Does the Market Value Value-Added? Evidence from Housing Prices After a Public Release of School and Teacher Value-Added

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Abstract

We study a public release of school and teacher value-added data in Los Angeles to identify how this information is capitalized into housing prices. Via difference-in-differences, we find no evidence of a response to either school or teacher value-added rank, even though test score levels are capitalized into home prices. Given ample evidence that this information was new to residents, widely dispersed, and was easily available, our results suggest that either homeowners do not understand value-added models, leading people to discount value-added in decision making or, if they do understand value-added, that they do not value it on the margin.

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1 Introduction

There is a large and growing body of research showing the importance of both school and teacher quality in driving student academic achievement and long-run life outcomes (e.g., Chetty, Friedman and Rockoff, 2012b; Rivkin, Hanushek and Kain, 2005; Rockoff, 2004; Hastings and Weinstein, 2008; Card and Krueger, 1990; Abdulkadiroglu et al., 2011). This body of evidence has supported the increasing prevalence of "school choice," policies, such as open enrollment and charter schools, that seek to expand the choice set of families that may not have the financial resources to live in a district with higher-quality schools. Indeed, a core provision of the federal No Child Left Behind law mandates that students in certain low-performing schools are allowed to enroll in another school in the district, subject to there being room. The effectiveness of these policies is predicated on parents and students having sufficient information about school quality to make informed decisions about the best educational environment. Traditionally, schools, parents and researchers have relied on school-wide average test scores as their primary measure of school quality, since these measures are easily available and are simple to understand. However, these scores reflect many factors aside from the ability of schools to produce achievement improvements, such as peer composition. While many parents may independently value such characteristics of schools, a very important aspect of a given school that most families are likely to value is the quality of teachers and the ability of the school to increase student learning.

A core difficulty in providing information to parents such that they can make informed educational choices is the lack of salient and easy-to-digest data on which schools are the most productive. In recent years, however, the push to expand test-based accountability has led to a marked rise in the amount of educational outcome data that is available to both educators and parents. With this revolution in data availability has come a growth in the use of value-added models that seek to isolate the contribution of schools and teachers to test score growth. The information produced by these models is very difficult for parents to calculate on their own, but the statistical procedures used and the controversy that follows the use of value-added models also makes for an environment in which parents may have trouble discerning the quality of any value-added data they obtain. Nonetheless, a number of school districts, such as Los

Angeles, Houston, and New York City, have released such information, either voluntarily or by court order. Proponents argue that these data are valuable to parents in assessing which schools are best at producing test score gains and that they should be made publicly available. Opponents believe that these models are flawed and provide a misleading picture of school quality that could cause parents to make incorrect school choices for their children. The fact that these data are increasingly prevalent and that controversy typically surrounds their release underscores the importance of understanding how and whether parents value this information when it is provided to them in a simplified manner.

In this paper, we provide the first evidence on how housing markets in the US respond to the public release of school and teacher value-added information using a highly publicized, salient, and accessible data release in Los Angeles in 2010. The information experiment that forms the basis for our study began in August 2010, when the Los Angeles Times (LAT) published average value-added estimates for 470 elementary schools as well as individual value-added estimates for 6,000 third through fifth grade teachers in the Los Angeles Unified School District (LAUSD). We show that this value-added information was both not predictable from existing information and was not previously capitalized into home prices, suggesting that this was indeed new information to local residents. The main focus of our analysis is on the short-run effect of this information on property values, because in April 2011, LAUSD released its own value-added information and in May 2011, the LA Times updated their value-added data. Prior work has shown that home price responses to school quality information shocks occur quickly (Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011), which supports our focus on this short-run time period that was free from influence from other value-added information. However, we also examine longer-run impacts after the initial release, taking into account value-added rankings from all three releases to ensure that our results are not simply due to the short time horizon.

Using home sales data we obtained from the Los Angeles County Assessor's Office (LACAO) from April 2009 through September 2011, we first show that test score levels are capitalized at a rate similar to that found in the prior literature using boundary discontinuity methods. We then estimate difference-in-differences models that identify how home prices change after the release of value-added data as a function of the value-added scores. Despite the strong valuation of test score levels and the fact that value-added rank largely was not predictable from observable school characteristics prior to the release, we find no evidence that school or teacher value-added information affects property values. Our estimates are precise enough to rule out that learning one's school is 10 percentile points higher in the value-added distribution increases property values by more than 0.2 percent. This estimate indicates that a one standard deviation increase in value-added (corresponding to about 35 percentiles in rank at the median) would increase home prices by at most 0.7 percent, which is well below the capitalization estimates of test scores levels in prior studies (Black and Machin, 2011).[1] We also show that the size of the information shock relative to existing information did not affect property values. Overall, our results strongly indicate that the value-added information released by the LA Times was not valued by local residents.

We argue that our results are consistent with two underlying explanations that highlight the contributions of this analysis. First, our results could be driven by parents and homeowners ignoring value-added information because its release was highly contentious and value-added measures are derived from a complicated statistical model that is opaque to non-experts. The LA Times value-added model used in our context has been shown to exhibit little bias (Guarino, Reckase and Wooldridge, 2012; Chetty, Friedman and Rockoff, 2012a; Kane and Staiger, 2008; Kane et al., 2013) and appears to be a good measure of a teacher's contribution to long-run student outcomes, such as earnings and college-going (Chetty, Friedman and Rockoff, 2012b). That this value-added information is a strong measure of school and teacher quality does not mean parents valued it as such, however. Jacob and Lefgren (2007) show that *within* schools, parents have a revealed preference for teachers that are better at raising student test scores. But, parent information on teacher quality in that study does not come from value-added measures, *per se*. The uncertainty surrounding the validity of value-added information may reduce its value to parents because most parents lack the statistical knowledge to be able to assess the strengths and weaknesses of a given value-added model. This uncertainty as well as the contentiousness surrounding value-added releases is a fact of the current policy environment

[1] Our results are also consistent with evidence from Chile that signals of school quality beyond test scores do not affect enrollment patterns (Mizala and Urquiola, 2013).

that is unlikely to change in the near future.

Due to the increasing prevalence of value-added information and the likelihood that such information will continue to be released to local communities, understanding how housing markets, and individuals' behavior more generally, respond to this information in such a policy environment is of high interest. If markets do not value such information when it is widely disseminated, then this is a signal that public understanding of the models is weak, in which case it is important to improve how value-added data are disseminated and how the public is informed about the pluses and minuses of such data. Thus, simply releasing value-added data, even through a respected and impartial third party, may be insufficient to provide homeowners with the school and teacher quality information they desire without providing them with more of an understanding of how these quality measures are constructed and what they mean.

A second explanation for our results is that parents do not value information about the aspect of school quality that is measured by value-added data. In an important related study, Figlio and Lucas (2004) show that there are large home price responses to the release of "school report card" information in Florida. The grades for each school are constructed using school test score levels and pass rates, and these school quality measures can differ substantially from value-added due to the former measures also reflecting school and neighborhood composition as well as "peer quality." A large set of additional work also examines how average test score differences across schools are capitalized into home prices (Bayer, Ferreira and McMillan, 2007; Kane, Riegg and Staiger, 2006; Black, 1999) using boundary discontinuity methods at school attendance zone boundaries.[2] The results from these studies tend to find that a one standard deviation difference in test scores is associated with two to five percent higher property values. That the estimated effects of test scores on home prices is reduced significantly in these studies once they control for neighborhood characteristics (Bayer, Ferreira and McMillan, 2007; Kane, Riegg and Staiger, 2006) suggests that part of the capitalization of test scores into property values is due to the high value placed on the composition of school and neighborhood peers

[2]These studies relate differences in home values across school boundaries to differences in test scores across those boundaries. See Black and Machin (2011) for a comprehensive review of this literature. Much international work also uses this method, such as Gibbons and Machin (2003, 2006) and Gibbons, Machin and Silva (2013) in England, Fack and Grenet (2010) in France and Davidoff and Leigh (2008) in Australia.

rather than on the school's ability to educate students.[3]

In order to isolate the capitalization of school quality as it relates to the production of learning, a school quality measure that is less related to demographic characteristics than are test scores is needed. Value-added represents such a measure.[4] As we demonstrate, the correlation between the value-added scores in our study and student characteristics is much weaker than is the correlation between test score levels and these characteristics. Thus, our results provide new information about valuation of a school quality measure that provides previously unknown information about a school's or teacher's contribution to test score growth rather than information about the demographic makeup of the school.[5]

Our results indicate that releasing straightforward value-added rankings to the public does not affect property values, which suggests that homeowners do not value the information as currently constructed on the margin. Although we are not able to discern whether our results are driven by parents not valuing the aspect of schools that raises student test scores or whether they reflect difficulties in parents understanding and interpreting this information in the current context in which they were released, our findings have important implications for the benefits of releasing these data more broadly. Even though the information was widely disseminated, was available for free, and was highly publicized, we do not observe any housing market reaction. It is difficult to imagine a more effective way of disseminating school quality information than

[3]Cellini, Ferreira and Rothstein (2010) show that investments in school facilities are highly valued by local communities. These results are consistent with residents placing significant value on aspects of schools only indirectly related to learning.

[4]See Guarino, Reckase and Wooldridge (2012), Rothstein (2010), and Kane and Staiger (2008) for discussions of how different value-added models adjust for differences in underlying student ability and student demographics as well as the benefits and drawbacks of such models.

[5]A few prior studies have examined capitalization or revealed preferences of parents based on researcher-calculated value-added. The majority find no effect (e.g., Dills, 2004; Downes and Zabel, 2002; Brasington, 1999; Haurin and Brasington, 2006; Hastings, Kane and Staiger, 2010; Cullen, Jacob and Levitt, 2006), while Gibbons, Machin and Silva (2013) show evidence that test score levels and value-added are similarly valued. Although parents may know the quality of the local schools that is reflected in these value-added measures, we show in our data that the value-added information is largely not predictable from pre-existing information and was not already capitalized into home prices. If the same is true for value-added measures used in prior work, then one reason for the general lack of findings is that parents and homeowners did not have direct access to this information. In contrast, we study a unique and unanticipated release of value-added information that was designed to make this information known to the public at large. To our knowledge, this is the first analysis to identify the responsiveness of home prices to the release of this type of school quality information in the United States. Fiva and Kirkebøen (2011) study a question using a public VA release in Oslo in 2005. They find that housing prices increased as a function of this value-added information, but only for a couple months post-release. The myriad differences in housing markets and the public schooling environments between the US and Norway make it difficult to generalize their findings to the US context, however.

providing it free online and providing a lot of publicity in many media outlets surrounding the information release. If it is indeed the case that value-added data provide important information about school quality that could be of use to parents, it is important to consider methods of releasing this information that help parents and other stakeholders understand its content and use it appropriately. This is especially important from the standpoint of understanding what factors the public values in education. Until it is clear that the public understands and trusts the validity of value-added measures, we cannot be sure whether the lack of response is due to a failure of researchers and school officials to properly educate the public about these models or a more fundamental misunderstanding of what people value in schools.

2 The Release of Value-Added Information in Los Angeles

In 2010, the Los Angeles Times newspaper acquired individual testing records of elementary students in Los Angeles Unified School District via a public information request. The achievement scores were linked to teachers so that a teacher and school value-added analysis could be conducted. The LA Times hired Dr. Richard Buddin to conduct the statistical analysis. Details on the methodology can be found in Buddin (2010), but the basic strategy is to use a linear regression model with teacher fixed effects to calculate teacher value-added. Teacher fixed effects are replaced with school fixed effects to calculate school value-added. All models use data from the 2002-2003 through the 2008-2009 school years and control for lagged test scores and student characteristics. The use of several years of data has the benefit of increasing the precision of the value-added estimates relative to using only one year of recent data. Following completion of the analysis, the newspaper wrote a series of articles explaining the methodology and other issues in LAUSD throughout the month of August 2010 as a lead in to the release of the data in a simplified form on August 26, 2010. The value-added data were presented through an online database and could be accessed by anyone with a computer without charge or registration.[6] The database was searchable by school and teacher name and people also

[6]The current version of the database can be accessed at http://projects.latimes.com/value-added/. The web

could access information through various links off of the main web page.

Figure 1 shows an example of how the information was presented for a given school. Schools were categorized as "least effective," "less effective," "average," "more effective," and "most effective," which refer to the quintiles of the value-added score distribution for LAUSD. However, as Figure 1 demonstrates, the black diamond shows each school's exact location in the distribution, providing parents with the ability to easily estimate the school's percentile. Although value-added scores were generated separately for math and reading, the LA Times based their categorization on the mean of the two scores. The figure also shows the location of the school's API percentile. Although the API information was publicly available prior to August 2010, it was more difficult to find and was not accompanied by the heightened media attention that accompanied the value-added release. Thus, for many people, this API information could have been new. The value-added rank was not available in any form prior to August 2010. Finally, the web page provided passing rates on the math and English exams for each school, which was also publicly available prior to the value-added release. To keep our estimating equation simple, in our analyses we will assume that any response to the LA Times reprinting the passing rates will be reflected in responses to API.[7]

A critical question underlying our analysis is whether LA residents knew about the release of this information. Note that any school quality information intervention carries with it the difficulty of ensuring that those who are targeted receive the information. The structure of this information release, with the information being available online for free and the publicity that surrounded its release, we believe made the value-added information more salient than is typical with school quality information releases.[8] Indeed, there is substantial evidence to indicate that residents were well-informed about the LA Times database. First, the Los Angeles Times is the largest newspaper in Southern California and the fourth largest in the country by daily

portal is similar to the one that was available in August 2010 but now provides information for more teachers and more detail on the value-added measures. In most cases, one can access the original August 2010 release through links on the teacher and school web pages.

[7]This assumption is sensible because API scores are calculated almost entirely by using these test pass rates.

[8]Due to the prevalence of the Internet in 2010, the penetration of this information in Los Angeles likely was at least as large as in Florida when they first released school report card information in the late 1990s. Figlio and Lucas (2004) show that the Florida information release, which was less contentious, had less publicity surrounding it, and occurred in a period in which information was more difficult to obtain, had large effects on property values.

weekday circulation, with 616,575 copies according to the Audit Bureau of Circulations. The existence of the database was widely reported in the newspaper: from August 2010 to May 2011, a total of 37 articles or editorials were written about the database, public response to the database, or value-added issues more generally. Given the high level of circulation of the paper, the attention paid to this issue by the LA Times likely reached many residents. Further, the release of the value-added data was mentioned in other outlets, such as the New York Times, National Public Radio, the Washington Post, ABC News, CBS News, CNN and Fox News. It also received much radio and television attention in the LA area in both English and Spanish, which is of particular importance for the Spanish-speaking population that is less likely to read the LA Times but for whom radio and television are dominant sources of news.[9]

Second, the LAUSD teachers' union and the national American Federation of Teachers were highly vocal in their opposition to the public release of the data. This culminated in a series of highly publicized and widely covered protests of the LA Times by teachers. Furthermore, US Secretary of Education Arne Duncan spoke about the value-added measures, expressing his support. This indicates that news-makers were discussing the issue and gave it substantial media exposure. According to the LA Times, by late afternoon on the initial date of the release there were over 230,000 page views of the website for the database (Song, 2010). The article points out that this is an unusually large volume of views given that traffic tends to be higher during the week and provides *prima facia* evidence that the value-added release was well-publicized and known to a large number of residents. In part due to its contentious nature as well as the involvement of the largest newspaper in the area, it unlikely there could be a school quality information intervention in which the information was more readily available to local residents than was the case here.

