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

Value-added data are an increasingly common evaluation tool for schools and teachers. Many school districts have adopted these methods and released the results publicly. In this paper, we study the release of value-added data in Los Angeles by the Los Angeles Times newspaper to identify how measured value-added is capitalized into housing prices. This analysis is the first in the US school valuation literature to examine property value responses to a value-added information shock, which is of interest as this measure is less correlated with demographics than typical school quality measures. Unique to this setting as well is the release of both school and teacher-level value-added data, which allows us to examine how property values respond to both types of information. Using a difference-in-differences methodology surrounding the release, we find that neither school nor teacher value-added scores are capitalized into home prices. Our results suggest that, despite the contentiousness following these data releases, homeowners do not consider value-added models as currently constructed to be a relevant school quality measure on the margin.

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1 Introduction

The push to expand test-based accountability in US K-12 education has led to a significant rise in the amount of information available to the public about school quality. Such information typically consists of school-wide average test scores, which reflect many factors aside from the ability of schools to produce test score gains. Furthermore, information on individual teachers' performance largely has been kept private. As a result, recently there has been a growing interest in providing results of teacher and school "value-added" (VA) assessments to the public. A number of school districts, such as Los Angeles, Houston, and New York City, have released such information, either voluntarily or by court order. Ideally, such measures isolate the teachers' and schools' contributions to a student's achievement by removing the influences of other observed and unobserved factors. This information thus provides new data to parents and homeowners on the local schools' and teachers' contributions to test score growth. However, to the extent that there is noise and bias embedded in value-added measures, release of this information has the potential to distort parental decisions about where to live as well as school staffing decisions. Furthermore, because value-added information typically comes from a complex statistical model, it is unclear how it is interpreted by parents. With more and more school districts and states providing value-added data to parents and local communities, understanding the extent to which these communities value this information is of primary policy importance. It also is important for school administrators and policy makers to understand the impact of value-added on land values, as capitalization of value-added could affect the tax-base for school districts.

In this paper, we examine whether value-added information that is released to the public is capitalized into home prices. We make two contributions to the literature. First, there has been very little work done examining how parents value the value-added data generated by schools.[1] Due to the increasing prevalence of value-added information and the likelihood that such information will continue to be released to local communities, estimating the extent to which value-added affects property values is of importance in its own right.

[1]Jacob and Lefgren (2007) find that parents do value teachers who raise achievement, while Fiva and Kirkebøen (2011) analyze the impact of a value-added release in Norway.

The second contribution of this analysis is to the school valuation literature. A large set of prior work examines how average test score differences across schools are capitalized into home prices (Bayer, Ferreira and McMillan, 2007; Kane, Riegg and Staiger, 2006; Figlio and Lucas, 2004; Black, 1999). Most of these analyses use boundary discontinuity methods at school attendance zone boundaries, comparing differences in home values across school boundaries with different test scores.[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. However, a drawback of using average test scores to measure school quality is that they are highly correlated with the composition of schools and neighborhoods. Indeed, both Bayer, Ferreira and McMillan (2007) and Kane, Riegg and Staiger (2006) show that neighborhood and housing characteristics change at school boundaries due to endogenous parental sorting, and the estimated effects of test scores on home prices is reduced significantly in these studies once they control for neighborhood characteristics. These findings suggest 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 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 test scores is needed. Value-added represents such a measure, as it typically is generated using statistical models that control for students' prior test history and observable characteristics.[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

[2] 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.

[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 non-learning aspects of schools.

[4] This is done in a few different ways. Some models simply control for lagged achievement and/or student demographics and calculate residuals. Other more complex models include student fixed-effects or Bayesian smoothers. See Guarino, Reckase and Wooldridge (2012), Rothstein (2010), and Kane and Staiger (2008) for discussions of the benefits and drawbacks of such models. We also note that value-added models have come under considerable scrutiny on statistical grounds, suggesting they may yield a very noisy, and possibly biased, signal of school or teacher quality (Rothstein, 2010). Nonetheless, recent research has argued that if done correctly, value-added methods can produce accurate measures of teacher and school quality (Kane and Staiger, 2008; Chetty, Friedman and Rockoff, 2011; Kane et al., 2013).

characteristics. Furthermore, most of the information contained in the VA estimates was not predictable using observable school characteristics before their public release. Thus, our results provide new information about valuation of a school quality indicator that provides previously unknown information about a school or teacher's contribution to test score growth rather than information about the demographic makeup of the school.

While some prior work has shown that property values are unresponsive to value-added as calculated by the researcher (e.g., Dills, 2004; Downes and Zabel, 2002; Brasington, 1999; Haurin and Brasington, 2006),[5] parents and homeowners do not have direct access to this information. It is thus unlikely they would respond to it because the information is not salient. In contrast, we study a unique and unanticipated release of value-added information for schools in the Los Angeles Unified School District (LAUSD). As we show in detail, school rankings based on value-added scores were easily available and widely discussed in local and national news outlets, making it highly salient to home buyers and local residents. 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.[6]

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 LAUSD. Prior to the initial release, California already provided information on the effectiveness of LAUSD schools through published passing rates on the California Standards Tests and Academic Performance Index (API) scores. The API scores are based on average school performance on standardized exams and thus provide a summary measure of school-average test score levels for the whole school as well as some student subgroups. When the LA Times released the value-added data, they also provided school rankings based on API scores and exam passing rates on the same web page. Although these were already publicly available, the

[5]Gibbons, Machin and Silva (2013) is the only study of which we are aware whose results suggest that test score levels and value-added are similarly valued.

[6]The only other paper in the literature to examine housing market responses to public value-added information is in Norway. Fiva and Kirkebøen (2011) study the release of VA information in Oslo in 2005 and 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.

