

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 public release of value-added data in Los Angeles to identify how this measure of school quality is capitalized into housing prices. Via difference-in-differences, we find no evidence of a response to either school or teacher value-added rank, even though school-zone boundary fixed-effects estimates indicate that test score levels are capitalized into home prices. Given ample evidence that this information was new to residents, widely dispersed, and easily available, our results suggest that people did not significantly value it on the margin. This has implications for the effectiveness of providing value-added information as a tool to help parents choose schools.

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1 Introduction

Much prior research has been devoted to estimating the extent to which parents value the quality of their local schools. Typically, the economics literature on school valuation uses the capitalization of school quality measures into home prices to estimate the value local residents place on school quality. The majority of school quality valuation studies use test score levels as their measure of quality. Employing regression discontinuity methods at school attendance zone boundaries, these studies tend to find that a one standard deviation difference in test scores is associated with two to five percent higher property values (e.g., Bayer, Ferreira and McMillan, 2007; Kane, Riegg and Staiger, 2006; Black, 1999).¹ Cross-school variation in test score levels is driven by differences in the academic aptitude of the student body as well as the ability of each school to produce student learning outcomes. Hence, it is not possible to separate out parent valuation of high-achieving peers from parental valuation of the school’s ability to teach students using these methods.

A few prior studies have attempted to overcome this problem by examining capitalization or revealed preferences of parents based on “value-added” measures that seek to isolate the causal effect of schools on student learning. The majority find no effect (e.g., Hastings, Kane and Staiger, 2010; Brasington and Haurin, 2006; Dills, 2004; Downes and Zabel, 2002; Brasington, 1999), while Gibbons, Machin and Silva (2013) and Yinger (2014) show evidence that test score levels and value-added are similarly valued. A central limitation to these studies is that the value-added data are calculated by the researchers and likely are not known to parents. However, in recent years, the push to expand test-based accountability has led to a marked rise in the use and public release of school value-added estimates. This has been done in large school districts in Los Angeles, Houston, and New York City, amongst others. The fact that these data are increasingly prevalent and that controversy typically surrounds their release underscores the importance of understanding how and whether parents value this information when it is provided to them in a simplified manner.

In this paper, we provide what is to our knowledge the first evidence on how housing

¹See Black and Machin (2011) and Nguyen-Huang and Yinger (2011) for comprehensive reviews of this literature.

markets respond to the public release of school and teacher value-added information. To do this, we exploit a highly publicized, salient, and accessible data release in Los Angeles in 2010. The information experiment that forms the basis for our study began in August 2010, when the *Los Angeles Times* newspaper (LAT) published average value-added estimates for each elementary school (470 in total) as well as individual value-added estimates for 6,000 third through fifth grade teachers in the Los Angeles Unified School District (LAUSD). We show that this value-added information was not predictable from existing information, nor was it previously capitalized into home prices, suggesting that this was indeed new information for local residents. The main focus of our analysis is on the short-run effect of this information on property values, because in April 2011 LAUSD released its own value-added information and in May 2011 the LA Times updated their value-added data to include more teachers. Prior work has shown that home price responses to school quality information shocks occur quickly (Figlio and Lucas, 2004; Fiva and Kirkebøen, 2011). This supports our focus on the seven-month time period following the first value-added release that was free from influence from other value-added information. Nonetheless, we also examine longer-run impacts (up to 13 months) after the initial release, taking into account value-added rankings from all three releases to ensure that our results are not simply due to the short time horizon.

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

capitalization estimates of test scores levels in prior studies (Black and Machin, 2011).² We also show that the size of the information shock relative to existing information did not affect property values.

Our empirical approach closely follows that of Figlio and Lucas (2004), who study the release of “school report card” information in Florida as well that of Fiva and Kirkebøen (2011), who examine the release of school ranking information in Oslo, Norway. Both of these papers find that the new information on school quality had a large effect on property values but that the capitalization effect dissipated within a year. Relative to this prior research, we make several contributions to the literature. First, our study examines the effect of value-added measures of school quality that can more credibly isolate the contribution of each school to student learning. The school report cards studied by Figlio and Lucas (2004) are based on test score levels and pass rates, which can differ substantially from value-added as they are much more strongly correlated with school and neighborhood composition than with value-added. The information examined by Fiva and Kirkebøen (2011) was based on student grade point averages (GPAs) that were adjusted for student background characteristics. These estimates are closer to value-added measures than are the school report cards in Figlio and Lucas (2004), but the lack of lagged GPA controls makes it likely this information remains correlated with underlying student quality differences across schools.³

Second, the estimates in Fiva and Kirkebøen (2011) are difficult to generalize to the US context because of underlying differences in housing markets between Oslo and Los Angeles as well as the fact that the 48 schools they study are, on average, high performing relative to the rest of the country. The Los Angeles schools serve a much more diverse set of students and include many low-performing schools in terms of test score levels. As we show below, many of these low-test-score schools are actually calculated to be high value-added schools, which allows us to disentangle parental valuation of test score levels from value-added in a setting with a wide variance across schools in both measures.

²Our results also are consistent with evidence from Chile that signals of school quality beyond test scores do not affect enrollment patterns (Mizala and Urquiola, 2013).

³We also highlight that our approach differs from those who have used researcher-calculated value-added (e.g., Downes and Zabel, 2002) due to the fact that in our setup parents actually observe value-added.

