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 have become an increasingly common evaluation tool for schools and teachers. Many school districts have begun to adopt these methods and have released results publicly. In this paper, we use the unique release of value-added data in Los Angeles by the Los Angeles Times newspaper and the Los Angeles Unified School District to identify how school quality, as measured by value-added, is capitalized into housing prices. Unique to this setting is the release of both school and teacher-level value-added data, and this analysis is the first in the school valuation literature to examine property value responses to variation in teacher quality information. Using a difference-in-differences methodology surrounding several releases of value-added information, we find no effect on property values of receiving a higher value-added ranking post-information release. Neither the school or teacher value-added information is capitalized into home prices, even though we find evidence that test score levels are capitalized into home prices. Our results suggest that, despite the contentiousness following these data releases, homeowners and parents do not consider value-added 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 administrators, parents and teachers have about the effectiveness of specific schools and teachers. Consequently, in recent years there has been an increasing interest in providing results of teacher and school "value-added" 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. This influx of new information can be helpful to parents in assessing to which schools to send their children and can aid administrators in determining which teachers are more or less effective at raising student achievement. However, to the extent that there is noise and bias embedded in these school effectiveness 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 parents interpret this information. To our knowledge there has been no work done examining how parents value the value-added data generated by schools, although Jacob and Lefgren (2007) find that parents do value teachers who raise achievement. 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 the extent to which value-added information that is released to the public is capitalized into home prices. This is the first analysis to identify the responsiveness of home prices to the release of this type of information. While prior work has examined whether home prices respond to value-added as calculated by the researcher, because parents and homeowners do not have this information, it is unclear how responsive they will be to it. Indeed, the results from most of these analyses suggest that housing prices are unresponsive to value-added (Dills, 2004; Downes and Zabel, 2002; Brasington, 1999; Haurin and Brasington, 2006)[1], although Gibbons, Machin and Silva (2013) present evidence that test score levels and value-added are similarly valued. The lack of a response of home prices to researcher-calculated value-added in much of the previous literature could either be driven by a fundamental lack of relation between value-added and housing prices or the inability of home buyers to calculate value-added from the underlying measures the researchers use. To address this issue, we study a unique and unanticipated release of value-added information for schools in the Los Angeles Unified School District (LAUSD). The value-added measures were easily available and widely discussed in local and national news outlets, making them highly salient to home buyers and local residents.

In August 2010, the Los Angeles Times (LAT) published average value-added estimates for 470 elementary schools as well as individual value-added estimates for 6000 third through fifth grade teachers in LAUSD. The value-added estimates were generated by Dr. Richard Buddin using individual-level student and teacher linked data from LAUSD. Math and English value-added scores were calculated for both teachers and schools, and the LA Times averaged the two measures and then published each teacher and school's ranking relative to other teachers and schools in LAUSD. In April 2011, LAUSD released their own value-added estimates and in May 2011 the LAT updated their estimates to reflect an additional year of data. 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. When the LA Times released the value-added data, they also provided information about API scores and passing rates on the same web page. Although these were already publicly available, the LA Times intervention potentially increased public awareness of these scores. This setup allows us to identify separately how home prices respond to new information about average test scores and value-added, which is unique in the school valuation literature.

Disentangling how value-added versus test score levels are capitalized into home prices is of particular interest given the ample evidence from previous work that housing prices are

[1] See Black and Machin (2011) for a comprehensive review of this literature.

responsive to test score level differences across schools. Black (1999), Bayer, Ferreira and McMillan (2007) and Kane, Riegg and Staiger (2006) estimate regression discontinuity models across school zone boundaries to identify how school-average test scores are capitalized into housing prices.[2] They find a 1 standard deviation increase in test scores leads to about a 2% increase in home prices.[3] Figlio and Lucas (2004) examine the effect of the release of "school report card" data in Florida on property values. These report cards rated schools from A to F based on average performance on statewide exams, and the release of this information led to sizable increases in home prices in the areas that had higher performance. The results from these studies suggest that parents place significant value on school quality as measured by school-average test score levels.

While past work has shown a strong relationship between test score levels and property values, it is unclear what characteristics of the schools that are correlated with average test scores are being valued by residents. Test scores are highly correlated with the demographic makeup of the schools and the constituent 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. No previous studies have been able to fully disentangle the valuation of school/neighborhood composition from the valuation of the school's contribution to learning.[4] In order to isolate the capitalization of school quality as it relates to the production of learning, one needs a school quality measure that is less related

[2]International work also has used this method, such as Gibbons and Machin (2003, 2006) and Gibbons, Machin and Silva (2009) in England, Fack and Grenet (2010) in France and Davidoff and Leigh (2008) in Australia. We focus on the US evidence as it is the most relevant for our estimates.

[3]Kane, Riegg and Staiger (2006) report the effect of a 1 student-level standard deviation change in test scores on home prices, while the other papers in this literature report the effect of a 1 school-level standard deviation difference. We make the standard assumption that a school-level standard deviation is 10% of a student-level standard deviation in order to compare the results across these analyses.

[4]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.

to demographic characteristics than are test score levels is needed. Value-added represents such a measure, as it typically is generated using statistical models that control for students' prior history in order to estimate the current teacher's and school's contribution to learning through the student's growth in test scores.[5] As we demonstrate, the value-added scores released by the LA Times are much more weakly correlated with student observable characteristics than API scores, and the most of the information contained in these estimates was not predictable using observable school characteristics before they were published. Thus, our results provide 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. This is the first analysis in the school valuation literature to examine directly how housing markets respond to the provision of this type of information.[6]

Using housing sales data we obtained from the LA County Assessor's Office from April 2009 through September 2011, we estimate difference-in-difference models at the elementary school level that identify how home prices change after the release of each set 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 as a function of value-added, which supports the use of our empirical methodology. However, we also find no evidence that the value-added information is valued by local residents: the estimates are universally small, are not statistically different from zero, and are sufficiently precise that we can rule out all but very small positive effects. We supplement this analysis with a boundary-discontinuity difference-in-difference technique, in which we limit our sample to properties in a narrow band around school zone boundaries and add boundary fixed-effects. Thus, we compare the change in valuation in properties relative to properties on the other side of an attendance

[5] 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 Kane and Staiger (2008) and Rothstein (2010) for discussions of the benefits and drawbacks of such models.

[6] Though increasingly popular in education assessment, these models have come under considerable scrutiny on statistical grounds, suggesting value-added models 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).

boundary. The resulting estimates also provide no evidence that property values respond to value-added information. Additionally, while boundary-discontinuity estimates of API scores pre-August-2010 show that higher API scores are capitalized into home prices, there is no change in the relationship between API scores and property values post-August 2010. These results suggest that API information already was capitalized into prices.

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 mean 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 provide no evidence that home prices respond to the distribution of estimated teacher quality either.

Finally, we examine several potential sources of heterogeneity. We estimate whether property values respond more to the size or direction of the information "shock," as defined by the difference between the value-added and API rank. Our estimates are inconsistent with larger information shocks having larger effects on home prices. We also allow the effects of value-added information to vary by 2009 API decile, pre-release average sales price, percent eligible for free and reduced price lunch, and racial/ethnic composition of the school; these estimates consistently show no significant effect of value-added information on local property values.

Overall, our results indicate that value-added information is not valued by local communities. Our estimates are consistent with prior work examining the effect of researcher constructed value-added measures on property values, and it suggests the lack of effects found in those papers was not due to salience but rather that the value-added information is not valued by residents. This finding has important implications for the release of these data more broadly in the US. 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 Los Angeles Times and LAUSD Value-Added Releases

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 teacher fixed-effects to calculate teacher value-added and school fixed effects to calculate school value-added, controlling for lagged test scores, student fixed effects, and time-varying student and school controls. 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 referred to the bottom, second, third, fourth and top quintiles of the value-added score distribution for LAUSD, respectively. 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

[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.

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 be new. The value-added rank was not available in any form prior to August 2010. Finally, the web page provided passing rates on the math and English exams for each school, which was also publicly available prior to the value-added release. To keep our estimating equation simple, in our analyses we will assume that any response to the LA Times reprinting the passing rates will be reflected in responses to API.

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, 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.[8]

Second, the LAUSD teachers' union and the national American Federation of Teachers was highly vocal in their opposition to the public release of the data. This culminated in a series

[8]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).

of highly publicized and widely covered protests of the LA Times by teachers.[9] Further, 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. Further, according to the LA Times, by late afternoon on the initial date of the release there were over 230,000 page views of the website for the database (Song, 2010). The article points out that this is an unusually large volume of views given that traffic tends to be higher during the week and provides *prima facia* evidence that the value-added release was well-publicized and known to a large number of residents.[10]

The initial August 2010 data release was followed up with two more information releases. In April 2010, largely in response to the LA Times value-added release, LAUSD provided its own school-level (but not teacher-level) value-added measure called Achievement Growth over Time (AGT). Then, in May 2011, the LA Times updated the value-added results on its webpage to include another year of data, more teachers and some changes in the value-added methodology.[11] Figure 2 presents comparisons of the three school-level value-added measures. 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. However, each of the LA Times value-added measures is 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 differences in the methodology used to calculate value-added.[12] Below, we will examine the effect of all three data releases on property values, but we believe the first release by the LA

[9]One of these protests occurred after an incidence where a teacher committed suicide where a low value-added score was ostensibly a factor. This incidence was also widely covered by local media.

[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]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.

[12]Unlike the LAT method, the LAUSD method does not rely on fixed-effects. Instead, student achievement growth is predicted based on observable characteristics. The differences between predicted and actual achievement are then averaged together across all students in a school with sufficient data to form the school value-added estimates. Details on the LAUSD methodology can be found at http://portal.battelleforkids.org/BFK/LAUSD/FAQ.html.