LA Times intervention potentially increased public awareness of these scores. The main focus of our analysis is on the short-run effect of this information on property values. We truncate our main analysis at 7 months post-release because in April 2011, LAUSD released its own value-added information and in May 2011, the LA Times updated their value-added data. The 7 month window allows us to identify the capitalization of value-added information that is free of influence from these other information releases. While this time period may seem short, prior work has shown that home price responses to school quality information shocks occur quickly (Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011). Nonetheless, we also examine impacts up to thirteen months 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 LA County Assessor's Office from April 2009 through September 2011, we 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. We find no evidence that the composition of home sales changed due to the information release, nor do we observe any change in foreclosure rates or differential pre-release trends as a function of value-added, which supports the use of our empirical methodology. Using boundary fixed-effects methods, we also show that API scores are similarly capitalized into home prices as has been reported in other studies, indicating that this school quality measure is valued in LAUSD. We find no evidence, however, that value-added information is valued by local residents: the difference-in-differences estimates are universally small and are not statistically different from zero regardless of whether we use shorter or longer analysis window. 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).

Unlike previous work on school quality valuation, we are able to examine how within-school variation in teacher quality is capitalized into property values, rather than just the school-level mean. It could be the case that home prices react more to the presence of a set of very good or very bad teachers, which school-level value-added can miss. We identify how home prices change as a function of the standard deviation of teacher value-added and the proportion of teachers in each school in each quintile of the value-added distribution. Our estimates are inconsistent with all but a small home price response to the distribution of estimated teacher quality. This lack of valuation of teacher quality is occurring despite the fact that similar teacher quality measures have been shown to increase long-run student outcomes (Chetty, Friedman and Rockoff, 2013). Finally, we examine several potential sources of heterogeneity and find suggestive, albeit largely statistically insignificant, evidence that value-added information is more highly valued in lower SES schools.

Overall, our results indicate that value-added information, as presently constructed, is not valued by local communities. One potential conclusion that could be drawn from our estimates is that marginal homebuyers do not value the aspect of school quality that is embedded in value-added, namely the ability of schools and teachers to raise test scores. Alternatively, the public could ignore value-added information due to its statistical complexity as well as the uncertainty amongst the research community as to the accuracy of these measures.

Our findings have important implications for the release of these data more broadly. Typically, the public release of value-added is contentious, with teacher groups arguing value-added is flawed and uninformative and with community advocates arguing that people have a right to know this information. Our results suggest that in their current form, the public does not respond to value-added information, and that while this information may not be causing the distortions about which the opponents of publishing value-added data worry, they also are not being valued as relevant school quality information that constitutes the main reason for publishing these data.

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.[7] The database was searchable by school and teacher name and people also 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

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

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.[8]

A critical question underlying our analysis is whether LA residents knew about the release of this information and how to access these data. 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 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

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

[9] Some examples of Spanish language coverage include a story on Channel 22 on Nov. 8, 2010 covering a protest of the value-added after a teacher committed suicide (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).

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.[10]

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 April 2011 and the LA Times updating its value-added measure in May 2011.[11] 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

[10]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.

[11]LAUSD's value-added measure was called Achievement Growth over Time (AGT) and was only calculated 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.

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 correlation 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 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.[12] 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.[13] 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.[14] The property sales data additionally contain information on the dates of the three

[12]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.

[13]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. Indeed, 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, provides almost identical results.

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

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 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.[15] 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 sales 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.[16] 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

[15] 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.

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

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 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,[17] 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 API scores. The figure presents the non-free/reduced-price (FRP) lunch rate, API percentile (within LAUSD) and value-added per-

[17]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.

centile 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 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 the myriad observable indicators of quality in our main empirical model. Column (1) shows the results for API percentile, and as expected, with an adjusted 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 second LAT value-added rank (columns 4 and 5) and the LAUSD value-added rank (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 also 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.[18] 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,[19] within-LAUSD API percentile rank in the given academic year,[20] 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

[18]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.

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

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

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, where VA and API are interacted with a series of indicator variables for time relative to the August 2010 LA Times release. 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 estimates 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, 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 support for any demographic or housing type changes that could seriously impact our estimates. There are 58 estimates of housing and neighborhood characteristics in the table; none are significantly different from zero at the 5% level and only 3 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 foreclo-

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

[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.

sures 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 number 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 estimate on LA Times release 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]

Note that this decline was smaller than the 7% rate for the US as a whole during this period.

[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.

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 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

[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).

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 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 value-added was not already capitalized into home prices in the pre-release period, indicating 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.

In Panel B of Table 5, we present estimates of equation (2) using the extended sample that include 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 lead to significant changes in property values. The same result holds for the API rank estimates in both panels of the table. The posting of API scores on the LA Times website did not affect home prices, which also is consistent with the evidence in Table 4.

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 variation in 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 at even the 10% level. It also is small, pointing to an increase in property values of only 0.007% for a one point increase in the standard 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%. This result is surprising, given the strong correlation between teacher quality and student academic achievement as well as future earnings (Rivkin, Hanushek and Kain, 2005; Rockoff, 2004; Chetty, Friedman and Rockoff, 2011). However, we note that it could be sensible to ignore teacher value-added scores if there is a significant amount of teacher turnover from year to year.

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.

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). The estimate is very similar to the column (1) estimate and is not statistically significantly different from zero. 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. Again, the estimate is negative, small in absolute value, and not statistically significant. In the final column, we 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. 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. 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 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 as estimated by 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.[30] 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

[30]Appendix Table A-1 provides these estimates using the full sample period and including all value-added releases. Results are similar to those seen in Table 8.

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.