The 2010 LA Times value-added information is the focus of our analysis. This focus necessitates an examination of short-run impacts on property values because this initial value-added data release was followed up with LAUSD releasing its own school-level value-added measure in

[9] Some examples of Spanish language coverage include a story on Channel 22 on Nov. 8, 2010 covering a protest after a teacher committed suicide in part due to value-added results (http://www.youtube.com/watch?v=RWKR8Ch06wY), a story covering an earlier protest on Channel 62 (http://www.youtube.com/watch?v=n1iNXtyPlRk), and a story on Univision 34 discussing LAUSD's own value-added measures (http://www.youtube.com/watch?v=05dE0xLdpu8).

April 2011 and the LA Times updating its value-added measure in May 2011.[10] While examining the effect of the initial LA Times release provides a more pure information experiment, it limits the analysis to 7 months post-release. In their analysis of the capitalization of value-added information in Norway, Fiva and Kirkebøen (2011) show that the positive effects were very short-run, on the order of 3 months. Figlio and Lucas (2004) further show evidence that the positive impact of school report card information in Florida on property values were largest in the first year post-release. This evidence supports our examination of short-run effects.

We also will analyze longer-run effects that account for the subsequent value-added releases. It thus is important to highlight several differences between the first LA Times release and subsequent data releases. First, we believe the LA Times used a more econometrically sound value-added model than LAUSD, as the former model controls for lagged achievement and includes multiple years of data. Guarino, Reckase and Wooldridge (2012) argue that models like this (which they call "dynamic ordinary least squares") are the most accurate. The LAUSD model, on the other hand, predicts student achievement growth from observable characteristics using one year of data, after which the differences between predicted and actual achievement are averaged together across all students in a school. While the LA Times methodology may be more appealing to researchers, we acknowledge that this does not necessarily indicate that parents believed it more. Second, there was substantial discussion of the intial LA Times release in the news and responses by education organizations, while the subsequent releases garnered less attention. Finally, it is easier to access the LA Times information. While both are available on the web, to access the LAUSD data people need to navigate through a series of links on the LAUSD website.

It also is interesting to note that the correlations between both of the LA Times releases and the LAUSD value-added scores are very low. Figure 2 presents comparisons of the three school-level value-added measures using scatter plots with each school as an observation. The

[10] LAUSD's value-added measure was called Achievement Growth over Time (AGT) and was only provided to the public at the school level. The details of their methodology can be found at http://portal.battelleforkids.org/BFK/LAUSD/FAQ.html. Details on the May 2011 LA Times methodology can be found in Buddin (2011). For this release, the LA Times also gave people the option to see how value-added scores changed using variations in methodology through an interactive program on the website. Since it is likely that most people who accessed the database did not attempt to compare different methods, we only use the value-added scores directly published on the website by the LA Times in our data.

top left panel shows that the percentiles of the 2010 LA Times value-added are highly correlated with the 2011 LA Times value-added, with a correlation coefficient of 0.74.[11] However, each of the LA Times value-added measures are very weakly correlated with the LAUSD measure - the correlation coefficients are 0.15 and 0.39 for the August and May releases, respectively. This likely reflects the differences in the methodology described above and the amount of data used.

3 Data

To assess the impact of the value-added data release on property values, we combine data from several sources. First, we use home price sales data from the Los Angeles County Assessor's Office (LACAO). The data contain the most recent sale price of most homes in LA County as of October, 2011, which in addition to LAUSD encompasses 75 other school districts. We restrict our data to include all residential sales in LAUSD that occurred between April 1, 2009 and September 30, 2011.[12] From LACAO, we also obtained parcel-specific property maps, which we overlay with the school zone maps provided to us by LAUSD to link properties to school zones.[13] Although there is open enrollment throughout LAUSD, spaces are very limited at around 1.5% of total enrollment. Thus, these catchment zones define the relevant school for the vast majority of students in the District. The property sales data additionally contain information on the dates of the three most recent sales, the square footage of the house, the number of bedrooms and bathrooms, the number of units and the age of the house that we will use to control for any potential changes in the composition of sales that are correlated with value-added information.

To remove outliers, we drop all properties with sale prices above $1.5 million (5% of households) and limit our sample to properties in elementary school zones in Los Angeles Unified

[11] An important question arises as to why the value-added estimates differed across LA Times data releases. This was due to three factors: methodology changes, increases in the number of teachers included in the value-added calculations, and an additional year of data on teachers included in the first release. If we drop all schools with percentile rank changes greater than 20, the correlation between value-added ranks across LAT releases is 0.96. Critically, our estimates are unaffected by this sample restriction. These results are available upon request.

[12] Given that the value-added information only varies across schools within LAUSD, the addition of school fixed effects leaves little to be gained from adding the rest of LA County. Specifications using home price sales from all of the county, setting value-added percentiles equal to zero outside of LAUSD and controlling for school district fixed effects, provide almost identical results.

[13] The school zones are for the 2011-2012 school year.

School District that received value-added scores in the August 2010 release. About 25% of the residential properties in the data do not have a sale price listed. Usually, these are property transfers between relatives or inheritances.[14] Hence, we limit our sample to those sales that have "document reason code" of "A," which denotes that it is a "good transfer" of property. After making this restriction, only 7% of observations are missing sale prices. For these observations, we impute sale prices using the combined assessed land and improvement values of the property. For observations that have all three measures recorded, the correlation between actual sale price and the imputed sale price is 0.89, indicating that the imputation is a very close approximation to the actual market value. Furthermore, we know of no reason why the accuracy of the imputation procedure should be correlated with value-added information, which supports the validity of this method. Nonetheless, in Section 5, we provide results without imputed values and show they are very similar. Our final analysis data set contains 63,122 sales, 51,514 of which occur prior to April 2011.

We obtained the exact value-added score for each school directly from Richard Buddin, and the April 2011 LA Times school value-added data as well as the August 2010 teacher-level value-added data were provided to us by the LA Times. The LAUSD value-added information was collected directly from Battelle for Kids, with whom LAUSD partnered to generate the value-added measures.[15] The value-added data were combined with school-by-academic-year data on overall API scores, API scores by ethnic and racial groups, school-average racial composition, percent on free and reduced price lunch, percent disabled, percent gifted and talented, average parental education levels, and enrollment. These covariates, which are available through the California Department of Education, control for possible correlations between value-added information and underlying demographic trends in each school. To maintain consistency with the LA Times value-added data, we convert both the LAUSD value-added scores and API scores into percentile rankings within LAUSD.

Similar to Black (1999), we also link each property to its Census block group characteristics

[14] California allows relatives to transfer property to each other without a reassessment of the home's value for property tax purposes. Due to property tax caps, this rule creates large incentives for within-family property transfers in California, and hence there are a lot of such transactions in the data. Because these transfers do not reflect market prices, we do not include them in our analysis.

[15] The data are available at http://portal.battelleforkids.org/BFK/LAUSD/Home.html.

from the 2007-2011 American Communities Survey (ACS) to use as controls. In particular, we use the age distribution of each block group (in 5 year intervals), the percentage with each educational attainment level (less than high school, high school diploma, some college, BA or more), the percentage of female headed households with children, and median income. We also collect a host of additional Census tract level data from the 2007-2011 ACS. These are used to help test the validity of our identifying assumptions.

Summary statistics of some key analysis variables are shown in Table 1. The table presents means and standard deviations for the full sample as well as for the sample above and below the median value-added score for the 2010 LA Times release. On average, home sales in LAUSD are in Census block groups that are over 50% black and Hispanic,[16] but the schools these properties are zoned to are 74% black and Hispanic, with the difference ostensibly due to enrollments in private, charter and magnet schools. The schools in our data set also have a large proportion of free and reduced price lunch students. The second two columns of Table 1 show that value-added is not completely uncorrelated with school or block group demographics, although housing characteristics are balanced across columns. The higher value-added areas have a lower minority share, higher property values, a more educated populace and have higher API scores. These correlations could be driven by the fact that better schools are indeed located in the higher socioeconomic areas, or they could be an indication that the value-added models used do not fully account for underlying differences across students.

Figure 3 shows that, despite the differences shown in Table 1, value-added is far less correlated with student demographic makeup than are API scores. The figure presents the non-free/reduced-price (FRP) lunch rate, API percentile (within LAUSD) and value-added percentile for each elementary school in LAUSD. The boundaries denote the attendance zone for each school. As expected, API percentiles, which are based on test score proficiency rates, map closely to poverty rates. High-poverty (low non-FRP lunch) schools tend to have lower API scores. While this relationship remains when replacing API with value-added, it is far less robust. There are many schools, particularly in the eastern and northern sections of the

[16] Note that since the ACS counts Hispanic as a separate category from race, some of the black and white populations are also counted as Hispanic.

district, where API scores are low but value-added scores are high. Similarly, some schools with high API scores have low value-added scores. Figure 4 further illustrates this point. It provides scatter plots of API percentiles versus value-added percentiles for each of the three value-added measures. While there is a positive relationship between value-added and test score levels, it is quite weak: the correlation between the 2010 LAT value-added rank and API rank is only 0.45. As seen in Figure 3, there are a number of schools which, based on API, are at the top of the distribution but according to the value-added measure are at the bottom, and vice-versa. For example, Wilbur Avenue Elementary had an API percentile of 91 in 2009 but an initial value-added percentile of 13. On the other end of the spectrum, Broadous Elementary had an API percentile of 5 but a value-added percentile of 97.

The fact the API rank and value-added rank are only weakly related to each other does not mean that the value-added information provided by the LA Times was new information. It is possible that each of these measures could be predicted based on existing observable characteristics of the school. In Table 2, we examine this issue directly, by predicting API percentile and the percentiles of each value-added measure as a function of school observables in the pre-release period. We use as our predictors of school quality all of the school-level variables included in our property value analysis in order to show how much unexplained variation there is in value-added rank after controlling for school characteristics included in our main empirical model. Column (1) shows the results for API percentile, and as expected, with an R^2 of 0.71, school demographics explain a substantial amount of the variation. In contrast, as shown in column (2), the value-added estimates are much more weakly correlated with school demographics. Only two of the estimates are statistically significant at the 5% level, and the R^2 is only 0.22. In Column (3), we add overall API, within-LAUSD API rank, and each student subgroup's API scores as well as two years of lags of each of the API scores as regressors. The R^2 rises to 0.41, but it remains low. Thus, almost 60% of the value-added variation is unpredictable from the observable characteristics of the school, including test score levels. In the final four columns, we show results from similar models that use the percentiles in the second LAT value-added release (columns 4 and 5) and the LAUSD value-added release (columns 6 and 7) as dependent variables. The results are similar to those using the first LAT release.

Table 2 and Figures 3-4 show that the value-added data released to the public by the LA Times and LAUSD contained new and unique information about school quality that was not predictable from observed demographics and school test score levels. Our empirical model exploits this new information by identifying the impact of value-added on housing prices *conditional* on API along with many other observable characteristics of schools and neighborhoods. Since these characteristics are observable to homeowners as well, we are able to identify the impact of this new information given the information set that already exists.

4 Empirical Strategy

Our main empirical strategy is to estimate difference-in-difference models that compare changes in property values surrounding the information releases as a function of value-added rank conditional on observable school and neighborhood characteristics, including API. Since value-added only was released for elementary schools, we ignore middle and high school zones. Our main empirical model is of the following form:

$$\begin{aligned} Y_{ist} &= \beta_0 + \beta_1 VA_{st} + \beta_2 API_{st} + \beta_3 API_{st} \times Post_t \\ &\quad + \mathbf{X}_{st}\Gamma + \mathbf{H}_i\Phi + \lambda_t + \gamma_s + \epsilon_{ist}, \end{aligned} \tag{1}$$

where Y_{ist} is the log sale price of property i in elementary school zone s in month t. The key explanatory variable of interest is VA_{st}, which is the August 2010 LA Times value-added percentile. This variable is set equal to zero prior to the first release in September, 2010 and is equal to the LA Times value-added percentile rank thereafter. In order to focus on the first LA Times information shock, we estimate this model using data from April 1, 2009 to March 31, 2011. This sample restriction allows for 7 months of property sale observations post-treatment.

As discussed in Section 2, the LA Times also posted API rank on their website, which may have made this information more salient to residents. Thus, in equation (1) we allow for the effect of API to vary post-August 2010. Furthermore, we include in the model school fixed effects (γ_s) that control for any fixed differences across schools that reflect fixed school quality differences and month-by-year fixed effects (λ_t) that control for any district-level changes in home prices occurring contemporaneously with the information release, including seasonal changes. Our inclusion of these fixed effects implies that all parameters are identified off of within-school changes in home prices over time. The coefficients β_1 and β_2 thus represent difference-in-difference estimates of the effect of having a higher value-added or API score on property values after the information release relative to before the release.[17] In order to account for the fact that there are multiple sales per school zone, all estimates are accompanied by robust standard errors that are clustered at the school-zone level.

Equation (1) also includes an extensive set of controls to account for any confounding effects driven by the correlation between the value-added release and contemporaneous changes in school demographics or housing characteristics. The vector X contains the set of school observables discussed above, including current and two years of lagged overall API, current and two years of lagged API for each student subgroup,[18] within-LAUSD API percentile rank in the given academic year,[19] the percent of students who are black, Hispanic, and Asian, the percent on free/reduced price lunch, who are gifted, who are in special education and who are English language learners. School-by-year enrollment and the percent of the school's parents who are high school graduates, have some college, have a BA and have graduate school training are included in X as well. The vector H is the set of house-specific characteristics and Census block group characteristics discussed above that further control for local demographic differences that are correlated with value-added and for any changes in the types of houses being sold as a function of value-added when the information is released.

There are two main assumptions underlying identification of β_1 in equation (1). First, the model assumes that home prices were not trending differentially by value-added prior to the data release. Using the panel nature of our data, we can test for such differential trends directly in an event-study framework. In Figure 5, we present estimates using the first value-added release,

[17]Note that unlike API, which changes each year, each value-added release provides a single value for each school, and thus the main effect is removed by the school fixed effects. In models that do not include school fixed effects, the main effect is included as a control variable.