Third, this paper is the first in the literature to examine how parents value direct measures of teacher quality. Prior work has focused solely on school quality valuation, but the importance of teachers has been overlooked. Because the LA Times released teacher value-added measures as well as school measures, we can estimate how home prices respond to teacher quality, *per se*. The LA Times teacher value-added model used in our context has been shown to exhibit little bias (Guarino, Reckase and Wooldridge, 2015; Chetty, Friedman and Rockoff, 2014a; Kane et al., 2013; Kane and Staiger, 2008) and appears to be a good measure of a teacher’s contribution to long-run student outcomes, such as earnings and college-going (Chetty, Friedman and Rockoff, 2014b). That this value-added information is a strong measure of school and teacher quality does not mean parents valued it as such, however; this study is the first to be able to examine this question directly.⁴

Overall, our results indicate that releasing straightforward value-added rankings to the public does not affect property values, which suggests that homeowners do not value the information as currently constructed on the margin. The lack of responsiveness to this information either could be driven by parents placing little value on the ability of schools and teachers to increase test scores or by parents and homeowners ignoring value-added information because its release was highly contentious and the measures are derived from a complicated statistical model that is opaque to non-experts. Ultimately, we are unable to disentangle these two hypotheses. We argue the preponderance of the evidence is consistent with the former mechanism, however, because the information was presented in a simple-to-understand manner by a highly-respected and impartial newspaper, the release was highly publicised and salient, and there was no response to the release of a separate value-added measure by LAUSD which parents may have trusted more because it came directly from the schools. Indeed, this finding is consistent with the fact that boundary-discontinuity estimates of school quality are reduced significantly once neighborhood characteristics are controlled for (Bayer, Ferreira and McMillan, 2007; Kane, Riegg and Staiger, 2006) as well as the fact that most prior research has not found an effect of researcher-calculated value-added on property values. Rothstein (2006) also provides indirect

⁴Jacob and Lefgren (2007) show that *within* schools, parents have a revealed preference for teachers that are better at raising student test scores. But, parent information on teacher quality in that study does not come from value-added measures.

evidence that parents do not highly value the ability of schools to raise test scores, as observed residential sorting is inconsistent with these preferences. This paper provides a more direct test of this question than has been possible in prior studies, but our results are consistent with much of the existing research in this area. Thus, our results provide new information about valuation of a school quality measure that provides previously unknown information about a school's or teacher's contribution to test score growth rather than information about the demographic makeup of the school.

2 The Release of Value-Added Information in Los Angeles

In 2010, the *Los Angeles Times* newspaper acquired individual testing records of elementary students in Los Angeles Unified School District via a public information request. The achievement scores were linked to teachers so that a teacher and school value-added analysis could be conducted. The LA Times hired Dr. Richard Buddin to conduct the statistical analysis. Details on the methodology can be found in Buddin (2010), but the basic strategy is to use a linear regression model with teacher fixed effects to calculate teacher value-added. Teacher fixed effects are replaced with school fixed effects to calculate school value-added. All models use data from the 2002-2003 through the 2008-2009 school years and control for lagged test scores and student characteristics. The use of several years of data has the benefit of increasing the precision of the value-added estimates relative to using only one year of recent data. Following completion of the analysis, the newspaper wrote a series of articles explaining the methodology and other issues in LAUSD throughout the month of August 2010 as a lead in to the release of the data in a simplified form on August 26, 2010. The value-added data were presented through an online database and could be accessed by anyone with a computer without charge or registration.⁵ The database was searchable by school and teacher name, and people also

⁵The 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 details 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.

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

Figure 1 shows an example of how the information was presented for a given school. Schools were categorized as “least effective,” “less effective,” “average,” “more effective,” and “most effective,” which refer to the quintiles of the value-added score distribution for LAUSD. However, as Figure 1 demonstrates, the black diamond shows each school’s exact location in the distribution, providing parents with the ability to easily estimate the school’s percentile. Although value-added scores were generated separately for math and reading, the LA Times based their categorization on the mean of the two scores. The figure also shows the location of the school’s Academic Performance Index (API) percentile. API is an summary measure provided by the state of California that measures school quality via a weighted average primarily composed of test scores along with some other outputs such as attendance. 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 generated by the value-added release. Thus, for many people, this API information could have been new. The value-added rank was not available in any form prior to August 2010. Finally, the web page provides passing rates on the math and English exams for each school, which was also publicly available prior to the value-added release.⁶ To keep our estimating equation simple, in our analyses we will assume that any response to the LA Times reprinting the passing rates will be reflected in responses to API.⁷

A critical question underlying our analysis is whether LA residents knew about the release of this information. Note that any school quality information intervention carries with it the difficulty of ensuring that those who are targeted receive the information. We believe the structure of this information release, with the information being available online for free and the publicity that surrounded its release, made the value-added information more salient than is typical with school quality information releases.⁸ Indeed, there is substantial evidence to

⁶The upper, thicker bars under this section is the school’s percent passing while the lower, thinner bars are the statewide pass rates.

⁷This assumption is sensible because API scores are calculated almost entirely by using scores on these exams.

⁸Due 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.

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

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

A related issue is whether most parents were able to access the data. Given the low income

⁹Some examples of Spanish language coverage include a story on Channel 22 on Nov. 8, 2010 covering a protest after a teacher committed suicide in part due to value-added results (<http://www.youtube.com/watch?v=RWKR8Ch06wY>), a story covering an earlier protest on Channel 62 (<http://www.youtube.com/watch?v=n1iNXtyPIrk>), and a story on Univision 34 discussing LAUSD's own value-added measures (<http://www.youtube.com/watch?v=05dE0xLdpu8>).

of many families with children in LAUSD and the fact that there was no print release of the value-added scores (they were only provided online), this is not obvious. To check this we use data from the October 2010 Current Population Survey supplement on computer and Internet usage. While the sample size is small (295 observations), 87% of adults in Los Angeles age 25 or older and who never attended college had Internet access at home. Using the far larger sample of all Californians 25 or older who never attended college (2,156 observations), 91% have access to the Internet at home. These data indicate that the residents of Los Angeles who ought to have the largest interest in the value-added scores were able to access them.