Times in August 2010 is the most relevant to identifying how this information is valued as the information shock was the largest for this release.

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 31, 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 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.

We drop all properties with sale prices above $1.5 million (5% of households) and limit our sample to elementary schools 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 those observations that have all three measures recorded, the correlation between actual sale price and the imputed sale

[13] Given that the value-added information only varies across schools within LAUSD, there is 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.

[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 "sales" do not reflect market prices, we do not include them in our analysis.

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 62,977 sales.

We obtained the exact value-added score for each school published by the LA Times in August 2010 directly from Richard Buddin, and the April 2011 LA Times 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 API scores, school average racial composition, percent on free and reduced price lunch, percent disabled, percent gifted and talented, average parental education levels and enrollment. These covariates, which are available through the California Department of Education, control for possible correlations between value-added information and underlying demographic trends in each school. To maintain consistency with the LA Times value-added data we thus converted both the LAUSD value-added scores and API scores into percentile rankings within LAUSD.

We also link each property to its Census Tract characteristics from the 2005-2009 American Community Survey (ACS). Given the strong correlation between test scores and demographic characteristics as well as the strong evidence of sorting by families in response to cross-sectional differences in test scores (Bayer, Ferreira and McMillan, 2007; Kane, Riegg and Staiger, 2006), it is important to control, to the extent possible, for differences in the demographic and socioeconomic makeup of neighborhoods as they relate to observed school quality. For each Census Tract, we collected the percent who are children and senior citizens, median age, percent male, racial composition, the percent of households with children (overall and by single parent status), the percent of households with senior citizens, average household and family size, percent of homes vacant and owner-occupied, marriage rate (separately by gender), fertility rate, e ducational attainment composition, the percent veteran, the percent who moved in the last year,

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

the percent born in the US and percent native speaker. We also measure the labor force participation rate, the unemployment rate, the percent who commute using public transportation, median household income, the percent on social security, SSI, cash assistance, and food stamps and the poverty rate.

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 Tracts that are about 50% black and Hispanic[17], but the schools these properties are zoned to are 73% black and Hispanic, with the difference ostensibly due to large enrollments in private, charter and magnet schools. The schools in our dataset also have a large proportion of free and reduced price lunch students. A core contribution of this analysis is to identify how school quality measures that are less reflective of demographic characteristics than test score levels are capitalized into home prices. The second two columns of Table 1, however, show that value-added is not completely uncorrelated with school or Census Tract 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 correlations shown in Table 1, value-added is far less correlated with student demographic makeup than API scores are. The figure presents the non-free/reduced-price (FRP) lunch rate, API percentile (within LAUSD) and value-added percentile for each elementary school in LAUSD. The boundaries denote the attendance zone for each school. As expected, API percentiles, which are based on test score proficiency rates, map closely to poverty rates. High-poverty (low non-FRP lunch) schools tend to have lower API scores. While this relationship remains when replacing API with value-added, it is far less robust. There are many schools, particularly in the eastern and northern sections of the

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

district, where API scores are low but value-added scores are high. Similarly, some schools with high API scores have low value-added scores. Figure 4 further illustrates this point. It provides a scatter plot of API percentiles versus value-added percentiles for each of the value-added measures. The figure shows an enormous amount of within-school variability in these measures and demonstrates the weak correlation between value-added scores and test score levels. While there is a positive relationship between the two measures[18], it is quite weak - the average correlation between the two types of outcomes 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 a 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. 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, the percentile from the first LA Times value-added release, and the LAUSD value-added percentile as a function of school observables in the pre-release period.[19] Column (1) shows the results for API percentile, and as expected, with an R^2 is 0.71, it is highly related to school demographics. In contrast, the value-added estimates are much more weakly correlated with school demographics. In column (2), 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 API as a regressor to the model. While API is correlated with value-added, the R^2 still is only 0.27. Thus, almost 3/4 of the value-added variation is unpredictable from the observable characteristics of the school, including test score levels. Further, in Columns (5) and (6) we see that these observables do an even poorer job of predicting the LAUSD value-added rank, with R^2s of 0.03 and 0.20 with and without including API as a regressor, respectively.

[18]A linear regression of value-added percentile on API percentile provides an estimate of 0.43 (standard error 0.04) but an R-squared of only 0.19.

[19]Note that API and value-added scores are based on data from the same pre-release period, even though the resulting measures have not yet been released at this time.

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 simply a measure of the school composition or prior test scores. Our identification 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. Initially, we allow for each information release as well as API to have an independent effect on property values. Our main empirical model is of the following form:

$$\begin{aligned} Y_{ist} &= \beta_0 + \beta_1 VA^{LAT1}_{st} + \beta_2 VA^{LAT2}_{st} + \beta_3 VA^{LAUSD}_{st} + \beta_4 API_{st} + \beta_5 API_{st} \times Post_t \\ &\quad + \mathbf{X}_{st}\Gamma + \mathbf{H}_i\Phi + \lambda_t + \gamma_s + \epsilon_{ist}, \end{aligned} \tag{1}$$

where Y_{ist} is the log sale price of property i in elementary school zone s in month t. The three treatment variables in equation (1) are VA^{LAT1}, VA^{LAT2} and VA^{LAUSD}, which are the value-added percentiles from the first LA Times release, the second LA Times release and the LAUSD release, respectively. Each one of these variables is set to zero before the associated release date,[20] so these variables include the interaction with post-release indicator variables. In addition, the model allows for the effect of API scores to change post-August 2010. Our inclusion of school fixed-effects in the model (γ_s) implies that the coefficients on the VA and $API * Post$ variables represent the difference-in-difference estimate of the effect of the value-

[20] VA^{LAT1} is set to zero before September 2010, VA^{LAT2} is set to zero before May 2011 and VA^{LAUSD} is set to zero before April 2011.

added or API information release on property values.[21] In order to account for the fact that there are multiple sales per school zone, all estimates are accompanied by standard errors that are clustered at the school level.

Equation (1) also includes an extensive set of controls to account for any confounding effects driven by the correlation between value-added and school demographic or housing characteristics. The vector X contains the set of school observables discussed above, including two lags of API, within-LAUSD API percentile in the given year, and the decile of the school's API in comparison to other "similar" schools, as defined by the California Department of Education. The vector H is the set of house-specific characteristics and Census tract characteristics discussed above that further control for local demographic differences that are correlated with value-added and for any changes in the types of houses being sold as a function of value-added when each release occurs. Equation (1) contains both month-by-year fixed effects(λ_t) and school fixed effects (γ_s) as well, so all parameters are identified off of within-school changes in home prices over time and control for any general shocks to home prices in LAUSD. The coefficients of interest in equation (1) are β_1-β_3 and β_5, which show the effect of a 1 percentage point change in value-added or API ranking on home prices after each data release.

We also provide a modified model similar to equation (1) but where we combine both LA Times releases by replacing VA^{LAT1} with VA^{LAT2} in month 8 to create a single "pooled" value-added variable for the LAT releases. Thus our model becomes

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

This model allows us to simplify the analysis and eases interpretation. As we show below, our results are similar regardless of whether we estimate equations (1) or (2).

There are two main identifying assumptions underlying identification of the value-added parameters. First, the model assumes that home prices were not trending differentially by

[21] Note that unlike API, which changed each year, each value-added release provides a single value for each school, and thus main effects are removed by the school fixed effects. In models that do not include school fixed effects, main effects are included as controls as well.

value-added prior to each of the data releases. 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 of the effect of each value-added and API release, where the pooled value-added measure in equation (2) is interacted with a series of indicator variables for time relative to the August 2010 LA Times release. In the top two panels of Figure 5, there is no evidence of a pre-release trend in home prices as a function of LAT or LAUSD 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 are no clear pre-treatment trends for either information release that would bias the estimates for the value-added releases. For API, while there appears to be a slight downward trend in earlier months, the trend is not statistically different from zero and by 7 months prior to the release, 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 nor API post-release for any of the releases. However, these estimates are relatively imprecise, as the estimates in Figure 5 are demanding of the data. We thus favor the more parametric models given by equations (1) and (2). Nonetheless, Figure 5 demonstrates that pooling the estimates over each post-release period does not mask any time-varying treatment effects.

The second main identification assumption required by equations (1) and (2) is that the value-added score, conditional on school characteristics, is not correlated with unobserved characteristics of the households. While this assumption is harder to test than the parallel trends assumption, given the rich set of observable information we have about the homes sold, examining how these observables shift as a function of demographic characteristics will provide some insight into the veracity of this assumption. Thus, in Table 3, we show estimates in which we use each of the variables in the H vector as dependent variables in regressions akin to equation (2) but excluding the H and X controls. Each column in the table comes from a separate regression, and each set of estimates shows how the observable characteristic changes as a function of value-added percentile after each 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 94 estimates in the table, three of which are significant at the 5% level or higher and eight more of which 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 nine times in a table with 94 estimates.[22] For the LA Times release, which is our main focus, only four estimates out of 47 are significant at the 10% level or higher. Furthermore, the estimates, even when significant, are small. For example, a 10 percentage point increase in LA Times value-added post-release is associated with a decrease in the percent of household with children of -0.04 percentage points, which is a very small effect relative to the mean of 32%. Additionally, the signs of the estimates do not suggest any particular patterns that could cause a systematic bias in either direction in our capitalization results.