[18]Student subgroups include blacks, whites, Asians, Filipinos, Hispanics, gifted students, special education, economically disadvantaged and English language learners.

[19]For this study we define the academic year as running from September through August.

where VA and API are interacted with a series of indicator variables for time relative to the August 2010 LA Times release.[20] These estimates stop at 7 months post-treatment due to the subsequent data releases. The top panel of Figure 5 shows no evidence of a pre-release trend in home prices as a function of LAT value-added. The estimates exhibit a fair amount of noise, but home prices are relatively flat as a function of future value-added rank in the pre-treatment period. Thus, there is no evidence of pre-treatment trends that would bias our estimates. For API shown in the bottom panel, there is a slight downward trend in earlier months, but it is not statistically different from zero. By 7 months prior to the release, however, property values flatten as a function of API.

Figure 5 also previews the main empirical finding of this analysis: home prices do not change as a function of value-added or API post-release. The figure shows as well that these estimates are relatively imprecise, as event study models are demanding of the data. We thus favor the more parametric model given by equation (1). Nonetheless, Figure 5 demonstrates that there do not appear to be any time-varying treatment effects that are masked by the equation (1) specification.

The second main identification assumption required by equation (1) is that the value-added percentile, conditional on school characteristics, is not correlated with unobserved characteristics of households that could affect prices. While this assumption is difficult to test, given the rich set of observable information we have about the homes sold, examining how these observables shift as a function of value-added will provide some insight into the veracity of this assumption. Thus, in Table 3, we show estimates in which we use neighborhood characteristics (measured using both Census block group and Census tract characteristics), school demographics and housing characteristics as dependent variables in regressions akin to equation (1) but only including API percentiles, API percentile interacted with a post-release indicator, time fixed effects and school fixed effects as controls.[21] Each cell in the table comes from a separate regression and shows how the observable characteristic changes as a function of value-added percentile after the first LA Times data release. Overall, the results in Table 3 provide little

[20]Event studies using the full analysis period and including all three VA releases are provided in Online Appendix Figure 1.

[21]The school characteristics estimates in Panel C use data aggregated to the school-year level.

support for any demographic or housing type changes that could seriously impact our estimates. There are 53 estimates of housing and neighborhood characteristics in the table; two are significantly different from zero at the 5% level and only 5 are significant at the 10% level. While clearly these variables are not independent, if they were we would expect to falsely reject the null at the 10% level six times.[22] Furthermore, the estimates, even when significant, are small, and the signs of the estimates do not suggest any particular patterns that could cause a systematic bias in either direction.

Another concern is that the release of a value-added score may induce changes in the number of homes sold in a school catchment area. Since we only observe prices of homes that are sold, we may understate the magnitude of the effect if having a lower value-added reduces the number of homes sold and this reduction comes from the bottom of the price distribution. To test this hypothesis, we estimate a version of equation (1) in which we aggregate the data to the school-month level and use the total number of sales or the total number of sales with a valid sales price in each school-month as the dependent variable.[23] We find little evidence of a change in the number of sales. The estimate of the effect of LA Times value-added on total sales[24] is -0.0098 with a standard error of 0.0062. Taken at face value, this would suggest that a 10 percentile increase in value-added only reduces monthly sales by 0.1 off of a mean of 8.4. For sales with price data, the estimate is -0.0027 with a standard error of 0.0032.

The value-added releases we study come at a time of high volatility in the housing market, as home prices declined during this period throughout most of the United States. In the Los Angeles MSA, prices declined by 4.5%.[25] This was also a period with a large number of foreclosures in Los Angeles. If foreclosure rates are correlated with the value-added releases, it could bias our home price estimates because foreclosures tend to be sold at below market value. In order to provide some evidence on this potential source of bias, we use the num-

[22]Estimates that include the second LA Times release and the LAUSD data also show no evidence that the release of these data is correlated with demographic changes in schools or neighborhoods. These results are available upon request.

[23]We include neighborhood characteristics of properties sold in a school zone and school characteristics but do not control for aggregate individual property characteristics as these may be endogenous in this regression.

[24]Our data only cover the three most recent sales of a property. Thus, our measure of total sales will be slightly underestimated.

[25]This calculation comes from the Federal Housing Finance Agency's seasonally adjusted home price index. Note that this decline was smaller than the 7% rate for the US as a whole during this period.

ber of foreclosures in each month and zip code in LAUSD that were collected by the RAND Corporation.[26] We aggregate prices to the school-month level and use the zipcode-level data to approximate the number of foreclosures in the school catchment area in each month. The resulting estimates show little evidence of a correlation between value-added post-release and the number of foreclosures. The coefficient on the LA Times value-added variable is only 0.003 (0.009), which indicates that a 10 percentile value-added increase post-release increases the number of monthly foreclosures in a school zone by 0.03, off of a mean of 5.7. Overall, the estimates described above along with those provided in Table 3 and Figure 5 provide support for our identification strategy.

Equation (1) includes only 7 months of post-release property sales. In order to examine longer-run effects, we modify the estimating equation to account for the subsequent releases of value-added information by the LA Times and by LAUSD. The model we estimate is:

$$\begin{aligned} Y_{ist} &= \beta_0 + \beta_1 VA_{st}^{LAT1} + \beta_2 VA_{st}^{LAT2} + \beta_3 VA_{st}^{LAUSD} + \beta_4 API_{st} + \beta_4 API_{st} \times Post_t \\ &\quad + \mathbf{X}_{st}\Gamma + \mathbf{H}_i\Phi + \lambda_t + \gamma_s + \epsilon_{ist}, \end{aligned} \tag{2}$$

where VA_{st}^{LAT1} is the first LA Times value-added measures, which is equal to zero prior to the first release in September, 2010. The variable VA_{st}^{LAT2} is the second LA Times value-added measure and is equal to zero prior to June 2011, and VA_{st}^{LAUSD} is the LAUSD value-added measure, which is set equal to zero prior to May 2011. All other variables are as defined above.[27]

5 Results

5.1 Relationship Between House Prices and API

Before presenting the main difference-in-differences estimates, it is important to establish that some measures of school quality are indeed valued by LA residents. Whether public school

[26] These data are available at http://ca.rand.org/stats/economics/foreclose.html.

[27] Appendix Figure 1 shows event study estimates for this model. In no case is there evidence of pre-treatment trends as a function of future information, and there also is little evidence of any treatment effect.

quality, or public school characteristics more generally, are capitalized into home prices in Los Angeles is not obvious, as LAUSD has an active school choice system in which students can enroll in a non-neighborhood school. There also is a large charter school and private school presence in the district. Thus, any finding that property values do not respond to value-added information could be driven by a general lack of association between local school characteristics and property values. Nonetheless, there are a few reasons to believe that this is not a major concern in the Los Angeles context. First of all, the open-enrollment program is small relative to the size of the district. In 2010-2011, only 9,500 seats were available district-wide, accounting for at most 1.5% of the district's 671,000 students. Second, while LAUSD has a number of magnet programs, they are highly sought after and oversubscribed, hence admission to a desired magnet is far from guaranteed. Third, Los Angeles is a very large city with notorious traffic problems and poor public transportation, making it difficult for parents to send their children to schools any substantial distance from home.

To further address this issue, we estimate boundary fixed effects models in which API percentile is the dependent variable. This model is similar to the one used in Black (1999) as well as in the subsequent other boundary fixed effects analyses in the literature (Black and Machin, 2011) and allows us to establish whether average test scores are valued in LA as they have been shown to be in other areas. We estimate boundary fixed effects models using only data from prior to the first release of the LA Times value-added data so that none of these estimates can be affected by this information.

Panel A of Table 4 contains results comparing home prices within 0.2 miles of an elementary attendance zone boundary. In column (1), which includes no controls other than boundary fixed-effects, properties just over the border from a school with a higher API rank are worth substantially more. For ease of exposition, all estimates are multiplied by 100, so a 10 percentage point increase in API rank is associated with a 4.5% increase in home values in the pre-release period. In column (2), we control for housing characteristics, which have little impact on the estimates. However, controlling for Census block group demographics in column (3) significantly reduces this association. This result is not surprising given the findings in Bayer, Ferreira and

McMillan (2007) and Kane, Riegg and Staiger (2006).[28] Nonetheless, in column (3), we find a 10 percentage point increase in API rank is correlated with a statistically significant 1.3% increase in property values. This estimate is roughly equivalent in magnitude to those in Black (1999) and Bayer, Ferreira and McMillan (2007). Thus, this school characteristic is similarly valued in Los Angeles as in the areas studied in these previous analyses (Massachusetts and San Francisco, respectively). Estimates using properties within 0.1 mile of a school zone boundary are similar, as shown in Panel B.[29] It remains unclear, however, whether the capitalization of API scores is driven by valuation of schools' contribution to learning or by valuation of neighborhood or school composition that is correlated with API levels. Our analysis of capitalization of value-added information is designed to provide insight into resolving this question, which is very difficult to do without a school quality measure that is only weakly correlated with student demographics.

In order to underscore the fact that, conditional on achievement levels, value-added is weakly correlated with student demographics and is difficult to predict with pre-release observables, the final column of Table 4 tests whether value-added information is capitalized into property values prior to the public release. If parents know which schools are the highest value-added from reputation or from factors we cannot observe, the value-added release should not provide additional information about school quality and should already be capitalized into home prices. In column (4) of Table 4, we estimate the same boundary fixed effects model as in column (3) but include the first LA Times VA percentile as well. The estimate, based off of data in the pre-release period, tests whether future information about value-added is already capitalized into home prices. The results show that in the pre-release period, property values were not higher right across a school catchment boundary when future value-added is higher. The estimate is small and is not statistically significant at conventional levels regardless of whether we limit to 0.2 or 0.1 miles from the boundary. However, the API boundary effect is very similar to the estimate in column (3), suggesting that the capitalization of API scores is not being driven

[28] We do not control for school demographics because these demographics may be part of what determines the valuation of API.

[29] The 0.2 and 0.1 bandwidths were chosen to be consistent with prior work, most notably Black (1999) and Bayer, Ferreira and McMillan (2007).

by value-added information and that any information contained in the LA Times value-added estimate is not already capitalized into home prices prior to August 2010. Overall, we view the results in Table 4 as showing that the value-added information released through the LA Times website was not previously known to residents.

5.2 Difference-in-Difference Estimates

Table 5 presents the baseline estimates from equation (1). In each column, we add controls sequentially in order to observe the effects of the controls on the estimates. All estimates are multiplied by 100, so they show the effect of a 100 percentile increase in value-added on home prices post-release. Panel A shows results examining just the first LA Times value-added information. We include no controls except API and VA main effects in column (1) and then add in the school, neighborhood and housing characteristics discussed in Sections 3 and 4 in column (2). Column (3) contains our preferred estimates, which include school zone and month fixed effects. Across columns, there is no evidence that a higher value-added leads to higher home prices. Regardless of the controls used, the estimates are small and are not statistically significant. In column (3), the point estimates indicate that a 10 percentage point increase in value-added decreases property values by 0.3 percent. This estimate is precise enough that we can rule out a 10 percentage point increase in value-added increases home prices by more than 0.2% post-release. To relate this estimate to the prior literature, at the median a one standard deviation increase in value-added corresponds to a roughly 35 percentile increase in rank. Using the upper bound of the 95% confidence interval, this translates into at most a 0.7% increase in home prices. This estimate is well below capitalization effects found using test score levels in prior work (Black and Machin, 2011).

Columns (4) and (5) of Table 5 provide further evidence that value-added information does not affect property values. In these columns, we provide results from a model similar to those used in Table 4 that restricts to properties within 0.1 miles of a school zone boundary and includes boundary fixed effects. Thus, the estimates are identified off of changes in property values between properties on either side of a given attendance zone boundary when the value-added data are released. Note that unlike in Table 4, these models also include school zone fixed effects and API controls. These estimates show little evidence of a positive capitalization effect of the LA Times value-added information.[30]

In Panel B of Table 5, we present estimates of equation (2) using the longer time frame that includes the second LA Times release and the LAUSD release. Similar to the results in Panel A, the estimates all are small and are not statistically significantly different from zero at conventional levels. None of the value-added releases we examine leads to significant changes in property values, which suggests the lack of effects in Panel A of Table 5 is not being driven by our use of a short post-treatment window. The same result holds for the API rank estimates in both panels of the table. There was no *change* in the relationship between API scores and home prices when the LA Times posted API percentiles on its website.

As discussed above, a unique feature of the LA Times information release was that it included both school-average value-added and value-added rankings for over 6,000 teachers in LAUSD. We now examine whether property values respond to the release of information on teacher quality, which is the first evidence in the literature on this question. Because the extended sample provides little additional information but increases the complexity of the analysis due to multiple data releases, for simplicity we examine the capitalization of teacher quality for the first LA Times release only.

In column (1) of Table 6, we add the standard deviation of the value-added scores across teachers in each school interacted with an indicator for the post-release period. If high-quality teachers are disproportionately valued (or if low-quality teachers have a disproportionately negative valuation), then a higher standard deviation will lead to higher (lower) property values conditional on school-wide value-added. The estimate on the standard deviation of teacher value-added is positive, but it not statistically significantly different from zero. It also is small, pointing to an increase in property values of only 0.007% for a one point increase in the standard

[30] Another outcome that reflects parents' valuation of schools is changes in enrollment patterns. Unfortunately, our data do not allow us to track transfers between schools. However, we are able to look at whether overall school enrollment is affected by value-added scores. When using enrollment as an outcome at the school-year level, we find an impact estimate of the VA percentile of 0.09 (s.e. 0.11), which suggests an insignificant increase of 0.9 students for every 10 percentile increase in VA. Interestingly, the estimate on API$\times$Post is significant at the 10% level with an estimate of 0.32 (0.18), or 3 students per 10 percentiles of API.

deviation of teacher value-added rank.

In column (2), we interact the proportion of teachers in each quintile of the value-added distribution with being in the post-August 2010 period. Again, we see little evidence that having a higher proportion of teachers with high value-added leads to higher property values, nor does a high proportion of low VA teachers reduce property values. Aside from the 3^{rd} quintile estimate, the coefficients all are positive, but they are small: moving 10% of the teachers from the bottom to the top quintile would increase property values by 0.1%. Because the distribution of teacher value-added within a school might be highly correlated with school value-added, in column (3) we re-estimate the teacher value-added model without controlling for school value-added. There is even less evidence that a higher proportion of high-VA teachers leads to higher property values in this specification. This result is surprising, given the strong correlation between teacher quality and student academic achievement as well as future earnings that has been shown in prior research (Rivkin, Hanushek and Kain, 2005; Rockoff, 2004; Chetty, Friedman and Rockoff, 2012b).