The 2010 LA Times value-added information is the focus of our analysis. This focus necessitates an examination of short-run impacts on property values because this initial value-added data release was followed up with LAUSD releasing its own school-level value-added measure in April 2011 and the LA Times updating its value-added measure in May 2011.¹⁰ While examining the effect of the initial LA Times release provides a purer information experiment, it limits the analysis to 7 months post-release. Even so, in their analysis of the capitalization of value-added information in Norway, Fiva and Kirkebøen (2011) show that the positive effects were very short-run, on the order of 3 months. Figlio and Lucas (2004) further show evidence that the positive impact of school report card information in Florida on property values were largest in the first year post-release. This evidence supports our examination of short-run effects.

We also analyze longer-run effects that account for the subsequent value-added releases. Thus, it is important to highlight several differences between the first LA Times release and subsequent data releases. First, we believe the LA Times used a more econometrically sound value-added model than LAUSD, as the former model controls for lagged achievement and includes multiple years of data. Guarino, Reckase and Wooldridge (2015) argue that models like this (which they call “dynamic ordinary least squares”) are the most accurate.¹¹ The LAUSD

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

¹¹The May 2011 LA Times release updated this model to include an extra year of data, more teachers and applied Bayesian shrinkage adjustments as in Kane and Staiger (2008) to the estimates.

model, on the other hand, predicts student achievement growth from observable characteristics using one year of data, after which the differences between predicted and actual achievement are averaged together across all students in a school. While the LA Times methodology may be more appealing to researchers, we acknowledge that this does not necessarily indicate that parents believed it more. Second, there was substantial discussion of the initial LA Times release in the news and responses by education organizations, while the subsequent releases garnered less attention. Finally, it is easier to access the LA Times information. While both are available on the web, to access the LAUSD data people need to navigate through a series of links on the LAUSD website.

It also is interesting to note that the correlations between both of the LA Times releases and the LAUSD value-added scores are very low. Online Appendix Figure 1 presents comparisons of the three school-level value-added measures using scatter plots with each school as an observation. The top left panel shows that the percentiles of the 2010 LA Times value-added are highly correlated with the 2011 LA Times value-added, with a correlation coefficient of 0.74.¹² However, each of the LA Times value-added measures are very weakly correlated with the LAUSD measure - the correlation coefficients are 0.15 and 0.39 for the August and May releases, respectively. This likely reflects the differences in the methodology described above and the amount of data used.

3 Data

To assess the impact of the value-added data release on property values, we combine data from several sources. First, we use home price sales data from the Los Angeles County Assessor's Office (LACAO). The data contain the most recent sale price of most homes in LA County as of October, 2011, which in addition to LAUSD encompasses 75 other school districts. We restrict our data to include all residential sales in LAUSD that occurred between April 1, 2009

¹²An important question arises as to why the value-added estimates differed across LA Times data releases. This was due to three factors: methodology changes, increases in the number of teachers included in the value-added calculations, and an additional year of data on teachers included in the first release. If we drop all schools with percentile rank changes greater than 20, the correlation between value-added ranks across LAT releases is 0.96. Critically, our estimates are unaffected by this sample restriction. These results are available upon request.

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 Although there is open enrollment throughout LAUSD, spaces are very limited at around 1.5% of total enrollment. Thus, these catchment zones define the relevant school for the vast majority of students in the District. The property sales data additionally contain information on the dates of the three most recent sales, the square footage of the house, the number of bedrooms and bathrooms, the number of units and the age of the house that we will use to control for any potential changes in the composition of sales that are correlated with value-added information.

To remove outliers, we drop all properties with sale prices above \$1.5 million (5% of households) and limit our sample to properties in elementary school zones in Los Angeles Unified 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 sale prices using the combined assessed land and improvement values of the property.¹⁶ For observations that have all three measures recorded, the correlation between actual sale price and the imputed sale price is 0.89, indicating that the imputation is a very close approximation to the actual market value. Furthermore, we know of no reason why the accuracy of the imputation procedure should be correlated with value-added information, which

¹³Given that the value-added information only varies across schools within LAUSD, the addition of school fixed effects leaves little to be gained from adding the rest of LA County. Specifications using home price sales from all of the county, setting value-added percentiles equal to zero outside of LAUSD and controlling for school district fixed effects, provide almost identical results.

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

¹⁵California allows relatives to transfer property to each other without a reassessment of the home’s value for property tax purposes. Due to property tax caps, this rule creates large incentives for within-family property transfers in California, and hence there are a lot of such transactions in the data. Because these transfers do not reflect market prices, we do not include them in our analysis.

¹⁶Rather than impute the values one could simply drop the observations with missing sale price. However, to do this one would have to assume that sale prices are missing at random, at least conditional on controls. In Online Appendix Table A-1 we estimate models that look at correlations between property characteristics and whether the sale price is missing. Even when controlling for school and time fixed effects we find a substantial number of characteristics are significantly correlated with a property missing the sale price. This suggests the observations are unlikely to be missing at random.

supports the validity of this method. Nonetheless, in Section 5, we provide results without imputed values and show they are very similar. Our final analysis data set contains 63,122 sales, 51,514 of which occur prior to April 2011.