As discussed above, we impute property values for about 7% of the sales using the combined assessed land and improvement values. As shown in column (6) of Table 8, excluding these imputed sale prices from our regression makes the value-added estimate more 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). In each of these cases, the estimates are quantitatively and qualitatively similar to our baseline results. Finally, in column (10), we allow for there to be a lag between when the information is released and when it impacts the housing market. We allow for a 3 month lag, 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.[31]

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. Since value-added models, by design, seek to measure school and teacher contributions to learning, the results presented thus far suggest this aspect of school quality is not highly valued on the margin. Another possibility

[31] 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-1 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.

is that parents value the ability of schools to improve student performance, but they do not believe the value-added information provided to them due to controversies over their accuracy. However, there are several other possible mechanisms driving our results other than parents not valuing the component of school quality measured by value-added. 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. 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. 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.[32] Further, news reports at the time indicated that the housing market was recovering.[33] Finally, 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. Thus, while the market was still sluggish, it appears that many of the rigidities that were present in Los Angeles during the crash had dissipated by the time of our study.

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

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

[33]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 it comes from a complex statistical model and/or because they received several, often conflicting pieces of information regarding value-added rank. While we acknowledge that parents may not have examined the details of the empirical models used to generate the value-added results, Figure 1 shows that the information was presented in a very clear and non-technical manner. Thus, it is unlikely that the information itself confused the public. It also could be the case that the school district and teachers attempted to discredit the value-added results. If such a campaign were responsible for our null results, though, it does not explain why parents are unresponsive to LAUSD's own value-added measure.

The release of multiple, conflicting measures of school quality also could have caused homeowners to dismiss the information altogether. This scenario is inconsistent with the lack of an effect of value-added information prior to the second value-added release. 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.

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.[34] 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.

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.

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. 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 one of the first to examine how publicly released school and teacher value-added information is capitalized into property values. We exploit a series of information releases about value-added by the Los Angeles Times and the Los Angeles Unified School District,

[34] These estimates are available upon request.

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 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 literature 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. Thus, 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 was 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. Property values may respond less to these measures because the information shock about school quality is smaller or because the computational complexity of the value-added models, as well as the associated statistical noise in the estimates, render them uninformative for the marginal home buyer.

That we find no effect of school or teacher value-added information on home prices suggests these school quality measures are not valued by local residents, at least on the margin. This is a surprising result, given the strong relationship found in other studies between these measures and student academic and future labor market success (Rivkin, Hanushek and Kain, 2005; Chetty, Friedman and Rockoff, 2011) as well as the contentiousness that tends to accompany the release of value-added data. In some sense, however, the heightened controversy could have driven the public to ignore the value-added. Not only did the public debate and the widespread coverage of the LA Times' release in the media likely increase awareness of these methods, it also probably made the public more aware of the flaws in these measures. Thus, the public may be rationally waiting for the research community to decide on what value-added measures are accurate before changing behavior in response to them. As a result, while value-added scores will undoubtedly be generated by more and more school districts and will be disseminated to the public in the near future, the evidence presented here suggests that in the current environment homeowners and parents do not value value-added as a relevant measure of school quality.

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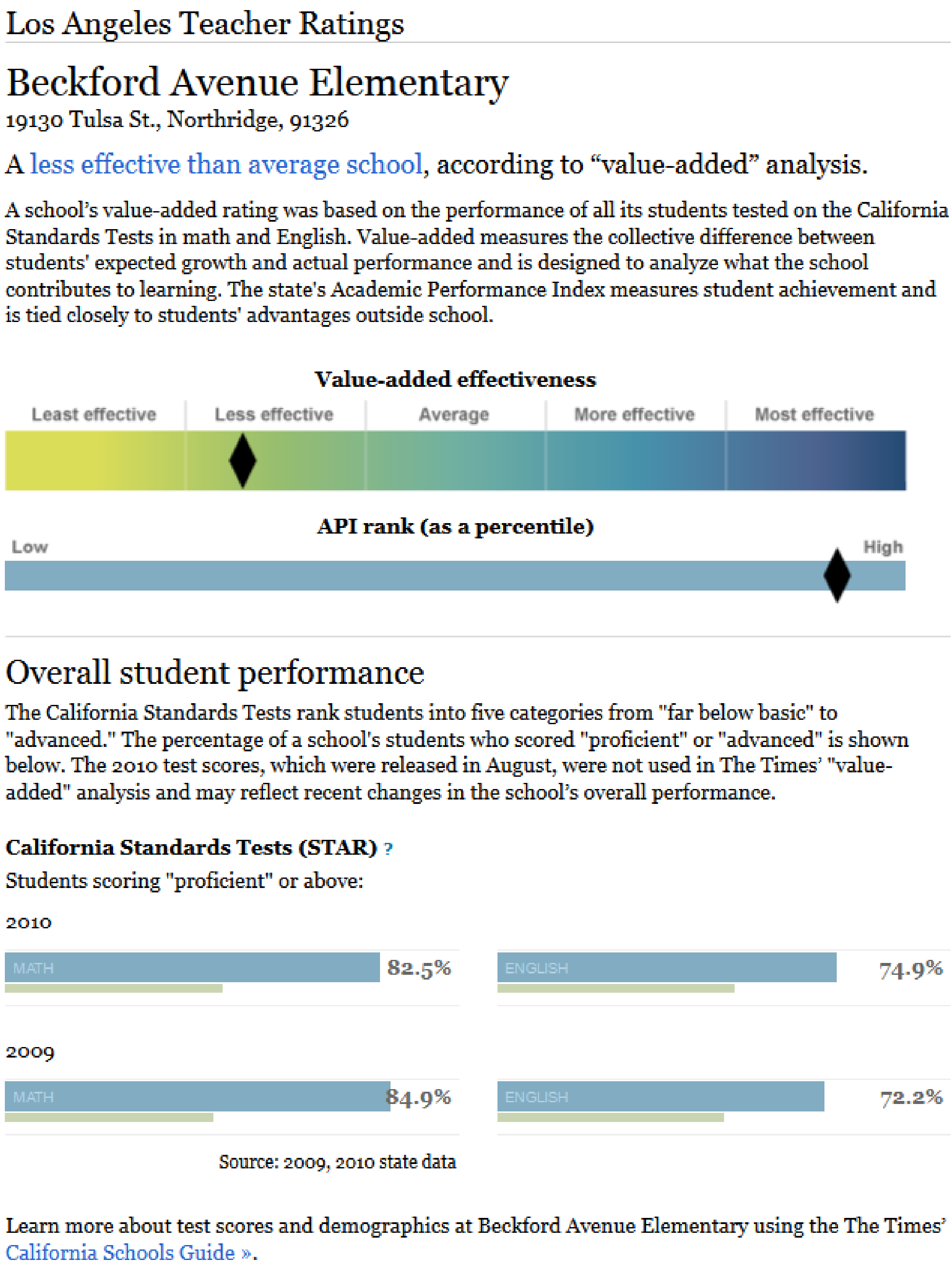
Figure 1: Example of Information Displayed in LATimes Database