One potential concern with examining valuation of teacher quality at the school level is if teacher turnover is high, parents might rationally ignore this information. Although we were unable to obtain direct turnover data from the District, we collected yearly data at the school level on the size and experience of the teacher workforce from the California Longitudinal Pupil Achievement Data System (CALPADS). The data span the 2000-2001 through the 2008-2009 school years for all elementary schools in California, and they suggest the workforce is relatively stable from year to year in LAUSD. First, the year-to-year correlation in the size of the teacher workforce is high, at 0.99. There still could be turnover, however, with exiting teachers being replaced by entering ones. But, the median school has one teacher with less than one year of experience (out of 32 total teachers), which is inconsistent with large amounts of turnover. The year-to-year correlation in teacher experience is 0.93 as well, suggesting the workforce within each school is stable. Finally, we can observe the number of teachers with two years of experience, and the difference between the number of teachers with one year of experience in the prior year and the number with two years of experience in the current year is 0 for 75% of schools. Thus, even among less-experienced teachers there is little turnover. These tabulations suggest the lack of responsiveness of housing prices to teacher value-added information is not driven by families rationally ignoring this information due to high teacher turnover.

The remaining columns of Table 6 present estimates based on some alternative modeling assumptions. In column (3), we use the school value-added quintile rank instead of the percentile rank. This is because, as shown in Figure 1, the quintile was the most salient value-added information on the LA Times website. The results are consistent with those in Table 5. The top two quintile estimates are negative, and the 2^{nd} and 3^{rd}, while positive, are not statistically different from zero.

Finally, if a neighborhood has fewer school choice options, it is possible there would be more capitalization of the local school's quality. To test this hypothesis, in column (4) we interact the value-added score with the number of charter schools within a one mile radius of the property. We find no evidence that the capitalization of value-added varies with the number of charter schools nearby. Results were similar using a two mile radius.

As shown in Table 2, the value-added information was largely not predictable by the set of observable school characteristics that existed prior to August 2010. However, the LA Times release occurred in a context where there was a lot of existing information about school quality in terms of observed test score levels and student composition. In Table 7, we test whether the value-added information had a larger effect when it deviated more from this existing information. In column (1), we use as our deviation measure the difference between the LA Times value-added percentile rank and the API percentile rank in 2009. The estimate is negative and is not statistically significantly different from zero, suggesting that positive value-added information relative to existing API information did not increase property values.

In the subsequent columns of Table 7, we characterize existing school quality information using a factor model that includes 2009 API scores, overall and by racial/ethnic group, the racial/ethnic composition of the school, the parental education distribution of the school, and the percent of free/reduced price lunch, disabled, gifted, and English language learners. We also include two years of lags of each of these variables. This factor model thus incorporates a large set of the publicly available observable characteristics about a school in the current year and in the prior two years that a parent could use to generate beliefs about school quality.

The model isolates 22 factors that explain over 85% of the variation in these variables. In column (2) of Table 6, we examine the capitalization of the difference between the LA Times value-added percentile rank and the percentile rank of the first primary factor (explaining 26% of the variance). In column (3), we combine all 22 factors by calculating the percentile rank for each factor and then taking a weighted average, where the weight is the percent of the variance explained by the factor divided by 0.85. The final column shows results that allow for the deviations from the first primary component rank and from a weighted average of all other factor ranks to have different effects on property values. In all cases, we find no evidence that when the LA Times value-added differs from these factor ranks property values rise post-LA Times release. These estimates indicate little support for the contention that the relative size of the information shock affected home prices.

Although there is no average effect of value-added information on property values, the extent of capitalization could vary among different types of schools or among different populations.[31] We now turn to an examination of several potential sources of heterogeneity in value-added capitalization. In Figure 6, we present estimates broken down by observable characteristics of the school: 2009 within-LAUSD API quintile, median pre-release home price quintile, percent free and reduced price lunch, percent black, percent Hispanic, and percent white. Although the precision of the estimates varies somewhat, the point estimates are universally small in absolute value and are only statistically significantly different from zero at the five percent level in two cases (out of 45 estimates).

Nonetheless, the estimates in the second panel do show a small but notable negative gradient in prior house prices, suggesting that lower-priced neighborhoods are more affected by value-added. Percent free/reduced-price lunch and percent Hispanic show similar patterns, although the estimates are not statistically significantly different from each other. Given that all three of these measures are correlated with socioeconomic status, these figures provide suggestive evidence that - to the extent the value-added scores are capitalized - the impact is larger in

[31] In Online Appendix Table A-1, we also redefined the treatment to be value-added rank among schools within 2, 4, 6, 8 or 10 miles in order to account for the fact that school choice markets may be highly localized. We also match schools to demographically similar schools and examine the effect of relative rank amongst these similar school types. None of these estimates indicate an effect of value-added information on property values.

lower-income neighborhoods.

5.3 Robustness Checks

The last row of Figure 6 provides insight into two potential criticisms of using housing prices as our outcome measure. The first panel addresses concerns that many neighborhoods in Los Angeles have high rates of private schooling and thus are likely to be less sensitive to the quality of the local public school. We show estimates that are interacted with the private schooling rate in the Census tract of each property from the American Communities Survey. The mean private schooling rate in our sample is 20%, with a standard deviation of 31%. The estimates show little difference in capitalization by private schooling rate. In the second panel of the last row, we measure variation by owner-occupancy rates, also calculated from the ACS. The concern here is that in neighborhoods with low owner-occupancy rates, sale prices may be less sensitive to school quality. The mean of this measure is 50.1%, with a standard deviation of 23.3%. Once again, we see little evidence of heterogeneity along this margin.

Table 8 provides a series of additional robustness checks in order to assess the fragility of our results with respect to several modeling assumptions.[32] In column (1), we include Census tract fixed effects. Relative to the baseline estimate in column (3) of Table 5, The LA Times value-added estimate becomes even more negative. Next, we exclude the lagged API measures in case they are capturing a large amount of the value-added variation. The results are very similar to those in Table 5. In column (3), we use sale prices in levels rather than in logs. Converting the estimate to percent terms using the mean home price in Table 1 yields an almost identical result to baseline. In the next two columns, we limit to homes with less than 2 and at least 3 bedrooms, respectively, in order to better isolate homes that have children in them. The estimates do not provide any evidence of a link between value-added information and property values for these samples.

Although we impute property values for about 7% of the sales, column (6) of Table 8 shows excluding these imputed sale prices from our regression makes the value-added estimate more

[32]Appendix Table A-2 provides these estimates using the full sample period and including all value-added releases. Results are similar to those seen in Table 8.

negative. We next exclude properties with more than 8 bedrooms in column (7), which either are very large homes or are multiple unit dwellings. We alternatively exclude properties over 5,000 square feet in column (8) and drop multiple unit properties in column (9). For each of these cases, the estimates are quantitatively and qualitatively similar to our baseline results. In column (10), we allow for there to be a 3 month lag between when the information is released and when it impacts the housing market by setting the value-added to zero in first 3 months post-release. We continue to find no effect of value-added information on property values. Taken together, the results from Table 8 suggest that our findings are not being driven by outliers, the manner in which we measure home prices, or by the timing of the treatment.[33] Finally in Table 8 we estimate a model that excludes *API*Post*, which has little impact on the value-added coefficient we obtain.

6 Alternative Mechanisms

Our preferred interpretation of the results is that homeowners place, at most, a negligible valuation on value-added information as currently constructed. A likely reason for this non-response is that parents do not understand how to interpret the value-added information provided due to the controversy surrounding it and the statistical complexity involved, which causes them to ignore the information. Since value-added models, by design, seek to measure school and teacher contributions to learning, the results presented thus far also are consistent with this aspect of school quality not being highly valued on the margin. However, there are several other possible mechanisms that could drive our results. In this section, we discuss these alternative mechanisms and provide evidence that our preferred interpretation of the empirical results is most consistent with the data.

First, as discussed above, our analysis takes place in a time period just after an historic housing market decline that was accompanied by significant rigidities in the housing market.

[33] One additional concern is that if the housing market is not efficient, impacts might not show up until the summer when families with children are more likely to move. While we cannot test this using the restricted sample, in Appendix Table A-2 we provide estimates using the full sample restricted only to summer months (June through August). The results for the VA estimates are similar to baseline, though interestingly the API$\times$Post estimate is positive and significant.

It could be the case that such rigidities affect the capitalization of new information. If so, our estimates still would identify the effect of the LA Times and LAUSD information releases, but the external validity of our results would be more limited. We note that there currently is no evidence in the literature that capitalization is responsive to housing market rigidities. In addition, it is possible that when home prices decline, people become more sensitive to the characteristics of the home they are purchasing because concerns about resale value may be more salient.

Nonetheless, trends in home prices in LA suggest that the market was not especially rigid. First, we note that the most severe problems in the Southern California housing market were in the "Inland Empire" region far to the east of Los Angeles. Second, the Case-Shiller Home Price Index for Greater Los Angeles shows that housing prices in Los Angeles reached their trough in mid 2009 and had increased 9% by the time of the release in September 2010. Afterwards, prices remained roughly steady through our study period.[34] Further, news reports at the time indicated that the housing market was recovering.[35] Our own data confirm these reports and the Case-Shiller index. Figure 7 plots quarterly sales and median sale prices in LAUSD using LACAO sale price data. For sale prices we see that the peak occurs in 2007Q2 and the trough in 2009Q1. By the time of the VA release, sale prices had been stable for over a year. Further we can see from the figure that while the number of sales fell markedly from 2006Q2 through 2008Q1 by 2009Q2 they had recovered to pre-collapse levels. Thus, the entirety of our analysis period occurs after the housing market in LAUSD had stabilized. We also have estimated models that include interactions between value-added rank and housing price changes from 2007 to 2009, which reflect the degree to which different areas in LAUSD were affected by the housing market downturn. We find no evidence of different effects by the size of price declines during the bust, which is inconsistent with housing market rigidities biasing our estimates.

Another important piece of evidence that our results are unlikely to be due to housing market rigidities is from the results in Table 4 that show API scores are highly valued by the

[34] These housing price data were retrieved from http://www.nytimes.com/interactive/2011/05/31/business/economy/case-shiller-index.html

[35] See, for example, *Los Angeles Times* on May 19, 2010; *Orange County Register* on July 27, 2010; and *Los Angeles Times* on July 13, 2011.

housing market in this time period and that the magnitude of these effects is consistent with other research. So LA during our study period does not appear to be less responsive to school quality in general than has been found in prior research in other locations.

Second, it is possible that parents and homeowners dismiss the value-added information because they received several, often conflicting pieces of information regarding value-added rank. This scenario is inconsistent with the lack of an effect of value-added information prior to the second value-added release, though. In this period, there was no conflicting information, and prior work has shown school quality information shocks affect property values in the very short run. Table 9 shows direct evidence that the multiple doses of information is unlikely to be a primary driver of our results. In column (1), we include an indicator for whether the 1^{st} LA Times VA quintile and the LAUSD quintile are the sample, as well as interactions between this indicator and both the LA Times and LAUSD VA percentiles. If conflicting information is affecting capitalization of the value-added release, then these interactions should be positive as parents should value this information when it is consistent. However, we see no evidence that higher value-added rank led to higher home prices even when the measures agree. In column (2), we repeat this exercise using all three measures. Although noisy, the estimates still do not point to homeowners valuing this information in the cases in which the value-added ranks tell a consistent story.

Another concern is that the value-added data are based off of historical information - the calculations published in the LA Times use data from 2002-2003 through 2008-2009. Using this longer time span of data has the benefit of making the value-added estimates more stable and reliable, but if schools are changing rapidly, then the yearly API scores might be a better contemporaneous measure of school quality than value-added. However, there is very little evidence that schools are changing rapidly over time, at least as measured by API scores. An anova analysis shows the intra-school correlation in API rank to be 0.93, and the standard deviation within a school is only 9 percentiles (versus 32 percentiles overall). Even when the first and second LA Times value-added rankings disagree, there is no evidence that this is reflective of a trend in achievement. If we split schools into quartiles by the difference between their first and second LA Times value-added percentile, the trend in API scores across the quartiles from 2006 to 2010 are identical. Furthermore, our estimates of the impact of value-added information are very similar across these quartiles.[36] We also note that the LAUSD data are based off of one year of recent data. While this feature makes them much more noisy, if the data lags associated with the LA Times estimates made them irrelevant for housing prices, there still should have been a capitalization effect of the LAUSD value-added information. Together, these pieces of evidence suggest that the lagged data used in the LA Times VA measures are not the reason the housing market does not respond to this information.

A related issue is that school zones themselves may be changing too frequently for school quality information to be capitalized. Our boundary fixed-effects results for API in Table 4 indicate that this is unlikely to be true as that measure does appear to be capitalized. Further, we check how often a given property sold in our data would have been in a different school had that property been sold in the 2002-03 school-year, an additional year for which we were able to acquire school zone maps. Between 2002-03 and 2011-12 less than 5% of properties changed school zones. If we separate these rates by the 2011-12 school's LA Times VA quintile we see little difference: the switch rates range from 2% to 6%. Thus, school zones during this period were relatively stable.

Finally, as discussed above, low salience of the value-added release information could preclude markets from reacting. However, as documented in Section 2, coverage of these releases was extensive and pervasive through many media outlets in LA at the time. The unfortunate suicide by a teacher in reaction to her value-added rank only intensified this media coverage. That Figlio and Lucas (2004) find large capitalization effects of school information in a time period in which information was more difficult to access and in an environment where the information received less press attention suggests our results are not being driven by low salience of the value-added information.

[36]These estimates are available upon request.

7 Conclusion

School districts across the country have begun to use value-added methodologies to evaluate teachers and schools. Although only a few large districts have released these results publicly, it is likely that more will in the future. Thus, it is important to understand whether and how this information is valued by local residents. This is particularly important because recent evidence suggests parents *should* value this information, as value-added has large positive effects on future student outcomes (Chetty, Friedman and Rockoff, 2012b). Furthermore, value-added measures provide information about school quality that is less correlated with the school demographic makeup than are test score levels. Identifying how value-added information in particular is capitalized into housing prices therefore can lend new insight into the valuation of school quality that research focusing on test score levels as a school quality measure cannot.

This paper is the first to examine how publicly released school and teacher value-added information is capitalized into property values in the US. We exploit a series of information releases about value-added by the Los Angeles Times and the Los Angeles Unified School District, which provided local residents with value-added rankings of all elementary schools and over 6,000 teachers in the LA Unified School District. Using housing sales data from the LA County Assessor's Office, we estimate difference-in-differences models that show how home prices change as a function of value-added after each data release. Across myriad specifications and variations in modeling choices and data assumptions, we show that property values do not respond to released value-added information. Our estimates are sufficiently precise to rule out all but very small positive effects on average. However, using boundary fixed-effects methods, we find that achievement differences across schools are capitalized into home prices, which indicates that school quality as measured by test scores is valued by Los Angeles residents.