We obtained the exact value-added score for each school directly from Richard Buddin, and the April 2011 LA Times school value-added data as well as the August 2010 teacher-level value-added data were provided to us by the LA Times. The LAUSD value-added information was collected directly from Battelle for Kids, with whom LAUSD partnered to generate the value-added measures.¹⁷ The value-added data were combined with school-by-academic-year data on overall API scores, API scores by ethnic and racial groups, school-average racial composition, percent on free and reduced price lunch, percent disabled, percent gifted and talented, average parental education levels, and enrollment. These covariates, which are available through the California Department of Education, control for possible correlations between value-added information and underlying demographic trends in each school. To maintain consistency with the LA Times value-added data, we convert both the LAUSD value-added scores and API scores into percentile rankings within LAUSD.

Similar to Black (1999), we also link each property to its Census block group characteristics from the 2007-2011 American Communities Survey (ACS) to use as controls. In particular, we use the age distribution of each block group (in 5 year intervals), the percentage with each educational attainment level (less than high school, high school diploma, some college, BA or more), the percentage of female headed households with children, and median income. We also collect a host of additional Census tract level data from the 2007-2011 ACS. These are used to help test the validity of our identifying assumptions.

Summary statistics of some key analysis variables are shown in Table 1. The table presents means and standard deviations for the full sample as well as for the sample above and below the median value-added score for the 2010 LA Times release. On average, home sales in LAUSD are in Census block groups that are over 50% black and Hispanic,¹⁸ but the schools these properties are zoned to are 74% black and Hispanic, with the difference ostensibly due

¹⁷The data are available at <http://portal.battelleforkids.org/BFK/LAUSD/Home.html>.

¹⁸Note that since the ACS counts Hispanic as a separate category from race, some of the black and white populations are also counted as Hispanic.

to enrollments in private, charter and magnet schools. The schools in our data set also have a large proportion of free and reduced price lunch students. The second two columns of Table 1 show that value-added is not completely uncorrelated with school or block group demographics, although housing characteristics are balanced across columns. The higher value-added areas have a lower minority share, higher property values, a more educated populace and have higher API scores. These correlations likely are driven by better schools being located in the higher socioeconomic areas.

Figure 2 shows that, despite the differences seen in Table 1, value-added is far less correlated with student demographic makeup than are API scores. The figure presents the non-free/reduced-price (FRP) lunch rate, API percentile (within LAUSD) and value-added percentile for each elementary school in LAUSD. The boundaries denote the attendance zone for each school. As expected, API percentiles, which are based on test score proficiency rates, map closely to poverty rates. High-poverty (low non-FRP lunch) schools tend to have lower API scores. In particular, the correlation between API percentile and the percentile of non-FRP lunch eligibility is 0.72. While this relationship remains when replacing API with value-added, it is far less robust. As a result the correlation between value-added percentile and non-FRP eligibility percentile is only 0.33.

While there is a positive relationship between value-added and test score levels, it is quite weak. There are many schools, particularly in the eastern and northern sections of the district, where API scores are low but value-added scores are high. Similarly, some schools with high API scores have low value-added scores. Overall the correlation between the 2010 LAT value-added rank and API rank is only 0.45.¹⁹ Indeed, there are a number of schools which, based on API, are at the top of the distribution but according to the value-added measure are at the bottom, and vice-versa. For example, Wilbur Avenue Elementary had an API percentile of 91 in 2009 but an initial value-added percentile of 13. On the other end of the spectrum, Broadous Elementary had an API percentile of 5 but a value-added percentile of 97.

The fact the API rank and value-added rank are only weakly related to each other does not mean that the value-added information provided by the LA Times was new information.

¹⁹Scatter plots are provided in Online Appendix Figure 2.

It is possible that each of these measures could be predicted based on existing observable characteristics of the school. In Table 2, we examine this issue directly, by predicting API percentile and the percentiles of each value-added measure as a function of school observables in the pre-release period. We use all of the school-level variables included in our property value analysis as our predictors of school quality in order to show how much unexplained variation there is in value-added rank after controlling for the school characteristics included in our main empirical model. Column (1) shows the results for API percentile, and as expected, with an R^2 of 0.71, school demographics explain a substantial amount of the variation. In contrast, as shown in column (2), the value-added estimates are much more weakly correlated with school demographics. Only two of the estimates are statistically significant at the 5% level, and the R^2 is only 0.22. In Column (3), we add overall API, within-LAUSD API rank, and each student subgroup’s API scores as well as two years of lags of each of the API scores as regressors. The R^2 rises but remains low, at 0.41. Thus, almost 60% of the value-added variation is unpredictable from the observable characteristics of the school, including test score levels. In the final four columns, we show results from similar models that use the percentiles in the second LAT value-added release (columns 4 and 5) and the LAUSD value-added release (columns 6 and 7) as dependent variables. The results are similar to those using the first LAT release.

