re-sort themselves based on value-added rankings, potentially fueling segregation, our results tell a different story. Table A14, Models 1 and 2 reveals no detectable effects of value-added rankings on total White K-5 enrollment or White enrollment shares, both of which appear to instead grow disproportionately in schools with higher average test scores (i.e., API). Total Black K-5 enrollment and Black enrollment shares do not correspond to value-added rankings or to API rankings (Table A14, Models 3-4).

However, Table A15 suggests that both total Asian K-5 enrollment and share of students do appear to be very modestly but significantly boosted if a school was ranked in the highest value-added category; the former outcome is robust to the inclusion of school fixed effects. Table A16 similarly shows that both total Latino K-5 enrollment and share of students are both significantly, if modestly, boosted based on schools' value-added rankings, though the top category's coefficient is only significant when predicting the total K-5 enrollment outcome with school fixed effects included. Tables A17, A18, and A19 present robustness check models that include a continuous, time-varying rather than categorical, time-invariant operationalization of the API control and replicate the same racial heterogeneity patterns.

Figure 2 provides additional evidence of the *LAT* rankings' effects on Latino and Asian enrollment levels. The top panel's graphs show that across the study's entire timeframe, unadjusted year-to-year enrollment patterns among Whites and Blacks were virtually perfectly parallel between schools ranked in the "Least" and "Most" effective categories. But for Latinos, the year-to-year enrollment patterns are parallel only until the information shock occurred; afterward, the Latino enrollment decline moderates for the most effective schools and continues unabated for the least effective ones. The Asian enrollment pattern is slightly more nuanced but similarly shows a sharper increase from 2010-11 to 2011-12 among schools ranked as the most versus least effective.

Please insert Figure 2 here

Aggregate School Segregation Implications

The results thus far suggest *LAT*'s digital information shock may have led some Asian and Latino students to pursue intra- or interdistrict transfers facilitating access to schools with higher value-added rankings. But the school segregation implications of these shifts hinge on whether the higher value-added schools gaining Latino and Asian students diverge in racial composition compared to the lower value-added schools the students may have selected in a non-information shock counterfactual.

We assess this possibility first by generating a yearly estimate of a commonly-used measures capturing neighborhood/school racial segregation: the Dissimilarity Index. These annual, unadjusted measures gauge the unevenness of Latino/White/Asian/Black total K-5 enrollment across all analytic sample schools relative to the pooled racial composition of all these schools; higher index values indicate higher segregation levels. Figure A1 displays the unadjusted Dissimilarity Index values for all pairs of race/ethnic groups. The figure reveals stubbornly high levels of segregation throughout the study's timeframe.

There is a very slight Latino-White and Asian-White Dissimilarity Index dip in the immediate post-shock school year, but counterfactual analysis suggests these dips are likely not attributable to the digital information shock. When using coefficient estimates from our most complete model of K-5 Asian student enrollment (Table A15, Model 2) and K-5 Latino student enrollment (Table A16, Model 2) as inputs to generate a counterfactual estimate of what the

Dissimilarity Index estimates *would have been* in the post-information shock school years (i.e., 2011-12/2012-13) had the value-added rankings remained unknown, we find that the re-sorting of Latino and Asian students to higher-value-added counterfactual alternatives has trivial effects on our segregation measures. These trivial effects on segregation reflect both the modest magnitude of the value-added rankings' boost on Latino and Asian enrollment, and the fact that, on average, schools in the "Most" and "Least" effective categories do not diverge sharply in racial composition (see Table A3, Panel B). Although the information shock appears to have shifted a small number of Latino and Asian students into higher-value-added schools, it did not necessarily lead them into more racially-mixed ones.

DISCUSSION & CONCLUSION

Whether the saturation of residential and educational markets with new digital information reshapes longstanding urban inequalities remains unresolved due to theoretical ambiguities and methodological challenges. We set out to clarify these issues by exploiting an exogenous digital information shock revealing the value-added quality of public elementary schools in LAUSD, a large and diverse core-city school district where school choice was increasingly available but residentially-zoned schools remained intact.

Our results tell a nuanced story. The school value-added information shock had no detectable effects on residential sorting or neighborhood segregation, yet it did fuel slightly increased enrollment within higher value-added schools, particularly among Latinos and Asians. The preexisting API rankings, on the other hand, predicted neighborhood child population and school enrollment growth among White and Asian children. The introduction of API and value-added rankings over different time horizons, as well as unobserved capacity constraints shaping access to high-ranking schools and their surrounding neighborhoods, precludes a direct comparison of how various race/ethnic groups interpret and act on each set of rankings. However, we believe our findings reinforce the possibility of racial heterogeneity in preferences for particular school quality proxies that future research should directly probe. As noted earlier, prior research based on both neighborhood and school sorting processes suggests the average test score-based measures (like the API) and associated sociodemographic proxies are disproportionately appealing to affluent, and often White, families. Latino and Black families may place less emphasis on these measures, leaving room for new information– like value-added rankings– to play an amplified role in their school decisions; Asian families may weigh both types of school features simultaneously. Future research with distinct empirical designs is needed to further test these possibilities, to adjudicate among them and alternative explanations (e.g., meaningful differences in the interpretability of various ranking schemes, racially heterogeneous constraints in bringing school feature preferences to fruition), and to specifically assess whether any type of school quality rankings materially impact Black families' residential or educational decision-making.

Setting aside the particular mechanisms explaining the sorting patterns, the racial segregation implications of the observed enrollment shifts were trivial because low- and high-value-added schools did not differ sharply in racial composition. Although this digital information shock failed to reshape short-term segregation dynamics, the shock may have still had implications for long-term urban stratification processes. This would be the case, for example, if the enrollment shifts spurred by the digital information shock led a higher proportion of Latino and Asian children to access higher-quality school contexts than would have otherwise been the case. Our results are congruent with this possibility. Importantly, recent research finds that sustained exposure to higher-value-added schools yields meaningful effects on children's cognitive and socioemotional trajectories (Jackson et al., 2020; Jennings et al., 2015; Lloyd and Schachner, 2021), with implications for their residential and income mobility as adults (Chetty et al., 2014).

Our findings thus suggest that digital information may have long-term implications for urban stratification that prior studies have missed by focusing primarily on short-term neighborhood segregation shifts. To the extent digital information increases disadvantaged groups' access to high-quality schools, it may have durable, equity-enhancing effects— even if these effects do not reshape neighborhood or school segregation patterns in the short term. In order to generate these equity-enhancing effects at any meaningful scale, the intervention must exert sorting effects that are much larger in magnitude than the *LAT* intervention appeared to. Future research on educational information and sorting should examine why this particular intervention exerted such modest effects (e.g., due to low take-up of the information) and consider whether similar information delivered through other channels (e.g., a grassroots marketing campaign) may have been more impactful. Simulations of more ambitious informational interventions' effects on disparities in exposure to high-quality neighborhoods and schools would be useful, as would analyses that employ a longer time horizon (i.e., beyond the 2012-2013 school year) and probe a broader set of outcomes, beyond sorting-related ones (e.g., academic achievement and educational attainment).

These studies would ideally overcome this one's limitations by analyzing student- and household-level data. Our lack of micro, student-level data precluded us from clarifying the extent to which modest enrollment boosts (/declines) associated with a high (/low) value-added ranking reflected: increased intradistrict transfers of LAUSD students from lower- to higher-value added schools; interdistrict transfers of students residing outside of LAUSD into the district's highest value-added schools or interdistrict transfers from LAUSD low value-added schools to non-district schools; exits to private or charter schools among students who would've attended the "least effective" schools; or residential relocations across district boundaries to access the highest value-added schools or avoid the lowest value-added ones. We also lacked schools' enrollment capacity data, which would have enabled us to gauge whether the limited enrollment boosts generated by a high value-added ranking reflected constrained capacity within these schools. Qualitative methods— specifically, interviews with LAUSD families— could clarify these nuances as well, revealing precisely how families accessed, and acted upon, the digital information provided by *LAT*.

Applying this type of mixed-methods approach to digital information shocks in other metropolitan and national contexts would help bolster our findings' external validity. We see the LAUSD case as generating close to an upper bound on the effects of digital value-added information on school enrollment patterns and close to a lower bound on its effects on residential sorting, given its vast scale and excess enrollment capacity, robust school choice system, large non-White population, and high housing costs. In racially diverse districts with a less robust school choice system– as well as less cost-prohibitive and spatially fragmented housing markets– new value-added information may yield the type of residential re-sorting into higher value-added schools' catchment zones (especially among Latino and Asian families) that was not seen in LAUSD, where school enrollment sorting was the primary channel through which the information generated modest effects. We believe LAUSD's dense school choice sets and rapidly liberalizing, market-oriented approach to school enrollment during the 2000s and 2010s helped open this channel for accessing value-added schools. Its well-documented enrollment declines likely contributed, as well, by creating ample capacity for additional students within high value-added schools. As these nuances become clearer, and as urban scholars identify what specific types of digital information have what specific types of effects on which groups in which specific spatial and temporal contexts, urban policymakers should reconceive how they use digital information to drive equity accordingly.

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ENDNOTES

[1] Although this timeframe is not perfectly aligned with that of our outcome, LAUSD's catchment boundaries change very little over time.

[2] Figure 1 reveals moderating enrollment declines across both the highest and lowest quintile schools immediately after the LAT published its value-added rankings. However, supplementary analyses of enrollment trajectories in other Los Angeles County districts surrounding LAUSD (available upon request) show a similar pattern of moderating enrollment decline during this time, suggesting the digital information shock was not responsible for stemming LAUSD's enrollment loss.

TABLE 1

Two-level Hierarchical Linear Models Predicting Neighborhood Outcomes, Partial Model Output

Tract N = 1,000, L.A. Community Area N = 144

Tract-level Outcome (ACS 2012-16)	Model 1 **Total # of All children < 10**	Model 2 **Total # of White children < 10**	Model 3 **Total # of Black children < 10**	Model 4 **Total # of Asian children < 10**	Model 5 **Total # of Latino children < 10**
Catchment School's LAT VA Ranking					
Least effective (ref)					
Less effective	-6.480	7.130	-4.461	0.456	-12.947
	(15.234)	(5.997)	(5.016)	(3.830)	(13.285)
Average	-4.033	9.367	-7.767	-2.325	-6.696
	(16.155)	(6.334)	(5.383)	(4.067)	(13.882)
More effective	-10.918	9.992	-13.120*	-3.579	-6.735
	(15.774)	(6.211)	(5.234)	(3.972)	(13.712)
Most effective	1.423	8.460	-10.291	-0.245	-4.977
	(15.824)	(6.241)	(5.279)	(4.000)	(13.712)
Catchment School's API Quintile					
Lowest performing (ref)					
Low performing	-31.796*	0.768	-5.347	3.095	-33.052**
	(14.742)	(5.713)	(4.876)	(3.685)	(12.445)
Average performing	-21.014	6.579	-0.381	3.795	-42.797**
	(17.244)	(6.705)	(5.701)	(4.310)	(14.657)
Better performing	-20.503	16.684*	-7.240	9.193	-54.474**
	(20.056)	(7.575)	(6.453)	(4.832)	(16.174)
Best performing	33.425	37.327**	-10.472	23.925**	-39.720*
	(24.728)	(9.383)	(7.881)	(5.806)	(19.604)
Tract control variables					
Lagged dependent variable	136.254**	54.505**	23.593**	14.908**	156.576**
	(8.146)	(4.537)	(3.803)	(2.529)	(9.707)
Lagged dependent variable, squared	-1.112	2.104	6.244**	3.263**	-0.534
	(3.747)	(1.286)	(0.817)	(0.719)	(4.260)
% residents who are Black	17.055*				
	(7.735)				
% residents who are Latino	43.296**				
	(16.216)				
% residents who are Asian/Pacific Islander	-11.098				
	(7.497)				

Notes: [1] Additional tract-level controls included across all models (all from ACS 2007-11): median housing value (logged), total number of residents who moved within L.A. County in past year, total number of housing units, median year structure built, total population ages 18-39 (logged), and total populations of foreign born (logged) and bachelor's degree holders (logged). All controls, including lagged dependent variables, are standardized (mean = 0, SD = 1). [2] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE 2

Three-level Hierarchical Linear Models Predicting School-Year Total K-5 Enrollment (2000-01 – 2012-13)

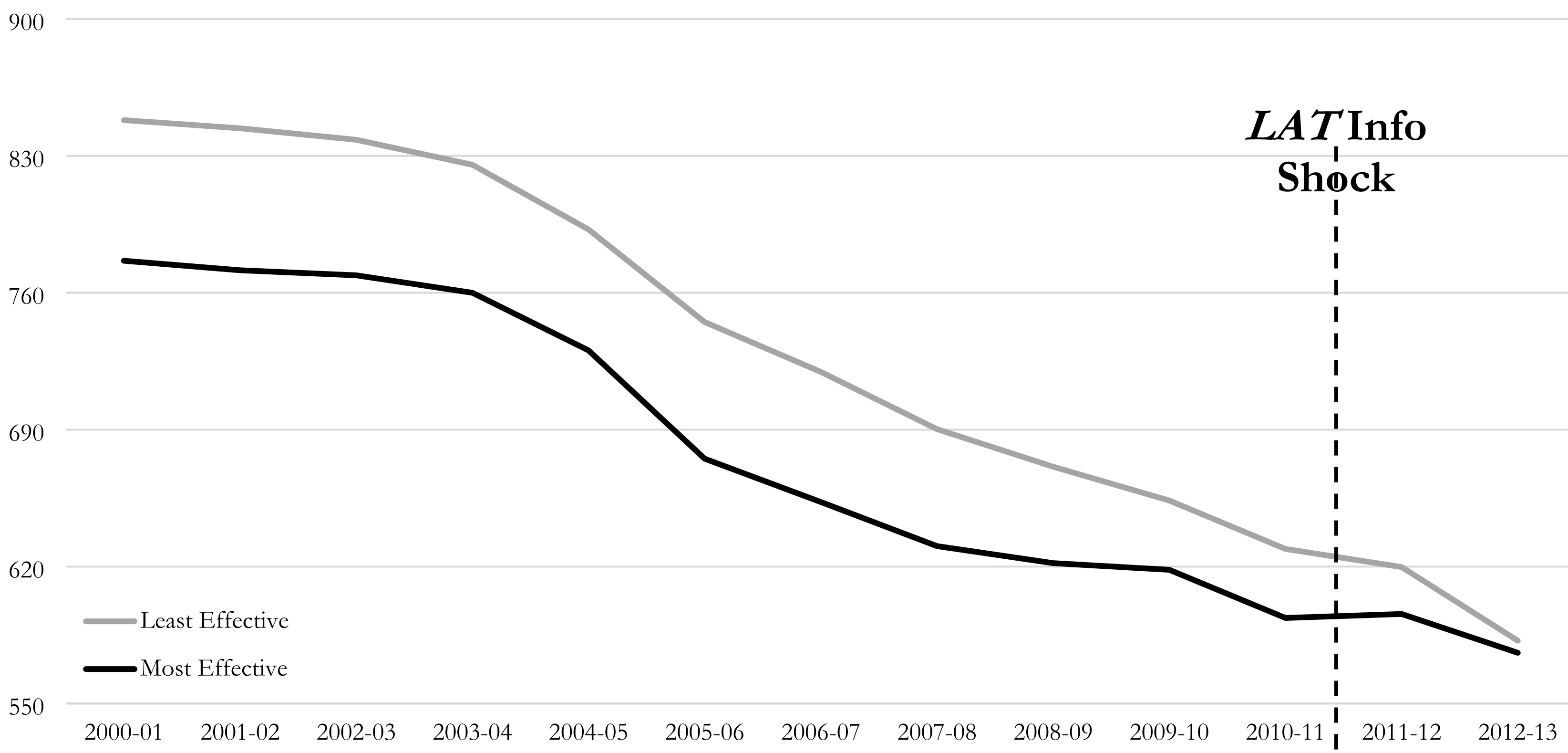
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
School LA Times Value-Added Ranking						
Least effective X post-2011-12 (ref)						
Less effective X post-2011-12				7.071	7.705	6.499
				(5.193)	(5.214)	(5.342)
Average X post-2011-12				6.001	6.457	4.973
				(5.264)	(5.253)	(5.361)
More effective X post-2011-12				5.356	4.640	6.309
				(5.373)	(5.310)	(5.420)
Most effective X post-2011-12				13.340*	10.924*	13.390*
				(5.444)	(5.301)	(5.414)
School API Quintile (time-invariant)						
Lowest performing (ref)						
Low performing			2.385	2.220	3.988	
			(2.548)	(2.550)	(2.476)	
Average performing			3.602	3.071	6.057	
			(3.215)	(3.224)	(3.094)	
Better performing			3.252	2.421	7.286	
			(4.188)	(4.201)	(3.947)	
Best performing			4.641	3.851	8.861	
			(6.132)	(6.149)	(5.865)	
School control variables						
Prior school year total K-5 Enrollment (LDV)	333.246**	332.668**	332.903**	332.813**	331.514**	290.377**
	(1.283)	(1.329)	(1.387)	(1.389)	(1.352)	(3.095)
Prior school year total K-5 Enrollment squared	1.246*	1.402**	1.350**	1.366**	1.369**	12.377**
	(0.495)	(0.503)	(0.510)	(0.511)	(0.494)	(0.821)
Magnet school on-site	6.746**	7.526**	7.001**	7.102**	4.949*	
	(2.283)	(2.363)	(2.490)	(2.490)	(2.435)	
Charter school	9.981**	5.985	5.901	6.147	5.301	
	(3.609)	(3.756)	(3.768)	(3.770)	(3.526)	
Year school opened	2.850*	2.619*	2.651*	2.667*	5.352**	
	(1.100)	(1.107)	(1.118)	(1.118)	(0.882)	
% Black (lagged)		-5.589**	-5.169**	-5.233**	-5.062**	-22.452**
		(1.703)	(1.935)	(1.936)	(1.905)	(6.025)
% Latino (lagged)		-0.704	-0.148	-0.329	1.585	-20.038**
		(2.732)	(3.019)	(3.020)	(2.980)	(6.385)
% Asian (lagged)		1.826	1.674	1.775	1.674	-0.842
		(1.443)	(1.458)	(1.458)	(1.448)	(4.342)
Parental education index (lagged)		5.120**	4.899**	4.975**	4.817**	6.867**
		(1.666)	(1.701)	(1.701)	(1.690)	(1.964)
School Fixed Effects	N	N	N	N	N	Y