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.

Value-added effectiveness

Least effective | Less effective | Average | More effective | Most effective

API rank (as a percentile)

Low | High

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:

2010

MATH 82.5% | ENGLISH 74.9%

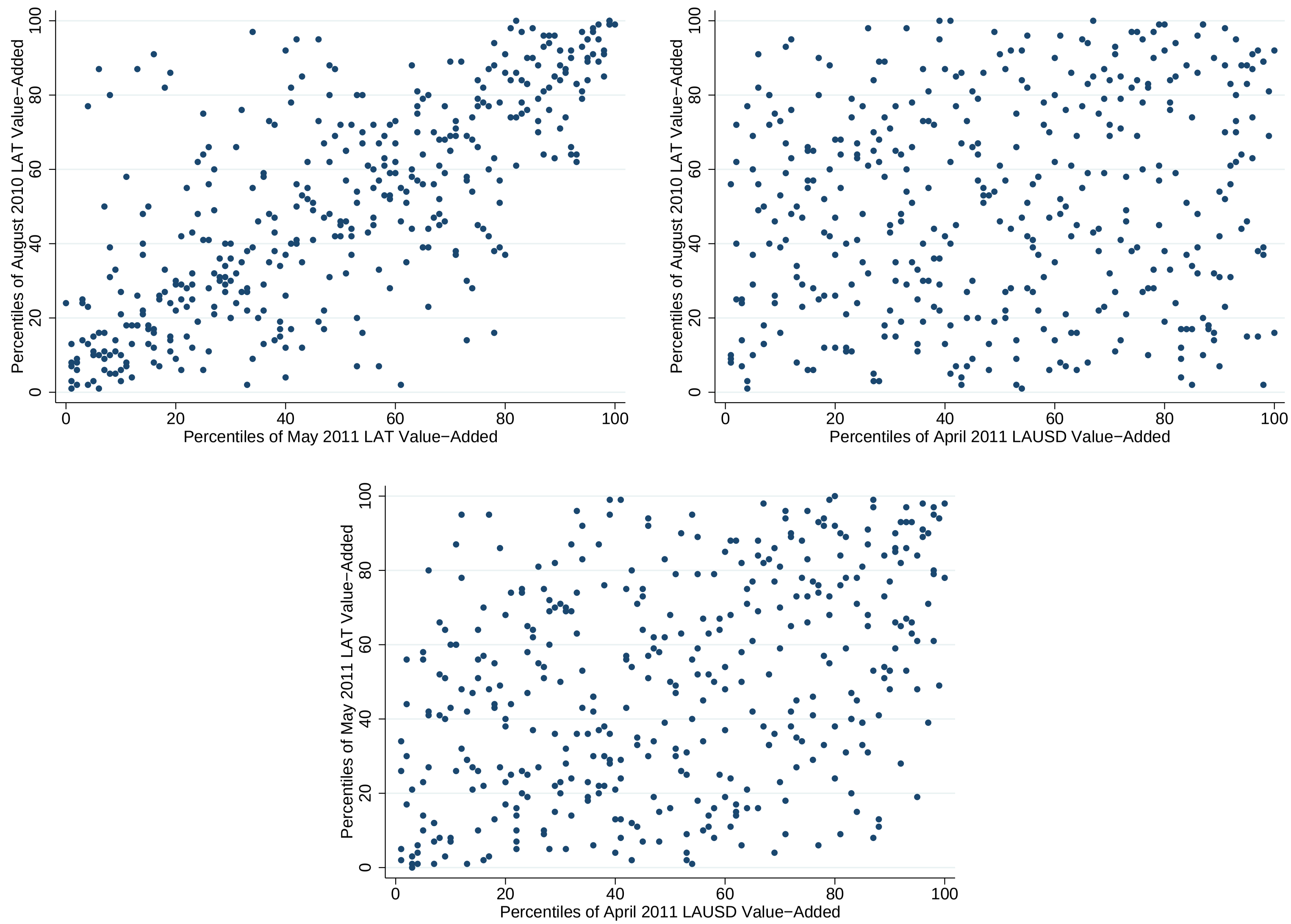
2009

MATH 84.9% | ENGLISH 72.2%