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

4 Valuation of Existing School Quality Information

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

To further address this issue, we estimate boundary fixed effects models in which API percentile is the key independent variable. This model is similar to the one used in Black (1999) as well as in the subsequent other boundary fixed effects analyses in the literature (Black and Machin, 2011) and allows us to establish whether average test scores are valued in LA as they have been shown to be in other areas. We estimate boundary fixed effects models using only data from prior to the first release of the LA Times value-added data so that none of these estimates can be affected by this information.²⁰

Panel A of Table 3 contains results comparing home prices within 0.2 miles of an elementary attendance zone boundary. In column (1), which includes no controls other than boundary fixed-effects, properties just over the border from a school with a higher API rank are worth substantially more. For ease of exposition, all estimates are multiplied by 100, so a 10 percentage point increase in API rank is associated with a 4.5% increase in home values in the pre-release period. In column (2), we control for housing characteristics, which have little impact on the estimates. However, controlling for Census block group demographics in column (3) significantly

²⁰More precisely, we estimate $Y_{istb} = \gamma_0 + \gamma_1 API_{st} + \mathbf{H}_i \Omega + v_t + \zeta_{s_i, s_k} + \mu_{istb}$, where Y is log sales price, H is the set of Census block and property characteristics described above, v_t is a set of month-by-year fixed effects and ζ_{s_i, s_k} is a set of attendance zone boundary fixed effects for each contiguous school pair i and k .

reduces this association. This result is not surprising given the findings in Bayer, Ferreira and McMillan (2007) and Kane, Riegg and Staiger (2006).²¹ Nonetheless, in column (3), we find a 10 percentage point increase in API rank is correlated with a statistically significant 1.3% increase in property values. This estimate is roughly equivalent in magnitude to those in Black (1999) and Bayer, Ferreira and McMillan (2007). Thus, this school characteristic is similarly valued in Los Angeles as in the areas studied in these previous analyses (Massachusetts and San Francisco, respectively). Estimates using properties within 0.1 mile of a school zone boundary are similar, as shown in Panel B.²² It remains unclear, however, whether the capitalization of API scores is driven by valuation of schools' contribution to learning or by valuation of neighborhood or school composition that is correlated with API levels. Our analysis of capitalization of value-added information is designed to provide insight into resolving this question, which is very difficult to do without a school quality measure that is only weakly correlated with student demographics.

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

²¹We do not control for school demographics because these demographics may be part of what determines the valuation of API.

²²The 0.2 and 0.1 bandwidths were chosen to be consistent with prior work, most notably Black (1999) and Bayer, Ferreira and McMillan (2007).

is very similar to the estimate in column (3), suggesting that the capitalization of API scores is not being driven by value-added information and that any information contained in the LA Times value-added estimate is not already capitalized into home prices prior to August 2010. Overall, we view the results in Table 3 as showing that the value-added information released through the LA Times website was not previously known to residents.

5 Empirical Strategy

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

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

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

As discussed in Section 2, the LA Times also posted API rank on their website, which may have made this information more salient to residents. Thus, in equation (1) we allow for the effect of API to vary post-August 2010. Furthermore, we include in the model school fixed effects (γ_s) that control for any fixed differences across schools that reflect fixed school quality differences and month-by-year fixed effects (λ_t) that control for any district-level changes

in home prices occurring contemporaneously with the information release, including seasonal changes. Our inclusion of these fixed effects implies that all parameters are identified off of within-school changes in home prices over time. The coefficients β_1 and β_3 thus represent difference-in-difference estimates of the effect of having a higher value-added or API score on property values after the information release relative to before the release.²³ In order to account for the fact that there are multiple sales per school zone, all estimates are accompanied by robust standard errors that are clustered at the school-zone level.

Equation (1) also includes an extensive set of controls to account for any confounding effects driven by the correlation between the value-added release and contemporaneous changes in school demographics or housing characteristics. The controls further allow us to condition as best we can on the existing information set. The vector X contains the set of school observables discussed above, including current and two years of lagged overall API, current and two years of lagged API for each student subgroup,²⁴ within-LAUSD API percentile rank in the given academic year,²⁵ the percent of students who are black, Hispanic, and Asian, the percent on free/reduced price lunch, who are gifted, who are in special education and who are English language learners. School-by-year enrollment and the percent of the school’s parents who are high school graduates, have some college, have a BA and have graduate school training are included in X as well. The vector H is the set of house-specific characteristics and Census block group characteristics discussed above that further control for local demographic differences that are correlated with value-added and for any changes in the types of houses being sold as a function of value-added when the information is released.

There are two main assumptions underlying identification of β_1 in equation (1). First, the model assumes that home prices were not trending differentially by value-added prior to the data release. Using the panel nature of our data, we can test for such differential trends directly in an event-study framework. In Figure 3, we present estimates using the first value-added release,

²³Note that unlike API, which changes each year, each value-added release provides a single value for each school, and thus the main effect is removed by the school fixed effects. In models that do not include school fixed effects, the main effect is included as a control variable.

²⁴Student subgroups include blacks, whites, Asians, Filipinos, Hispanics, gifted students, special education, economically disadvantaged and English language learners.

²⁵For this study we define the academic year as running from September through August.

where VA and API are interacted with a series of indicator variables for time relative to the August 2010 LA Times release.²⁶ These estimates stop at 7 months post-treatment due to the subsequent data releases. The top panel of Figure 3 shows no evidence of a pre-release trend in home prices as a function of LAT value-added. The estimates exhibit a fair amount of noise, but home prices are relatively flat as a function of future value-added rank in the pre-treatment period. Thus, there is no evidence of pre-treatment trends that would bias our estimates. For API shown in the bottom panel, the pre-treatment estimates are somewhat noisy but do not show any systematic evidence of prior differential trends.

Figure 3 also previews the main empirical finding of this analysis: home prices do not change as a function of value-added or API post-release. The figure shows as well that these estimates are relatively imprecise, as event study models are demanding of the data. We thus favor the more parametric model given by equation (1). Nonetheless, Figure 3 demonstrates that there do not appear to be any time-varying treatment effects that are masked by the equation (1) specification.