School *N*	419	419	419	419	450	450
School-Year *N*	5,447	5,447	5,447	5,447	5,687	5,687

Notes: [1] All models include academic year, community area fixed effects. [2] Continuous controls are standardized to have mean = 0, SD = 1. [3] ** $p < 0.01$, * $p < 0.05$ (two-tailed)

FIGURE 1

LAUSD School K-5 Enrollment Patterns Over Time by *Los Angeles Times* Value-Added Ranking, 2000-01 through 2012-13 School Years (Unadjusted)

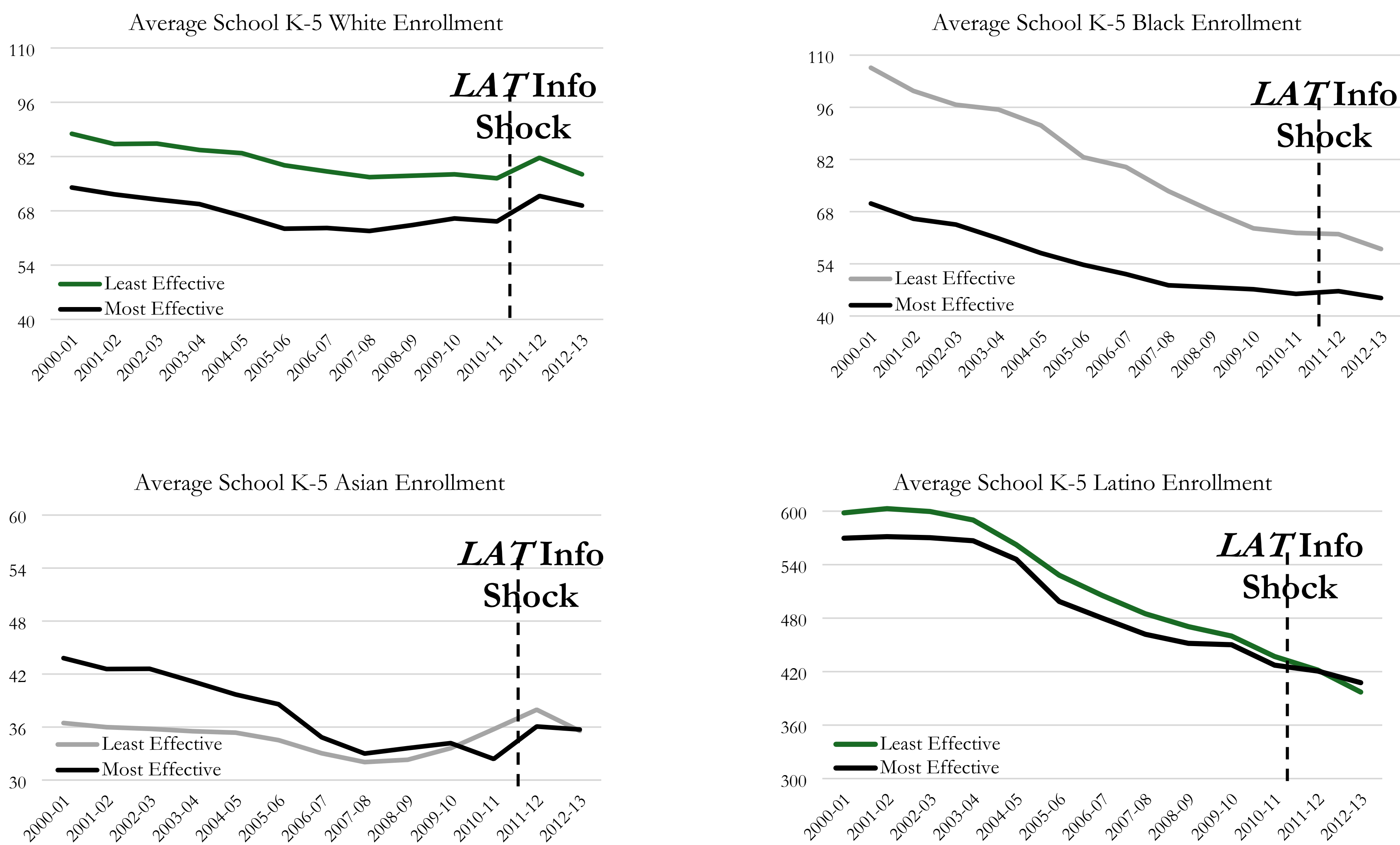


Notes

[1] Figure is based on LAUSD analytic sample schools that the *Los Angeles Times* ranked in the "Least Effective" (*N*=87) or "Most Effective" (*N*=77) category in 2011.

FIGURE 2

LAUSD School K-5 Enrollment Patterns Over Time by Student Race/Ethnicity, 2000-01 through 2012-13 School Years (Unadjusted)



Notes: [1] Figures are based on LAUSD analytic sample schools that the *Los Angeles Times* ranked in the "Least Effective" (*N*=87) or "Most Effective" (*N*=77) category in 2011.

ONLINE SUPPLEMENT
METHODOLOGICAL APPENDIX

Background Information on School Choice in LAUSD

Unlike more liberalized districts like New Orleans, which have centralized enrollment systems and no geographically-based school assignments, district-drawn attendance boundaries determine the "default" school of elementary school-aged students within LAUSD. However, students have long had the option of bypassing their catchment zone school, by applying to a *private school* or an LAUSD *magnet school*. Students can apply to up to three magnet programs in a given year through a centralized district process that determines admissions based on the number of "Magnet Priority Points" the student has. Points are granted based on: whether the student attended a magnet program or was on the waiting list for a magnet program in the prior year; whether the student attended a school deemed by the district to be overcrowded or predominantly Hispanic, Black, Asian, and other non-Anglo in the prior year; and whether the student had a sibling in the same magnet program/school.

Since the 2000s, the longstanding private and magnet school alternatives have been supplemented by a rapid expansion of *charter schools* in LAUSD (see Schachner, 2022b). There are two types of charter schools in the district: independent (i.e., operating largely independently of LAUSD) and affiliated (i.e., operating under the control of the LAUSD Board of Education). Students can apply to the latter through a centralized district application system; if sufficient slots are available in the desired school, the student can enroll. If not, slots are awarded through a lottery system, with applications sorted in priority order and then randomly drawn. Priority is given to students of siblings who attend the selected charter school, as well as to students who live within LAUSD boundaries.

Beyond these charter, magnet, and private school options, intradistrict transfers to non-assigned traditional public schools also enable many students to bypass their residentially assigned schools. The intradistrict transfer process within LAUSD is generally not facilitated in a centralized manner by the district but instead often relies on a given child's assigned school and desired school approving the desired transfer. This decentralized approach with minimal oversight, along with the widely-documented sharp declines in overall student enrollment within the district, likely explains why such a large portion of LAUSD students attend traditional public schools other than that to which they are residentially assigned (Schachner, 2022b).

Analytic Sample Specification

Of all 470 LAT-ranked elementary schools, we were able to match 450 to the California Department of Education's official enrollment data for some portion of the 2000-01 through 2012-13 school years. We further specify our sample to include only schools that enrolled at least one student across grades K-5 for every school year during the study's entire timeframe (2000-01—2012-13), since difference-in-differences analyses require outcome data for both pre- and post-information shock time periods. This specification removes twenty-eight value-added-ranked schools that opened at some point after the 1999-2000 school year (given that lagged enrollment measures were required for every time period), as well three LAUSD schools that either stopped enrolling K-5 students at any point or stopped reporting valid enrollment data. Records suggest that none of these thirty-one schools closed during the time period in question.

The remaining 419 public LAUSD schools in our final analytic sample have uninterrupted annual enrollment K-5 for all thirteen years and school-level value-added quintile rankings on the LAT website and valid measures of all control variables below (School-Year

N=5,447). In robustness checks, we relax the uninterrupted annual enrollment restriction, which increases the analytic sample to include all public LAUSD schools with school-level value-added quintile rankings and valid measures of enrollment and control variables for some portion of the 2000-01—2012-13 timeframe. Substantive results remain unchanged.

As noted in the manuscript, our neighborhood-level analytic sample begins with these 419 LAUSD public elementary schools in our core analytic sample and uses geospatial data on all of these schools' catchment boundaries (as of the 2017-18 school year) to assign census tracts that are fully or partially subsumed by the catchment boundaries of the 419 campuses to one of these schools. 1,000 Los Angeles County tracts fit these parameters and contain values on all tract-level variables below.

Operationalizing Community Area Fixed Effects

Census tracts, which are U.S. Census-defined geographic areas containing 1,200 to 8,000 residents, are often employed by social scientists as an operationalization of neighborhoods in U.S. metropolitan areas. However, census tracts are not suitable to include as fixed effects that control for difficult-to-observe spatial dynamics that could confound elementary school sorting patterns because the vast majority of census tracts in U.S. cities are so small that they only have one elementary school located within their boundaries, at most.

In some metropolitan areas like Chicago and Los Angeles, non-governmental entities have developed an alternative set of spatial units beyond the census tract to approximate the construct of neighborhoods, or "community areas." The *Los Angeles Times*' Mapping L.A. project was intended to do just this. Around this study's timeframe, 2009–2010, a group of *Times* reporters and web developers developed a set of neighborhood boundaries and refined them using crowdsourced input on the *Times* website. The current boundaries are available for free online at https://maps.latimes.com/about/.

Although these spatial units span considerably larger areas and populations than do census tracts, they are broadly conceived as capturing symbolically salient boundaries that encompass areas perceived as distinct among Angelenos (e.g., Westwood, Highland Park, and Pacific Palisades). Many government agencies and nonprofits have adopted these boundaries, as well. Using ArcGIS software, we spatially merge the *Times*-provided Mapping L.A. boundaries with school locations and use these spatial units as fixed effects in certain models to adjust for differences in spatial dynamics across the vast and varied expanse of LAUSD.

List of Additional Control Variables Included in Neighborhood Sorting Models

All measured, using American Community Survey (ACS) 2007-11 census tract-level data:

Housing market conditions

- Median home value (log)
- Number of residents who moved within L.A. County in past year
- Number of housing units
- Median year structure built
- Number of residents who are ages 18-39 (log)

Community sociodemographics

- Number of residents who are foreign born (log)
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ONLINE SUPPLEMENT
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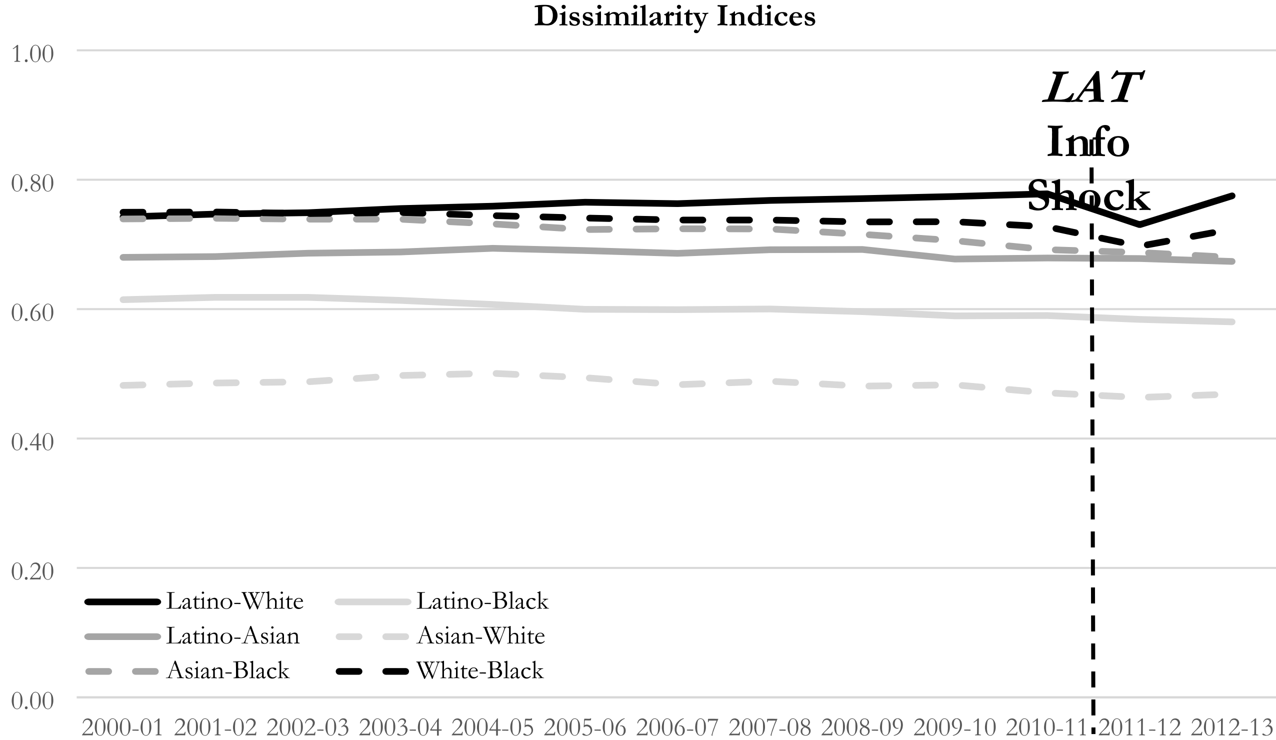
ONLINE SUPPLEMENT
FIGURE A1
LAUSD School Segregation Patterns among K-5 Students Over Time, 2000-01 through 2012-13 (Unadjusted)



Notes
[1] The Dissimilarity Index varies between 0 and 1, capturing the proportion of group A students that would have to switch schools to exhibit the same distribution across schools as group B does.