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

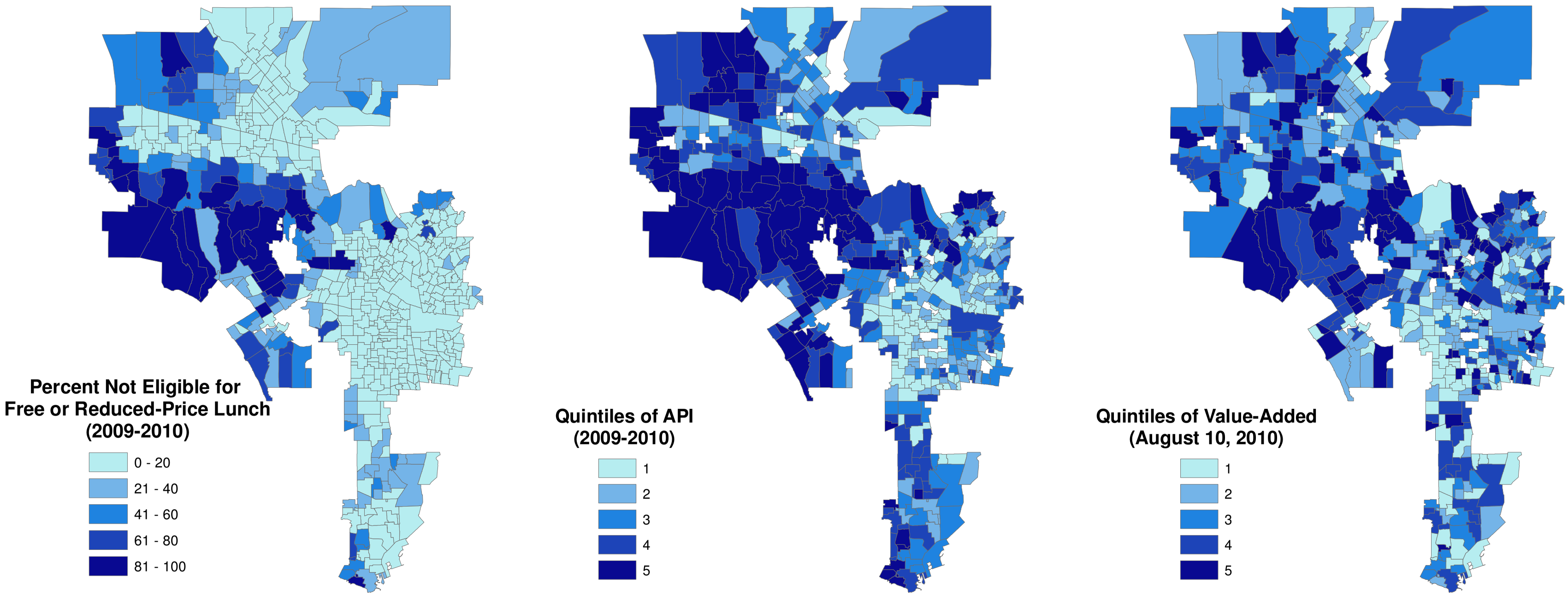
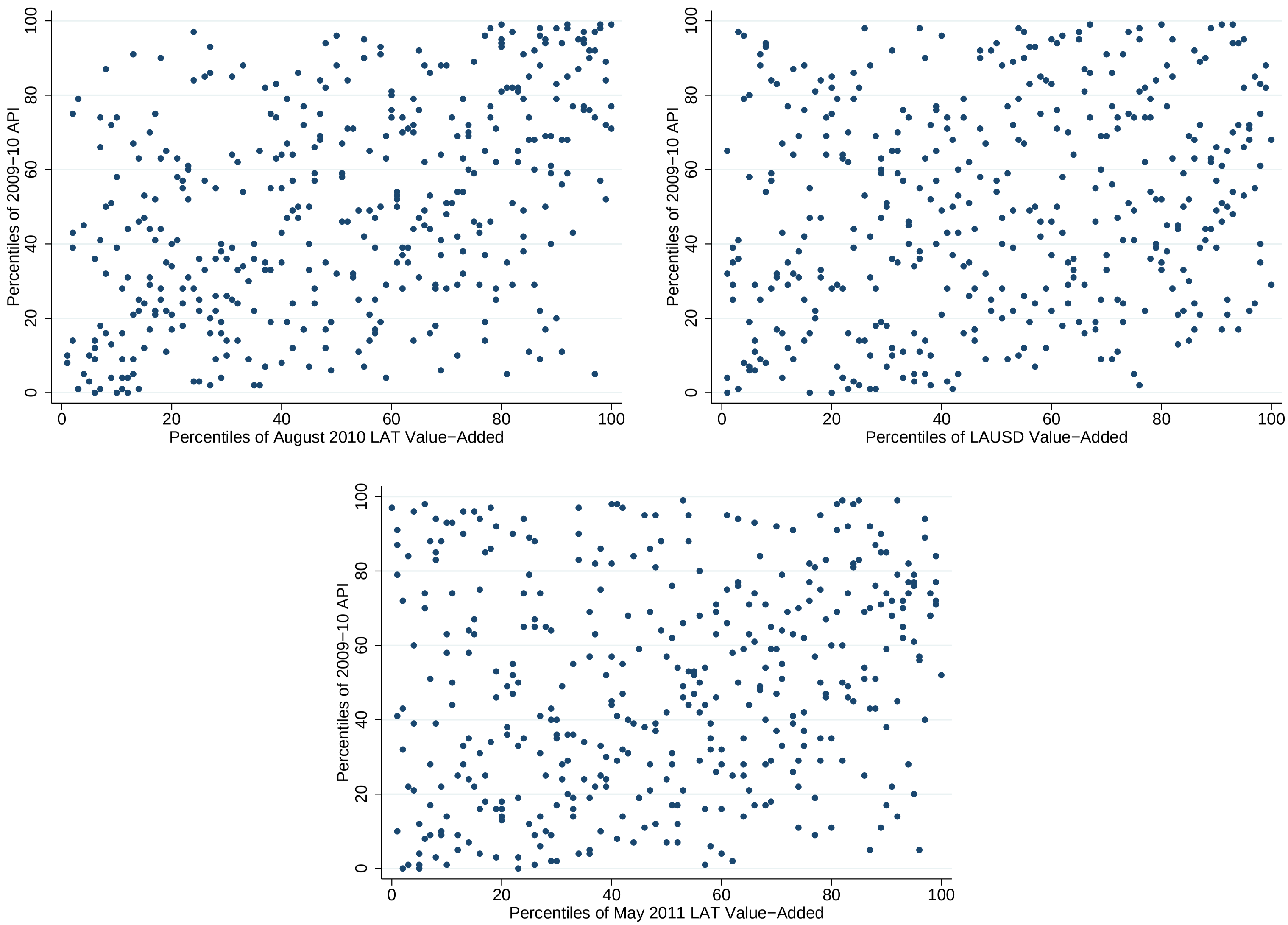
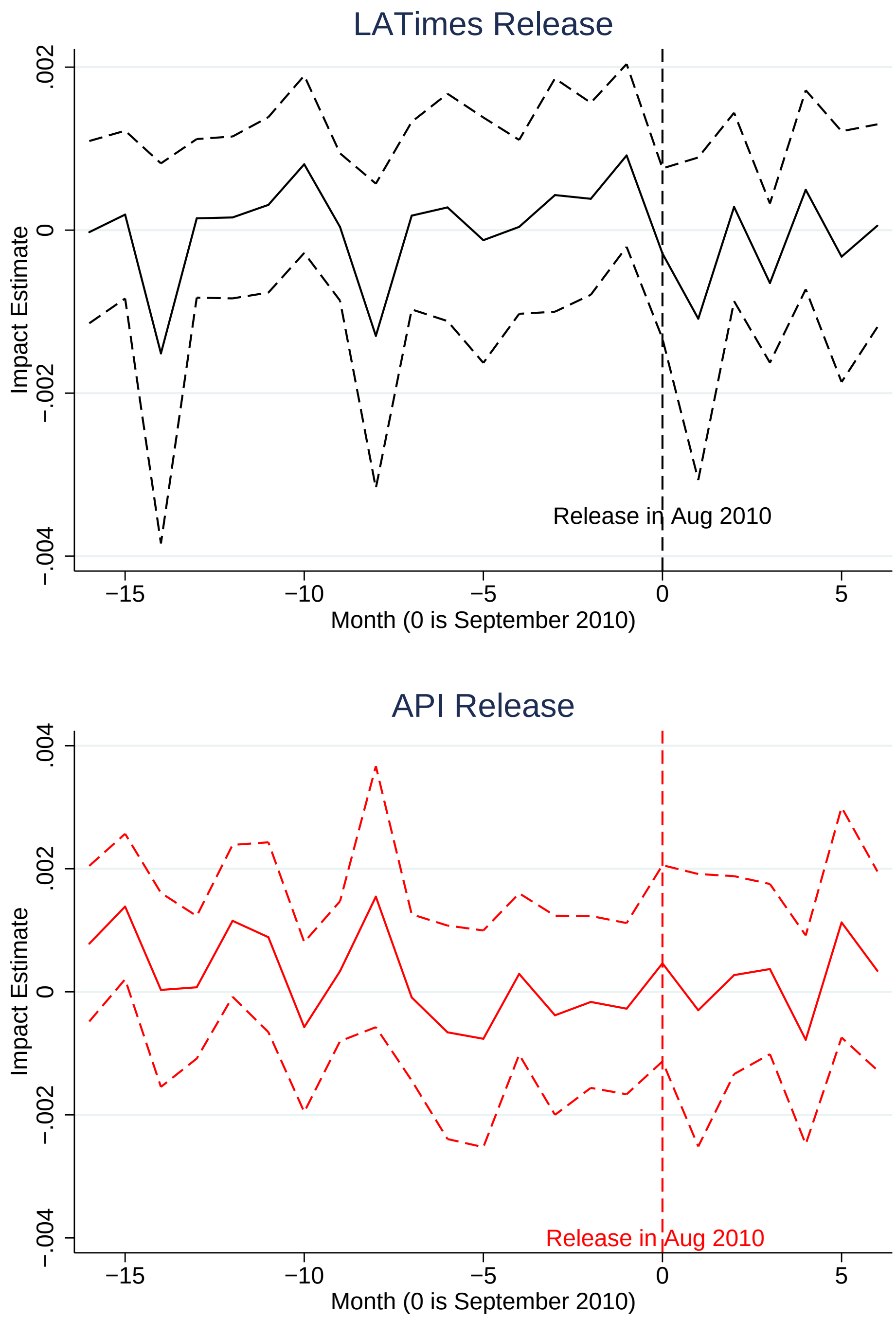