A concern related to the fact that the value-added information change may be correlated with the types of houses sold in a school catchment area is that the value-added information causes a change in the number of homes sold. Because 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. The strong correlation between price and the observable characteristics of a home, combined with the fact that we see no change in the types of homes sold in Table 3, suggest this scenario is unlikely. Nevertheless, in Table 4, we estimate a version of equations (1) and (2) 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] Table 4 presents the results from these regressions. In the first column, we use all sales in our data during the time period, which covers the three most recent sales as of October 2011. In the second column, we restrict to our estimation sample. The point estimates are small, are not statistically significant in any case, and vary in sign. These estimates suggest the value-added information did not cause a change in the number of homes sold in each school, which supports the validity of using prices derived from sales data.

[22] While not shown in the table, the estimates for API*post are significant at the 10% or lower level for only two variables - labor force participation and share of census tract receiving Supplemental Security Income assistance.

[23] We include mean Census Tract 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.

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. During the period studied, home prices declined by about 4.5% in the Los Angeles MSA.[24] This also was a period with large amounts of foreclosures. If foreclosures are correlated with the value-added releases, it could bias our home price estimates because foreclosures are not counted as sold property in our data. 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.[25] We aggregate the data to the school-month level, and using the zipcode-level data 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. None of the estimates for any of the three data releases is statistically significant. The estimate on the first LA Times release is the largest in absolute value, at -0.012 (0.009), which indicates that a 10 percentile value-added increase post-release decreases the number of foreclosures by 0.1, off of a mean of 5.7. Thus, while the point estimate is negative, it is very small relative to the base number of foreclosures and it is not statistically significantly different from zero.

Overall, the estimates from Tables 3 and 4 along with Figure 5 do not show any evidence of differential pre-treatment trends by value-added, nor do they point to systematic changes in the type or number of properties sold as a function of value-added post-release. We also find no evidence of a relationship between value-added and foreclosures. As these are the most likely sources of bias in estimation of equations (1) and (2), these results support our use of this model to identify the extent to which value-added information is capitalized into home prices. However, we also will supplement our analysis with a boundary-discontinuity difference-in-difference model in which we restrict to a 0.1 mile area around each school boundary and include boundary fixed effects in equations (1) and (2). This model identifies how property values change as a function of value-added local to catchment zone boundaries when the value-added information is released, and the results provide a check on the more general difference-

[24]This calculation comes from the Federal Housing Finance Agency's seasonally adjusted home price index. Note that this decline was smaller than the US as a whole, which experienced a decline of 7% over this period.

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

in-difference estimates provided by equations (1) and (2).

5 Results

5.1 Pre-Release School Quality Valuation Estimates

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 their non-neighborhood school and there 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. To address this issue, we estimate boundary fixed effects models using pre-release data from April 2009 to August 2010 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).

Table 5 contains boundary fixed effects results, comparing home prices within 0.1 mile of elementary attendance zone boundaries. In column (1), which includes no other controls, properties just over the border with a higher API rank are worth substantially more. For ease of interpretation, 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 column (2) we control for housing characteristics, which has little impact on the estimates. On the other hand controlling for demographic characteristics significantly reduces this association. This is not surprising given the findings in Bayer, Ferreira and McMillan (2007) and Kane, Riegg and Staiger (2006). Nonetheless, in column (3), we find a 10 percentage point increase in API rank leads leads to 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). 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.[26] 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 less correlated with student demographics than test scores.

In order to underscore the fact the value-added is not highly correlated with student demographics and that it is difficult to predict with pre-release observables, the remaining columns of Table 5 test whether value-added information is capitalized into property values prior to their release. If parents know which schools are the highest value-added from reputation or from factors we cannot observe, the value-added releases will not provide additional information about school quality. In columns (4) and (5) of Table 5, we estimate the same boundary fixed effects model as in column (3) but using the first release of LAT value-added or the LAUSD value-added as a dependent variable. Since all of the sales data used in Table 5 is pre-August-2010, these models test whether future information about value-added is already capitalized into home prices. In column (4), there is a positive relationship between the LA Times value-added and property value differences across boundaries. However, some of this effect is likely due to the weak correlation between LA Times value-added and API (see Table 2 and Figure 4). As a result, when add API percentile as a control in column (5) the relationship between value-added and test scores becomes smaller and no longer is statistically significant. The magnitudes of the estimates also are very small. However, the API estimate is almost identical to that found 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 and LAUSD value-added estimates are not already capitalized into home prices prior to August 2010.[27]

[26]Ideally one would also like to control for neighborhood characteristics as well. However, typically the boundary areas in LAUSD are smaller than Census tracts, leaving most boundary areas entirely within a single tract. When we control for Census tract observables, the API coefficient becomes smaller and no longer is statistically significant. This finding suggests either that the aspect of API that is capitalized into property values is neighborhood composition or that including our set of neighborhood controls leaves too little variation for identifying the role of API.

[27]The lack of value-added effects in Table 5 is not being driven by collinearity from the inclusion of LA Times

5.2 Difference-in-Difference Estimates

Table 6 presents the baseline estimates from estimation of equations (1) in the first panel and equation (2) in the second. In each column, we add controls sequentially in order to observe the effect 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. In column (1), we included no controls other than those shown in the table, API score, API percentile, lagged and twice lagged API score, and school rank compared to 'similar' schools in California as determined by the California Department of Education. There is a small but negative relationship between the LA Times value-added measures and home prices post-release and a positive relationship for LAUSD value-added. When we add school and month fixed effects, however, the second LA Times and LAUSD value-added coefficients become attenuated and no longer are statistically different from zero at even the 10% level. The estimates in Panel (1) remain rather stable between columns (3) and (6) when observable characteristics are included in the regressions. In column (6), which shows our preferred estimates, the upper bound of the 95% confidence interval can rule out effects for a 10 percentile increase in value-added rank of 0.18% for the first LA Times release, of 0.72% for the second LA Times release and of 0.45% for the LAUSD release. Our results thus point to no effect of the value-added information on home prices, as we can rule out even small impacts.

When we combine the LA Times estimates in Panel (2), the LAUSD coefficient changes little. The LA Times estimate is negative but similar in magnitude to the first-release estimate in Panel (1). the upper bound of the 95% confidence interval of the LAT value-added effect is 0.10% for each 10 percentile point value-added change. Furthermore, in neither panel is the effect of API changes post-August 2010 large or significantly different from zero, and in fact we can rule out effects of more than 0.1% for a 10 percentile increase in API. These estimates suggest there was no change in how API score information was capitalized into property values when the information was posted on the LA Times website. We believe this result is due to the fact that this information already was capitalized into home prices, as suggested by the

and LAUSD value-added in the same model. As shown in Figure 4, these measures are only weakly correlated with one another.

boundary discontinuity estimates in Table 5 and the fact that API scores are highly correlated with observable school characteristics (see Table 2).

Column (7) of Table 6 provides further evidence that value-added information does not affect property values. We restrict to properties within 0.1 miles of a school zone boundary and include boundary fixed effects in this model. Thus, the estimates are identified off of differences between properties on either side of a given attendance zone boundary. Table 5 shows that home prices do not vary systematically across borders with value-added in the pre-period, and the results from column (7) indicate that they do not change across these borders with respect to value-added when this information is released either.

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 6000 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. Given the similarity between the estimates in panels (1) and (2) in Table 6, for this model and all additional analyses we use the regression model in equation (2) as our baseline.

In column (1) of Table 7 we add the standard deviation of the value-added scores across teachers in each school interacted with the timing of the initial LA Times release. If high-quality teachers are valued (or if very poor teachers have a negative valuation), then a higher standard deviation will lead to higher (or lower) property values. The estimate on the standard deviation of teacher value-added estimate in column (1) of Table 7 is negative, but it is not statistically significantly different from zero at conventional levels. It also is small in absolute value, pointing to a decline in property values of only 0.006% for a one point increase in the standard deviation of teacher value-added.

In column (2), we include the proportion of teachers in each quintile of the value-added distribution interacted with being in the post August 2010 period in the model rather than the standard deviation. Again, we see little evidence that having a higher proportion of teachers with higher value-added leads to higher property values. 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, the teacher value-added as measured here could be rather unstable from year to year, as each estimate is based off of a small number of students assigned to each teacher.[28] It therefore could be sensible to not react to one year's teacher value-added scores if they are not strong indicators of actual teacher quality.

The remaining columns of Table 7 present robustness checks of several of the modeling assumptions we make. In column (3), we use sale levels instead of logs. The estimates, once converted back to percentage terms relative to baseline, are very similar to those in Table 6. In column (4), we average across all value-added measures in case home prices respond to consistent information across all of the different measures. We find no evidence that such consistent information is more valued, as the point estimate is negative and not statistically different from zero. In the final two columns, we examine estimates separately for homes with more than two bedrooms and two or fewer bedrooms, as the former homes are more likely to have families with children in them. Although the point estimates for the homes with more than two bedrooms are larger than those for homes with two or fewer bedrooms, none of the estimates is statistically significantly different from zero at even the 10% level and the estimates remain small. Thus, value-added information does not influence property values even among the homes that are most likely to have children in them.

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 how value-added is capitalized into home prices. First, it could be the case that home prices respond to positive or negative information. For example, finding out a low-test-score school is a high value-added school might raise its property value more than if the high value-added school also was a high-test-score school. Furthermore, positive and negative information may be capitalized differently into home prices. Because API scores were publicly available prior to the first LA Times release, we calculate the difference between API rank and both LA Times value-added rank and LAUSD value-added rank.

[28] Imberman and Lovenheim (2012) show that teacher value-added in Houston among elementary school teachers exhibits a large amount of noise from year to year, which reduces the responsiveness of teachers to value-added information in a teacher incentive pay system.