TABLE A1

School-Level Quality Rankings, by Academic Performance Index and LA Times Value-Added Ranking

		LA Times Value-Added Ranking					
		1 (low)	2	3	4	5 (high)	Total
Academic Performance Index Quintile	1	33	29	23	24	14	123
		37.93	32.58	26.74	30.00	18.18	29.36
	2	19	20	30	23	11	103
		21.84	22.47	34.88	28.75	14.29	24.58
	3	11	15	16	14	20	76
		12.64	16.85	18.60	17.50	25.97	18.14
	4	8	17	8	16	22	71
		9.20	19.10	9.30	20.00	28.57	16.95
	5	16	8	9	3	10	46
		18.39	8.99	10.47	3.75	12.99	10.98
Total		87	89	86	80	77	419
		100	100	100	100	100	100

Notes

[1] Percentages in cells are calculated based on column values.

[2] The bivariate correlation between schools' API quintile ranking and *Los Angeles Times* value-added quintile ranking is ~0.10

TABLE A2

Descriptive Statistics: Analytic Sample of LAUSD Census Tracts (N = 1,000), by *Los Angeles Times* Value-Added Rankings (2011)

A. Number of children under age 10					
LAT VA Ranking of Catchment School [1]	**Least Effective**	**Less Effective**	**Average**	**More Effective**	**Most Effective**
Pre-shock (ACS 2007-11, mean)					
Overall	556	504	553	539	510
White	92	81	81	69	86
Black	55	44	36	47	44
Asian	33	35	20	34	36
Latino	357	326	401	375	327
Neighborhood Pre- vs. Post- *Change* (ACS 2007-11 to ACS 2012-16)					
Overall	-20	-11	-12	-27	-12
White	-11	1	3	2	4
Black	-2	-4	-2	-15	-9
Asian	2	-1	3	-2	2
Latino	-4	-11	-16	-11	-14

B. Racial shares of children under age 10					
LAT VA Ranking of Catchment School [1]	**Least Effective**	**Less Effective**	**Average**	**More Effective**	**Most Effective**
Pre-shock (ACS 2007-11, mean)					
White	21.60%	21.27%	22.00%	15.97%	22.69%
Black	9.42%	8.26%	5.43%	8.72%	7.23%
Asian	7.33%	8.13%	5.38%	7.23%	8.37%
Latino	57.25%	57.18%	62.79%	65.36%	57.18%
Neighborhood Pre- vs. Post- *Change* (ACS 2007-11 to ACS 2012-16)					
White	-1.18pp	-0.81pp	0.43pp	0.94pp	0.89pp
Black	-0.34pp	-0.52pp	-0.32pp	-2.63pp	-1.33pp
Asian	0.42pp	-0.50pp	0.10pp	0.06pp	0.92pp
Latino	1.76pp	1.57pp	0.23pp	0.99pp	-1.10pp

Notes

[1] Using ArcGIS, 2010 census tract boundaries, and academic year 2017-18 catchment boundaries, a spatial merge process revealed which LAUSD public school's catchment boundaries subsumed the largest portion of the census tract. School-level data were assigned to each LAUSD census tract, accordingly.

[2] The analytic sample consists of LAUSD elementary schools with a valid *Los Angeles Times* Value-Added Ranking that were open during the entire timeframe of this study (2000-2013). See additional analytic sample details in Online Supplement: Methodological Appendix.

[3] Children who are categorized by the Census Bureau's American Community Survey as Black or Asian can also be categorized as Hispanic/Latino if their parents identify them as such.

TABLE A3

Descriptive Statistics: Analytic Sample of LAUSD Elementary Schools (N = 419), by *Los Angeles Times* Value-Added Rankings (2011)

A. Number of K-5 Students					
LAT VA Ranking	**Least Effective**	**Less Effective**	**Average**	**More Effective**	**Most Effective**
Pre-shock: 2000-01–2010-11, mean					
Overall	751	718	748	750	691
White	81	68	67	44	67
Black	84	78	64	67	56
Asian	35	22	17	22	38
Latino	531	529	581	596	509
Pre- vs. Post- *Change* (2010-11 to 2011-12), mean					
Overall	-9	-7	-13	-6	2
White	5	2	7	6	7
Black	0	-1	-1	-1	1
Asian	2	1	1	2	4
Latino	-15	-9	-19	-12	-7

B. Racial shares of K-5 Students					
LAT VA Ranking	**Least Effective**	**Less Effective**	**Average**	**More Effective**	**Most Effective**
Pre-shock: ACS 2007-11, mean					
White	13.99%	12.73%	12.03%	8.97%	12.71%
Black	12.12%	11.93%	9.62%	10.95%	8.81%
Asian	5.52%	3.81%	3.12%	3.39%	6.32%
Latino	65.41%	68.03%	72.18%	73.23%	68.21%
Pre- vs. Post- *Change* (2010-11 to 2011-12), mean					
White	0.64pp	0.54pp	0.97pp	0.93pp	0.95pp
Black	-0.04pp	-0.22pp	-0.21pp	-0.20pp	-0.05pp
Asian	0.27pp	0.25pp	0.21pp	0.29pp	0.64pp
Latino	-0.73pp	-0.37pp	-0.81pp	-0.86pp	-1.10pp

Notes

[1] The analytic sample consists of LAUSD elementary schools with a valid *Los Angeles Times* Value-Added Ranking that were open during the entire timeframe of this study (2000-2013).

TABLE A4

Two-level Hierarchical Linear Models Predicting Neighborhood Outcomes from ACS 2013-2017 and ACS 2014-2018, Partial Model Output

Tract N = 1,000, L.A. Community Area N = 144

Outcome	**Total # of All children < 10**	**Total # of White children < 10**	**Total # of Black children < 10**	**Total # of Asian children < 10**	**Total # of Latino children < 10**
Timeframe: ACS 2013-17	Model 1	Model 2	Model 3	Model 4	Model 5
Catchment School's API Quintile					
Low performing	-33.772*	0.626	-8.522	-0.541	-34.874**
	(14.759)	(5.649)	(4.902)	(3.908)	(12.224)
Average performing	-25.003	11.280	-3.906	1.150	-42.572**
	(17.256)	(6.624)	(5.737)	(4.572)	(14.382)
Better performing	-12.179	20.343**	-5.862	12.759*	-52.057**
	(20.110)	(7.494)	(6.443)	(5.124)	(15.908)
Best performing	20.364	32.626**	-8.059	18.253**	-46.616*
	(24.793)	(9.286)	(7.780)	(6.155)	(19.293)
Catchment School's LAT VA Ranking					
Less effective	-10.806	0.824	-0.299	0.407	-14.430
	(15.193)	(5.908)	(5.090)	(4.065)	(12.972)
Average	-3.577	2.089	-3.139	-0.102	-6.969
	(16.157)	(6.257)	(5.414)	(4.315)	(13.607)
More effective	-12.938	2.812	-11.334*	-1.011	-7.675
	(15.755)	(6.128)	(5.282)	(4.216)	(13.413)
Most effective	-2.392	-1.261	-8.811	3.987	-10.816
	(15.818)	(6.161)	(5.309)	(4.245)	(13.424)
Timeframe: ACS 2014-18	Model 6	Model 7	Model 8	Model 9	Model 10
Catchment School's API Quintile					
Low performing	-27.004	4.407	-9.631	0.235	-31.670**
	(14.556)	(5.605)	(5.044)	(3.848)	(12.146)
Average performing	-23.469	9.741	-8.095	-1.386	-30.085*
	(17.019)	(6.587)	(5.901)	(4.508)	(14.288)
Better performing	-9.951	23.733**	-10.464	10.813*	-48.813**
	(19.827)	(7.427)	(6.649)	(5.036)	(15.811)
Best performing	35.465	46.944**	-10.164	17.460**	-36.465
	(24.443)	(9.197)	(8.063)	(6.031)	(19.177)
Catchment School's LAT VA Ranking					
Less effective	-5.109	3.447	-1.259	-0.399	-10.896
	(14.994)	(5.921)	(5.214)	(4.032)	(12.878)
Average	-0.225	4.122	-4.019	-0.594	-4.759
	(15.937)	(6.226)	(5.569)	(4.259)	(13.516)
More effective	-10.093	3.187	-12.940*	-0.934	-4.692
	(15.544)	(6.119)	(5.424)	(4.171)	(13.320)
Most effective	-4.280	-2.524	-6.977	1.300	-9.980
	(15.604)	(6.142)	(5.460)	(4.195)	(13.332)

Notes: [1] Additional tract-level controls included across all models (all from ACS 2007-11): lagged dependent variable (LDV), LDV-squared, median housing value (log), total number of residents who moved within L.A. County in past year, total number of housing units, median year structure built, total population ages 18-39 (log), and total populations of foreign born (log) and bachelor's degree holders (log). Models 1,6 also include controls capturing racial composition of residents. All controls are standardized (mean=0, SD=1).[2] ** p<0.01, * p<0.05 (two-tailed).

TABLE A5

Two-level Hierarchical Linear Models Predicting Neighborhood Outcomes with Continuous API (Tract N=1,000, L.A. Community Area N=144), Partial Output

Outcome	Total # of All children < 10	Total # of White children < 10	Total # of Black children < 10	Total # of Asian children < 10	Total # of Latino children < 10
Timeframe: ACS 2012-16	Model 1	Model 2	Model 3	Model 4	Model 5
Catchment School's API	12.969	10.931**	-4.170	7.670**	-10.299
(2007-11 average, continuous)	(8.183)	(3.056)	(2.615)	(1.870)	(6.232)
Catchment School's LAT VA Ranking					
Less effective	-10.510	5.272	-4.321	-0.510	-13.856
	(15.240)	(5.975)	(4.981)	(3.810)	(13.278)
Average	-10.506	5.771	-7.240	-4.033	-7.477
	(16.119)	(6.310)	(5.329)	(4.041)	(13.849)
More effective	-21.070	7.136	-13.294*	-4.835	-11.733
	(15.577)	(6.123)	(5.139)	(3.904)	(13.543)
Most effective	-10.681	5.782	-8.915	-2.759	-13.490
	(15.572)	(6.144)	(5.168)	(3.907)	(13.471)
Timeframe: ACS 2013-17	Model 6	Model 7	Model 8	Model 9	Model 10
Catchment School's API	10.020	11.160**	-3.479	6.891**	-12.800*
(2007-11 average, continuous)	(8.234)	(3.020)	(2.550)	(1.980)	(6.170)
Catchment School's LAT VA Ranking					
Less effective	-14.288	-0.443	-0.617	-0.412	-15.199
	(15.178)	(5.877)	(5.061)	(4.046)	(12.961)
Average	-10.482	-0.926	-3.501	-2.305	-8.008
	(16.100)	(6.215)	(5.370)	(4.289)	(13.579)
More effective	-22.584	0.230	-12.454*	-2.791	-12.387
	(15.543)	(6.028)	(5.191)	(4.144)	(13.253)
Most effective	-11.807	-2.407	-8.141	2.326	-17.344
	(15.553)	(6.051)	(5.194)	(4.147)	(13.193)
Timeframe: ACS 2014-18	Model 11	Model 12	Model 13	Model 14	Model 15
Catchment School's API	13.046	14.218**	-3.522	5.909**	-10.871
(2007-11 average, continuous)	(8.112)	(2.989)	(2.657)	(1.930)	(6.137)
Catchment School's LAT VA Ranking					
Less effective	-9.126	1.112	-1.658	-1.332	-11.739
	(14.984)	(5.906)	(5.186)	(4.018)	(12.858)
Average	-7.240	-0.151	-4.521	-2.677	-5.373
	(15.886)	(6.215)	(5.523)	(4.238)	(13.481)
More effective	-19.308	0.186	-14.281**	-2.495	-9.067
	(15.338)	(6.039)	(5.333)	(4.103)	(13.153)
Most effective	-15.556	-6.041	-7.613	-0.779	-15.190
	(15.345)	(6.054)	(5.346)	(4.100)	(13.096)

Notes: [1] Additional tract-level controls included across all models (all from ACS 2007-11): lagged dependent variable (LDV), LDV-squared, median housing value (logged), total number of residents who moved within L.A. County in past year, total number of housing units, median year structure built, total population ages 18-39 (logged), and total populations of foreign born (logged) and bachelor's degree holders (logged). All controls, including lagged dependent variables, are standardized (mean = 0, SD = 1).[2] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A6

Two-level Hierarchical Linear Models Predicting Tract Racial Shares (Tract *N*=1,000, Community Area *N*=144), Partial Output

Outcome: % of children < 10 who are	**White**	**Black**	**Asian**	**Latino**
Timeframe: ACS 2012-16	Model 1	Model 2	Model 3	Model 4
Catchment School's API Quintile				
Low Performing	0.527	-0.934	0.063	0.954
	(1.232)	(0.797)	(0.852)	(1.357)
Average Performing	2.417	0.497	0.809	-4.332**
	(1.442)	(0.931)	(0.999)	(1.596)
Better Performing	4.633**	-0.976	2.430*	-6.521**
	(1.640)	(1.053)	(1.122)	(1.787)
Best Performing	3.951	-1.499	4.913**	-9.773**
	(2.015)	(1.285)	(1.356)	(2.205)
Catchment School's LAT VA Ranking				
Less effective	-0.587	-0.223	-0.216	0.575
	(1.280)	(0.823)	(0.882)	(1.428)
Average	1.415	-1.212	-0.726	-0.726
	(1.365)	(0.882)	(0.942)	(1.507)
More effective	0.630	-2.157*	-0.410	0.860
	(1.330)	(0.857)	(0.918)	(1.484)
Most effective	0.618	-1.798*	0.444	-0.212
	(1.337)	(0.864)	(0.925)	(1.488)
Timeframe: ACS 2013-17	Model 5	Model 6	Model 7	Model 8
Catchment School's API Quintile				
Low Performing	-0.169	-1.223	-0.341	1.127
	(1.230)	(0.799)	(0.927)	(1.309)
Average Performing	3.042*	0.072	0.117	-3.445*
	(1.440)	(0.933)	(1.086)	(1.541)
Better Performing	4.293**	-0.841	2.993*	-6.251**
	(1.636)	(1.055)	(1.218)	(1.722)
Best Performing	5.097*	-0.804	3.974**	-9.889**
	(2.008)	(1.288)	(1.470)	(2.126)
Catchment School's LAT VA Ranking				
Less effective	-0.991	0.772	0.215	0.029
	(1.283)	(0.825)	(0.962)	(1.383)
Average	0.992	-0.022	-0.097	-1.505
	(1.363)	(0.883)	(1.025)	(1.456)
More effective	-0.148	-1.567	0.857	0.047
	(1.331)	(0.858)	(1.000)	(1.435)
Most effective	-0.641	-1.075	1.538	-1.583
	(1.336)	(0.865)	(1.007)	(1.438)
Timeframe: ACS 2014-18	Model 9	Model 10	Model 11	Model 12
Catchment School's API Quintile				
Low Performing	1.123	-1.839*	-0.200	0.427
	(1.225)	(0.818)	(0.956)	(1.344)
Average Performing	3.728**	-0.878	-0.558	-1.993
	(1.437)	(0.955)	(1.122)	(1.583)
Better Performing	5.165**	-2.222*	2.920*	-6.525**
	(1.631)	(1.080)	(1.256)	(1.767)
Best Performing	6.914**	-2.058	3.183*	-8.712**
	(1.998)	(1.312)	(1.508)	(2.183)
Catchment School's LAT VA Ranking				
Less effective	-0.627	0.213	-0.211	0.202
	(1.285)	(0.847)	(1.000)	(1.426)
Average	0.598	-0.972	0.300	-0.498
	(1.361)	(0.905)	(1.059)	(1.497)
More effective	0.155	-2.224*	0.667	0.156
	(1.331)	(0.880)	(1.037)	(1.478)
Most effective	-1.809	-1.214	1.142	-0.466
	(1.336)	(0.887)	(1.043)	(1.481)