Figure 4: API Percentile vs. Value-Added Percentile



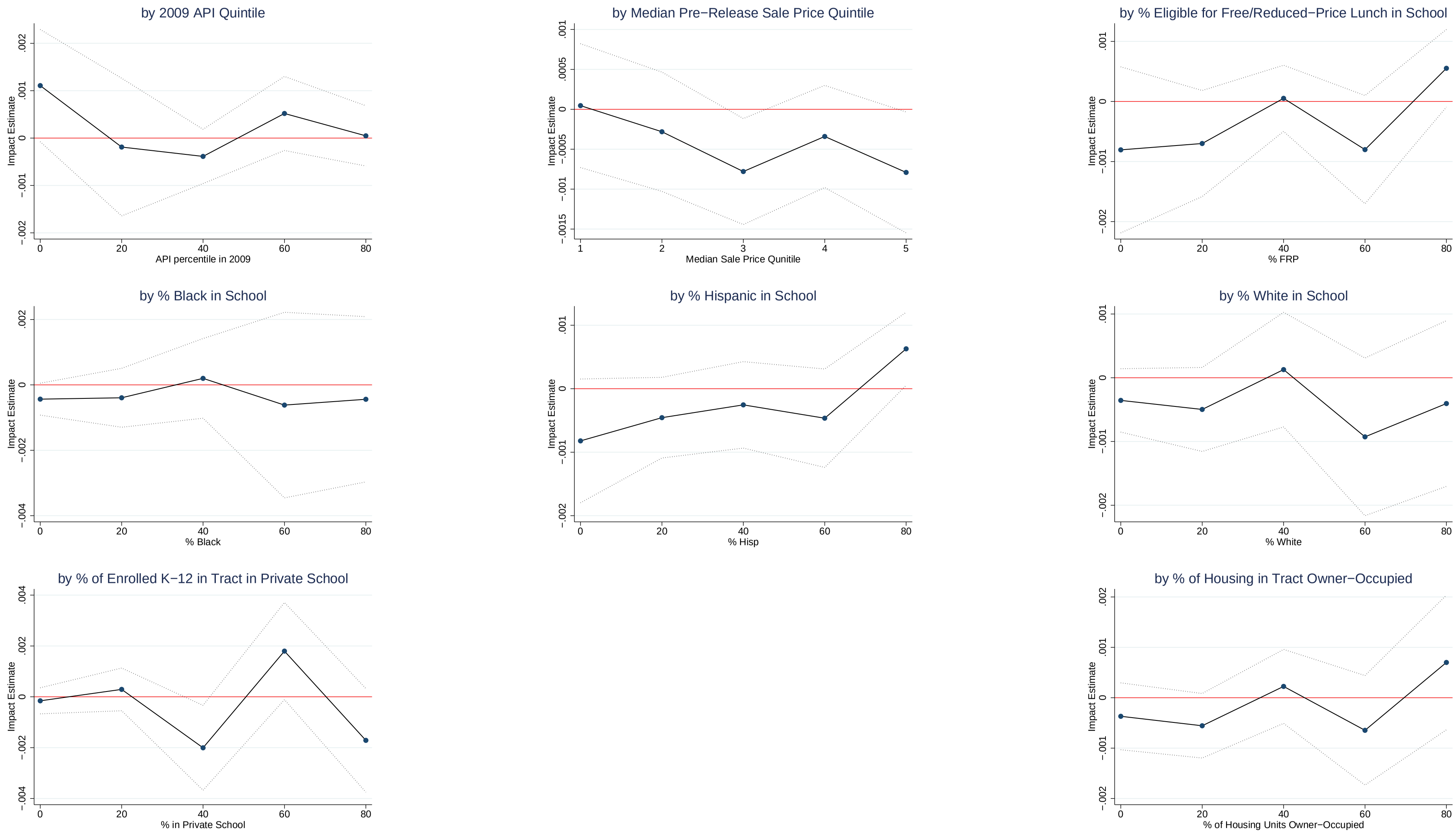
Percentile ranking amongst LAUSD elementary schools using 2009-10 API versus percentile rankings and the three value-added scores. Each dot is a single elementary school.

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



The estimates in 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. The estimates come from sales between April 1, 2009 to April 30, 2011. 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.

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



The value-added variable uses the LA Times value-added percentile from the August 2010 release until May 2011, at which point the variable is replaced with the value-added percentile from the May 2011 (2^{nd}) release. Similar measures for the LAUSD value-added are included in the regressions but are not shown. Controls include school fixed-effects, month of sale indicators, API, two years of lagged API, the California DOE similar school rank and the following: 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 tract level - percents 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 percent of adults who are married, institutionalized, veterans, of each education level, in the labor force, and unemployed, percent 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 characteristics are also interacted with a linear time trend. The dotted lines are the bounds of the 95% confidence intervals that are calculated using standard errors clustered at the school level.

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 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 ranking 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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable →	API Percentile	LAT 1^{st} VA Pctl	LAT 1^{st} VA Pctl	LAT 2^{nd} VA Pctl	LAT 2^{nd} VA Pctl	LAUSD VA Pctl	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) Avg Fam Size	(19) % Vacant
1^{st} LAT	-0.08	0.17	0.07	0.53	-0.28	-0.05	-0.08	0.25	-0.00	-0.00	-0.07
VA Pctl	(0.13)	(0.16)	(0.16)	(0.52)	(0.26)	(0.04)	(0.11)	(0.25)	(0.02)	(0.01)	(0.15)
	(20) % Owner Occupied	(21) % Male Married	(22) % Fem Married	(23) Fert Rate	(24) % Veteran	(25) % Same House 1Yr	(26) % Born in USA	(27) % English Speaker	(28) LFP Rate	(29) Unemp Rate	(30) % Commute Public Trans
1^{st} LAT	0.62	0.54	-0.02	-0.28	0.06	-0.36	0.55	0.48	-0.10	-0.05	-0.40*
VA Pctl	(0.78)	(0.34)	(0.36)	(1.01)	(0.09)	(0.41)	(0.39)	(0.58)	(0.41)	(0.12)	(0.24)
	(31) Mean Commute	(32) % On Social Sec	(33) % On SSI	(34) % On Cash Assist	(35) % On Food Stmp	(36) Poverty Rate					
1^{st} LAT	-0.08	0.19	-0.14	0.02	0.10	-0.29					
VA Pctl	(0.12)	(0.27)	(0.14)	(0.10)	(0.15)	(0.32)					
Panel C: Property Characteristics											
	(43) Mean # Units	(44) Mean Age of Structure	(45) Mean # Bedrooms	(46) Mean # Bathrooms	(47) 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											
	(48) % Black	(49) % Hisp	(50) % Asian	(51) % FRP Lunch	(52) % Gifted	(53) % ELL	(54) %Spec Ed	(55) Enroll	(56) % Parent HS Grad	(57) % Parent Some Col	(58) % 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 all census tract and census block group characteristics are 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. Panels A and B also include month fixed-effects while Panel C 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 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
$\times$ Apr 2009 - Aug 2010				(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
$\times$ Apr 2009 - Aug 2010				(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	Use Whether School in VA Quintile	Interact with # of Charters w/in 1 Mi
	(1)	(2)	(3)	(4)
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	0.042
× Post Aug 2010	(0.048)	(0.045)	(0.043)	(0.045)
LAT Teacher VA	0.007			
Standard Deviation	(0.099)			
2^{nd} Quintile		1.0	2.4	
		(6.5)	(2.1)	
3^{rd} Quintile		-0.0	2.2	
		(6.9)	(2.4)	
4^{th} Quintile		1.1	-1.9	
		(7.4)	(2.3)	
5^{th} Quintile		1.3	-0.9	
		(7.0)	(2.0)	
LAT 1^{st} VA				0.008
× Charters w/in 1 Mi				(0.010)
Observations	50,365	50,365	51,514	51,514

The data cover April 2009 through March 2010, 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 2010, 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.