Unique to our study in the school valuation literature is the ability to examine home price effects based on teacher quality information. Similar to the school-level results, though, we find that property values are unresponsive to the within-school variance in teacher value-added. Nonetheless, we do find suggestive evidence that the impact of value-added on housing prices has a negative gradient with SES.

Our estimates differ substantially from previous work on school valuation that uses test score levels as a measure of school quality. This literature typically has found an effect on the order of 2 to 5 percent higher housing prices for each standard deviation increase in test scores (Black, 1999; Bayer, Ferrreira and McMillan, 2007; Gibbons, Machin and Silva, 2009). Nonetheless, previous work examining how property values respond to researcher-calculated school value-added or changes in school test scores have findings similar to our own (Black and Machin, 2011), but those studies are distinct from ours as they implicitly assume that home buyers make the same calculations from available data. The fact that property values do not respond to these school quality measures could be due to a lack of awareness of this information.

The previous analysis most similar to this paper is Figlio and Lucas (2004), which examines the effect of property values from the public release of "school report cards." They find releasing this information leads to large property value increases in the higher-performing districts. There are several potential explanations for why our results differ from theirs. First, the school report cards in their study are based on test score levels, which are highly correlated with other aspects of schools, such as demographic composition. Even though demographic data were already available to the public, property values may be responding to the repackaging of that information into a simple and intuitive form rather than what the public perceived to be the school's quality, *per se*. Second, the type of information contained in the Florida school report cards already was available to LAUSD residents in the form of API scores. The value-added information releases we study provide school quality data on top of this pre-existing information.

That we find no effect of school or teacher value-added information on home prices suggests these school quality measures as they are currently constructed are not valued by local residents, at least on the margin. A central lesson from our results is that clear presentation of complex information may not be enough to induce people to respond to information, even when the information provides valid estimates of school quality. Our analysis indicates that simply providing parents with value-added information is not sufficient, even when it is supplied by an independent third party. As value-added information becomes an increasingly common aspect of the educational environment, it is important to consider how to provide parents and community members with this information in a way that allows them to use it effectively while making educational decisions for their children.

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Figure 1: Example of Information Displayed in LATimes Database

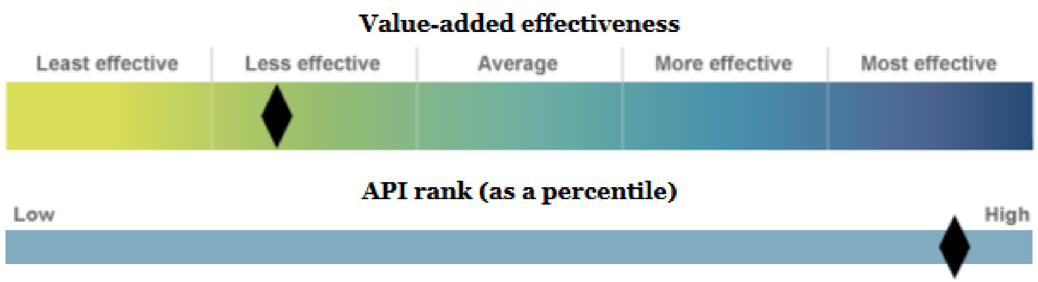
Los Angeles Teacher Ratings

Beckford Avenue Elementary

19130 Tulsa St., Northridge, 91326

A less effective than average school, according to "value-added" analysis.

A school's value-added rating was based on the performance of all its students tested on the California Standards Tests in math and English. Value-added measures the collective difference between students' expected growth and actual performance and is designed to analyze what the school contributes to learning. The state's Academic Performance Index measures student achievement and is tied closely to students' advantages outside school.

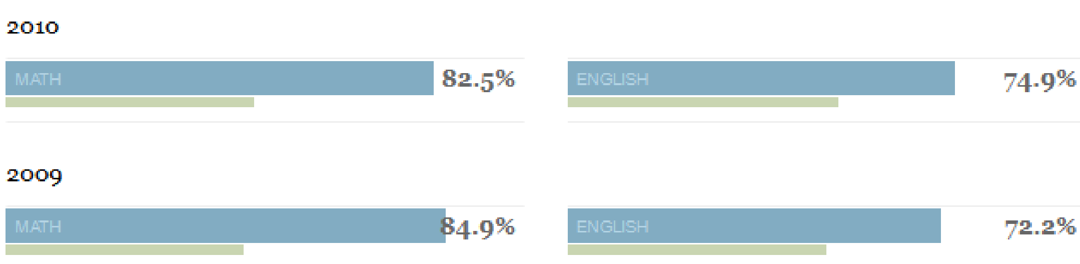


Overall student performance

The California Standards Tests rank students into five categories from "far below basic" to "advanced." The percentage of a school's students who scored "proficient" or "advanced" is shown below. The 2010 test scores, which were released in August, were not used in The Times' "value-added" analysis and may reflect recent changes in the school's overall performance.

California Standards Tests (STAR) ?

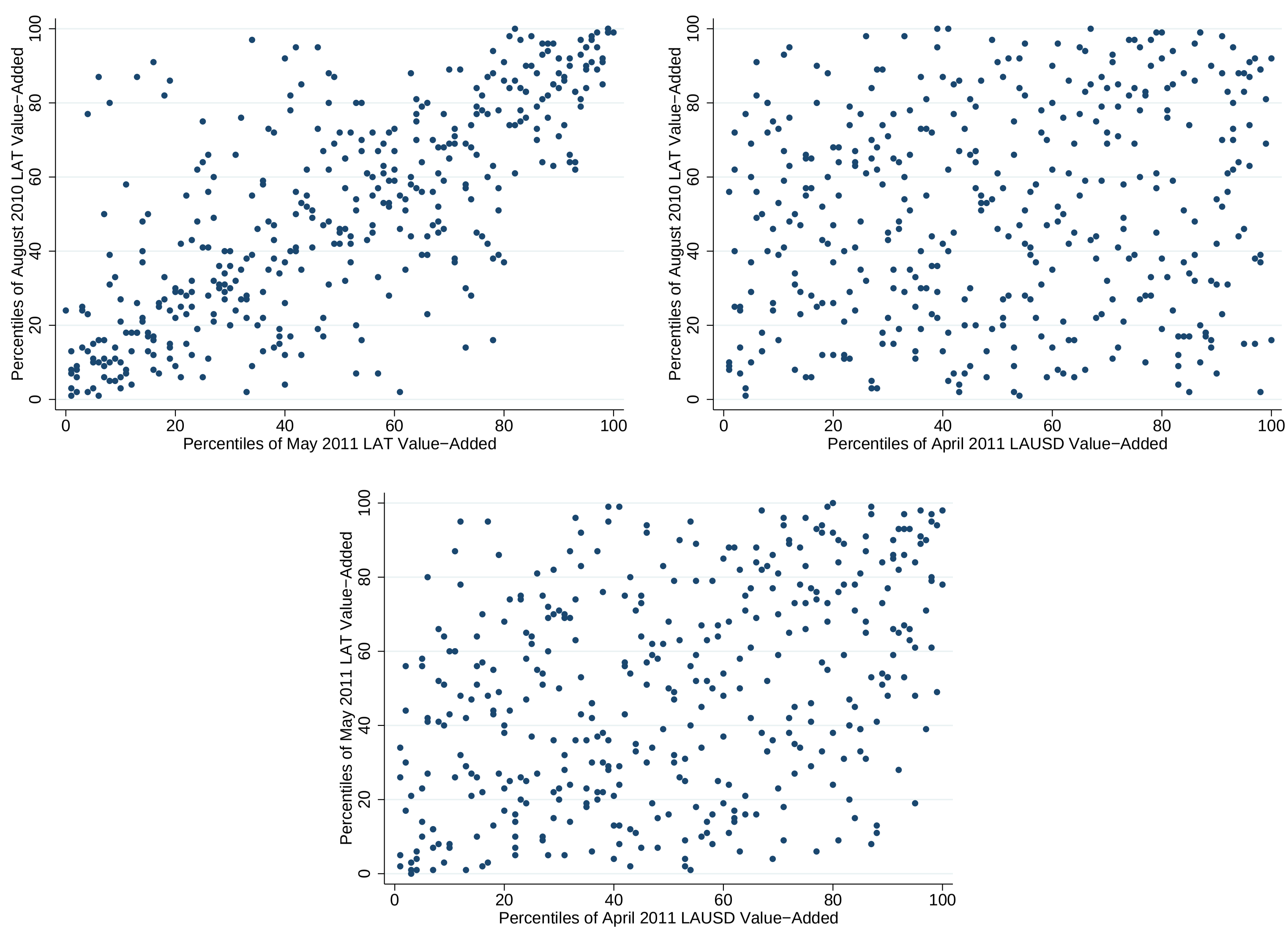
Students scoring "proficient" or above:



Source: 2009, 2010 state data

Learn more about test scores and demographics at Beckford Avenue Elementary using the The Times' California Schools Guide ».

Figure 2: Comparisons of the Three Value-Added Measures



Percentile ranking amongst LAUSD elementary schools using the three value-added scores. Each dot is a single elementary school.

Figure 3: API, Free/Reduced-Price Lunch, and Value-Added by Elementary School

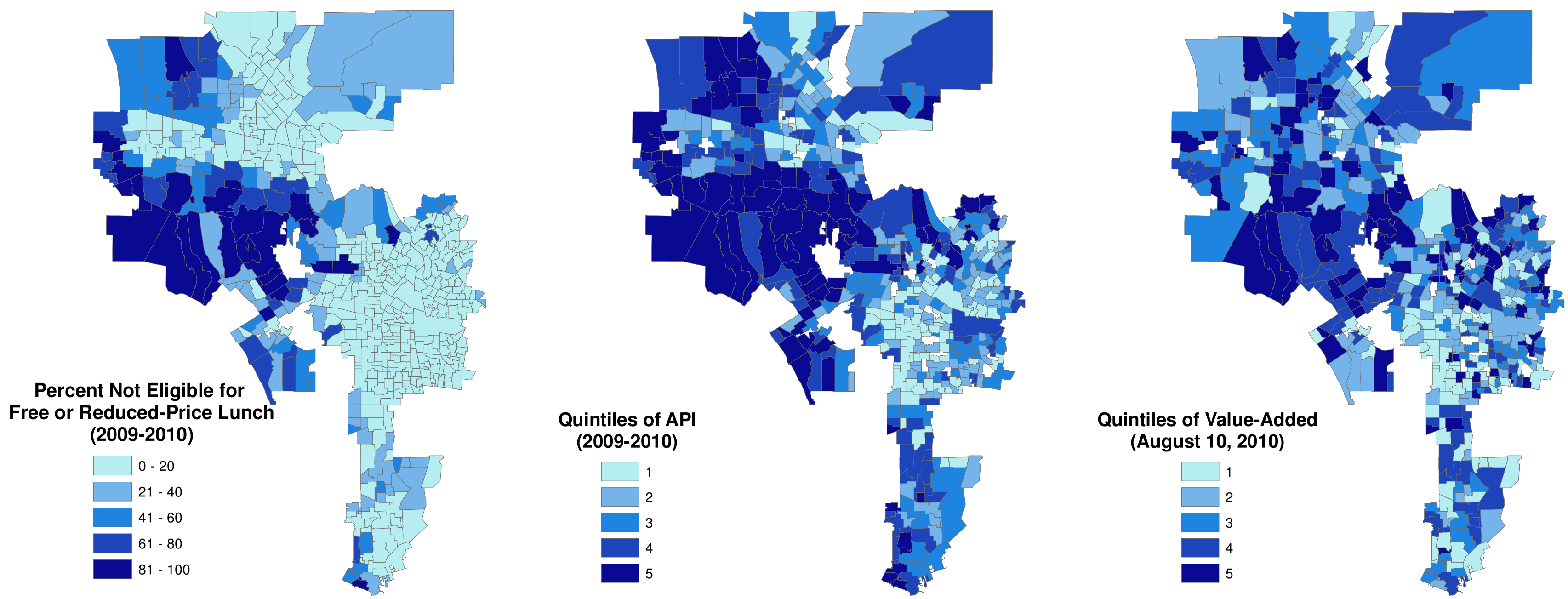
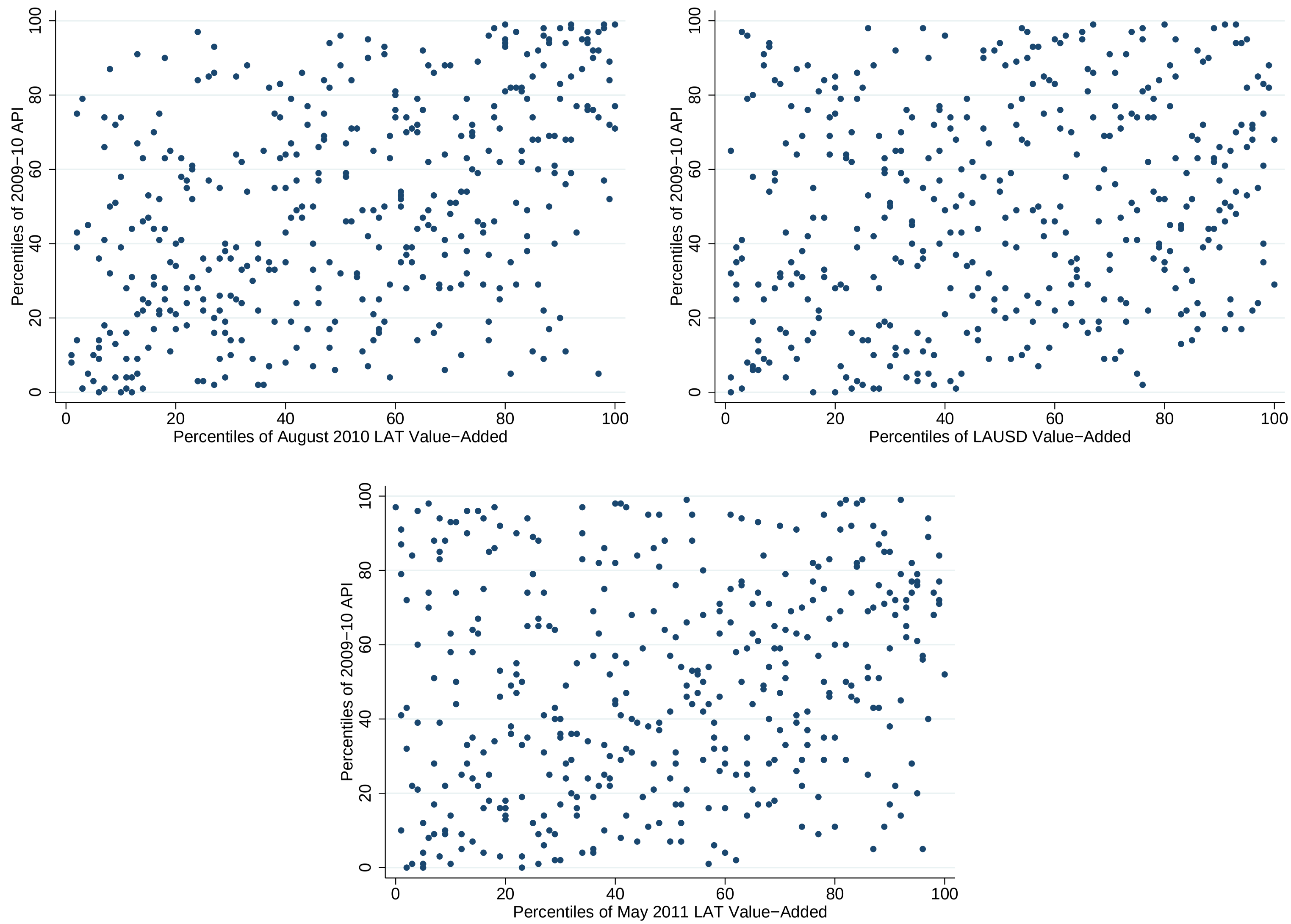
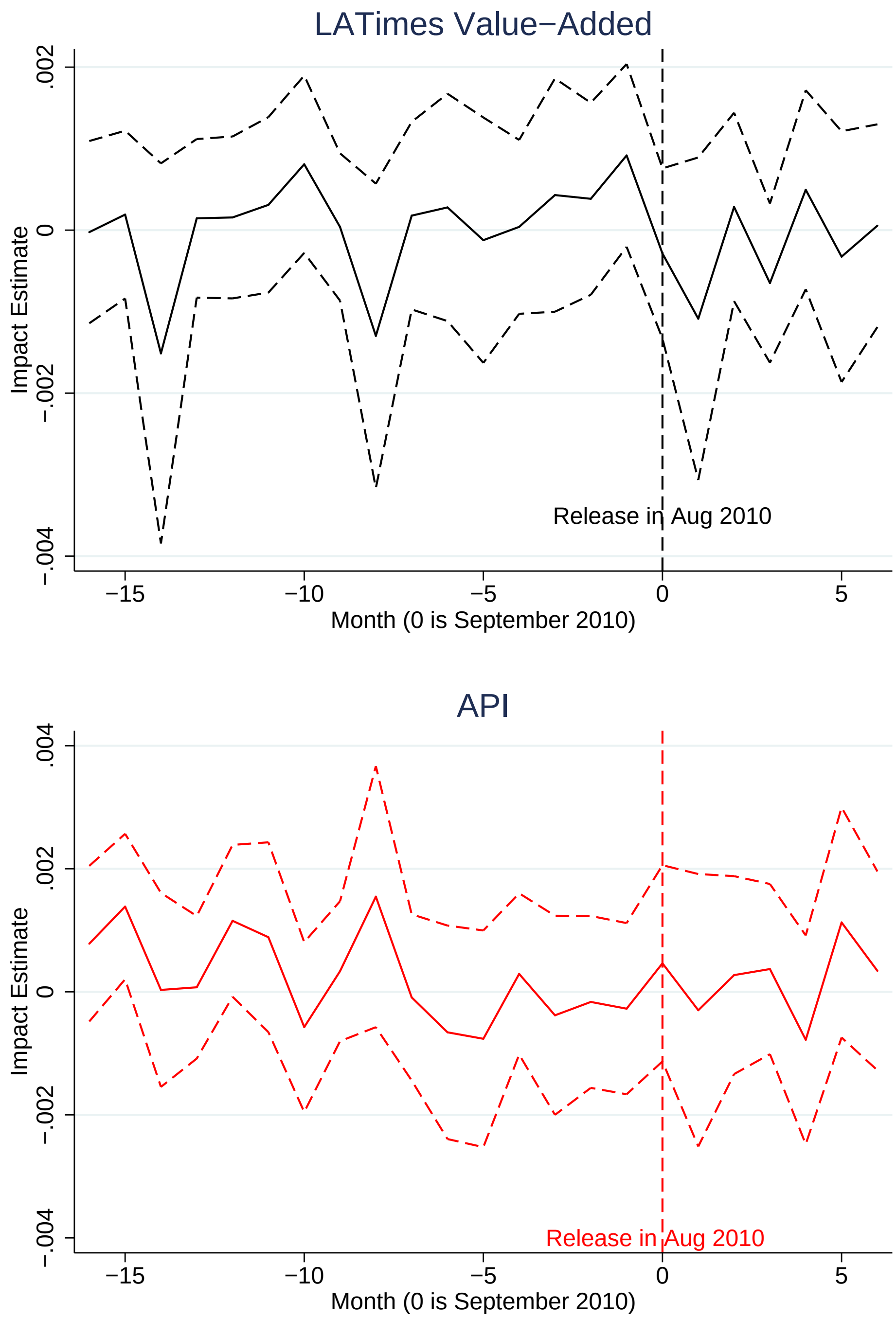