Notes: [1] Additional tract-level controls included across all models (all from ACS 2007-11): lagged dependent variable (LDV) , LDV-squared, median housing value (log), total number of residents who moved within L.A. County in past year, total number of housing units, median year structure built, total population ages 18-39 (log), and total populations of foreign born (log) and bachelor's degree holders (log). All controls, including LDVs, are standardized (mean = 0, SD = 1).[2] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A7

Two-level Hierarchical Linear Models Predicting Tract Racial Shares,
(Tract *N*=1,000, Community Area *N*=144) Partial Output

Outcome: % children < 10 who are:	**White**	**Black**	**Asian**	**Latino**
Timeframe: ACS 2012-16	Model 1	Model 2	Model 3	Model 4
Catchment School's API	1.938**	-0.894*	1.607**	-3.048**
(2007-11 average, continuous)	(0.655)	(0.424)	(0.440)	(0.717)
Catchment School's LAT VA Ranking				
Less effective	-0.596	-0.229	-0.441	0.943
	(1.273)	(0.818)	(0.878)	(1.430)
Average	1.164	-1.104	-1.167	0.101
	(1.351)	(0.873)	(0.935)	(1.510)
More effective	0.434	-2.178*	-0.791	1.733
	(1.308)	(0.842)	(0.903)	(1.472)
Most effective	0.806	-1.365	0.056	-0.316
	(1.307)	(0.845)	(0.905)	(1.471)
Timeframe: ACS 2013-17	Model 5	Model 6	Model 7	Model 8
Catchment School's API	2.459**	-0.564	1.378**	-3.031**
(2007-11 average, continuous)	(0.651)	(0.425)	(0.476)	(0.689)
Catchment School's LAT VA Ranking				
Less effective	-1.045	0.701	-0.001	0.451
	(1.274)	(0.820)	(0.959)	(1.386)
Average	0.567	-0.051	-0.601	-0.593
	(1.349)	(0.875)	(1.020)	(1.459)
More effective	-0.585	-1.734*	0.433	0.989
	(1.307)	(0.844)	(0.985)	(1.425)
Most effective	-0.619	-0.858	1.273	-1.460
	(1.305)	(0.847)	(0.986)	(1.422)
Timeframe: ACS 2014-18	Model 9	Model 10	Model 11	Model 12
Catchment School's API	2.735**	-0.980*	1.127*	-2.649**
(2007-11 average, continuous)	(0.646)	(0.432)	(0.486)	(0.704)
Catchment School's LAT VA Ranking				
Less effective	-0.725	0.127	-0.399	0.586
	(1.277)	(0.842)	(0.998)	(1.428)
Average	0.174	-0.985	-0.172	0.369
	(1.347)	(0.896)	(1.055)	(1.498)
More effective	-0.134	-2.438**	0.324	0.891
	(1.307)	(0.865)	(1.021)	(1.465)
Most effective	-1.848	-1.133	0.868	-0.290
	(1.306)	(0.867)	(1.022)	(1.464)

Notes: [1] Additional tract-level controls included across all models (all from ACS 2007-11): lagged dependent variable (LDV), LDV-squared, median housing value (log), total number of residents who moved within L.A. County in past year, total number of housing units, median year structure built, total population ages 18-39 (log), and total populations of foreign born (log) and bachelor's degree holders (log). All controls, including LDVs, are standardized (mean = 0, SD = 1).[2] ** $p < 0.01$, * $p < 0.05$ (two-tailed te

TABLE A8

Three-level Hierarchical Linear Models Predicting School-Year Total K-5 Enrollment (2000-01 – 2012-13), Robustness Checks – Partial Output
School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

	Model 1	Model 2	Model 3	Model 4	Model 5
Prior Year Controls					
Total K-5 Enrollment	330.866**	330.761**	228.283**	332.414**	290.296**
	(1.290)	(1.310)	(3.140)	(1.249)	(3.113)
Total K-5 Enrollment, squared	1.471**	1.472**	12.456**	1.099*	12.146**
	(0.489)	(0.489)	(0.821)	(0.480)	(0.817)
% Black	-6.061**	-6.350**	-26.864**		
	(1.700)	(1.810)	(6.128)		
% Latino	0.299	-0.137	-24.712**		
	(2.728)	(2.885)	(6.493)		
% Asian	1.985	2.027	-1.335		
	(1.432)	(1.435)	(4.339)		
Parental education index	5.167**	5.208**	6.245**	4.708**	7.453**
	(1.664)	(1.666)	(1.969)	(1.306)	(1.896)
Academic performance index		-0.847	-8.727**	1.578	-6.227**
		(1.823)	(2.291)	(1.625)	(2.236)
Time-invariant School Characteristics					
Magnet school on-site	5.982*	6.140*		3.214	
	(2.352)	(2.377)		(2.300)	
Charter school	5.386	5.427		5.741	
	(3.516)	(3.517)		(3.441)	
Year school opened	5.640**	5.632**		5.477**	
	(0.859)	(0.860)		(0.857)	
School LA Times Value-Added Ranking					
Least effective X post-2011-12 (ref)					
Less effective X post-2011-12	7.810	7.773	5.976	8.428	6.633
	(5.210)	(5.211)	(5.337)	(5.219)	(5.345)
Average X post-2011-12	6.921	6.964	5.206	6.852	6.188
	(5.240)	(5.241)	(5.355)	(5.251)	(5.359)
More effective X post-2011-12	5.039	5.155	7.061	5.080	7.947
	(5.305)	(5.310)	(5.417)	(5.321)	(5.423)
Most effective X post-2011-12	11.901*	12.079*	13.938*	11.648*	14.256**
	(5.273)	(5.286)	(5.409)	(5.281)	(5.401)
L.A. Community Area Fixed Effects	Y	Y	N	Y	N
School Fixed Effects	N	N	Y	N	Y

Notes
[1] All models include fixed effects capturing the academic year.
[2] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A9

Three-level Hierarchical Linear Models Predicting School-Year Total K-5 Enrollment (2000-01 – 2012-13) by Time Period, Partial Output

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Subsample	**Pre-LAT Ranking (2000-01 - 2010-11)**	**Post-LAT Ranking (Pooled: 2011-12, 12-13)**	**Pooled Model (All Years)**	**Pre-LAT Ranking (2000-01-2010-11)**	**Pre-LAT Ranking (2000-01-2010-11)**	**Pre-LAT Ranking (2000-01-2010-11)**	**Pre-LAT Ranking (2000-01-2010-11)**
Outcome	Total K-5 Enrollment	Total K-5 Enrollment	Total K-5 Enrollment	White K-5 Enrollment	Black K-5 Enrollment	Asian K-5 Enrollment	Latino K-5 Enrollment
School LAT VA Ranking							
Less effective	-4.029	7.011		-0.502	-0.162	-0.534	-3.151
	(2.554)	(4.925)		(0.583)	(0.582)	(0.349)	(2.284)
Average	-0.670	4.176		0.314	0.314	-0.715	-1.222
	(2.695)	(5.189)		(0.615)	(0.615)	(0.368)	(2.410)
More effective	-2.493	4.018		-0.151	0.207	-0.450	-2.334
	(2.828)	(5.442)		(0.645)	(0.642)	(0.386)	(2.524)
Most effective	1.140	12.973*		-0.001	0.094	-0.682	0.852
	(2.953)	(5.637)		(0.672)	(0.675)	(0.406)	(2.639)
Less effective X 2011-12			2.968				
			(7.505)				
Average X 2011-12			-3.709				
			(7.569)				
More effective X 2011-12			5.078				
			(7.712)				
Most effective X 2011-12			9.201				
			(7.792)				
Less effective X 2012-13			16.927*				
			(7.505)				
Average X 2012-13			17.364*				
			(7.570)				
More effective X 2012-13			9.596				
			(7.713)				
Most effective X 2012-13			16.155*				
			(7.793)				
Observations							
School-Year (Level-1) *N*	4,609	838	5,447	4,609	4,609	4,609	4,609
School (Level-2) *N*	419	419	419	419	419	419	419
LA County Area (Level-3) *N*	125	125	125	125	125	125	125

Notes

[1]All models include controls capturing: year school opened; prior year school racial composition; prior year parental education index; prior year total K-5 enrollment; prior year total K-5 enrollment-squared; and fixed effects capturing academic year, whether the school is a charter school, whether the school has a magnet program, L.A. community area. [2] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A10

Three-level Hierarchical Linear Models Predicting School-Year Total K-5 Enrollment (2000-01 – 2012-13) by School Sector, Partial Output

School Subsample	Model 1: **Traditional Public**	Model 2: **Magnet or Charter**	Model 3: **All Schools**	Model 4: **All Schools**
School LA Times Value-Added Ranking (2011)				
Less effective X post-2011-12	13.033*	-7.679	11.380*	11.424*
	(6.347)	(8.186)	(5.652)	(5.652)
Average X post-2011-12	4.109	5.622	3.599	3.502
	(6.462)	(8.201)	(5.761)	(5.759)
More effective X post-2011-12	7.777	-3.854	6.363	6.287
	(6.490)	(8.908)	(5.776)	(5.774)
Most effective X post-2011-12	18.041**	-4.925	16.584**	16.684**
	(6.617)	(8.747)	(5.901)	(5.899)
Magnet/Charter			16.299**	
			(4.952)	
Magnet on-site				13.511*
				(5.495)
Charter school				31.302**
				(10.966)
LAT VA Ranking Interactions with School Sector				
Less effective X post-2011-12 X Magnet/Charter			-14.962	
			(8.355)	
Average X post-2011-12 X Magnet/Charter			8.748	
			(8.435)	
More effective X post-2011-12 X Magnet/Charter			-2.248	
			(9.398)	
Most effective X post-2011-12 X Magnet/Charter			-13.239	
			(9.272)	
Less effective X post-2011 X Magnet				-10.260
				(10.622)
Average effective X post-2011 X Magnet				2.910
				(10.393)
More effective X post-2011 X Magnet				-10.544
				(11.934)
Most effective X post-2011 X Magnet				-18.782
				(10.227)
Less effective X post-2011 X Charter				-18.876
				(11.384)
Average effective X post-2011 X Charter				18.101
				(11.978)
More effective X post-2011 X Charter				9.983
				(13.220)
Most effective X post-2011 X Charter				1.713
				(17.971)
School-Year (Level-1) *N*	4,069	1,378	5,447	5,447
School (Level-2) *N*	313	106	419	419
L.A. County Area (Level-3) *N*	112	60	125	125

Notes: [1] All models include controls capturing: year school opened; prior year school racial composition and parental education index; prior year total K-5 enrollment; prior year total K-5 enrollment-squared; and fixed effects capturing academic year, whether the school is a charter and/or has a magnet program on-site, L.A. community area. [2] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A11

Three-level Hierarchical Linear Models Predicting School-Year Total K-5 Enrollment (2000-01 – 2012-13) by School API Quintile, Partial Output

School API Quintiles	Model 1 **Least/Low Performing**	Model 2 **Average Performing**	Model 3 **Better/Best Performing**	Model 4 **All Non-Average Performing**	Model 5 **All Schools**	Model 6 **All Schools**
School LA Times VA Ranking						
Less effective X post-2011-12	17.341*	-0.196	-8.877	7.822	7.233	11.595*
	(8.122)	(9.269)	(6.308)	(5.934)	(5.439)	(5.895)
Average X post-2011-12	11.778	-8.774	2.968	7.931	7.808	5.073
	(8.030)	(9.194)	(7.018)	(6.069)	(5.564)	(6.021)
More effective X post-2011-12	12.842	-6.131	-3.156	7.130	6.556	6.958
	(8.261)	(9.425)	(6.842)	(6.161)	(5.667)	(6.068)
Most effective X post-2011-12	8.998	22.459*	3.938	9.318	9.629	13.190*
	(10.009)	(8.839)	(6.042)	(6.418)	(5.904)	(6.267)
Average Performing Quintile					0.960	0.954
					(2.265)	(2.266)
Charter school	34.749**		1.417	6.455	5.895	5.073
	(13.222)		(3.165)	(4.310)	(3.762)	(6.021)
Magnet on-site	14.086**	1.881	3.167	8.389**	7.264**	8.442*
	(4.995)	(5.097)	(3.388)	(3.061)	(2.378)	(2.483)
LAT VA Ranking Interactions with School API Quintile						
Less effective X post-2011-12 X					-0.974	-2.591
Average Performing					(9.918)	(10.137)
Average X post-2011-12 X					-8.454	-7.898
Average Performing					(9.703)	(9.774)
More effective X post-2011-12 X					-6.558	-4.380
Average Performing					(10.261)	(10.427)
Most effective X post-2011-12 X					15.179+	16.770+
Average Performing					(9.106)	(9.132)
LAT VA - Magnet on-site interactions	N	N	N	N	N	Y
LAT VA - Charter school interactions	N	N	N	N	N	Y
Level-1 *N* (School-Year)	2,938	988	1,521	4,459	5,447	5,447
Level-2 *N* (School)	226	76	117	343	419	419
Level-3 *N* (Community Areas)	83	49	58	119	125	125

Notes:
[1] All models include controls capturing: year school opened; prior year school racial composition; prior year school parental education index; prior year total K-5 enrollment; prior year total K-5 enrollment-squared; fixed effects capturing academic year, and L.A. community area. [2] ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$ (two-tailed test).

TABLE A12

Three-level Hierarchical Linear Models Predicting School-Year Total K-5 Enrollment (2000-01 – 2012-13), Partial Model Output

School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

School-level moderator of interest	Model 1 **School % White**	Model 2 **School % Black**	Model 3 **School % Asian**	Model 4 **School % Latino**	Model 5 **School Parental Education Index**
School moderator direct effect	-14.433	-5.380	-4.719	1.231	4.264
	(33.205)	(3.468)	(7.410)	(5.319)	(3.039)
School LA Times Value-Added Ranking (2011)					
Less effective X post-2011-12	7.475	7.149	6.316	7.217	7.627
	(5.193)	(5.195)	(5.201)	(5.192)	(5.207)
Average X post-2011-12	6.295	6.560	6.479	6.870	5.998
	(5.267)	(5.300)	(5.322)	(5.281)	(5.271)
More effective X post-2011-12	6.029	5.305	5.243	5.833	5.643
	(5.423)	(5.388)	(5.399)	(5.430)	(5.397)
Most effective X post-2011-12	13.427*	13.416*	12.377*	13.407*	13.185*
	(5.452)	(5.526)	(5.499)	(5.452)	(5.486)
LAT VA Ranking Interactions with Moderators					
Less effective X post-2011-12 X school moderator	-3.252	0.623	-3.746	2.917	-3.898
	(3.614)	(4.013)	(5.029)	(3.729)	(3.708)
Average X post-2011-12 X school moderator	4.388	2.041	5.878	-5.102	4.888
	(3.480)	(4.269)	(6.144)	(3.712)	(3.644)
More effective X post-2011-12 X school moderator	2.829	-2.901	4.212	-0.848	0.994
	(4.933)	(4.000)	(5.499)	(4.435)	(4.520)
Most effective X post-2011-12 X school moderator	3.369	0.277	2.036	-5.448	2.018
	(4.074)	(5.797)	(3.025)	(4.368)	(4.208)

Notes:

[1] All models include controls capturing: year school opened; prior year school racial composition; prior year school parental education index; prior year total K-5 enrollment; prior year total K-5 enrollment-squared; fixed effects capturing academic year, whether the school is a charter and/or has a magnet program on-site, L.A. community area, School API Quintile, and School API Quintile-school moderator interactions. [2] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A13

Three-level Hierarchical Linear Models Predicting Grade-Specific School-Year Enrollment Outcomes (2000-01 – 2012-13), Partial Model Output

School-Year Outcome	Model 1 Kindergarten Enrollment	Model 2 Grades 1-5 Enrollment
School LA Times Value-Added Ranking (2011)		
Less effective X post-2011-12	0.403	6.402
	(2.161)	(4.359)
Average X post-2011-12	0.045	5.981
	(2.192)	(4.419)
More effective X post-2011-12	-1.081	5.318
	(2.238)	(4.510)
Most effective X post-2011-12	2.657	11.415*
	(2.267)	(4.569)
Level-1 *N* (School-Year)	5,447	5,447
Level-2 *N* (School)	419	419
Level-3 *N* (Community Areas)	125	125