Table 8 provides evidence on whether the size of the information shock affects the responsiveness of property values to value-added information. In column (1), we examine linear measures of the difference between LA Times and LAUSD value-added ranks and API rank. We find that larger information shocks do not have larger effects on property values. In the next three columns, we examine potential non-linearities in the size of the information shock by including dummy variables that indicate whether the VA-API difference is positive or negative (column 2), whether it is more than 20 percentile points apart in either direction (column 3) and whether it is more than 40 percentile points apart (column 4). If the size of the information shock is important than the "High" estimates should become positive and larger and the "Low" estimates should become negative and smaller across columns, which is inconsistent with the results. In the remaining columns of Table 8, we allow for the capitalization effect to vary by whether either or both of the LAT and LAUSD ranks are high or low. When both estimates are high or low, people may place more weight on them because they are providing a consistent set of information. However, in none of the columns is their any evidence of heterogeneous effects by whether the value-added estimates are large or small or by whether they are consistent with one another.

In Figure 6, we present additional estimates broken down by observable characteristics of the school: 2009 within-LAUSD API decile, median pre-release home price decile, percent free and reduced price lunch, percent black, percent Hispanic, and percent white.[29] Although the precision of the estimates vary somewhat, the point estimates are universally small in absolute value and are only statistically significantly different from zero at the five percent level in three cases (out of 45 estimates). Figure 6 thus provides little evidence of heterogenous treatment effects by observable school type, and overall the results from Tables 7-8 and Figure 6 suggest that the zero average effect of value-added information we report is not masking important sources of heterogeneity. Rather, regardless of the size of the information shock or the type of school, homeowners in Los Angeles do not value value-added information about schools and teachers.

[29]We use only five cuts of the data for % FRP , % black, and % white as there are few schools in LAUSD with low values of the the first and high values of the second two characteristics. On the other hand, there is wide variation in % Hispanic, so we use deciles for this variable.

Finally, in Table 9, we present a series of robustness checks that allow us to assess the sensitivity of our main results and conclusions to alternative modeling and data assumptions. In column (1), we do not control for lagged API, as changes in API may be correlated with value-added. Our estimates are unchanged by excluding these controls. In column (2), we drop the 7% of the sales data that are imputed (see Section 3). We then exclude properties with more than 8 bedrooms, which either are very large homes or are multiple unit dwellings. We alternatively exclude properties over 5000 square feet in column (4) and drop multiple unit properties in column (5). In each of these cases the estimates are quantitatively and qualitatively similar to our baseline estimates. In columns (6) and (7), we allow for there to be lags between when the information is released and when it impacts the housing market. We allow for both 3 and 6 month lags, setting the value-added to zero in first 3 and 6 months post-release, respectively. We continue to find no effect of value-added information on property values, although there is some weak evidence of a small impact due to making API information more salient. Taken together, the results from Table 9 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.

6 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. It thus 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 is test score levels. Identifying how value-added information in particular is capitalized into housing prices therefore can lend new insight into the valuation of school quality that research focusing on test score levels as a school quality measure cannot.

This paper is the first to examine how publicly released school and teacher value-added information is capitalized into property values. We exploit a series of information releases about value-added by the Los Angeles Times and the Los Angeles Unified School District, which provided local residents with value-added rankings of all elementary schools and over 6000 teachers in the LA Unified School District. Using housing sales data from the LA County Assessor's Office, we estimate difference-in-difference 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. We also find that property values are unresponsive to the LA Times concurrently publishing a summary of school test score levels data called the Academic Performance Index (API). While these data were publicly available prior to the LA Times publication, it is possible that the LA Times publication increased awareness of it. However, using boundary discontinuity methods, we find that API differences across schools are capitalized into home prices, which indicates that school quality as measured by this outcome is valued by Los Angeles residents. Our results show that the more direct measures of schools' contribution to learning that value-added models are meant to isolate are not valued by local residents despite the significant value they place on owning a home in a school zone with higher test score levels.

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 property values are unresponsive to the within-school variance in teacher value-added as well as the proportion of high or low value-added teachers. We also show evidence that the average effects we present are not masking heterogeneity across the distribution of the size of the value-added information shock relative to existing school quality information or by observable school demographic characteristics.

Our estimates differ substantially from much of the previous literature on school valuation, which typically has found an effect on the order of 2-5 percent higher housing prices for each standard deviation increase in test score levels (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 the similar types of information releases we study leads to different effects. First, the school report cards studied in Figlio and Lucas (2004) 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 forma rather than the school quality aspect, *per se*. Second, the type of information contained in the school report cards already was available to LAUSD residents in the form of API scores. The information releases we study provide school quality data on top of this pre-existing information. Property values may respond less to this value-added information 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. One other explanation is that the release of three, often conflicting, value-added measures in LAUSD may have lead to confusion amongst home buyers and thus led them to ignore all three measures. While this is possible, we note that there was a period of seven months (September 2010 - March 2011) during which the only value-added data available was that from the initial LA Times release. We find no evidence of increased property values during this period, nor do we see more capitalization when the value-added estimates agree.

That we find no effect of school or teacher value-added information on home prices suggests that these school quality measures are not valued by local residents or parents, 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. While such data 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

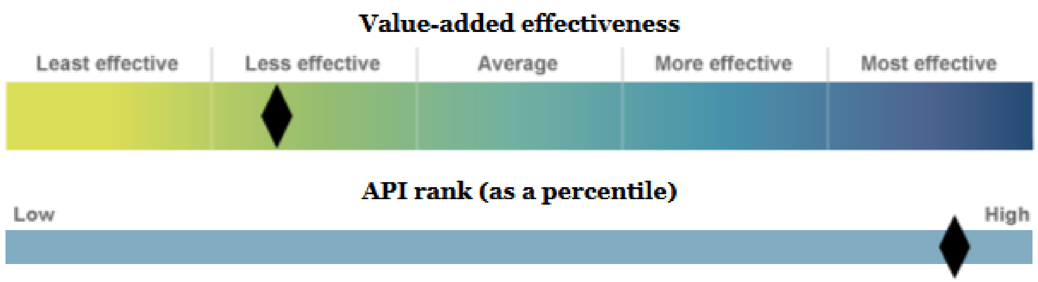
Los Angeles Teacher Ratings

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.

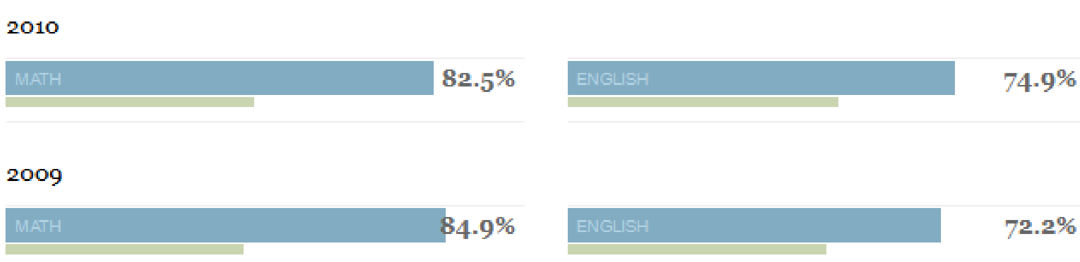


Overall student performance

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

California Standards Tests (STAR) ?

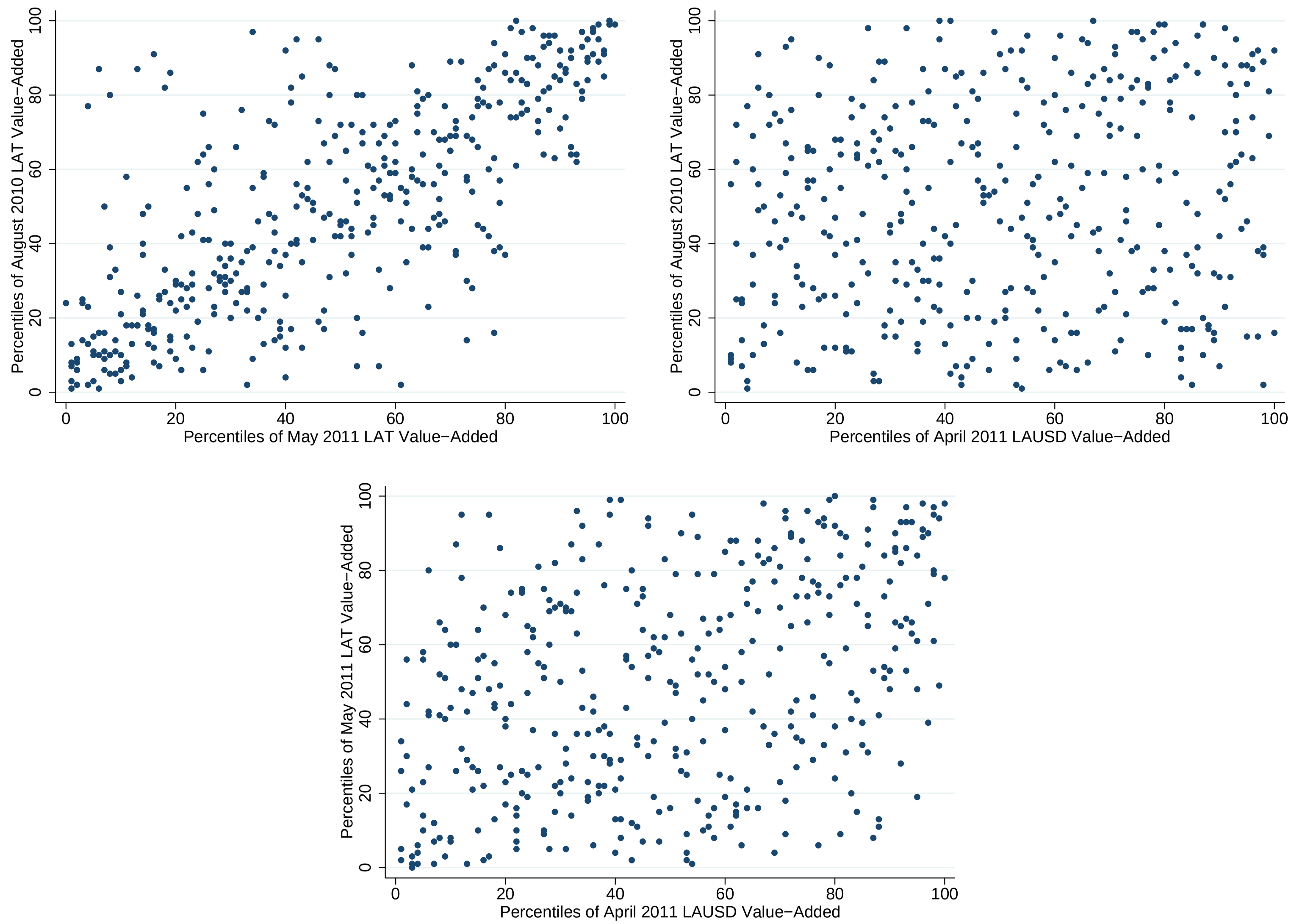
Students scoring "proficient" or above:



Source: 2009, 2010 state data

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

Figure 2: Comparisons of the Three Value-Added Measures



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

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

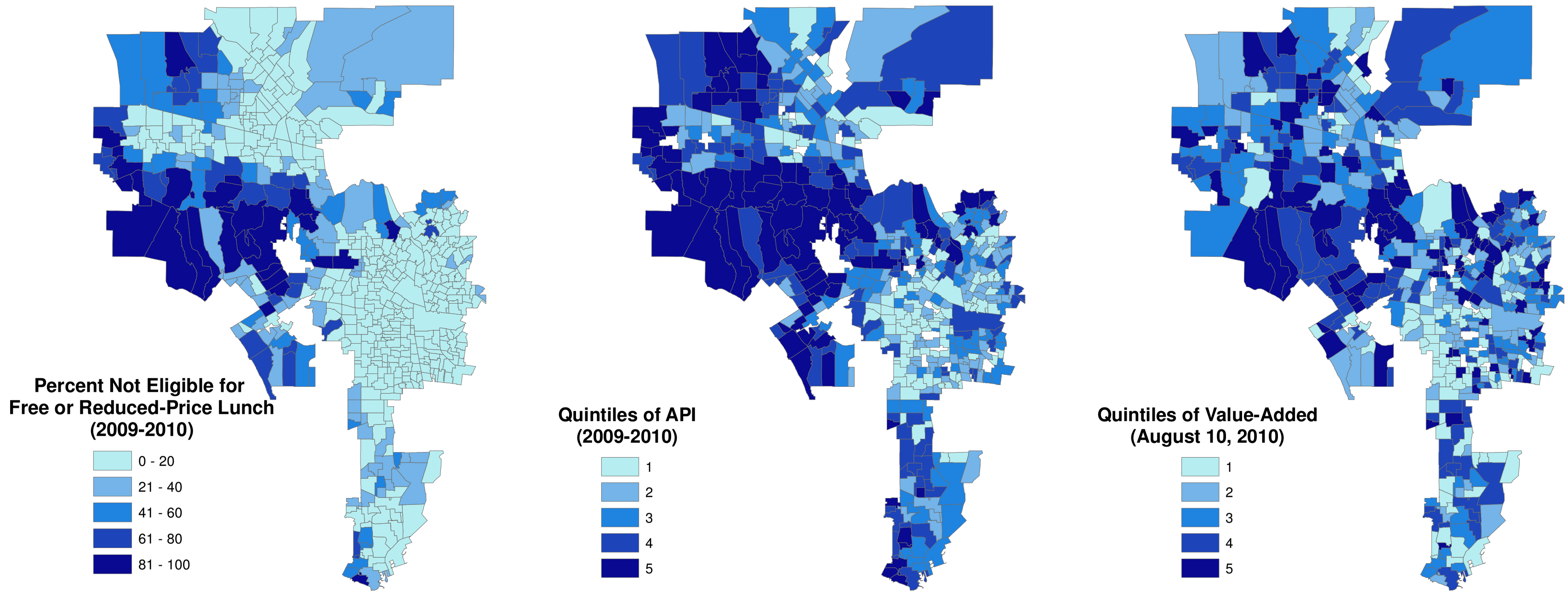
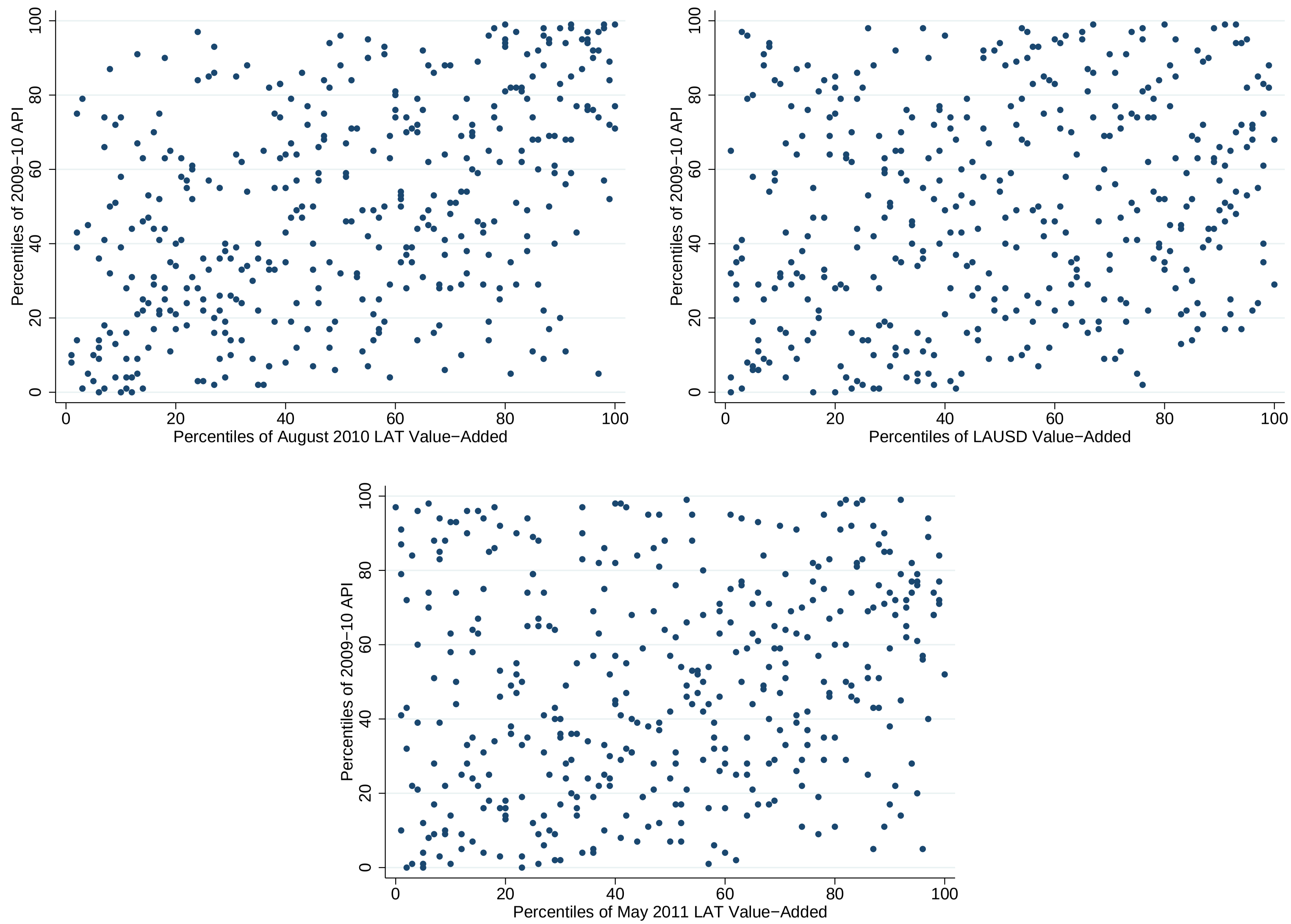
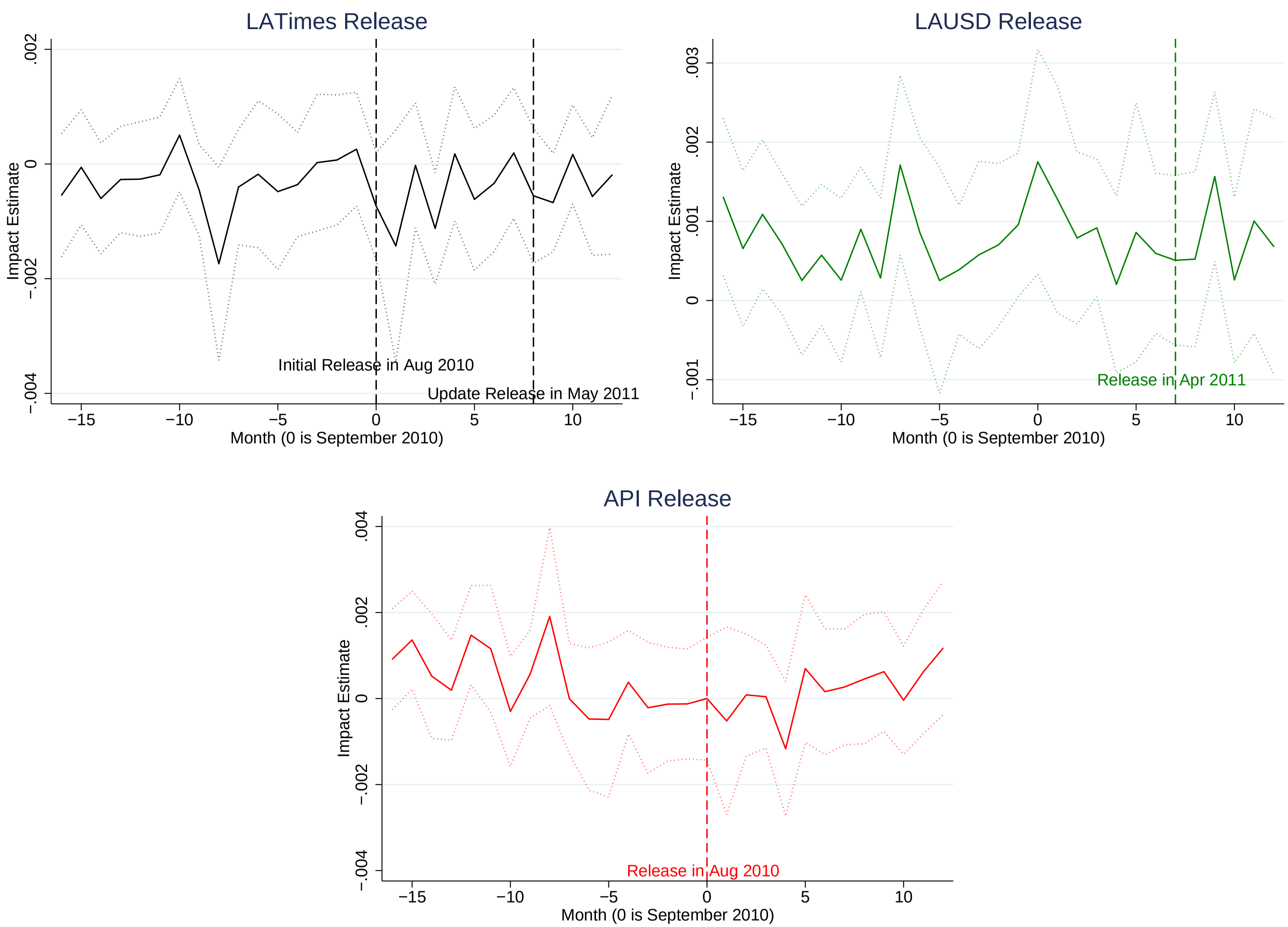