The second main identification assumption required by equation (1) is that the value-added percentile, conditional on school characteristics, is not correlated with secular changes in the unobserved characteristics of households, schools or neighborhoods that could independently affect prices. While this assumption is difficult to test, examining how the rich set of household, neighborhood and school observables in our data shift as a function of value-added will provide some insight into the veracity of this assumption. In Online Appendix Table A-2, we show estimates in which we use neighborhood characteristics (measured using both Census block group and Census tract characteristics), school demographics and housing characteristics as dependent variables in regressions akin to equation (1) but only including API percentiles, API percentile interacted with a post-release indicator, time fixed effects and school fixed effects as controls. Each cell in the table comes from a separate regression and shows how the observable characteristic changes as a function of value-added percentile after the first LA Times data release. Overall, the results provide little support for any demographic or housing type changes

²⁶Event studies using the full analysis period and including all three VA releases are provided in Online Appendix Figure 3.

that could seriously impact our estimates.²⁷

The value-added releases we study come at a time of high volatility in the housing market, though, as we describe below, our analysis begins after prices in Los Angeles had stabilized. Even so, this was a period with a large number of foreclosures in Los Angeles. If foreclosure rates are correlated with the value-added releases, it could bias our home price estimates because foreclosures tend to be sold at below market value. In order to provide some evidence on this potential source of bias, we use the number of foreclosures in each month and zip code in LAUSD that were collected by the RAND Corporation.²⁸ We aggregate prices to the school-month level and use the zipcode-level data to approximate the number of foreclosures in the school catchment area in each month. The resulting estimates show little evidence of a correlation between value-added post-release and the number of foreclosures. The coefficient on the LA Times value-added variable is only 0.003 (0.009), which indicates that a 10 percentile value-added rank increase post-release increases the number of monthly foreclosures in a school zone by 0.03, off of a mean of 5.7. Overall, the estimates described above along with those provided in Table 3 and Figure 3 provide support for our identification strategy.

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

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

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

In addition to models (1) and (2), we extend the boundary fixed-effect analysis in Table 3

²⁷In results available upon request, we also do not see an effect on the number of houses sold.

²⁸These data are available at <http://ca.rand.org/stats/economics/foreclose.html>.

to the difference-in-differences context. If one is concerned that our identification assumptions do not hold in general, they are much more likely to hold when we compare changes in housing prices generated by the value-added release to households on either side of an elementary school zone boundary. For these models, we restrict to properties within 0.1 mile of a school zone boundary and estimate (for the 7 month sample)

$$\begin{aligned}
Y_{ist} = & \beta_0 + \beta_1 VA_{st}^{LAT1} + \beta_2 API_{st} + \beta_3 API_{st} \times Post_t \\
& + \mathbf{X}_{st}\Gamma + \mathbf{H}_i\Phi + \lambda_t + \gamma_s + \zeta_{s_i,s_k} + \epsilon_{ist},
\end{aligned} \tag{3}$$

where ζ_{s_i,s_k} is an indicator that equals one if the property is on the boundary between school i and school k . We also extend equation (2) in a similar manner to equation (3) for the longer-term sample.

6 Results

6.1 Difference-in-Difference Estimates

Table 4 presents the baseline estimates from equation (1). In each column, we add controls sequentially in order to observe the effects of the controls on the estimates. All estimates are multiplied by 100, so they show the effect of a 100 percentile increase in value-added on home prices post-release. Panel A shows results examining just the first LA Times value-added information. We include no controls except API and VA main effects in column (1) and then add in the school, neighborhood and housing characteristics discussed in Sections 3 and 5 in column (2). Column (3) contains our preferred estimates, which include school zone and month fixed effects. Across columns, there is no evidence that a higher value-added rank leads to higher home prices. Regardless of the controls used, the estimates are small and are not statistically significant. In column (3), the point estimates indicate that a 10 percentile point increase in value-added decreases property values by 0.3 percent. This estimate is precise enough that we can rule out a 10 percentile point increase in value-added increases home prices by more than

0.2% post-release. To relate this estimate to the prior literature, at the median a one standard deviation increase in value-added corresponds to a roughly 35 percentile increase in rank. Using the upper bound of the 95% confidence interval, this translates into at most a 0.7% increase in home prices. This estimate is well below capitalization effects found using test score levels in prior work (Black and Machin, 2011).

Columns (4) and (5) of Table 4 provide further evidence that value-added information does not affect property values. In these columns, we provide results from model (3) where the estimates are identified off of changes in property values between properties on either side of a given attendance zone boundary when the value-added data are released. These estimates show little evidence of a positive capitalization effect of the LA Times value-added information.²⁹

In Panel B of Table 4, we present estimates of equation (2) using the longer time frame that includes the second LA Times release and the LAUSD release. Similar to the results in Panel A, the estimates all are small and are not statistically significantly different from zero at conventional levels. None of the value-added releases we examine leads to significant changes in property values, which suggests the lack of effects in Panel A of Table 4 is not being driven by our use of a short post-treatment window. The same result holds for the API rank estimates in both panels of the table as there was no change in the relationship between API scores and home prices when the LA Times posted API percentiles on its website.

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

²⁹Another outcome that reflects parents' valuation of schools is changes in enrollment patterns. Unfortunately, our data do not allow us to track transfers between schools. However, we are able to look at whether overall school enrollment is affected by value-added scores. When using enrollment as an outcome at the school-year level, we find an impact estimate of the VA percentile of 0.09 (s.e. 0.11), which suggests an insignificant increase of 0.9 students for every 10 percentile increase in VA. Interestingly, the estimate on $API \times Post$ is significant at the 10% level with an estimate of 0.32 (0.18), or 3 students per 10 percentiles of API.