Notes

[1] All models include controls capturing: year school opened; prior year school racial composition; prior year school parental education index; prior year total Kindergarten or Grades1-5 enrollment; prior year total Kindergarten or Grades1-5 enrollment-squared; fixed effects capturing academic year, whether the school is a charter and/or has a magnet program on-site, L.A. community area, school API quintile. [2] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A14

Three-level Hierarchical Linear Models Predicting School-Year Enrollment Patterns (2000-01 – 2012-13) by Student Race/Ethnicity, Partial Output
School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

Race/Ethnic Student Group	**White**		**Black**	
School-Year Outcome	Model 1 **Total Number of White K-5 Students**	Model 2 **K-5 Students % White**	Model 3 **Total Number of Black K-5 Students**	Model 4 **K-5 Students % Black**
Prior academic year controls				
Lagged dependent variable	102.411**	18.679**	99.215**	15.249**
	(0.672)	(0.115)	(0.627)	(0.089)
Lagged dependent variable, squared	1.236**	0.194**	1.185**	0.296**
	(0.158)	(0.035)	(0.137)	(0.021)
Parental education index	1.495**	0.172**	0.733*	-0.031
	(0.304)	(0.047)	(0.332)	(0.039)
Time-invariant school characteristics				
Magnet school on-site	-0.722	-0.188*	1.101*	0.139*
	(0.534)	(0.076)	(0.550)	(0.062)
Charter school	1.321	0.001	0.702	0.066
	(0.845)	(0.121)	(0.831)	(0.095)
Year school opened	-0.163	-0.001	0.181	0.026
	(0.246)	(0.035)	(0.246)	(0.028)
School API Quintile (time-invariant)				
Low Performing	-0.486	-0.060	0.793	0.037
	(0.573)	(0.081)	(0.571)	(0.066)
Average Performing	-0.362	-0.013	0.198	0.059
	(0.699)	(0.100)	(0.694)	(0.080)
Better Performing	1.601	0.201	-0.162	0.133
	(0.860)	(0.129)	(0.838)	(0.096)
Best Performing	7.050**	0.566**	-0.785	-0.038
	(1.212)	(0.177)	(1.169)	(0.135)
School LA Times Value-Added Ranking (2011)				
Less effective X post-2011-12	-1.552	-0.204	-0.811	-0.228
	(0.977)	(0.149)	(1.162)	(0.133)
Average X post-2011-12	0.775	0.042	0.099	-0.119
	(0.989)	(0.151)	(1.178)	(0.135)
More effective X post-2011-12	-0.222	-0.001	-0.812	-0.099
	(1.009)	(0.155)	(1.203)	(0.138)
Most effective X post-2011-12	1.275	0.150	0.557	-0.130
	(1.021)	(0.156)	(1.217)	(0.140)

Notes:
[1] All models include academic year and L.A. community area fixed effects.
[2] Parental education index is operationalized as a continuous variable and standardized to have mean of 0 and SD of 1.
[3] ** p < 0.01, * p < 0.05 (two-tailed test).

TABLE A15

Three-level Hierarchical Linear Models Predicting School-Year Race-Specific Outcomes among Asians (2000-01 – 2012-13), Partial Output
School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

School-Year Outcome	Total Number of Asian K-5 Students		K-5 Students % Asian	
	Model 1	Model 2	Model 3	Model 4
Prior academic year controls				
Lagged dependent variable	56.725**	47.315**	7.607**	6.215**
	(0.338)	(0.714)	(0.053)	(0.100)
Lagged dependent variable, squared	0.014	0.363**	0.052**	-0.048*
	(0.041)	(0.066)	(0.008)	(0.022)
Parental education index	0.240	0.468	0.050	0.075*
	(0.213)	(0.273)	(0.030)	(0.038)
Time-invariant school characteristics				
Magnet school on-site	-0.328		-0.093	
	(0.345)		(0.049)	
Charter school	0.503		0.075	
	(0.539)		(0.076)	
Year school opened	0.081		-0.009	
	(0.159)		(0.022)	
School API Quintile (time-invariant)				
Low Performing	0.117		-0.002	
	(0.370)		(0.052)	
Average Performing	0.032		0.073	
	(0.450)		(0.064)	
Better Performing	1.350*		0.187**	
	(0.541)		(0.078)	
Best Performing	3.510**		0.435**	
	(0.776)		(0.112)	
School LA Times Value-Added Ranking (2011)				
Less effective X post-2011-12	0.073	-0.070	0.031	0.024
	(0.754)	(0.769)	(0.106)	(0.107)
Average X post-2011-12	-0.061	0.140	-0.042	-0.025
	(0.764)	(0.775)	(0.108)	(0.108)
More effective X post-2011-12	0.665	0.523	0.121	0.086
	(0.780)	(0.790)	(0.110)	(0.110)
Most effective X post-2011-12	2.042*	1.739*	0.238*	0.211+
	(0.791)	(0.799)	(0.111)	(0.111)
L.A. Community Area Fixed Effects	Y	N	Y	N
School Fixed Effects	N	Y	N	Y

Notes:
[1] All models include academic year fixed effects; models 1 and 3 include L.A. community area fixed effects.
[2] Parental education index is operationalized as a continuous variable and standardized to have mean of 0 and SD of 1.
[3] ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$ (two-tailed test).

TABLE A16

Three-level Hierarchical Linear Models Predicting School-Year Race-Specific Outcomes among Latinos (2000-01 – 2012-13), Partial Output
School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

School-Year Outcome	**Total Number of Latino K-5 Students**		**K-5 Students % Latino**	
	Model 1	Model 2	Model 3	Model 4
Prior academic year controls				
Lagged dependent variable	381.566**	338.703**	27.087**	23.740**
	(1.642)	(3.827)	(0.103)	(0.246)
Lagged dependent variable, squared	0.058	12.062**	-0.355**	-0.665**
	(0.580)	(1.016)	(0.052)	(0.128)
Parental education index	2.332	3.906*	-0.119+	-0.206**
	(0.134)	(1.687)	(0.062)	(0.071)
Time-invariant school characteristics				
Magnet school on-site	4.955*		0.136	
	(2.101)		(0.088)	
Charter school	3.106		0.063	
	(3.302)		(0.139)	
Year school opened	2.297*		-0.026	
	(0.989)		(0.040)	
School API Quintile (time-invariant)				
Low Performing	1.827		-0.103	
	(2.267)		(0.094)	
Average Performing	6.154*		-0.198	
	(2.785)		(0.120)	
Better Performing	4.584		-0.568**	
	(3.377)		(0.148)	
Best Performing	-0.366		-0.878**	
	(4.589)		(0.196)	
School LA Times Value-Added Ranking (2011)				
Less effective X post-2011-12	10.151*	9.760*	0.463*	0.391*
	(4.608)	(4.761)	(0.192)	(0.193)
Average X post-2011-12	4.651	4.705	0.092	0.047
	(4.674)	(4.799)	(0.194)	(0.194)
More effective X post-2011-12	5.929	8.595+	0.051	0.030
	(4.773)	(4.892)	(0.199)	(0.198)
Most effective X post-2011-12	9.415+	11.056*	-0.142	-0.239
	(4.833)	(4.943)	(0.201)	(0.200)
L.A. Community Area Fixed Effects	Y	N	Y	N
School Fixed Effects	N	Y	N	Y

Notes:
[1] All models include academic year fixed effects; models 1 and 3 include L.A. community area fixed effects.
[2] Parental education index is operationalized as a continuous variable and standardized to have mean of 0 and SD of 1.
[3] ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$ (two-tailed test).

TABLE A17

Three-level Hierarchical Linear Models Predicting School-Year Enrollment Patterns (2000-01 – 2012-13) by Student Race/Ethnicity, Partial Output
School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

Race/Ethnic Student Group	**White**		**Black**	
	Model 1	Model 2	Model 3	Model 4
School-Year Outcome	**Total Number of White K-5 Students**	**K-5 Students % White**	**Total Number of Black K-5 Students**	**K-5 Students % Black**
Prior academic year controls				
Lagged dependent variable	103.261**	18.844**	99.643**	15.279**
	(0.650)	(0.105)	(0.623)	(0.088)
Lagged dependent variable, squared	1.136**	0.172**	1.143**	0.289**
	(0.153)	(0.032)	(0.137)	(0.020)
Parental education index	1.925**	0.210**	0.316	-0.035
	(0.293)	(0.045)	(0.298)	(0.034)
Academic Performance Index	1.283**	0.013	0.595	-0.001
	(0.347)	(0.052)	(0.377)	(0.043)
Time-invariant school characteristics				
Magnet school on-site	-1.167*	-0.203**	0.896	0.166**
	(0.528)	(0.073)	(0.534)	(0.060)
Charter school	1.695*	0.009	0.427	0.050
	(0.856)	(0.119)	(0.825)	(0.095)
Year school opened	0.057	0.016	0.140	0.022
	(0.248)	(0.034)	(0.244)	(0.028)
School LA Times Value-Added Ranking (2011)				
Less effective X post-2011-12	-1.659	-0.219	-0.710	-0.215
	(0.980)	(0.149)	(1.160)	(0.133)
Average X post-2011-12	0.443	0.014	0.188	-0.105
	(0.991)	(0.151)	(1.176)	(0.135)
More effective X post-2011-12	-0.551	-0.014	-0.870	-0.086
	(1.013)	(0.155)	(1.202)	(0.138)
Most effective X post-2011-12	1.122	0.157	0.422	-0.113
	(1.023)	(0.156)	(1.215)	(0.140)

Notes:

[1] All models include academic year and L.A. community area fixed effects.

[2] Parental education index and Academic Performance Index are operationalized as continuous variables and standardized to have mean of 0 and SD of 1.

[3] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A18

Three-level Hierarchical Linear Models Predicting School-Year Race-Specific Outcomes among Asians (2000-01 – 2012-13), Partial Output

School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

School-Year Outcome	Total Number of Asian K-5 Students		K-5 Students % Asian	
	Model 1	Model 2	Model 3	Model 4
Prior academic year controls				
Lagged dependent variable	56.965**	47.302**	7.651**	6.210**
	(0.326)	(0.714)	(0.051)	(0.100)
Lagged dependent variable, squared	-0.007	0.361**	0.047**	-0.047*
	(0.040)	(0.066)	(0.008)	(0.022)
Parental education index	0.462*	0.499	0.078**	0.079*
	(0.198)	(0.273)	(0.028)	(0.038)
Academic Performance Index	0.980**	0.496	0.106**	0.057
	(0.243)	(0.318)	(0.035)	(0.044)
Time-invariant school characteristics				
Magnet school on-site	-0.454		-0.092	
	(0.336)		(0.047)	
Charter school	0.629		0.094	
	(0.537)		(0.075)	
Year school opened	0.176		0.001	
	(0.158)		(0.022)	
School LA Times Value-Added Ranking (2011)				
Less effective X post-2011-12	0.058	-0.049	0.030	0.027
	(0.754)	(0.769)	(0.106)	(0.107)
Average X post-2011-12	-0.208	0.117	-0.057	-0.028
	(0.764)	(0.775)	(0.108)	(0.108)
More effective X post-2011-12	0.457	0.464	0.101	0.080
	(0.781)	(0.791)	(0.110)	(0.110)
Most effective X post-2011-12	1.944*	1.720*	0.238*	0.209+
	(0.790)	(0.800)	(0.111)	(0.111)
L.A. Community Area Fixed Effects	Y	N	Y	N
School Fixed Effects	N	Y	N	Y

Notes:

[1] All models include academic year fixed effects; models 1 and 3 include L.A. community area fixed effects.

[2] Parental education index and Academic Performance Index are operationalized as continuous variables and standardized to have mean of 0 and SD of 1.

[3] ** p < 0.01, * p < 0.05, + p < 0.10 (two-tailed test).

TABLE A19

Three-level Hierarchical Linear Models Predicting School-Year Race-Specific Outcomes among Latinos (2000-01 – 2012-13), Partial Output

School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

School-Year Outcome	**Total Number of Latino K-5 Students**		**K-5 Students % Latinos**	
	Model 1	Model 2	Model 3	Model 4
Prior academic year controls				
Lagged dependent variable	380.287**	335.278**	27.161**	23.728**
	(1.629)	(3.913)	(0.097)	(0.246)
Lagged dependent variable, squared	0.202	12.380**	-0.329**	-0.633**
	(0.575)	(1.017)	(0.046)	(0.129)
Parental education index	2.643*	3.480*	-0.167**	-0.221**
	(1.246)	(1.688)	(0.060)	(0.071)
Academic Performance Index	-2.655+	-8.286**	-0.233**	-0.172*
	(1.496)	(2.043)	(0.062)	(0.081)
Time-invariant school characteristics				
Magnet school on-site	6.568**		0.127	
	(2.041)		(0.086)	
Charter school	3.209		0.048	
	(3.284)		(0.138)	
Year school opened	1.907+		-0.039	
	(0.983)		(0.040)	
School LA Times Value-Added Ranking (2011)				
Less effective X post-2011-12	10.417*	9.205+	0.454*	0.384*
	(4.605)	(4.756)	(0.192)	(0.193)
Average X post-2011-12	5.358	4.988	0.110	0.053
	(4.667)	(4.792)	(0.194)	(0.194)
More effective X post-2011-12	6.830	9.409+	0.085	0.049
	(4.774)	(4.889)	(0.199)	(0.198)
Most effective X post-2011-12	10.812*	11.459*	-0.148	-0.236
	(4.827)	(4.937)	(0.201)	(0.200)
L.A. Community Area Fixed Effects	Y	N	Y	N
School Fixed Effects	N	Y	N	Y

Notes:

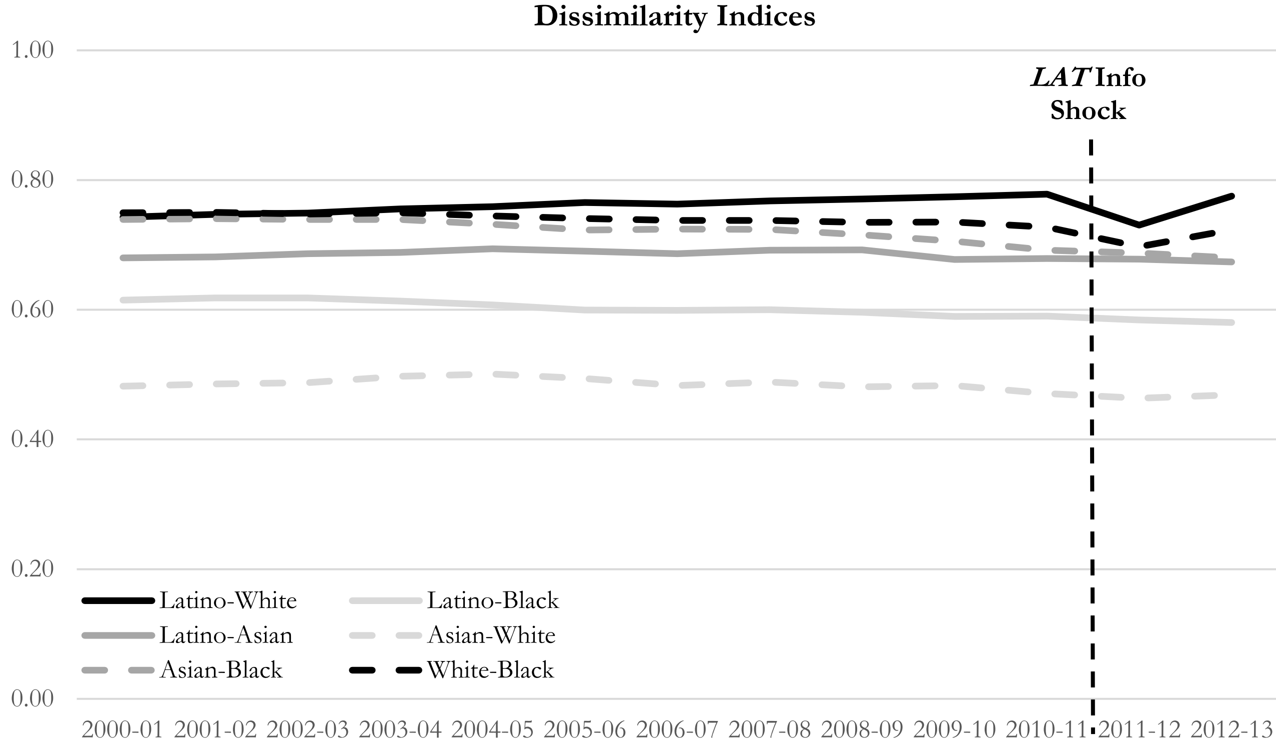
[1] All models include academic year fixed effects; models 1 and 3 include L.A. community area fixed effects.