Figure 4: API Percentile vs. Value-Added Percentile



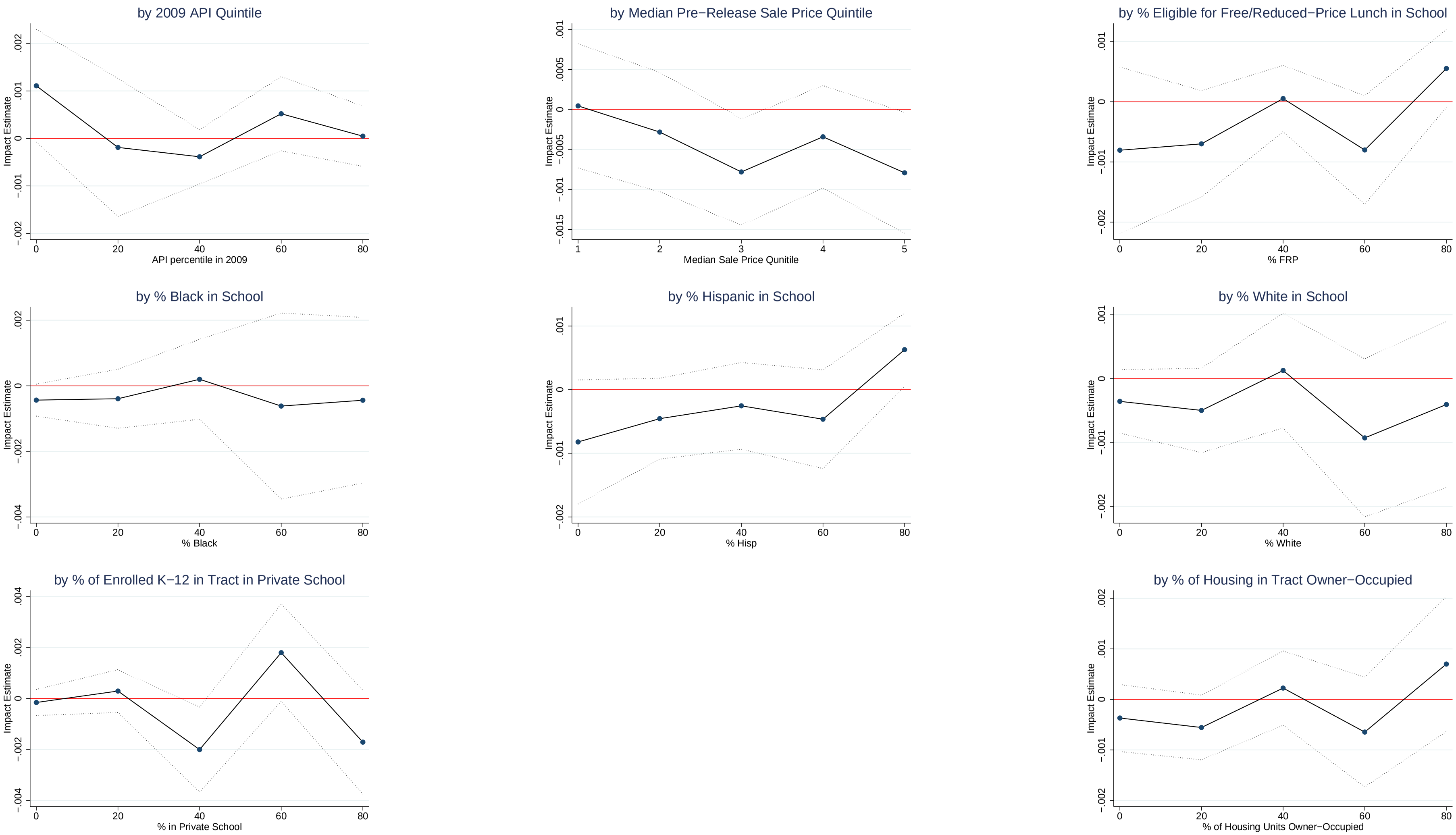
Percentile ranking amongst LAUSD elementary schools using 2009-10 API versus percentile rankings of the three value-added scores. Each dot is a single elementary school.

Figure 5: Effect of Value-Added Information on Log Sales Price by Month of Sale



The estimates in both panels come from a single regression and show the impact of an increase in value-added or API percentile on log sale price by month. The estimates come from sales between April 1, 2009 to March 31, 2011. Controls include school fixed effects, month of sale indicators, within-district API percentile, overall API and by racial/ethnic group, and two years of all lagged API measures; Housing characteristic controls - the number of bedrooms, bathrooms and units in the home, square footage, and year built; School characteristic controls - percent of students of each race, percent free lunch, percent gifted, percent English language learners, percent disabled, and parent education levels; Neighborhood characteristic controls at the census block group level - percents of the population in each age group, with less than a high school diploma, with a high school diploma, with some college, and with a BA or more, who are black, who are Hispanic, and who are female headed households with children as well as median income. The dotted lines are the bounds of the 95% confidence intervals that are calculated using standard errors clustered at the school level.

Figure 6: Heterogeneity in the Estimated Effect of LA Times Value-Added on Log Sale Price



The value-added variable is the LA Times value-added percentile from the August 2010 release, and the estimates come from sales between April 1, 2009 to March 31, 2011. Controls include school fixed effects, month of sale indicators, within-district API percentile, overall API and by racial/ethnic group, and two years of all lagged API measures; Housing characteristic controls - the number of bedrooms, bathrooms and units in the home, square footage, and year built; School characteristic controls - percent of students of each race, percent free lunch, percent gifted, percent English language learners, percent disabled, and parent education levels; Neighborhood characteristic controls at the census block group level - percents of the population in each age group, with less than a high school diploma, with a high school diploma, with some college, and with a BA or more, who are black, who are Hispanic, and who are female headed households with children as well as median income. The dotted lines are the bounds of the 95% confidence intervals that are calculated using standard errors clustered at the school level.

Figure 7: Quarterly Sales and Median Sale Price in LAUSD

Sales calculated using three most recent sales of each property as of October 2011. Sale price includes only the most recent sale of a property as of October 2011.

Table 1: Summary Statistics of Select Variables

Characteristic	All Schools	LAT 1^{st} VA Percentile ≥ 50	LAT 1^{st} VA Percentile < 50
Key Regression Variables			
Sale Price	410,736	448,825	365,979
	(265,893)	(278,216)	(243,135)
LAT Value-Added Percentile (Aug, 2010)	52.5	75.7	25.1
	(29)	(14.6)	(13.8)
LAT Value-Added Percentile (May, 2011)	49.1	66.4	28.8
	(29.5)	(24.6)	(20.5)
LAUSD Value-Added Percentile (Apr, 2011)	49.2	52.7	45.2
	(28.5)	(27.7)	(28.8)
API Percentile (2009-10)	55	65.2	43
	(29.1)	(25.7)	(28.3)
Characteristics of Census Block Group of Property			
% Black	10.6	5.7	16.2
	(18.5)	(10.5)	(23.5)
% Hispanic	41.7	36.7	47.7
	(31)	(30.4)	(30.6)
% of Households w/ Female Head	15.1	12.8	17.8
	(10.7)	(9.4)	(11.6)
% of Adults with No HS	24	19.6	29.2
	(20.2)	(18.9)	(20.5)
% of Adults with HS Degree	20.5	19.4	21.8
	(9.6)	(9.6)	(9.5)
% of Adults with Some College	25	25.1	24.9
	(9.3)	(8.8)	(9.9)
% of Adults with Bachelors or Higher	30.5	35.9	24.1
	(21.9)	(22)	(20.1)
Median Household Income	64,011	70,695	56,156
	(33,749)	(35,911)	(29,116)
School Characteristics			
% Black	12.6	9.4	16.4
	(17.2)	(11.8)	(21.3)
% Hispanic	61.6	57	67
	(29.5)	(30.9)	(26.9)
% Eligible for Free/Reduced-Price Lunch	72.1	64.2	81.4
	(29.4)	(31.6)	(23.5)
% Gifted	11.7	14	8.9
	(8.7)	(9.4)	(6.7)
% English Language Learner	28.9	26.3	32.0
	(17.1)	(17.2)	(16.6)
% Special Education	12.3	12.4	12.2
	(4.0)	(4.1)	(3.8)
Enrollment	417.9	397.1	441.8
	(164.4)	(164.5)	(165.3)
Property Characteristics			
# of Beds	2.9	2.8	2.9
	(1.8)	(1.7)	(2.0)
# of Baths	2.1	2.1	2.1
	(1.7)	(1.5)	(1.8)
Square Footage	1570	1572	1569
	(2157)	(1033)	(2977)
Observations	63,122	34,101	29,021

The sample is split based on the percentile rankings from the first value-added release by the LA Times in August, 2010. Standard deviations are shown in parentheses.