In column (1) of Table 5, we add the standard deviation of the value-added scores across teachers in each school interacted with an indicator for the post-release period. If high-quality teachers are disproportionately valued (or if low-quality teachers have a disproportionately negative valuation), then a higher standard deviation will lead to higher (lower) property values conditional on school-wide value-added. The estimate on the standard deviation of teacher value-added is positive, but it is not statistically significantly different from zero. It also is small, pointing to an increase in property values of only 0.007% for a one point increase in the standard deviation of teacher value-added rank.

In column (2), we interact the proportion of teachers in each quintile of the value-added distribution with being in the post-August 2010 period. Again, we see little evidence that having a higher proportion of teachers with high value-added leads to higher property values, nor does a high proportion of low VA teachers reduce property values. Aside from the 3rd quintile estimate, the coefficients all are positive, but they are small: moving 10% of the teachers from the bottom to the top quintile would increase property values by 0.1%. Because the distribution of teacher value-added within a school might be highly correlated with school value-added, in column (3) we re-estimate the teacher value-added model without controlling for school value-added. There is even less evidence that a higher proportion of high-VA teachers leads to higher property values in this specification. This result is surprising, given the strong correlation between teacher quality and student academic achievement as well as future earnings that has been shown in prior research (Chetty, Friedman and Rockoff, 2014b; Rivkin, Hanushek and Kain, 2005; Rockoff, 2004).³⁰

To test an alternative to our baseline model, in column (4), we use the school value-added quintile rank instead of the percentile rank.³¹ This is because, as shown in Figure 1, the quintile was the most salient value-added information on the LA Times website. The results are consistent with those in Table 4. The top two quintile estimates are negative and are not significantly different from zero, and the 2nd and 3rd quintiles, while positive, also are not

³⁰One potential concern with examining valuation of teacher quality at the school level is if teacher turnover is high, parents might rationally ignore this information. While we would like to test this directly, unfortunately we could not acquire data on teacher turnover.

³¹Appendix Table A-3 presents results from a similar specification that includes all three value-added releases.

statistically different from zero.

Finally, if a neighborhood has fewer school choice options, it is possible there would be more capitalization of the local school's quality. To test this hypothesis, in column (5) we interact the value-added score with the number of charter schools within a one mile radius of the property. We find no evidence that the capitalization of value-added varies with the number of charter schools nearby. Results were similar using a two mile radius.

As shown in Table 2, the value-added information was largely not predictable by the set of observable school characteristics that existed prior to August 2010. However, the LA Times release occurred in a context where there was a lot of existing information about school quality in terms of observed test score levels and student composition. In Table 6, we test whether the value-added information had a larger effect when it deviated more from this existing information. In column (1), we use as our deviation measure the difference between the LA Times value-added percentile rank and the API percentile rank in 2009. The estimate is negative and is not statistically significantly different from zero, suggesting that positive value-added information relative to existing API information did not increase property values.

In the subsequent columns of Table 6, we characterize existing school quality information using a factor model that includes 2009 API scores, overall and by racial/ethnic group, the racial/ethnic composition of the school, the parental education distribution of the school, and the percent of free/reduced price lunch, disabled, gifted, and English language learners. We also include two years of lags of each of these variables. This factor model thus incorporates a large set of the publicly available observable characteristics about a school in the current year and in the prior two years that a parent could use to generate beliefs about school quality. The model isolates 22 factors that explain over 85% of the variation in these variables. In column (2) of Table 6, we examine the capitalization of the difference between the LA Times value-added percentile rank and the percentile rank of the first primary factor (explaining 26% of the variance). In column (3), we combine all 22 factors by calculating the percentile rank for each factor and then taking a weighted average, where the weight is the percent of the variance explained by the factor divided by 0.85. The final column shows results that allow for the deviations from the first primary component rank and from a weighted average of all other

factor ranks to have different effects on property values. In no case do we find evidence that when the LA Times value-added differs from these factor ranks property values rise post-LA Times release. These estimates indicate little support for the contention that the relative size of the information shock affected home prices.

One remaining concern is the relatively high levels of segregation in Los Angeles: the LA metro is the most segregated in terms of white-Hispanic and 14th for white-black dissimilarity (Logan and Stults, 2011). However, the differences between segregation in LA and in other large urban areas with high Hispanic and African American populations are not large. In addition, LA exhibits similar levels of white-Hispanic and white-black school segregation to such urban centers (Stults 2011). There therefore is little evidence that segregation patterns threaten the generalizability of our results. To address this potential problem, however, in Table A-4 of the Online Appendix we provide estimates that look at housing price impacts when other highly-segregated schools dominated by the same racial group get higher value-added scores. We find little evidence to suggest that prices respond to the value-added in these sets of similarly-segregated schools.³²

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.³³ We now turn to an examination of several potential sources of heterogeneity in value-added capitalization. In Figure 4, we present estimates broken down by observable characteristics of the school: 2009 within-LAUSD API quintile, median pre-release home price quintile, percent free and reduced price lunch, percent black, percent Hispanic, and percent white. Although the precision of the estimates varies somewhat, the point estimates are universally small in absolute value and are only statistically significantly different from zero at the five percent level in two cases (out of 45 estimates).

³²Another potential way in which LA is different from other metro areas is in terms of residential mobility. Tabulations from the 2008-2012 ACS show that 9.1% of households across the US move within-PUMAs each year, and in LA 9.5% of households do so. These tabulations suggest within-city mobility is similar in LA as in the rest of the United States.