Figure 4: API Percentile vs. Value-Added Percentile



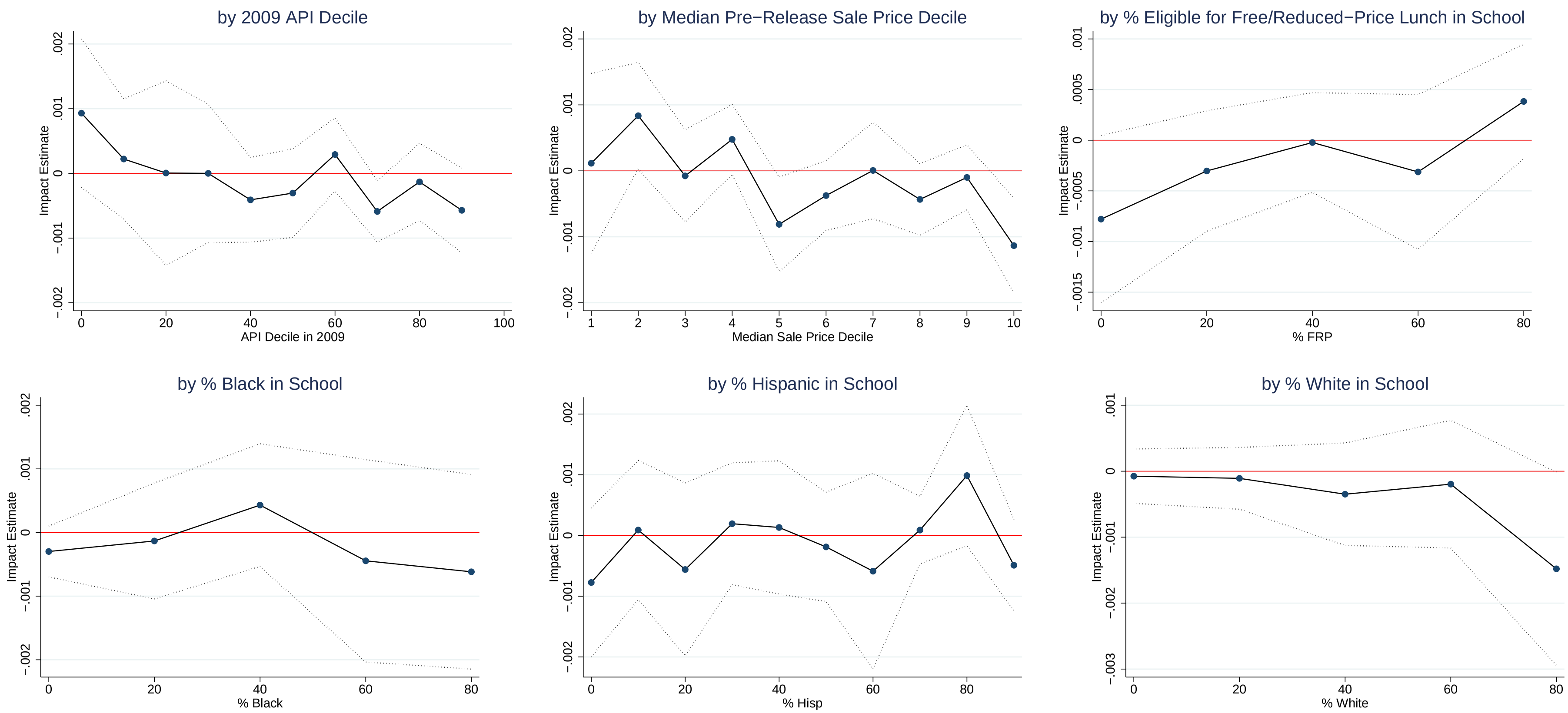
Percentile ranking amongst LAUSD elementary schools using 2009-10 API versus percentile rankings and the three value-added scores. Each dot is a single elementary school.

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



The estimates in both panels come from a single regression and show impact of an increase in value-added percentile on log sale price by month, using each value-added measure. The second LA Times value-added ranking replaces the first in month 8. Controls include school fixed-effects, month of sale indicators, API percentile, 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.

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



Each panel of the Figure shows impact of an increase in value-added percentile on log sale price by decile or quintile of listed characteristic. The value-added variable uses the value-added percentile from the August 2010 release until May 2011 at which point the variable is replaced with the value-added percentile from the May 2011 (2^{nd}) release. 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 Main Analysis Variables

Characteristic	All Schools	LAT Aug VA Percentile ≥ 50	LAT Aug VA Percentile < 50
Key Regression Variables			
Sale Price	406,975	448,656	357,156
	(259,887)	(278,007)	(226,722)
LAT Value-Added Percentile (Aug, 2010)	52.6	75.8	25.1
	(29.0)	(14.6)	(13.8)
LAT Value-Added Percentile (May, 2011)	49.3	66.5	29.0
	(29.5)	(24.6)	(20.5)
LAUSD Value-Added Percentile (Apr, 2011)	49.1	52.8	44.8
	(28.4)	(27.7)	(28.6)
API Percentile (2009-10)	55.0	65.3	43.0
	(29.2)	(25.7)	(28.4)
Characteristics of Census Tract of Property			
% White	53.3	59.8	45.5
	(21.5)	(19.6)	(21.1)
% Black	10.5	6.1	15.6
	(16.5)	(9)	(21.3)
% Hispanic	43.0	37.8	49.1
	(29.2)	(28.9)	(28.3)
% of Adults with No HS	10.0	8.3	12.0
	(7.1)	(6.6)	(7.1)
% of Adults with HS Degree	20.2	19.1	21.5
	(7.6)	(7.6)	(7.3)
% of Adults with Bachelor Degree	20.2	23.1	16.8
	(12.6)	(12.3)	(12.1)
Median Household Income	62,820	69,056	55,420
	(30,150)	(31,729)	(26,309)
School Characteristics			
% Black	12.7	9.4	16.5
	(17.2)	(11.8)	(21.3)
% Hispanic	61.5	57.0	66.7
	(29.5)	(30.8)	(26.9)
% Eligible for Free/Reduced-Price Lunch	72.0	64.2	81.3
	(29.4)	(31.5)	(23.5)
% Gifted	11.7	14.0	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	417.6	397.1	441.8
	(166.3)	(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	1573	1571	1575
	(2159)	(1032)	(2989)
Observations	62,977	34,177	28,800

Sample is split based on the percentile ranking from the first VA release by the LA Times in August, 2010. Standard deviations provided in parentheses.