Table 2: Predictability of API and Value-Added Using Observable School Characteristics

Dependent Variable →	(1) API Percentile	(2) LAT 1^{st} VA Pctl	(3) LAT 1^{st} VA Pctl	(4) LAT 2^{nd} VA Pctl	(5) LAT 2^{nd} VA Pctl	(6) LAUSD VA Pctl	(7) LAUSD VA Pctl
% Black	-0.559***	-0.370**	-0.132	-0.166	0.325	0.179	0.575*
	(0.101)	(0.175)	(0.344)	(0.199)	(0.355)	(0.215)	(0.336)
% Hispanic	-0.069	0.047	0.092	-0.256	-0.222	0.205	0.180
	(0.095)	(0.176)	(0.279)	(0.200)	(0.294)	(0.214)	(0.286)
% Asian	0.328***	0.292	0.259	0.059	0.074	-0.049	0.194
	(0.085)	(0.210)	(0.396)	(0.209)	(0.421)	(0.203)	(0.391)
% FRP Lunch	-0.070	-0.026	0.212	0.241	0.427	0.302	0.507**
	(0.113)	(0.187)	(0.240)	(0.207)	(0.261)	(0.200)	(0.209)
% Gifted	0.655***	0.561**	-0.222	1.266***	0.459	0.598*	-0.021
	(0.166)	(0.274)	(0.348)	(0.302)	(0.360)	(0.334)	(0.331)
% ELL	-0.541***	0.153	0.523***	0.144	0.649***	-0.080	0.285
	(0.112)	(0.178)	(0.193)	(0.189)	(0.191)	(0.208)	(0.184)
% Spec Ed	-0.441*	0.140	0.970*	0.502	1.489***	0.554	0.761*
	(0.239)	(0.391)	(0.495)	(0.424)	(0.506)	(0.393)	(0.449)
Enrollment	-0.011**	-0.010	0.003	-0.013	0.010	-0.012	0.004
	(0.006)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)
% Parents HS Grad	0.041	0.086	0.057	-0.063	-0.157	-0.362	-0.371**
	(0.139)	(0.191)	(0.202)	(0.214)	(0.198)	(0.243)	(0.189)
% Parents Some Col	0.356**	0.052	-0.104	-0.155	-0.469*	-0.376	-0.170
	(0.155)	(0.227)	(0.233)	(0.265)	(0.251)	(0.288)	(0.262)
% Parents BA	0.320	0.378	0.276	-0.169	-0.260	0.202	-0.023
	(0.202)	(0.301)	(0.338)	(0.348)	(0.390)	(0.354)	(0.327)
% Parents Grad	0.107	0.332	-0.107	-0.856***	-1.236***	0.221	-0.020
	(0.173)	(0.273)	(0.325)	(0.323)	(0.353)	(0.364)	(0.334)
API Percentile			-0.099		0.038		0.191
			(0.261)		(0.252)		(0.245)
API Level			0.071		0.063		0.305
			(0.291)		(0.295)		(0.230)
Black API			-0.011		0.121		0.130*
			(0.086)		(0.080)		(0.071)
Hispanic API			-0.084		0.023		0.199*
			(0.133)		(0.164)		(0.112)
White API			-0.220		-0.258		0.346***
			(0.167)		(0.181)		(0.121)
Disadv API			-0.031		-0.021		0.094
			(0.216)		(0.224)		(0.187)
ELL API			0.019		0.096		0.089
			(0.079)		(0.085)		(0.063)
Spec Ed API			0.048		0.004		0.066
			(0.056)		(0.064)		(0.051)
Observations	397	397	397	397	397	397	397
R^2	0.706	0.216	0.407	0.081	0.387	0.038	0.495
Adj R^2	0.696	0.192	0.295	0.052	0.270	0.008	0.399

All measures are for the 2009-10 school-year. Columns 3 and 5 also include Asian API, Filipino API, lags and second lags for all API levels and subgroup levels. Values for groups that were too small for API scores to be provided are set equal to zero and an indicator for that measure being missing is set equal to one. Robust standard errors are in parentheses.***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 3: Effect of Value-Added on Demographic and Housing Characteristics

Note: Estimates are multiplied by 100 for ease of presentation.

Panel A: Census Block Group Characteristics of Property											
	(1) % Hisp	(2) % Black	(3) % No HS	(4) % HS Grad	(5) % Some Col	(6) % BA+	(7) % Fem Head	(8) Med HH Inc			
1^{st} LAT	-1.03	0.18	-0.29	0.08	0.02	0.19	0.39	442			
VA Pctl	(0.67)	(0.40)	(0.46)	(0.35)	(0.33)	(0.56)	(0.34)	(1,278)			
Panel B: Census Tract Characteristics of Property											
	(9) % Children	(10) % Senior	(11) Median Age	(12) % Institu-tionalized	(13) % HH w/ Kids	(14) % Single M w/ Kids	(15) % Single F w/ Kids	(16) % HH w Seniors	(17) Avg HH Size	(18) % Vacant	
1^{st} LAT	-0.01	0.25	0.07	0.40	-0.10	-0.01	-0.09	0.47*	-0.01	0.06	
VA Pctl	(0.21)	(0.16)	(0.16)	(0.46)	(0.34)	(0.64)	(0.70)	(0.27)	(0.02)	(0.17)	
	(19) % Owner Occupied	(20) % Male Married	(21) % Fem Married	(22) Fert Rate	(23) % Veteran	(24) % Same House 1Yr	(25) % Born in USA	(26) % English Speaker	(27) LFP Rate	(28) Unemp Rate	
1^{st} LAT	-0.0106	0.44	-0.08	-0.0166	0.10	-0.49	-0.68**	-0.61	-0.17	0.11	
VA Pctl	(0.81)	(0.32)	(0.36)	(0.0140)	(0.08)	(0.34)	(0.35)	(0.40)	(0.41)	(0.15)	
	(29) % Commute Public Trans	(30) Mean Commute	(31) % On Social Sec	(32) % On SSI	(33) % On Cash Assist	(34) % On Food Stmp	(35) Poverty Rate	(36)	(37)		
1^{st} LAT	-615	-0.53**	-0.17	0.11	0.45*	-0.06	-0.04	-0.03	-0.54*		
VA Pctl	(1929)	(0.23)	(0.41)	(0.15)	(0.26)	(0.13)	(0.10)	(0.17)	(0.30)		
Panel C: Property Characteristics											
	(38) Mean # Units	(39) Mean Age of Structure	(40) Mean # Bedrooms	(41) Mean # Bathrooms	(42) Mean Sq Ft						
1^{st} LAT	0.07	-2.5*	0.08	-0.04	44						
VA Pctl	(0.08)	(1.4)	(0.07)	(0.08)	(69)						
Panel D: School Characteristics											
	(43) % Black	(44) % Hisp	(45) % Asian	(46) % FRP Lunch	(47) % Gifted	(48) % ELL	(49) %Spec Ed	(50) Enroll	(51) % Parent HS Grad	(52) % Parent Some Col	(53) % Parent BA
1^{st} LAT	0.09	0.09	-0.69*	-0.12	0.22	-1.4	-0.35	8.9	0.01	-0.20	-0.19
VA Pctl	(0.49)	(0.57)	(0.39)	(1.1)	(0.62)	(0.9)	(0.49)	(10.3)	(0.83)	(0.82)	(0.67)

Each cell is a separate regression. The data cover April 2009 through March 2010, prior to LAUSD's release of their value-added measure. Observations for census block group characteristics are 51,514. Due to some missing data, census tract characteristic sample sizes range from 51,487 to 51,514. For property characteristics, the sample sizes are 49,613, 49,800, 49,380, 49,702 and 49,920 for # of units, age of property, # of bedrooms, # of bathrooms and square-footage, respectively. For school characteristics, there are 1,189 school-year observations. All regressions include API percentile, API*post, and school fixed effects. Panel C also includes month fixed effects while Panel D includes academic year fixed effects. Standard errors clustered at the school level are in parentheses.***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 4: School-Zone Boundary Fixed Effects Estimates of the Impact of API on Ln(Sale Price) in the Pre-Release Period

Note: Estimates for all models are multiplied by 100 for ease of presentation.

Independent Variable	(1)	(2)	(3)	(4)
Panel A: Properties $\leq$ 0.2 Miles from Boundaries				
API Percentile	0.449***	0.411***	0.129***	0.111***
	(0.048)	(0.041)	(0.035)	(0.036)
LAT 1^{st} VA Percentile				0.039
				(0.027)
Observations	25,522	25,522	25,522	25,522
Panel B: Properties $\leq$ 0.1 Miles from Boundaries				
API Percentile	0.318***	0.286***	0.108***	0.091**
	(0.058)	(0.046)	(0.041)	(0.043)
LAT 1^{st} VA Percentile				0.036
				(0.032)
Observations	15,697	15,697	15,697	15,697
Housing Characteristics	N	Y	Y	Y
Census Block Characteristics	N	N	Y	Y

All regressions include month and boundary fixed effects. Each column comes from a separate regression that uses sales from April 2009 to August 2010. Housing characteristic controls include the number of bedrooms, bathrooms and units in the home, square footage, and year built. Census block group controls are % black, % Hispanic, % female headed households, educational attainment rates, % in each 5-year age group, and median household income. All models include month fixed effects. Standard errors clustered at the school level are in parentheses.***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 5: Effect of Value-Added Information on Log Sale Prices

Note: Estimates are multiplied by 100 for ease of presentation.					
Independent Variable ↓	(1)	(2)	(3)	(4)	(5)
Panel A: Limited to Before LAUSD Release (April 2009 - March 2011)					
LAT 1^{st} VA Percentile	0.003	0.029	-0.030	0.029	0.007
× Post Aug 2010	(0.062)	(0.038)	(0.025)	(0.032)	(0.033)
API Percentile	-0.045	-0.045	0.010	0.038	0.054
× Post Aug 2010	(0.049)	(0.063)	(0.047)	(0.049)	(0.052)
Observations	51,514	51,514	51,514	22,094	22,094
Panel B: Full Sample (April 2009 - August 2011)					
LAT 1^{st} VA Percentile	-0.004	0.027	-0.020	0.025	0.011
× Post Aug 2010	(0.053)	(0.035)	(0.022)	(0.029)	(0.029)
LAT 2^{nd} VA Percentile	0.007	0.048	0.027	-0.003	-0.002
× Post Apr 2011	(0.035)	(0.029)	(0.025)	(0.036)	(0.036)
LAUSD VA Percentile	-0.009	-0.044	-0.021	-0.034	-0.042
× Post Mar 2011	(0.037)	(0.033)	(0.029)	(0.033)	(0.034)
API Percentile	-0.011	-0.011	0.049	0.058	0.068
× Post Aug 2010	(0.047)	(0.058)	(0.043)	(0.044)	(0.043)
Observations	63,122	63,122	63,122	27,050	27,050
Controls	N	Y	Y	Y	Y
School Fixed-Effects	N	N	Y	N	Y
Boundary Fixed-Effects (0.1 mi)	N	N	N	Y	Y

All regressions without school fixed effects include controls for API percentile and value-added main effects. Models in columns (2) - (5) also control for the the following: month fixed effects; housing characteristic controls - number of bedrooms, bathrooms and units in the home, square footage, and year built; census block group controls: % black, % Hispanic, % female headed households, educational attainment rates, % in each 5-year age group, and median household income; School characteristics: API levels overall and for all subgroups, lags and second lags of overall and subgroup API scores, % of students of each race, % free lunch, % gifted, % English language learners, % disabled, and parent education levels. Columns (4) and (5) are limited to properties within 0.1 miles of a 2011 school zone boundary. Standard errors clustered at the school level are in parentheses. ***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 6: Effect of Value-Added Information on Log Sale Prices - Alternative Models

Note: Estimates for all models except (3) are multiplied by 100 for ease of presentation.

	Include Std Dev of Current Teacher VA	Include % Teachers in VA Quintile	Include % Teachers in VA Quintile (No School VA)	Use Whether School in VA Quintile	Interact with # of Charters w/in 1 Mi
	(1)	(2)	(3)	(4)	(5)
LAT 1^{st} VA Pctl	-0.029	-0.044			-0.052**
× Post Aug 2010	(0.025)	(0.031)			(0.025)
API Pctl	0.011	0.036	0.028	0.037	0.042
× Post Aug 2010	(0.048)	(0.045)	(0.043)	0.046	(0.045)
LAT Teacher VA	0.007				
Standard Deviation	(0.099)				
Teacher/School VA Quintile:					
2^{nd} Quintile		1.0	0.1	2.4	
		(6.5)	(6.3)	(2.1)	
3^{rd} Quintile		-0.0	-2.5	2.2	
		(6.9)	(6.5)	(2.4)	
4^{th} Quintile		1.1	-2.2	-1.9	
		(7.4)	(6.9)	(2.3)	
5^{th} Quintile		1.3	-3.4	-0.9	
		(7.0)	(5.7)	(2.0)	
Top Two Quintiles					
LAT 1^{st} VA					0.008
× Charters w/in 1 Mi					(0.010)
Observations	50,365	50,365	50,365	51,514	51,514

The data cover April 2009 through March 2011, prior to LAUSD's release of their value-added measure. All regression control for the following: month fixed effects; school zone fixed effects; housing characteristic controls - number of bedrooms, bathrooms and units in the home, square footage, and year built; census block group controls: % black, % Hispanic, % female headed households, educational attainment rates, % in each 5-year age group, and median household income; school characteristics: API levels overall and for all subgroups, lags and second lags of overall and subgroup API scores, % of students of each race, % free lunch, % gifted, % English language learners, % disabled, and parent education levels. Column (4) also controls for the number of charter schools within 1 mile of the property. Standard errors clustered at the school level are in parentheses. ***,** and * indicate significance at the 1%, 5% and 10% levels

Table 7: Effect of Value-Added Information Relative to Existing Information on Log Sale Prices

Note: Estimates for all models are multiplied by 100.

	API (1)	Primary Factor (2)	All Factors (3)	Primary & All Factors (4)
LAT - API Percentile	-0.022			
× Post Aug 2010	(0.024)			
LAT - 1^{st} Factor Percentile		-0.021		0.016
× Post Aug 2010		(0.025)		(0.050)
LAT - Mean of Factor Percentiles			-0.032	-0.051
× Post Aug 2010			(0.026)	(0.048)
API Percentile		-0.010	0.003	0.023
× Post Aug 2010		(0.046)	(0.046)	(0.059)
Observations	51,514	51,458	51,514	51,458

The data cover April 2009 through March 2011, prior to LAUSD's release of their value-added measure. The estimates in column (1) show the difference between the LA Times first release VA percentile and the API percentile. The second column uses the difference between the LA Times percentile and the percentile of the first primary factor component from the factor model discussed in the text. In column (3), we use a weighted average of the factor ranks, where the weights are the percentage of the variance explained by each factor. In column (4), we use both the difference between the LA Times VA percentile and the first factor and the difference between the LA Times VA percentile and a weighted average of all other factors. All regression control for the following: month fixed effects; school zone fixed effects; housing characteristic controls - number of bedrooms, bathrooms and units in the home, square footage, and year built; census block group controls: % black, % Hispanic, % female headed households, educational attainment rates, % in each 5-year age group, and median household income; school characteristics: API levels overall and for all subgroups, lags and second lags of overall and subgroup API scores, % of students of each race, % free lunch, % gifted, % English language learners, % disabled, and parent education levels. Standard errors clustered at the school level are in parentheses. ***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 8: Effect of Value-Added Information on Log Sale Prices - Specification Checks

Note: Estimates for all models are multiplied by 100 for ease of presentation.