[2] Parental education index and Academic Performance Index are operationalized as continuous variables and standardized to have mean of 0 and SD of 1.

[3] ** p < 0.01, * p < 0.05, + p < 0.10 (two-tailed test).

ONLINE SUPPLEMENT
FIGURE A1

LAUSD School Segregation Patterns among K-5 Students Over Time, 2000-01 through 2012-13 (Unadjusted)



Notes

[1] The Dissimilarity Index varies between 0 and 1, capturing the proportion of group A students that would have to switch schools to exhibit the same distribution across schools as group B does.

TABLE A1

School-Level Quality Rankings, by Academic Performance Index and LA Times Value-Added Ranking

		LA Times Value-Added Ranking					
		1 (low)	2	3	4	5 (high)	Total
Academic Performance Index Quintile	1	33	29	23	24	14	123
		37.93	32.58	26.74	30.00	18.18	29.36
	2	19	20	30	23	11	103
		21.84	22.47	34.88	28.75	14.29	24.58
	3	11	15	16	14	20	76
		12.64	16.85	18.60	17.50	25.97	18.14
	4	8	17	8	16	22	71
		9.20	19.10	9.30	20.00	28.57	16.95
	5	16	8	9	3	10	46
		18.39	8.99	10.47	3.75	12.99	10.98
Total		87	89	86	80	77	419
		100	100	100	100	100	100

Notes

[1] Percentages in cells are calculated based on column values.

[2] The bivariate correlation between schools' API quintile ranking and *Los Angeles Times* value-added quintile ranking is ~0.10

TABLE A2

Descriptive Statistics: Analytic Sample of LAUSD Census Tracts (N = 1,000), by *Los Angeles Times* Value-Added Rankings (2011)

A. Number of children under age 10					
LAT VA Ranking of Catchment School [1]	**Least Effective**	**Less Effective**	**Average**	**More Effective**	**Most Effective**
Pre-shock (ACS 2007-11, mean)					
Overall	556	504	553	539	510
White	92	81	81	69	86
Black	55	44	36	47	44
Asian	33	35	20	34	36
Latino	357	326	401	375	327
Neighborhood Pre- vs. Post- *Change* (ACS 2007-11 to ACS 2012-16)					
Overall	-20	-11	-12	-27	-12
White	-11	1	3	2	4
Black	-2	-4	-2	-15	-9
Asian	2	-1	3	-2	2
Latino	-4	-11	-16	-11	-14

B. Racial shares of children under age 10					
LAT VA Ranking of Catchment School [1]	**Least Effective**	**Less Effective**	**Average**	**More Effective**	**Most Effective**
Pre-shock (ACS 2007-11, mean)					
White	21.60%	21.27%	22.00%	15.97%	22.69%
Black	9.42%	8.26%	5.43%	8.72%	7.23%
Asian	7.33%	8.13%	5.38%	7.23%	8.37%
Latino	57.25%	57.18%	62.79%	65.36%	57.18%
Neighborhood Pre- vs. Post- *Change* (ACS 2007-11 to ACS 2012-16)					
White	-1.18pp	-0.81pp	0.43pp	0.94pp	0.89pp
Black	-0.34pp	-0.52pp	-0.32pp	-2.63pp	-1.33pp
Asian	0.42pp	-0.50pp	0.10pp	0.06pp	0.92pp
Latino	1.76pp	1.57pp	0.23pp	0.99pp	-1.10pp

Notes

[1] Using ArcGIS, 2010 census tract boundaries, and academic year 2017-18 catchment boundaries, a spatial merge process revealed which LAUSD public school's catchment boundaries subsumed the largest portion of the census tract. School-level data were assigned to each LAUSD census tract, accordingly.

[2] The analytic sample consists of LAUSD elementary schools with a valid *Los Angeles Times* Value-Added Ranking that were open during the entire timeframe of this study (2000-2013). See additional analytic sample details in Online Supplement: Methodological Appendix.

[3] Children who are categorized by the Census Bureau's American Community Survey as Black or Asian can also be categorized as Hispanic/Latino if their parents identify them as such.

TABLE A3

Descriptive Statistics: Analytic Sample of LAUSD Elementary Schools (*N* = 419), by *Los Angeles Times* Value-Added Rankings (2011)

A. Number of K-5 Students					
LAT VA Ranking	**Least Effective**	**Less Effective**	**Average**	**More Effective**	**Most Effective**
Pre-shock: 2000-01–2010-11, mean					
Overall	751	718	748	750	691
White	81	68	67	44	67
Black	84	78	64	67	56
Asian	35	22	17	22	38
Latino	531	529	581	596	509
Pre- vs. Post- *Change* (2010-11 to 2011-12), mean					
Overall	-9	-7	-13	-6	2
White	5	2	7	6	7
Black	0	-1	-1	-1	1
Asian	2	1	1	2	4
Latino	-15	-9	-19	-12	-7

B. Racial shares of K-5 Students					
LAT VA Ranking	**Least Effective**	**Less Effective**	**Average**	**More Effective**	**Most Effective**
Pre-shock: ACS 2007-11, mean					
White	13.99%	12.73%	12.03%	8.97%	12.71%
Black	12.12%	11.93%	9.62%	10.95%	8.81%
Asian	5.52%	3.81%	3.12%	3.39%	6.32%
Latino	65.41%	68.03%	72.18%	73.23%	68.21%
Pre- vs. Post- *Change* (2010-11 to 2011-12), mean					
White	0.64pp	0.54pp	0.97pp	0.93pp	0.95pp
Black	-0.04pp	-0.22pp	-0.21pp	-0.20pp	-0.05pp
Asian	0.27pp	0.25pp	0.21pp	0.29pp	0.64pp
Latino	-0.73pp	-0.37pp	-0.81pp	-0.86pp	-1.10pp

Notes

[1] The analytic sample consists of LAUSD elementary schools with a valid *Los Angeles Times* Value-Added Ranking that were open during the entire timeframe of this study (2000-2013).

TABLE A4

Two-level Hierarchical Linear Models Predicting Neighborhood Outcomes from ACS 2013-2017 and ACS 2014-2018, Partial Model Output

Tract *N* = 1,000, L.A. Community Area *N* = 144

Outcome	**Total # of All children < 10**	**Total # of White children < 10**	**Total # of Black children < 10**	**Total # of Asian children < 10**	**Total # of Latino children < 10**
Timeframe: ACS 2013-17	Model 1	Model 2	Model 3	Model 4	Model 5
Catchment School's API Quintile					
Low performing	-33.772*	0.626	-8.522	-0.541	-34.874**
	(14.759)	(5.649)	(4.902)	(3.908)	(12.224)
Average performing	-25.003	11.280	-3.906	1.150	-42.572**
	(17.256)	(6.624)	(5.737)	(4.572)	(14.382)
Better performing	-12.179	20.343**	-5.862	12.759*	-52.057**
	(20.110)	(7.494)	(6.443)	(5.124)	(15.908)
Best performing	20.364	32.626**	-8.059	18.253**	-46.616*
	(24.793)	(9.286)	(7.780)	(6.155)	(19.293)
Catchment School's LAT VA Ranking					
Less effective	-10.806	0.824	-0.299	0.407	-14.430
	(15.193)	(5.908)	(5.090)	(4.065)	(12.972)
Average	-3.577	2.089	-3.139	-0.102	-6.969
	(16.157)	(6.257)	(5.414)	(4.315)	(13.607)
More effective	-12.938	2.812	-11.334*	-1.011	-7.675
	(15.755)	(6.128)	(5.282)	(4.216)	(13.413)
Most effective	-2.392	-1.261	-8.811	3.987	-10.816
	(15.818)	(6.161)	(5.309)	(4.245)	(13.424)
Timeframe: ACS 2014-18	Model 6	Model 7	Model 8	Model 9	Model 10
Catchment School's API Quintile					
Low performing	-27.004	4.407	-9.631	0.235	-31.670**
	(14.556)	(5.605)	(5.044)	(3.848)	(12.146)
Average performing	-23.469	9.741	-8.095	-1.386	-30.085*
	(17.019)	(6.587)	(5.901)	(4.508)	(14.288)
Better performing	-9.951	23.733**	-10.464	10.813*	-48.813**
	(19.827)	(7.427)	(6.649)	(5.036)	(15.811)
Best performing	35.465	46.944**	-10.164	17.460**	-36.465
	(24.443)	(9.197)	(8.063)	(6.031)	(19.177)
Catchment School's LAT VA Ranking					
Less effective	-5.109	3.447	-1.259	-0.399	-10.896
	(14.994)	(5.921)	(5.214)	(4.032)	(12.878)
Average	-0.225	4.122	-4.019	-0.594	-4.759
	(15.937)	(6.226)	(5.569)	(4.259)	(13.516)
More effective	-10.093	3.187	-12.940*	-0.934	-4.692
	(15.544)	(6.119)	(5.424)	(4.171)	(13.320)
Most effective	-4.280	-2.524	-6.977	1.300	-9.980
	(15.604)	(6.142)	(5.460)	(4.195)	(13.332)

Notes: [1] Additional tract-level controls included across all models (all from ACS 2007-11): lagged dependent variable (LDV), LDV-squared, median housing value (log), total number of residents who moved within L.A. County in past year, total number of housing units, median year structure built, total population ages 18-39 (log), and total populations of foreign born (log) and bachelor's degree holders (log). Models 1,6 also include controls capturing racial composition of residents. All controls are standardized (mean=0, SD=1).[2] ** p<0.01, * p<0.05 (two-tailed).

TABLE A5

Two-level Hierarchical Linear Models Predicting Neighborhood Outcomes with Continuous API (Tract *N*=1,000, L.A. Community Area *N*=144), Partial Output

Outcome	**Total # of All children < 10**	**Total # of White children < 10**	**Total # of Black children < 10**	**Total # of Asian children < 10**	**Total # of Latino children < 10**
Timeframe: ACS 2012-16	Model 1	Model 2	Model 3	Model 4	Model 5
Catchment School's API	12.969	10.931**	-4.170	7.670**	-10.299
(2007-11 average, continuous)	(8.183)	(3.056)	(2.615)	(1.870)	(6.232)
Catchment School's LAT VA Ranking					
Less effective	-10.510	5.272	-4.321	-0.510	-13.856
	(15.240)	(5.975)	(4.981)	(3.810)	(13.278)
Average	-10.506	5.771	-7.240	-4.033	-7.477
	(16.119)	(6.310)	(5.329)	(4.041)	(13.849)
More effective	-21.070	7.136	-13.294*	-4.835	-11.733
	(15.577)	(6.123)	(5.139)	(3.904)	(13.543)
Most effective	-10.681	5.782	-8.915	-2.759	-13.490
	(15.572)	(6.144)	(5.168)	(3.907)	(13.471)
Timeframe: ACS 2013-17	Model 6	Model 7	Model 8	Model 9	Model 10
Catchment School's API	10.020	11.160**	-3.479	6.891**	-12.800*
(2007-11 average, continuous)	(8.234)	(3.020)	(2.550)	(1.980)	(6.170)
Catchment School's LAT VA Ranking					
Less effective	-14.288	-0.443	-0.617	-0.412	-15.199
	(15.178)	(5.877)	(5.061)	(4.046)	(12.961)
Average	-10.482	-0.926	-3.501	-2.305	-8.008
	(16.100)	(6.215)	(5.370)	(4.289)	(13.579)
More effective	-22.584	0.230	-12.454*	-2.791	-12.387
	(15.543)	(6.028)	(5.191)	(4.144)	(13.253)
Most effective	-11.807	-2.407	-8.141	2.326	-17.344
	(15.553)	(6.051)	(5.194)	(4.147)	(13.193)
Timeframe: ACS 2014-18	Model 11	Model 12	Model 13	Model 14	Model 15
Catchment School's API	13.046	14.218**	-3.522	5.909**	-10.871
(2007-11 average, continuous)	(8.112)	(2.989)	(2.657)	(1.930)	(6.137)
Catchment School's LAT VA Ranking					
Less effective	-9.126	1.112	-1.658	-1.332	-11.739
	(14.984)	(5.906)	(5.186)	(4.018)	(12.858)
Average	-7.240	-0.151	-4.521	-2.677	-5.373
	(15.886)	(6.215)	(5.523)	(4.238)	(13.481)
More effective	-19.308	0.186	-14.281**	-2.495	-9.067
	(15.338)	(6.039)	(5.333)	(4.103)	(13.153)
Most effective	-15.556	-6.041	-7.613	-0.779	-15.190
	(15.345)	(6.054)	(5.346)	(4.100)	(13.096)

Notes: [1] Additional tract-level controls included across all models (all from ACS 2007-11): lagged dependent variable (LDV), LDV-squared, median housing value (logged), total number of residents who moved within L.A. County in past year, total number of housing units, median year structure built, total population ages 18-39 (logged), and total populations of foreign born (logged) and bachelor's degree holders (logged). All controls, including lagged dependent variables, are standardized (mean = 0, SD = 1).[2] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A6

Two-level Hierarchical Linear Models Predicting Tract Racial Shares (Tract *N*=1,000, Community Area *N*=144), Partial Output

Outcome: % of children < 10 who are	White	Black	Asian	Latino
Timeframe: ACS 2012-16	Model 1	Model 2	Model 3	Model 4
Catchment School's API Quintile				
Low Performing	0.527	-0.934	0.063	0.954
	(1.232)	(0.797)	(0.852)	(1.357)
Average Performing	2.417	0.497	0.809	-4.332**
	(1.442)	(0.931)	(0.999)	(1.596)
Better Performing	4.633**	-0.976	2.430*	-6.521**
	(1.640)	(1.053)	(1.122)	(1.787)
Best Performing	3.951	-1.499	4.913**	-9.773**
	(2.015)	(1.285)	(1.356)	(2.205)
Catchment School's LAT VA Ranking				
Less effective	-0.587	-0.223	-0.216	0.575
	(1.280)	(0.823)	(0.882)	(1.428)
Average	1.415	-1.212	-0.726	-0.726
	(1.365)	(0.882)	(0.942)	(1.507)
More effective	0.630	-2.157*	-0.410	0.860
	(1.330)	(0.857)	(0.918)	(1.484)
Most effective	0.618	-1.798*	0.444	-0.212
	(1.337)	(0.864)	(0.925)	(1.488)
Timeframe: ACS 2013-17	Model 5	Model 6	Model 7	Model 8
Catchment School's API Quintile				
Low Performing	-0.169	-1.223	-0.341	1.127
	(1.230)	(0.799)	(0.927)	(1.309)
Average Performing	3.042*	0.072	0.117	-3.445*
	(1.440)	(0.933)	(1.086)	(1.541)
Better Performing	4.293**	-0.841	2.993*	-6.251**
	(1.636)	(1.055)	(1.218)	(1.722)
Best Performing	5.097*	-0.804	3.974**	-9.889**
	(2.008)	(1.288)	(1.470)	(2.126)
Catchment School's LAT VA Ranking				
Less effective	-0.991	0.772	0.215	0.029
	(1.283)	(0.825)	(0.962)	(1.383)
Average	0.992	-0.022	-0.097	-1.505
	(1.363)	(0.883)	(1.025)	(1.456)
More effective	-0.148	-1.567	0.857	0.047
	(1.331)	(0.858)	(1.000)	(1.435)
Most effective	-0.641	-1.075	1.538	-1.583
	(1.336)	(0.865)	(1.007)	(1.438)
Timeframe: ACS 2014-18	Model 9	Model 10	Model 11	Model 12
Catchment School's API Quintile				
Low Performing	1.123	-1.839*	-0.200	0.427
	(1.225)	(0.818)	(0.956)	(1.344)
Average Performing	3.728**	-0.878	-0.558	-1.993
	(1.437)	(0.955)	(1.122)	(1.583)
Better Performing	5.165**	-2.222*	2.920*	-6.525**
	(1.631)	(1.080)	(1.256)	(1.767)
Best Performing	6.914**	-2.058	3.183*	-8.712**
	(1.998)	(1.312)	(1.508)	(2.183)
Catchment School's LAT VA Ranking				
Less effective	-0.627	0.213	-0.211	0.202
	(1.285)	(0.847)	(1.000)	(1.426)
Average	0.598	-0.972	0.300	-0.498
	(1.361)	(0.905)	(1.059)	(1.497)
More effective	0.155	-2.224*	0.667	0.156
	(1.331)	(0.880)	(1.037)	(1.478)
Most effective	-1.809	-1.214	1.142	-0.466
	(1.336)	(0.887)	(1.043)	(1.481)