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

Dependent Variable →	(1) API Percentile	(2) LAT 1^{st} VA Percentile	(3) LAT 1^{st} VA Percentile	(4) LAUSD VA Percentile	(5) LAUSD VA Percentile
% Black	-0.559***	-0.370**	-0.134	0.179	0.598***
	(0.101)	(0.175)	(0.182)	(0.215)	(0.212)
% Hispanic	-0.069	0.047	0.076	0.205	0.257
	(0.095)	(0.176)	(0.174)	(0.214)	(0.195)
% Asian/Pac Islander	0.328***	0.292	0.153	-0.049	-0.294
	(0.085)	(0.210)	(0.205)	(0.203)	(0.190)
% FRP	-0.070	-0.026	0.004	0.302	0.355*
	(0.113)	(0.187)	(0.182)	(0.187)	(0.187)
% Gifted	0.655***	0.561**	0.284	0.598*	0.107
	(0.166)	(0.274)	(0.280)	(0.334)	(0.322)
% ELL	-0.541***	0.153	0.381**	-0.080	0.325*
	(0.112)	(0.178)	(0.172)	(0.200)	(0.191)
% Special Ed	-0.441*	0.140	0.326	0.598	0.884***
	(0.239)	(0.391)	(0.383)	(0.393)	(0.340)
Enrollment	-0.011**	-0.010	-0.005	0.012	-0.004
	(0.006)	(0.009)	(0.008)	(0.010)	(0.009)
% Parents HS Grad	0.041	0.086	0.068	-0.362	-0.393*
	(0.139)	(0.191)	(0.181)	(0.243)	(0.200)
% Parents Some College	0.356**	0.052	-0.098	-0.376	-0.643**
	(0.155)	(0.227)	(0.214)	(0.243)	(0.251)
% Parents Bachelors	0.320	0.378	0.243	0.202	-0.037
	(0.202)	(0.301)	(0.295)	(0.354)	(0.332)
% Parents Graduate	0.107	0.332	0.287	0.221	0.141
	(0.173)	(0.273)	(0.272)	(0.364)	(0.363)
API Percentile			0.422***		0.749***
			(0.081)		(0.084)
Observations	397	397	397	397	397
R-squared	0.706	0.216	0.269	0.038	0.203

All measures are for the 2009-10 school-year. Robust standard errors are in parentheses.***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

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

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

Panel A: Census Tract Characteristics of Property

	(1) % Children	(2) % Senior	(3) Median Age	(4) % Male	(5) % Black	(6) % Asian	(7) % Pac Island	(8) % Other Race	(9) % Mult Race	(10) % Hisp
Pooled LA Times	-0.14	0.20	0.14	-0.11*	0.16	-0.18	-0.01	-0.03	-0.02	-0.13
VA Percentile	(0.10)	(0.12)	(0.12)	(0.06)	(0.22)	(0.19)	(0.01)	(0.19)	(0.02)	(0.33)
LAUSD VA	-0.23*	-0.07	-0.08	0.01	0.80	0.13	0.01**	-0.14	0.01	-0.59
Percentile	(0.12)	(0.16)	(0.16)	(0.08)	(0.56)	(0.23)	(0.01)	(0.26)	(0.03)	(0.46)

	(11) % Institu-tionalized	(12) % HH w/ Children	(13) % Single Male w/ Children	(14) % Single Fem w/ Children	(15) % HH w Seniors	(16) Avg HH Size	(17) Avg Family Size	(18) % Vacant	(19) % Owner Occupied	(20) % Male Married
Pooled LA Times	-0.00	-0.39**	-0.03	-0.12	0.22	-0.00	-0.00	-0.03	0.36	0.21
VA Percentile	(0.04)	(0.19)	(0.02)	(0.08)	(0.19)	(0.01)	(0.01)	(0.10)	(0.56)	(0.24)
LAUSD VA	-0.10*	-0.45*	-0.04	0.08	-0.16	-0.02	-0.02*	0.21	-0.0113	-0.46
Percentile	(0.06)	(0.25)	(0.03)	(0.10)	(0.28)	(0.01)	(0.01)	(0.16)	(0.70)	(0.33)

	(21) % Fem Married	(22) Fertility Rate	(23) % No HS	(24) % HS	(25) % Some College	(26) % Associate	(27) % Bachelor	(28) % Graduate	(29) % Veteran	(30) % Same House 1Yr
Pooled LA Times	-0.11	0.19	-0.07	-0.04	0.07	0.02	0.22	-0.00	0.08	0.06
VA Percentile	(0.29)	(0.73)	(0.11)	(0.17)	(0.13)	(0.09)	(0.21)	(0.15)	(0.07)	(0.24)
LAUSD VA	-0.44	0.0132	-0.01	-0.53***	0.25*	0.05	0.28	0.11	-0.01	-0.57*
Percentile	(0.40)	(0.88)	(0.14)	(0.19)	(0.15)	(0.11)	(0.26)	(0.16)	(0.08)	(0.34)

	(31) % Born in USA	(32) % English Speaker	(33) LFP Rate	(34) Unemp Rate	(35) % Commute Public Trans	(36) Mean Commute	(37) Mean HH Income	(38) % On Social Sec	(39) % On SSI	(40) % On Cash Assist
Pooled LA Times	-0.04	0.04	0.30*	-0.01	-0.10	0.02	667	0.18	-0.06	-0.02
VA Percentile	(0.23)	(0.36)	(0.16)	(0.09)	(0.18)	(0.09)	(626)	(0.21)	(0.11)	(0.08)
LAUSD VA	0.28	0.33	0.04	0.12	0.10	-0.02	-1374	0.06	-0.03	-0.02
Percentile	(0.33)	(0.46)	(0.20)	(0.12)	(0.17)	(0.11)	(875)	(0.28)	(0.11)	(0.09)

			Panel B: Property Characteristics				
	(41) % On Food Stamps	(42) Poverty Rate	(43) Mean # Units	(44) Mean Age of Structure	(45) Mean # Bedrooms	(46) Mean # Bathrooms	(47) Mean Sq Ft
Pooled LA Times	-0.02	-0.21	0.11*	-1.67	0.08	0.03	74
VA Percentile	(0.11)	(0.22)	(0.06)	(1.11)	(0.05)	(0.06)	(61)
LAUSD VA	0.08	0.11	-0.12	1.44	-0.05	-0.03	-8.8
Percentile	(0.13)	(0.27)	(0.07)	(1.04)	(0.07)	(0.07)	(6.7)

Each column is a separate regression. The data cover April 2009 through September 2011. Observations for all Census Tract characteristics are 62,997. For property characteristics, the sample sizes are 60,631, 60,855, 60,345, and 61,004 for # of units, age of property, # of bedrooms, # of bathrooms and square-footage, respectively. The pooled LA Times value-added variable uses the value-added percentile from the August 2010 release until May 2011, at which point the variable is replaced with the VA percentile from the May 2011 (2^{nd}) release. All regressions include API, API*post, school and 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 4: Effect of Value-Added Information on Number of Sales in a School Zone

	Independent Variable	Number of Total Sales†	Number of Sales with Sale Price Data
(1)	LAT 1^{st} VA Percentile	0.00006	-0.0023
		(0.0059)	(0.0031)
	LAT 2^{nd} VA Percentile	-0.0082	-0.0020
		(0.0050)	(0.0027)
	LAUSD VA Percentile	0.0014	0.0006
		(0.0049)	(0.0027)
	Observations	11,970	11,970
(2)	LA Times Pooled VA Percentile	-0.0066	-0.0043
		(0.0051)	(0.0025)
	LAUSD VA Percentile	0.0004	0.0007
		(0.0046)	(0.0025)
	Observations	11,970	11,970

† Total sales in a school zone only cover the three most-recent sales as of October, 2011.

Observations are school-zone by month. The data cover April 2009 through September 2011. The pooled LA Times value-added variable uses the value-added percentile from the August 2010 release until May 2011 at which point the variable is replaced with the VA percentile from the May 2011 (2^{nd}) release. All regressions include school and month fixed-effects along with controls for API, two years of lagged API, API times post August 2010, API percentile, and the school's rank relative to comparison schools defined by the California DOE. All regressions also include the following: school characteristics - percent of students of each race, percent free lunch, percent gifted, percent English language learners, percent disabled, and parent education levels; neighborhood characteristics at the census tract level - percent 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. Standard errors clustered at the school level are in parentheses.***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 5: School-Zone Boundary Fixed-Effects Estimates of Impact of API on Ln(SalePrice) - 0.1 Mile Buffer Using pre-August 2010 Sales

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

Independant Variable	(1)	(2)	(3)	(4)	(5)
API Percentile	0.449***	0.411***	0.133***		0.132***
	(0.048)	(0.041)	(0.044)		(0.048)
LAT 1^{st} VA Percentile				0.053*	0.030
				(0.031)	(0.032)
LAUSD VA Percentile				-0.012	-0.029
				(0.026)	(0.027)
Observations	25,316	25,316	25,316	25,316	25,316
Housing Characteristics	N	Y	Y	Y	Y
School Characteristics	N	N	Y	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. School characteristics include percent of students of each race, percent free lunch, percent gifted, percent English language learners, percent disabled, and parent education levels. Housing characteristic controls include the number of bedrooms, bathrooms and units in the home, square footage, and year built. Housing characteristics are also interacted with a linear time trend. Standard errors clustered at the school level are in parentheses.***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 6: 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)	(6)	(7)
(1)	LAT 1^{st} VA Percentile	-0.009	-0.009	-0.031	-0.028	-0.025	-0.023	-0.010
	× Post Aug 2010	(0.079)	(0.045)	(0.028)	(0.022)	(0.022)	(0.021)	(0.033)
	LAT 2^{nd} VA Percentile	-0.073**	-0.104*	0.008	0.025	0.024	0.029	0.033
	× Post Apr 2011	(0.032)	(0.054)	(0.027)	(0.024)	(0.024)	(0.022)	(0.024)
	LAUSD VA Percentile	0.053*	0.056	-0.009	-0.011	-0.011	-0.004	-0.044*
	× Post Mar 2011	(0.028)	(0.067)	(0.029)	(0.026)	(0.026)	(0.025)	(0.024)
	API Percentile	-0.036	-0.036	-0.001	-0.013	-0.009	-0.013	-0.007
	× Post Aug 2010	(0.052)	(0.044)	(0.026)	(0.026)	(0.027)	(0.026)	(0.029)
	Observations	62,977	62,977	62,977	62,977	62,977	62,977	43,714
(2)	LAT Pooled VA Percentile	-0.061	-0.085**	-0.042*	-0.030	-0.029	-0.027	-0.014
	× Post Aug 2010	(0.069)	(0.036)	(0.023)	(0.020)	(0.020)	(0.019)	(0.021)
	LAUSD VA Percentile	0.008	0.041	0.001	0.004	0.003	0.011	-0.029
	× Post Mar 2011	(0.021)	(0.064)	(0.028)	(0.028)	(0.027)	(0.025)	(0.023)
	API Percentile	-0.018	-0.012	0.000	-0.013	-0.009	-0.013	-0.005
	× Post Aug 2010	(0.043)	(0.038)	(0.023)	(0.025)	(0.026)	(0.025)	(0.028)
	Observations	62,977	62,977	62,977	62,977	62,977	62,977	43,714
Month of Sale		N	N	Y	Y	Y	Y	Y
Housing Characteristics		N	N	N	Y	Y	Y	Y
School Characteristics		N	N	N	N	Y	Y	Y
Neighborhood Characteristics		N	N	N	N	N	Y	Y
School Fixed-Effects		N	Y	Y	Y	Y	Y	Y
Boundary Fixed-Effects (0.1 mi)		N	N	N	N	N	N	Y