	Add Census Tract FE (1)	Exclude Lagged API (2)	Use Sale Levels (3)	Limit to 0-2 Bedrooms (4)	Limit to 3+ Bedrooms (5)	Drop Imputed Sales (6)	Drop Properties w/ > 8 Bedrooms (7)	Drop Properties w/ > 5000 sf (8)	Drop Multi Unit (9)	3 Month Lead (10)	No API* Post (11)
LAT 1^{st} VA Pctl	-0.041*	-0.028	-120.2	-0.010	0.005	-0.049**	-0.027	-0.029	-0.017	-0.023	-0.029
× Post Aug 2010	(0.024)	(0.024)	(82.3)	(0.029)	(0.017)	(0.025)	(0.024)	(0.024)	(0.016)	(0.030)	(0.024)
API Pctl	0.004	0.013	319.6*	0.006	-0.018	0.046	-0.002	0.006	-0.003	0.045	
× Post Aug 2010	(0.040)	(0.036)	(193.1)	(0.049)	(0.029)	(0.044)	(0.044)	(0.044)	(0.033)	(0.039)	
Observations	51,514	51,514	51,514	19,191	30,189	47,926	51,044	50,959	45,575	51,514	

The data cover April 2009 through March 2011, prior to LAUSD's release of their value-added measure. All regression control for the following: month fixed effects; school zone fixed effects; housing characteristic controls - number of bedrooms, bathrooms and units in the home, square footage, and year built; census block group controls: % black, % Hispanic, % female headed households, educational attainment rates, % in each 5-year age group, and median household income; school characteristics: API levels overall and for all subgroups, lags and second lags of overall and subgroup API scores, % of students of each race, % free lunch, % gifted, % English language learners, % disabled, and parent education levels. Standard errors clustered at the school level are in parentheses. ***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

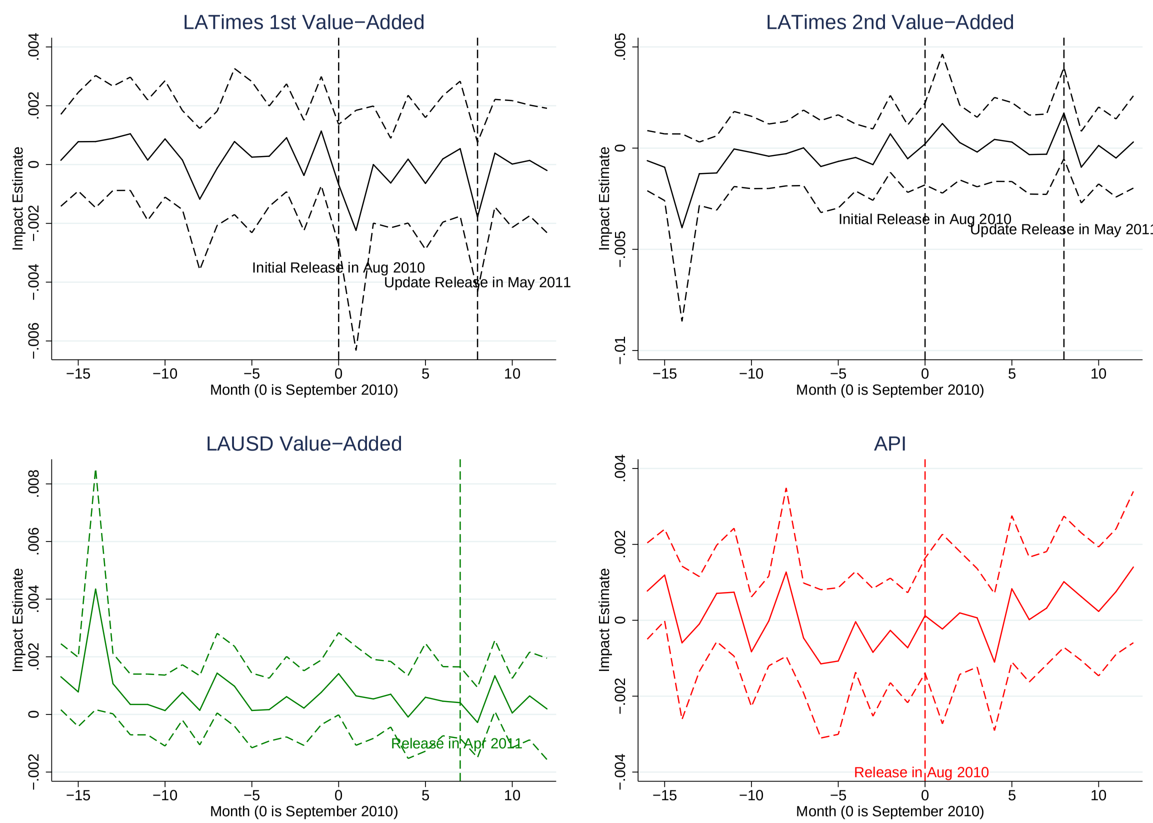
Table 9: Effect of Value-Added Information on Log Sale Prices - Interactions Between VA Measures

Note: Estimates for all models are multiplied by 100 for ease of presentation.

	(1)	(2)
LAT 1^{st} VA Percentile	-0.021	-0.018
× Post Aug 2010	(0.023)	(0.022)
LAT 2^{nd} VA Percentile	0.026	0.029
× Post Apr 2011	(0.026)	(0.027)
LAUSD VA Percentile	-0.023	-0.017
× Post Mar 2011	(0.033)	(0.029)
LAT1 & LAUSD Same Quintile	-0.852	
× Post Mar 2011	(3.968)	
LAT1 VA Percentile	0.093	
× LAT1 & LAUSD Same Quintile	(0.163)	
× Post Mar 2011		
LAUSD VA Percentile	-0.081	
× LAT1 & LAUSD Same Quintile	(0.168)	
× Post Mar 2011		
LAT1, LAT2 & LAUSD Same Quintile		1.938
× Post Apr 2011		(5.601)
LAT1 VA Percentile		-0.201
LAT1, LAT2 & LAUSD Same Quintile		(0.307)
× Post Apr 2011		
LAT2 VA Percentile		0.305
LAT1, LAT2 & LAUSD Same Quintile		(0.312)
× Post Apr 2011		
LAUSD VA Percentile		-0.148
LAT1, LAT2 & LAUSD Same Quintile		(0.254)
× Post Apr 2011		
API Percentile	0.049	0.037
× Post Aug 2010	(0.043)	(0.042)
Observations	63,122	63,122

The data cover April 2009 through September 2011 and are at the property sale level. The pooled LA Times value-added variable uses the value-added percentile from the August 2010 release until May 2011 at which point the variable is replaced with the VA percentile from the May 2011 (2^{nd}) release. All regressions include school and month fixed-effects along with controls for API, two years of lagged API, API percentile, and the school's rank relative to comparison schools defined by the California Department of Education. School characteristics include, % of students of each race, % free lunch, % gifted, % English language learners, % disabled, and parent education levels. Neighborhood characteristic controls are at the census tract level and include % of the population who are adult, minor, senior, foreign born, of each race, speak a language other than English, and who lived in the same house one year prior, the % of adults who are married, institutionalized, veterans, of each education level, in the labor force, and unemployed, % of households vacant and owner-occupied, average household size, family size, commute time and household income, the percent of households with children, single-parent families, receiving social security, receiving cash public assistance, and receiving food stamps and the poverty rate. Housing characteristic controls include the number of bedrooms, bathrooms and units in the home, square footage, and year built. Housing characteristics are also interacted with a linear time trend. Standard errors clustered at the school level are in parentheses.***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Figure A-1: Effect of Value-Added Information on Log Sales Price by Month of Sale, Including All Value-Added Releases



The estimates in all panels come from a single regression and show the impact of an increase in value-added percentile on log sale price by month, using each quality measure. Controls include school fixed effects, month of sale indicators, within-district API percentile, overall API and by racial/ethnic group, two years of all lagged API measures; Housing characteristic controls - the number of bedrooms, bathrooms and units in the home, square footage, and year built; school characteristic controls - percent of students of each race, percent free lunch, percent gifted, percent English language learners, percent disabled, and parent education levels; neighborhood characteristic controls at the census block group level - percents of the population in each age group, with less than a high school diploma, with a high school diploma, with some college, and with a BA or more, who are black, who are Hispanic, and who are female headed households with children as well as median income. The dotted lines are the bounds of the 95% confidence intervals that are calculated using standard errors clustered at the school level.

Table A-1: Effect of Value-Added Information Using Quintiles of VA - All Releases

LAT 1^{st} VA Percentile × Post Aug 2010 × Quartile 2	2.79 (1.92)
LAT 1^{st} VA Percentile × Post Aug 2010 × Quartile 3	1.59 (2.1)
LAT 1^{st} VA Percentile × Post Aug 2010 × Quartile 4	-2.61 (2.61)
LAT 1^{st} VA Percentile × Post Aug 2010 × Quartile 5	-2.13 (2.53)
LAUSD VA Percentile × Post Apr 2010 × Quartile 2	-2.79 (1.77)
LAUSD VA Percentile × Post Apr 2011 × Quartile 3	-2.19 (1.86)
LAUSD VA Percentile × Post Apr 2011 × Quartile 4	-0.67 (1.97)
LAUSD VA Percentile × Post Apr 2011 × Quartile 5	-3.03 (2.72)
LAT 2^{nd} VA Percentile × Post May 2011 × Quartile 2	-0.31 (2.28)
LAT 2^{nd} VA Percentile × Post May 2011 × Quartile 3	3.71 (2.26)
LAT 2^{nd} VA Percentile × Post May 2011 × Quartile 4	0.89 (2.69)
LAT 2^{nd} VA Percentile × Post May 2011 × Quartile 5	3.91 (3.36)
API Percentile × Post Aug 2010	0.75* (0.04)
Observations	63,122

The data cover April 2009 through March 2011, prior to LAUSD's release of their value-added measure. All regression control for the following: month fixed effects; school zone fixed effects; housing characteristic controls - number of bedrooms, bathrooms and units in the home, square footage, and year built; census block group controls: % black, % Hispanic, % female headed households, educational attainment rates, % in each 5-year age group, and median household income; school characteristics: API levels overall and for all subgroups, lags and second lags of overall and subgroup API scores, % of students of each race, % free lunch, % gifted, % English language learners, % disabled, and parent education levels. Standard errors clustered at the school level are in parentheses. ***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table A-2: Effect of Value-Added Information Relative to Mean of Geographic and Ethnic Markets

Note: Estimates for all models are multiplied by 100.

	Geographic Markets Other Schools Within X Miles of School					Ethnic Markets "High": $\geq 25\%$ of Race in School
	2 mi	4 mi	6 mi	8 mi	10 mi	
	(1)	(2)	(3)	(4)	(5)	(6)
LAT 1^{st} VA Percentile	-0.039*	-0.043*	-0.039*	-0.042*	-0.043*	-0.046*
× Post Aug 2010	(0.023)	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)
Mean VA Nearby Schools	0.027	0.022	-0.174	0.041	0.195	
× Post Aug 2010	(0.048)	(0.077)	(0.106)	(0.123)	(0.152)	
High Black × Mean VA Other High Black						-0.026
× Post Aug 2010						(0.064)
High Hisp × Mean VA Other High Hisp						0.080
× Post Aug 2010						(0.076)
High White × Mean VA Other High White						0.028
× Post Aug 2010						(0.038)
High Asian × Mean VA Other High Asian						0.083
× Post Aug 2010						(0.055)
API Percentile	0.032	0.036	0.061	0.035	0.027	0.030
× Post Aug 2010	(0.044)	(0.044)	(0.044)	(0.044)	(0.045)	(0.049)
Observations	49,809	50,873	50,873	50,873	50,873	51,514

The data cover April 2009 through March 2011, prior to LAUSD's release of their value-added measure. All regression control for the following: month fixed effects; school zone fixed effects; housing characteristic controls - number of bedrooms, bathrooms and units in the home, square footage, and year built; census block group controls: % black, % Hispanic, % female headed households, educational attainment rates, % in each 5-year age group, and median household income; school characteristics: API levels overall and for all subgroups, lags and second lags of overall and subgroup API scores, % of students of each race, % free lunch, % gifted, % English language learners, % disabled, and parent education levels. Standard errors clustered at the school level are in parentheses. ***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table A-3: Effect of Value-Added Information on Log Sale Prices - Specification Checks, All Releases

Note: Estimates for all models are multiplied by 100 for ease of presentation.

	Add Census Tract FE (1)	Exclude Lagged API (2)	Use Sale Levels (3)	Limit to 0-2 Bedrooms (4)	Limit to 3+ Bedrooms (5)	Drop Imputed VA (6)	Drop Properties w/ > 8 Bedrooms (7)	Drop Properties w/ > 5000 sf (8)	Drop Multi Unit (9)	3 Month Lead (10)	No API* Post (11)	Summer Only (12)
LAT 1^{st} VA Pctl	-0.026	-0.028	-110.3	-0.006	0.008	-0.030	-0.017	-0.018	-0.009	-0.011	-0.11	-0.014
× Post Aug 2010	(0.021)	(0.022)	(73.3)	(0.026)	(0.017)	(0.023)	(0.022)	(0.021)	(0.016)	(0.022)	(0.22)	(0.058)
LAT 2^{nd} VA Pctl	0.021	0.024	55.0	0.046	0.006	0.031	0.023	0.026	0.031	0.003	0.025	0.028
× Post Apr 2011	(0.022)	(0.025)	(90.8)	(0.032)	(0.021)	(0.024)	(0.025)	(0.025)	(0.020)	(0.036)	(0.025)	(0.060)
LAUSD VA Pctl	-0.007	-0.014	-100.2	-0.029	0.024	-0.027	-0.019	-0.019	-0.022	-0.034	-0.019	-0.042
× Post Mar 2011	(0.027)	(0.027)	(97.2)	(0.029)	(0.022)	(0.027)	(0.029)	(0.028)	(0.019)	(0.038)	(0.028)	(0.044)
API Pctl	0.023	0.048	457.8**	0.021	0.002	0.069*	0.035	0.035	0.011	0.081***	0.173**	
× Post Aug 2010	(0.032)	(0.031)	(197.0)	(0.044)	(0.025)	(0.041)	(0.041)	(0.041)	(0.032)	(0.029)	(0.074)	
Observations	63,122	63,122	63,122	23,444	37,061	58,546	62,504	62,401	55,708	63,122	20,307	

The data cover April 2009 through September 2011. All regression control for the following: month fixed effects; school zone fixed effects; housing characteristic controls - number of bedrooms, bathrooms and units in the home, square footage, and year built; census block group controls: % black, % Hispanic, % female headed households, educational attainment rates, % in each 5-year age group, and median household income; school characteristics: API levels overall and for all subgroups, lags and second lags of overall and subgroup API scores, % of students of each race, % free lunch, % gifted, % English language learners, % disabled, and parent education levels. Standard errors clustered at the school level are in parentheses. ***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.