Notes: [1] Additional tract-level controls included across all models (all from ACS 2007-11): lagged dependent variable (LDV) , LDV-squared, median housing value (log), total number of residents who moved within L.A. County in past year, total number of housing units, median year structure built, total population ages 18-39 (log), and total populations of foreign born (log) and bachelor's degree holders (log). All controls, including LDVs, are standardized (mean = 0, SD = 1).[2] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A7
Two-level Hierarchical Linear Models Predicting Tract Racial Shares,
(Tract *N*=1,000, Community Area *N*=144) Partial Output

Outcome: % children < 10 who are:	**White**	**Black**	**Asian**	**Latino**
Timeframe: ACS 2012-16	Model 1	Model 2	Model 3	Model 4
Catchment School's API	1.938**	-0.894*	1.607**	-3.048**
(2007-11 average, continuous)	(0.655)	(0.424)	(0.440)	(0.717)
Catchment School's LAT VA Ranking				
Less effective	-0.596	-0.229	-0.441	0.943
	(1.273)	(0.818)	(0.878)	(1.430)
Average	1.164	-1.104	-1.167	0.101
	(1.351)	(0.873)	(0.935)	(1.510)
More effective	0.434	-2.178*	-0.791	1.733
	(1.308)	(0.842)	(0.903)	(1.472)
Most effective	0.806	-1.365	0.056	-0.316
	(1.307)	(0.845)	(0.905)	(1.471)
Timeframe: ACS 2013-17	Model 5	Model 6	Model 7	Model 8
Catchment School's API	2.459**	-0.564	1.378**	-3.031**
(2007-11 average, continuous)	(0.651)	(0.425)	(0.476)	(0.689)
Catchment School's LAT VA Ranking				
Less effective	-1.045	0.701	-0.001	0.451
	(1.274)	(0.820)	(0.959)	(1.386)
Average	0.567	-0.051	-0.601	-0.593
	(1.349)	(0.875)	(1.020)	(1.459)
More effective	-0.585	-1.734*	0.433	0.989
	(1.307)	(0.844)	(0.985)	(1.425)
Most effective	-0.619	-0.858	1.273	-1.460
	(1.305)	(0.847)	(0.986)	(1.422)
Timeframe: ACS 2014-18	Model 9	Model 10	Model 11	Model 12
Catchment School's API	2.735**	-0.980*	1.127*	-2.649**
(2007-11 average, continuous)	(0.646)	(0.432)	(0.486)	(0.704)
Catchment School's LAT VA Ranking				
Less effective	-0.725	0.127	-0.399	0.586
	(1.277)	(0.842)	(0.998)	(1.428)
Average	0.174	-0.985	-0.172	0.369
	(1.347)	(0.896)	(1.055)	(1.498)
More effective	-0.134	-2.438**	0.324	0.891
	(1.307)	(0.865)	(1.021)	(1.465)
Most effective	-1.848	-1.133	0.868	-0.290
	(1.306)	(0.867)	(1.022)	(1.464)

Notes: [1] Additional tract-level controls included across all models (all from ACS 2007-11): lagged dependent variable (LDV), LDV-squared, median housing value (log), total number of residents who moved within L.A. County in past year, total number of housing units, median year structure built, total population ages 18-39 (log), and total populations of foreign born (log) and bachelor's degree holders (log). All controls, including LDVs, are standardized (mean = 0, SD = 1).[2] ** $p < 0.01$, * $p < 0.05$ (two-tailed te

TABLE A8

Three-level Hierarchical Linear Models Predicting School-Year Total K-5 Enrollment (2000-01 – 2012-13), Robustness Checks – Partial Output

School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

	Model 1	Model 2	Model 3	Model 4	Model 5
Prior Year Controls					
Total K-5 Enrollment	330.866**	330.761**	228.283**	332.414**	290.296**
	(1.290)	(1.310)	(3.140)	(1.249)	(3.113)
Total K-5 Enrollment, squared	1.471**	1.472**	12.456**	1.099*	12.146**
	(0.489)	(0.489)	(0.821)	(0.480)	(0.817)
% Black	-6.061**	-6.350**	-26.864**		
	(1.700)	(1.810)	(6.128)		
% Latino	0.299	-0.137	-24.712**		
	(2.728)	(2.885)	(6.493)		
% Asian	1.985	2.027	-1.335		
	(1.432)	(1.435)	(4.339)		
Parental education index	5.167**	5.208**	6.245**	4.708**	7.453**
	(1.664)	(1.666)	(1.969)	(1.306)	(1.896)
Academic performance index		-0.847	-8.727**	1.578	-6.227**
		(1.823)	(2.291)	(1.625)	(2.236)
Time-invariant School Characteristics					
Magnet school on-site	5.982*	6.140*		3.214	
	(2.352)	(2.377)		(2.300)	
Charter school	5.386	5.427		5.741	
	(3.516)	(3.517)		(3.441)	
Year school opened	5.640**	5.632**		5.477**	
	(0.859)	(0.860)		(0.857)	
School LA Times Value-Added Ranking					
Least effective X post-2011-12 (ref)					
Less effective X post-2011-12	7.810	7.773	5.976	8.428	6.633
	(5.210)	(5.211)	(5.337)	(5.219)	(5.345)
Average X post-2011-12	6.921	6.964	5.206	6.852	6.188
	(5.240)	(5.241)	(5.355)	(5.251)	(5.359)
More effective X post-2011-12	5.039	5.155	7.061	5.080	7.947
	(5.305)	(5.310)	(5.417)	(5.321)	(5.423)
Most effective X post-2011-12	11.901*	12.079*	13.938*	11.648*	14.256**
	(5.273)	(5.286)	(5.409)	(5.281)	(5.401)
L.A. Community Area Fixed Effects	Y	Y	N	Y	N
School Fixed Effects	N	N	Y	N	Y

Notes

[1] All models include fixed effects capturing the academic year.

[2] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A9

Three-level Hierarchical Linear Models Predicting School-Year Total K-5 Enrollment (2000-01 – 2012-13) by Time Period, Partial Output

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Subsample	**Pre-LAT Ranking (2000-01 - 2010-11)**	**Post-LAT Ranking (Pooled: 2011-12, 12-13)**	**Pooled Model (All Years)**	**Pre-LAT Ranking (2000-01-2010-11)**	**Pre-LAT Ranking (2000-01-2010-11)**	**Pre-LAT Ranking (2000-01-2010-11)**	**Pre-LAT Ranking (2000-01-2010-11)**
Outcome	Total K-5 Enrollment	Total K-5 Enrollment	Total K-5 Enrollment	White K-5 Enrollment	Black K-5 Enrollment	Asian K-5 Enrollment	Latino K-5 Enrollment
School LAT VA Ranking							
Less effective	-4.029	7.011		-0.502	-0.162	-0.534	-3.151
	(2.554)	(4.925)		(0.583)	(0.582)	(0.349)	(2.284)
Average	-0.670	4.176		0.314	0.314	-0.715	-1.222
	(2.695)	(5.189)		(0.615)	(0.615)	(0.368)	(2.410)
More effective	-2.493	4.018		-0.151	0.207	-0.450	-2.334
	(2.828)	(5.442)		(0.645)	(0.642)	(0.386)	(2.524)
Most effective	1.140	12.973*		-0.001	0.094	-0.682	0.852
	(2.953)	(5.637)		(0.672)	(0.675)	(0.406)	(2.639)
Less effective X 2011-12			2.968				
			(7.505)				
Average X 2011-12			-3.709				
			(7.569)				
More effective X 2011-12			5.078				
			(7.712)				
Most effective X 2011-12			9.201				
			(7.792)				
Less effective X 2012-13			16.927*				
			(7.505)				
Average X 2012-13			17.364*				
			(7.570)				
More effective X 2012-13			9.596				
			(7.713)				
Most effective X 2012-13			16.155*				
			(7.793)				
Observations							
School-Year (Level-1) *N*	4,609	838	5,447	4,609	4,609	4,609	4,609
School (Level-2) *N*	419	419	419	419	419	419	419
LA County Area (Level-3) *N*	125	125	125	125	125	125	125

Notes

[1]All models include controls capturing: year school opened; prior year school racial composition; prior year parental education index; prior year total K-5 enrollment; prior year total K-5 enrollment-squared; and fixed effects capturing academic year, whether the school is a charter school, whether the school has a magnet program, L.A. community area. [2] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A10

Three-level Hierarchical Linear Models Predicting School-Year Total K-5 Enrollment (2000-01 – 2012-13) by School Sector, Partial Output

School Subsample	Model 1: **Traditional Public**	Model 2: **Magnet or Charter**	Model 3: **All Schools**	Model 4: **All Schools**
School LA Times Value-Added Ranking (2011)				
Less effective X post-2011-12	13.033*	-7.679	11.380*	11.424*
	(6.347)	(8.186)	(5.652)	(5.652)
Average X post-2011-12	4.109	5.622	3.599	3.502
	(6.462)	(8.201)	(5.761)	(5.759)
More effective X post-2011-12	7.777	-3.854	6.363	6.287
	(6.490)	(8.908)	(5.776)	(5.774)
Most effective X post-2011-12	18.041**	-4.925	16.584**	16.684**
	(6.617)	(8.747)	(5.901)	(5.899)
Magnet/Charter			16.299**	
			(4.952)	
Magnet on-site				13.511*
				(5.495)
Charter school				31.302**
				(10.966)
LAT VA Ranking Interactions with School Sector				
Less effective X post-2011-12 X Magnet/Charter			-14.962	
			(8.355)	
Average X post-2011-12 X Magnet/Charter			8.748	
			(8.435)	
More effective X post-2011-12 X Magnet/Charter			-2.248	
			(9.398)	
Most effective X post-2011-12 X Magnet/Charter			-13.239	
			(9.272)	
Less effective X post-2011 X Magnet				-10.260
				(10.622)
Average effective X post-2011 X Magnet				2.910
				(10.393)
More effective X post-2011 X Magnet				-10.544
				(11.934)
Most effective X post-2011 X Magnet				-18.782
				(10.227)
Less effective X post-2011 X Charter				-18.876
				(11.384)
Average effective X post-2011 X Charter				18.101
				(11.978)
More effective X post-2011 X Charter				9.983
				(13.220)
Most effective X post-2011 X Charter				1.713
				(17.971)
School-Year (Level-1) *N*	4,069	1,378	5,447	5,447
School (Level-2) *N*	313	106	419	419
L.A. County Area (Level-3) *N*	112	60	125	125

Notes: [1] All models include controls capturing: year school opened; prior year school racial composition and parental education index; prior year total K-5 enrollment; prior year total K-5 enrollment-squared; and fixed effects capturing academic year, whether the school is a charter and/or has a magnet program on-site, L.A. community area. [2] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A11

Three-level Hierarchical Linear Models Predicting School-Year Total K-5 Enrollment (2000-01 – 2012-13) by School API Quintile, Partial Output

School API Quintiles	Model 1 **Least/Low Performing**	Model 2 **Average Performing**	Model 3 **Better/Best Performing**	Model 4 **All Non-Average Performing**	Model 5 **All Schools**	Model 6 **All Schools**
School LA Times VA Ranking						
Less effective X post-2011-12	17.341*	-0.196	-8.877	7.822	7.233	11.595*
	(8.122)	(9.269)	(6.308)	(5.934)	(5.439)	(5.895)
Average X post-2011-12	11.778	-8.774	2.968	7.931	7.808	5.073
	(8.030)	(9.194)	(7.018)	(6.069)	(5.564)	(6.021)
More effective X post-2011-12	12.842	-6.131	-3.156	7.130	6.556	6.958
	(8.261)	(9.425)	(6.842)	(6.161)	(5.667)	(6.068)
Most effective X post-2011-12	8.998	22.459*	3.938	9.318	9.629	13.190*
	(10.009)	(8.839)	(6.042)	(6.418)	(5.904)	(6.267)
Average Performing Quintile					0.960	0.954
					(2.265)	(2.266)
Charter school	34.749**		1.417	6.455	5.895	5.073
	(13.222)		(3.165)	(4.310)	(3.762)	(6.021)
Magnet on-site	14.086**	1.881	3.167	8.389**	7.264**	8.442*
	(4.995)	(5.097)	(3.388)	(3.061)	(2.378)	(2.483)
LAT VA Ranking Interactions with School API Quintile						
Less effective X post-2011-12 X Average Performing					-0.974	-2.591
					(9.918)	(10.137)
Average X post-2011-12 X Average Performing					-8.454	-7.898
					(9.703)	(9.774)
More effective X post-2011-12 X Average Performing					-6.558	-4.380
					(10.261)	(10.427)
Most effective X post-2011-12 X Average Performing					15.179+	16.770+
					(9.106)	(9.132)
LAT VA - Magnet on-site interactions	N	N	N	N	N	Y
LAT VA - Charter school interactions	N	N	N	N	N	Y
Level-1 *N* (School-Year)	2,938	988	1,521	4,459	5,447	5,447
Level-2 *N* (School)	226	76	117	343	419	419
Level-3 *N* (Community Areas)	83	49	58	119	125	125

Notes:
[1] All models include controls capturing: year school opened; prior year school racial composition; prior year school parental education index; prior year total K-5 enrollment; prior year total K-5 enrollment-squared; fixed effects capturing academic year, and L.A. community area. [2] ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$ (two-tailed test).

TABLE A12

Three-level Hierarchical Linear Models Predicting School-Year Total K-5 Enrollment (2000-01 – 2012-13), Partial Model Output
School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

School-level moderator of interest	Model 1 **School % White**	Model 2 **School % Black**	Model 3 **School % Asian**	Model 4 **School % Latino**	Model 5 **School Parental Education Index**
School moderator direct effect	-14.433	-5.380	-4.719	1.231	4.264
	(33.205)	(3.468)	(7.410)	(5.319)	(3.039)
School LA Times Value-Added Ranking (2011)					
Less effective X post-2011-12	7.475	7.149	6.316	7.217	7.627
	(5.193)	(5.195)	(5.201)	(5.192)	(5.207)
Average X post-2011-12	6.295	6.560	6.479	6.870	5.998
	(5.267)	(5.300)	(5.322)	(5.281)	(5.271)
More effective X post-2011-12	6.029	5.305	5.243	5.833	5.643
	(5.423)	(5.388)	(5.399)	(5.430)	(5.397)
Most effective X post-2011-12	13.427*	13.416*	12.377*	13.407*	13.185*
	(5.452)	(5.526)	(5.499)	(5.452)	(5.486)
LAT VA Ranking Interactions with Moderators					
Less effective X post-2011-12 X school moderator	-3.252	0.623	-3.746	2.917	-3.898
	(3.614)	(4.013)	(5.029)	(3.729)	(3.708)
Average X post-2011-12 X school moderator	4.388	2.041	5.878	-5.102	4.888
	(3.480)	(4.269)	(6.144)	(3.712)	(3.644)
More effective X post-2011-12 X school moderator	2.829	-2.901	4.212	-0.848	0.994
	(4.933)	(4.000)	(5.499)	(4.435)	(4.520)
Most effective X post-2011-12 X school moderator	3.369	0.277	2.036	-5.448	2.018
	(4.074)	(5.797)	(3.025)	(4.368)	(4.208)

Notes:
[1] All models include controls capturing: year school opened; prior year school racial composition; prior year school parental education index; prior year total K-5 enrollment; prior year total K-5 enrollment-squared; fixed effects capturing academic year, whether the school is a charter and/or has a magnet program on-site, L.A. community area, School API Quintile, and School API Quintile-school moderator interactions. [2] ** p < 0.01, * p < 0.05 (two-tailed test).