The data cover April 2009 through September 2011 and are at the property sale level. The pooled LA Times value-added variable uses the value-added percentile from the August 2010 release until May 2011 at which point the variable is replaced with the VA percentile from the May 2011 (2^{nd}) release. All regressions include school and month fixed-effects along with controls for API, two years of lagged API, API percentile, and the school's rank relative to comparison schools defined by the California DOE. School characteristics include, percent of students of each race, percent free lunch, percent gifted, percent English language learners, percent disabled, and parent education levels. Neighborhood characteristic controls are at the census tract level and include 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 characteristic controls include the number of bedrooms, bathrooms and units in the home, square footage, and year built. Housing characteristics are also interacted with a linear time trend. School-average value added measures are included as controls in column (i). Standard errors clustered at the school level are in parentheses. ***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 7: Effect of Value-Added Information on Log Sale Prices - Including Teacher Value-added and Alternative Models

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

	Include Std Dev of Current Teacher VA (1)	Include % of Teachers in VA Quintile (2)	Use Sale Price Levels (3)	Use Avg VA (4)	≤ 2 Bedrooms (5)	> 2 Bedrooms (6)
LAT Pooled VA Pctl	-0.027	-0.022	-35.5		-0.017	0.006
× Post Aug 2010	(0.020)	(0.023)	(63.8)		(0.020)	(0.014)
LAUSD VA Pctl	0.014	0.015	72.4		0.003	0.030
× Post Mar 2011	(0.025)	(0.026)	(69.7)		(0.024)	(0.019)
API Pctl	-0.007	-0.003	-98.7	-0.013	-0.053**	-0.027
× Post Aug 2010	(0.026)	(0.026)	(91.6)	(0.025)	(0.023)	(0.021)
LAT Teacher VA	-0.006					
Standard Deviation	(0.085)					
LAT Teacher VA		-0.5				
% in 2^{nd} Quintile		(4.4)				
LAT Teacher VA		3.2				
% in 3^{rd} Quintile		(4.5)				
LAT Teacher VA		-3.2				
% in 4^{th} Quintile		(4.4)				
LAT Teacher VA		-0.4				
% in 5^{th} Quintile		(5.6)				
Average Across				-0.018		
All VA Measures				(0.019)		
Observations	61,534	61,534	62,977	62,977	23,280	37,065

The data cover April 2009 through September 2011 and are at the property sale level. The pooled LA Times value-added variable uses the value-added percentile from the August 2010 release until May 2011 at which point the variable is replaced with the VA percentile from the May 2011 (2^{nd}) release. LAT Teacher Value-Added uses value-added scores from the Aug 2010 release for teachers working in a givn school in 2009-10. All regressions include school and month fixed-effects along with controls for API, two years of lagged API, API percentile, and the school's rank relative to comparison schools defined by the California Department of Education. School characteristics include, percent of students of each race, percent free lunch, percent gifted, percent English language learners, percent disabled, and parent education levels. Neighborhood characteristic controls are at the census tract level and include 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 characteristic controls include the number of bedrooms, bathrooms and units in the home, square footage, and year built. Housing characteristics are also interacted with a linear time trend. Standard errors clustered at the school level are in parentheses.***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 8: Non-Linear Value-Added Impacts

	Diff in VA & API Linear (1)	Diff in VA & API High > 0 Low < 0 (2)	Diff in VA & API High > 20 Low < -20 (3)	Difference in VA & API High > 40 Low < -40 (4)	VA Pctl High > 50 Low < 50 (5)	VA Pctl High > 70 Low < 30 (6)	VA Pctl High > 90 Low < 10 (7)
LAT minus API	-0.00016						
	(0.00019)						
LAUSD minus API	-0.00030*						
	(0.00018)						
High LAT minus API		-0.003	-0.014	-0.013			
		(0.019)	(0.013)	(0.016)			
Low LAT minus API		-0.030	0.033**	0.036*			
		(0.019)	(0.015)	(0.018)			
High LAUSD minus API		0.041	0.005	-0.007			
		(0.031)	(0.017)	(0.017)			
Low LAUSD minus API		-0.008	-0.014	0.017			
		(0.033)	(0.019)	(0.011)			
High LAT					0.058	-0.030**	0.001
					(0.042)	(0.014)	(0.017)
Low LAT					0.074*	-0.008	0.012
					(0.042)	(0.011)	(0.015)
High LAUSD					-0.024	0.014	0.011
					(0.020)	(0.017)	(0.030)
Low LAUSD					-0.024	0.004	0.008
					(0.020)	(0.014)	(0.024)
High LAT & High LAUSD					0.041	-0.005	-0.016
					(0.038)	(0.023)	(0.025)
Only LAT High					0.057	-0.037**	0.005
					(0.044)	(0.015)	(0.018)
Only LAUSD High					-0.030	-0.006	0.017
					(0.019)	(0.020)	(0.035)
Low LAT & Low LAUSD					0.049	-0.006	0.029
					(0.036)	(0.018)	(0.025)
Only LAT Low					0.056	-0.033*	-0.020
					(0.040)	(0.017)	(0.020)
Only LAUSD Low					-0.033	-0.007	-0.001
					(0.027)	(0.016)	(0.024)

Each regression has 62,977 observations. The data cover April 2009 through September 2011 and are at the property sale level. The LA Times value-added variable uses the value-added percentile from the August 2010 release until May 2011 at which point the variable is replaced with the VA percentile from the May 2011 (2^{nd}) release. *Delta* LAT/API is the difference between the LAT value-added and the 2009 API percentiles for the school. Similarly for the LAUSD VA measure for Δ LAUSD/API. A variable denoted by 'high' is an indicator variable for being above the value indicated in each column while 'low' is an indicator for being below the value indicated in each column. All LAT VA variables are multiplied by an indicator for the sale occurring post August 2010. All LAUSD VA variables are multiplied by an indicator for the sale occurring post March 2011. All regressions include school and month fixed-effects along with controls for API, two years of lagged API, API percentile, and the school's rank relative to comparison schools defined by the California Department of Education, school characteristics (percent of students of each race, percent free lunch, percent gifted, percent English language learners, percent disabled, and parent education levels), neighborhood characteristic 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) and housing characteristics (number of bedrooms, bathrooms and units in the home, square footage, and year built). Housing characteristics are also interacted with a linear time trend. Standard errors clustered at the school level are in parentheses.***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 9: Effect of Value-Added Information on Log Sale Prices - Specification Checks

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

	Exclude Lagged API	Drop Imputed VA	Drop Properties w/ > 8 Bedrooms	Drop Properties w/ > 5000 sf	Drop Multi-Unit Properties	3 Month Lead	6 Month Lead
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LAT Pooled VA Pctl	-0.031	-0.025	-0.033*	-0.033*	-0.015	-0.009	-0.011
× Post Aug 2010	(0.019)	(0.019)	(0.019)	(0.018)	(0.013)	(0.020)	(0.019)
LAUSD VA Pctl	0.021	0.009	0.011	0.013	0.006	0.011	
× Post Mar 2011	(0.024)	(0.023)	(0.025)	(0.025)	(0.016)	(0.035)	
API Pctl	-0.011	-0.009	-0.009	-0.009	-0.030*	0.011	0.044*
× Post Aug 2010	(0.025)	(0.025)	(0.023)	(0.022)	(0.016)	(0.021)	(0.026)
Observations	62,977	58,398	62,359	62,256	55,557	62,977	62,977

The data cover April 2009 through September 2011 and are at the property sale level. The pooled LA Times value-added variable uses the value-added percentile from the August 2010 release until May 2011 at which point the variable is replaced with the VA percentile from the May 2011 (2^{nd}) release. LAT Teacher Value-Added uses value-added scores from the Aug 2010 release for teachers working in a givn school in 2009-10. All regressions include school and month fixed-effects along with controls for API, two years of lagged API, API percentile, and the school's rank relative to comparison schools defined by the California Department of Education. School characteristics include, percent of students of each race, percent free lunch, percent gifted, percent English language learners, percent disabled, and parent education levels. Neighborhood characteristic controls are at the census tract level and include 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 characteristic controls include the number of bedrooms, bathrooms and units in the home, square footage, and year built. Housing characteristics are also interacted with a linear time trend. Standard errors clustered at the school level are in parentheses.***,** and * indicate significance at the 1%, 5% and 10% levels, respectively.