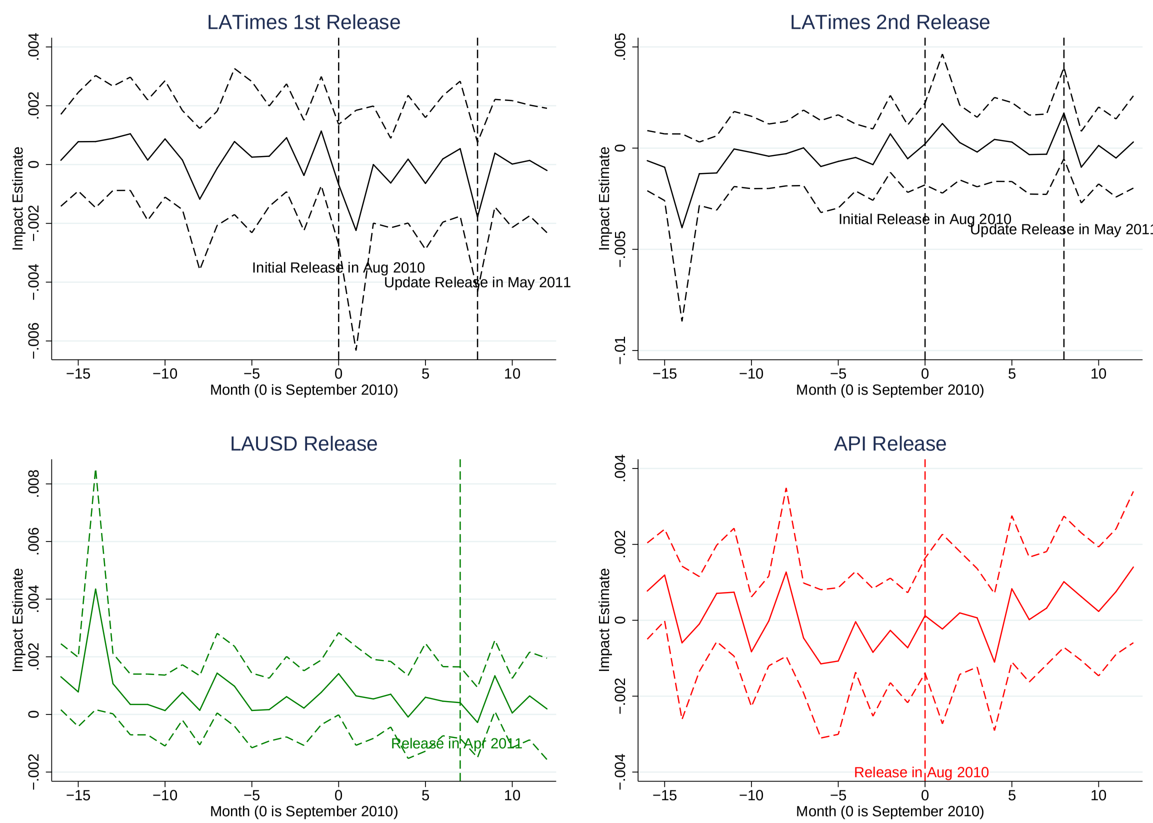
Table 8: Effect of Value-Added Information on Log Sale Prices - Specification Checks

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

	Add Census Tract FE	Exclude Lagged API	Use Sale Levels	Limit to 0-2 Bedrooms	Limit to 3+ Bedrooms	Drop Imputed Sales	Drop Properties w/ > 8 Bedrooms	Drop Properties w/ > 5000 sf	Drop Multi Unit	3 Month Lead
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
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
× Post Aug 2010	(0.024)	(0.024)	(82.3)	(0.029)	(0.017)	(0.025)	(0.024)	(0.024)	(0.016)	(0.030)
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 2010, 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.

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. The second LA Times value-added ranking replaces the first in month 8. 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 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	Exclude Lagged API	Use Sale Levels	Limit to 0-2 Bedrooms	Limit to 3+ Bedrooms	Drop Imputed VA	Drop Properties w/ > 8 Bedrooms	Drop Properties w/ > 5000 sf	Drop Multi Unit	3 Month Lead	Summer Only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
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	-0.014
× Post Aug 2010	(0.021)	(0.022)	(73.3)	(0.026)	(0.017)	(0.023)	(0.022)	(0.021)	(0.016)	(0.022)	(0.058)
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	0.028
× Post Apr 2011	(0.022)	(0.025)	(90.8)	(0.032)	(0.021)	(0.024)	(0.025)	(0.025)	(0.020)	(0.036)	(0.060)
LAUSD VA Pctl	-0.007	-0.014	-100.2	-0.029	0.024	-0.027	-0.019	-0.019	-0.022	-0.034	-0.042
× Post Mar 2011	(0.027)	(0.027)	(97.2)	(0.029)	(0.022)	(0.027)	(0.029)	(0.028)	(0.019)	(0.038)	(0.044)
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 March 2010, 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.