TABLE A13

Three-level Hierarchical Linear Models Predicting Grade-Specific School-Year Enrollment Outcomes (2000-01 – 2012-13), Partial Model Output

School-Year Outcome	Model 1 Kindergarten Enrollment	Model 2 Grades 1-5 Enrollment
School LA Times Value-Added Ranking (2011)		
Less effective X post-2011-12	0.403	6.402
	(2.161)	(4.359)
Average X post-2011-12	0.045	5.981
	(2.192)	(4.419)
More effective X post-2011-12	-1.081	5.318
	(2.238)	(4.510)
Most effective X post-2011-12	2.657	11.415*
	(2.267)	(4.569)
Level-1 *N* (School-Year)	5,447	5,447
Level-2 *N* (School)	419	419
Level-3 *N* (Community Areas)	125	125

Notes

[1] All models include controls capturing: year school opened; prior year school racial composition; prior year school parental education index; prior year total Kindergarten or Grades1-5 enrollment; prior year total Kindergarten or Grades1-5 enrollment-squared; fixed effects capturing academic year, whether the school is a charter and/or has a magnet program on-site, L.A. community area, school API quintile. [2] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A14

Three-level Hierarchical Linear Models Predicting School-Year Enrollment Patterns (2000-01 – 2012-13) by Student Race/Ethnicity, Partial Output
School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

Race/Ethnic Student Group	**White**		**Black**	
	Model 1	Model 2	Model 3	Model 4
School-Year Outcome	**Total Number of White K-5 Students**	**K-5 Students % White**	**Total Number of Black K-5 Students**	**K-5 Students % Black**
Prior academic year controls				
Lagged dependent variable	102.411**	18.679**	99.215**	15.249**
	(0.672)	(0.115)	(0.627)	(0.089)
Lagged dependent variable, squared	1.236**	0.194**	1.185**	0.296**
	(0.158)	(0.035)	(0.137)	(0.021)
Parental education index	1.495**	0.172**	0.733*	-0.031
	(0.304)	(0.047)	(0.332)	(0.039)
Time-invariant school characteristics				
Magnet school on-site	-0.722	-0.188*	1.101*	0.139*
	(0.534)	(0.076)	(0.550)	(0.062)
Charter school	1.321	0.001	0.702	0.066
	(0.845)	(0.121)	(0.831)	(0.095)
Year school opened	-0.163	-0.001	0.181	0.026
	(0.246)	(0.035)	(0.246)	(0.028)
School API Quintile (time-invariant)				
Low Performing	-0.486	-0.060	0.793	0.037
	(0.573)	(0.081)	(0.571)	(0.066)
Average Performing	-0.362	-0.013	0.198	0.059
	(0.699)	(0.100)	(0.694)	(0.080)
Better Performing	1.601	0.201	-0.162	0.133
	(0.860)	(0.129)	(0.838)	(0.096)
Best Performing	7.050**	0.566**	-0.785	-0.038
	(1.212)	(0.177)	(1.169)	(0.135)
School LA Times Value-Added Ranking (2011)				
Less effective X post-2011-12	-1.552	-0.204	-0.811	-0.228
	(0.977)	(0.149)	(1.162)	(0.133)
Average X post-2011-12	0.775	0.042	0.099	-0.119
	(0.989)	(0.151)	(1.178)	(0.135)
More effective X post-2011-12	-0.222	-0.001	-0.812	-0.099
	(1.009)	(0.155)	(1.203)	(0.138)
Most effective X post-2011-12	1.275	0.150	0.557	-0.130
	(1.021)	(0.156)	(1.217)	(0.140)

Notes:
[1] All models include academic year and L.A. community area fixed effects.
[2] Parental education index is operationalized as a continuous variable and standardized to have mean of 0 and SD of 1.
[3] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A15

Three-level Hierarchical Linear Models Predicting School-Year Race-Specific Outcomes among Asians (2000-01 – 2012-13), Partial Output
School-year (level-1) *N* = 5,447, school (level-2) *N* = 419, community area (level-3) *N* = 125

School-Year Outcome	Total Number of Asian K-5 Students		K-5 Students % Asian	
	Model 1	Model 2	Model 3	Model 4
Prior academic year controls				
Lagged dependent variable	56.725**	47.315**	7.607**	6.215**
	(0.338)	(0.714)	(0.053)	(0.100)
Lagged dependent variable, squared	0.014	0.363**	0.052**	-0.048*
	(0.041)	(0.066)	(0.008)	(0.022)
Parental education index	0.240	0.468	0.050	0.075*
	(0.213)	(0.273)	(0.030)	(0.038)
Time-invariant school characteristics				
Magnet school on-site	-0.328		-0.093	
	(0.345)		(0.049)	
Charter school	0.503		0.075	
	(0.539)		(0.076)	
Year school opened	0.081		-0.009	
	(0.159)		(0.022)	
School API Quintile (time-invariant)				
Low Performing	0.117		-0.002	
	(0.370)		(0.052)	
Average Performing	0.032		0.073	
	(0.450)		(0.064)	
Better Performing	1.350*		0.187**	
	(0.541)		(0.078)	
Best Performing	3.510**		0.435**	
	(0.776)		(0.112)	
School LA Times Value-Added Ranking (2011)				
Less effective X post-2011-12	0.073	-0.070	0.031	0.024
	(0.754)	(0.769)	(0.106)	(0.107)
Average X post-2011-12	-0.061	0.140	-0.042	-0.025
	(0.764)	(0.775)	(0.108)	(0.108)
More effective X post-2011-12	0.665	0.523	0.121	0.086
	(0.780)	(0.790)	(0.110)	(0.110)
Most effective X post-2011-12	2.042*	1.739*	0.238*	0.211+
	(0.791)	(0.799)	(0.111)	(0.111)
L.A. Community Area Fixed Effects	Y	N	Y	N
School Fixed Effects	N	Y	N	Y

Notes:
[1] All models include academic year fixed effects; models 1 and 3 include L.A. community area fixed effects.
[2] Parental education index is operationalized as a continuous variable and standardized to have mean of 0 and SD of 1.
[3] ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$ (two-tailed test).

TABLE A16

Three-level Hierarchical Linear Models Predicting School-Year Race-Specific Outcomes among Latinos (2000-01 – 2012-13), Partial Output
School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

School-Year Outcome	**Total Number of Latino K-5 Students**		**K-5 Students % Latino**	
	Model 1	Model 2	Model 3	Model 4
Prior academic year controls				
Lagged dependent variable	381.566**	338.703**	27.087**	23.740**
	(1.642)	(3.827)	(0.103)	(0.246)
Lagged dependent variable, squared	0.058	12.062**	-0.355**	-0.665**
	(0.580)	(1.016)	(0.052)	(0.128)
Parental education index	2.332	3.906*	-0.119+	-0.206**
	(0.134)	(1.687)	(0.062)	(0.071)
Time-invariant school characteristics				
Magnet school on-site	4.955*		0.136	
	(2.101)		(0.088)	
Charter school	3.106		0.063	
	(3.302)		(0.139)	
Year school opened	2.297*		-0.026	
	(0.989)		(0.040)	
School API Quintile (time-invariant)				
Low Performing	1.827		-0.103	
	(2.267)		(0.094)	
Average Performing	6.154*		-0.198	
	(2.785)		(0.120)	
Better Performing	4.584		-0.568**	
	(3.377)		(0.148)	
Best Performing	-0.366		-0.878**	
	(4.589)		(0.196)	
School LA Times Value-Added Ranking (2011)				
Less effective X post-2011-12	10.151*	9.760*	0.463*	0.391*
	(4.608)	(4.761)	(0.192)	(0.193)
Average X post-2011-12	4.651	4.705	0.092	0.047
	(4.674)	(4.799)	(0.194)	(0.194)
More effective X post-2011-12	5.929	8.595+	0.051	0.030
	(4.773)	(4.892)	(0.199)	(0.198)
Most effective X post-2011-12	9.415+	11.056*	-0.142	-0.239
	(4.833)	(4.943)	(0.201)	(0.200)
L.A. Community Area Fixed Effects	Y	N	Y	N
School Fixed Effects	N	Y	N	Y

Notes:

[1] All models include academic year fixed effects; models 1 and 3 include L.A. community area fixed effects.

[2] Parental education index is operationalized as a continuous variable and standardized to have mean of 0 and SD of 1.

[3] ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$ (two-tailed test).

TABLE A17

Three-level Hierarchical Linear Models Predicting School-Year Enrollment Patterns (2000-01 – 2012-13) by Student Race/Ethnicity, Partial Output

School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

Race/Ethnic Student Group	**White**		**Black**	
School-Year Outcome	Model 1 **Total Number of White K-5 Students**	Model 2 **K-5 Students % White**	Model 3 **Total Number of Black K-5 Students**	Model 4 **K-5 Students % Black**
Prior academic year controls				
Lagged dependent variable	103.261**	18.844**	99.643**	15.279**
	(0.650)	(0.105)	(0.623)	(0.088)
Lagged dependent variable, squared	1.136**	0.172**	1.143**	0.289**
	(0.153)	(0.032)	(0.137)	(0.020)
Parental education index	1.925**	0.210**	0.316	-0.035
	(0.293)	(0.045)	(0.298)	(0.034)
Academic Performance Index	1.283**	0.013	0.595	-0.001
	(0.347)	(0.052)	(0.377)	(0.043)
Time-invariant school characteristics				
Magnet school on-site	-1.167*	-0.203**	0.896	0.166**
	(0.528)	(0.073)	(0.534)	(0.060)
Charter school	1.695*	0.009	0.427	0.050
	(0.856)	(0.119)	(0.825)	(0.095)
Year school opened	0.057	0.016	0.140	0.022
	(0.248)	(0.034)	(0.244)	(0.028)
School LA Times Value-Added Ranking (2011)				
Less effective X post-2011-12	-1.659	-0.219	-0.710	-0.215
	(0.980)	(0.149)	(1.160)	(0.133)
Average X post-2011-12	0.443	0.014	0.188	-0.105
	(0.991)	(0.151)	(1.176)	(0.135)
More effective X post-2011-12	-0.551	-0.014	-0.870	-0.086
	(1.013)	(0.155)	(1.202)	(0.138)
Most effective X post-2011-12	1.122	0.157	0.422	-0.113
	(1.023)	(0.156)	(1.215)	(0.140)

Notes:

[1] All models include academic year and L.A. community area fixed effects.

[2] Parental education index and Academic Performance Index are operationalized as continuous variables and standardized to have mean of 0 and SD of 1.

[3] ** $p < 0.01$, * $p < 0.05$ (two-tailed test).

TABLE A18

Three-level Hierarchical Linear Models Predicting School-Year Race-Specific Outcomes among Asians (2000-01 – 2012-13), Partial Output
School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

School-Year Outcome	**Total Number of Asian K-5 Students**		**K-5 Students % Asian**	
	Model 1	Model 2	Model 3	Model 4
Prior academic year controls				
Lagged dependent variable	56.965**	47.302**	7.651**	6.210**
	(0.326)	(0.714)	(0.051)	(0.100)
Lagged dependent variable, squared	-0.007	0.361**	0.047**	-0.047*
	(0.040)	(0.066)	(0.008)	(0.022)
Parental education index	0.462*	0.499	0.078**	0.079*
	(0.198)	(0.273)	(0.028)	(0.038)
Academic Performance Index	0.980**	0.496	0.106**	0.057
	(0.243)	(0.318)	(0.035)	(0.044)
Time-invariant school characteristics				
Magnet school on-site	-0.454		-0.092	
	(0.336)		(0.047)	
Charter school	0.629		0.094	
	(0.537)		(0.075)	
Year school opened	0.176		0.001	
	(0.158)		(0.022)	
School LA Times Value-Added Ranking (2011)				
Less effective X post-2011-12	0.058	-0.049	0.030	0.027
	(0.754)	(0.769)	(0.106)	(0.107)
Average X post-2011-12	-0.208	0.117	-0.057	-0.028
	(0.764)	(0.775)	(0.108)	(0.108)
More effective X post-2011-12	0.457	0.464	0.101	0.080
	(0.781)	(0.791)	(0.110)	(0.110)
Most effective X post-2011-12	1.944*	1.720*	0.238*	0.209+
	(0.790)	(0.800)	(0.111)	(0.111)
L.A. Community Area Fixed Effects	Y	N	Y	N
School Fixed Effects	N	Y	N	Y

Notes:
[1] All models include academic year fixed effects; models 1 and 3 include L.A. community area fixed effects.
[2] Parental education index and Academic Performance Index are operationalized as continuous variables and standardized to have mean of 0 and SD of 1.
[3] ** p < 0.01, * p < 0.05, + p < 0.10 (two-tailed test).

TABLE A19

Three-level Hierarchical Linear Models Predicting School-Year Race-Specific Outcomes among Latinos (2000-01 – 2012-13), Partial Output
School-year (level-1) N = 5,447, school (level-2) N = 419, community area (level-3) N = 125

School-Year Outcome	Total Number of Latino K-5 Students		K-5 Students % Latinos	
	Model 1	Model 2	Model 3	Model 4
Prior academic year controls				
Lagged dependent variable	380.287**	335.278**	27.161**	23.728**
	(1.629)	(3.913)	(0.097)	(0.246)
Lagged dependent variable, squared	0.202	12.380**	-0.329**	-0.633**
	(0.575)	(1.017)	(0.046)	(0.129)
Parental education index	2.643*	3.480*	-0.167**	-0.221**
	(1.246)	(1.688)	(0.060)	(0.071)
Academic Performance Index	-2.655+	-8.286**	-0.233**	-0.172*
	(1.496)	(2.043)	(0.062)	(0.081)
Time-invariant school characteristics				
Magnet school on-site	6.568**		0.127	
	(2.041)		(0.086)	
Charter school	3.209		0.048	
	(3.284)		(0.138)	
Year school opened	1.907+		-0.039	
	(0.983)		(0.040)	
School LA Times Value-Added Ranking (2011)				
Less effective X post-2011-12	10.417*	9.205+	0.454*	0.384*
	(4.605)	(4.756)	(0.192)	(0.193)
Average X post-2011-12	5.358	4.988	0.110	0.053
	(4.667)	(4.792)	(0.194)	(0.194)
More effective X post-2011-12	6.830	9.409+	0.085	0.049
	(4.774)	(4.889)	(0.199)	(0.198)
Most effective X post-2011-12	10.812*	11.459*	-0.148	-0.236
	(4.827)	(4.937)	(0.201)	(0.200)
L.A. Community Area Fixed Effects	Y	N	Y	N
School Fixed Effects	N	Y	N	Y

Notes:
[1] All models include academic year fixed effects; models 1 and 3 include L.A. community area fixed effects.
[2] Parental education index and Academic Performance Index are operationalized as continuous variables and standardized to have mean of 0 and SD of 1.
[3] ** $p < 0.01$, * $p < 0.05$, + $p < 0.10$ (two-tailed test).