³³In Online Appendix Table A-4, we redefined the treatment to be value-added rank among schools within 2, 4, 6, 8 or 10 miles in order to account for the fact that school choice markets may be highly localized. We also match schools to demographically-similar schools and examine the effect of relative rank amongst these similar school types. None of these estimates indicate an effect of value-added information on property values.

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

6.2 Robustness Checks

The last row of Figure 4 provides insight into two potential criticisms of using housing prices as our outcome measure. The first panel addresses concerns that many neighborhoods in Los Angeles have high rates of private schooling and thus are likely to be less sensitive to the quality of the local public school. We show estimates that are interacted with the private schooling rate in the Census tract of each property from the American Communities Survey. The mean private schooling rate in our sample is 20%, with a standard deviation of 31%. The estimates show little difference in capitalization by private schooling rate. In the second panel of the last row, we measure variation by owner-occupancy rates, also calculated from the ACS. The concern here is that in neighborhoods with low owner-occupancy rates, sale prices may be less sensitive to school quality. The mean of this measure is 50.1%, with a standard deviation of 23.3%. Once again, we see little evidence of heterogeneity along this margin.

Table 7 provides a series of additional robustness checks in order to assess the fragility of our results with respect to several modeling assumptions.³⁴ In column (1), we include Census tract fixed effects. Relative to the baseline estimate in column (3) of Table 4, The LA Times value-added estimate becomes even more negative. Next, we exclude the lagged API measures in case they are capturing a large amount of the value-added variation. The results are very

³⁴Appendix Table A-5 provides these estimates using the full sample period and including all value-added releases. Results are similar to those seen in Table 7.

similar to those in Table 4. In column (3), we use sale prices in levels rather than in logs. Converting the estimate to percent terms using the mean home price in Table 1 yields an almost identical result to baseline. In the next two columns, we limit to homes with less than 2 and at least 3 bedrooms, respectively, in order to better isolate homes that have children in them. The estimates do not provide any evidence of a link between value-added information and property values for these samples.

Although we impute property values for about 7% of the sales, column (6) of Table 7 shows excluding these imputed sale prices from our regression makes the value-added estimate more negative. While this estimate is statistically significant, as previously noted and shown in online appendix table A-1, since these properties are unlikely to be conditionally missing-at-random we believe the models that include imputed values are more appropriate. Further, we note that the estimate in column (6) does not statistically significantly differ from baseline. We next exclude properties with more than 8 bedrooms in column (7), which either are very large homes or are multiple unit dwellings. We alternatively exclude properties over 5,000 square feet in column (8) and drop multiple unit properties in column (9). For each of these cases, the estimates are quantitatively and qualitatively similar to our baseline results. In column (10), we allow for there to be a 3 month lag between when the information is released and when it impacts the housing market by setting the value-added to zero in first 3 months post-release. We continue to find no effect of value-added information on property values. Taken together, the results from Table 7 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.³⁵ Additionally, in column (11) of Table 7 we estimate a model that excludes $API*Post$, which has little impact on the value-added coefficient we obtain. Finally, in column (12) we add properties with sale prices greater than \$1.5 million back into the sample. Doing so substantially reduces precision, but nonetheless does not appreciably change our results.

³⁵One additional concern is that if the housing market is not efficient, impacts might not show up until the summer when families with children are more likely to move. While we cannot test this using the restricted sample, in Online Appendix Table A-5 we provide estimates using the full sample restricted only to summer months (June through August). The results for the VA estimates are similar to baseline, though interestingly the $API \times Post$ estimate is positive and significant.

7 Potential Mechanisms

Our results show that homeowners place, at most, a negligible valuation on value-added information as currently constructed. While there are a few alternative explanations, our preferred interpretation is that parents do not value the aspect of school quality related to the ability of schools and teachers to raise test scores. In this section, we discuss some alternative explanations for our findings and argue that our preferred interpretation best fits the evidence we have shown, though we acknowledge that we cannot rule out other explanations.

First, while it is possible that parents and homeowners dismiss the value-added information because they received several, often conflicting pieces of information regarding value-added rank, this scenario is inconsistent with the lack of an effect of value-added information prior to the second value-added release. In this period, there was no conflicting information, and prior work has shown school quality information shocks affect property values in the very short run. Furthermore, Table 8 shows direct evidence that the multiple doses of information is unlikely to be a primary driver of our results. In column (1), we include an indicator for whether the 1st LA Times VA release and the LAUSD score are in the same quintile, as well as interactions between this indicator and both the LA Times and LAUSD VA percentiles. If conflicting information is affecting capitalization of the value-added release, then these interactions should be positive as parents should value this information more when it is consistent. However, we see no evidence that higher value-added rank led to higher home prices even when the measures agree. In column (2), we repeat this exercise using all three measures. Although noisy, the estimates still do not point to homeowners valuing this information in the cases in which the value-added ranks tell a consistent story.

One also may think that the public just did not trust the value-added scores provided by the LA Times. However, two pieces of evidence argue against this interpretation. First, even if people did not respond because of a lack of trust in the LA Times calculations, it does not explain the lack of response to the school district's own measure. Second, work by Bergman and Hill (2015) find that after the initial release, high achieving students sorted into classrooms with high value-added teachers. Responses on this low-cost margin (as opposed to the higher-

transaction cost response of moving) suggests that many parents did understand and care about the value-added scores. While this may seem at first glance to run counter to our preferred explanation, their results easily can be reconciled with our results by noting that while there may be incentives to make low-cost adjustments, the incentives are not strong enough to make relatively high-cost adjustments such as moving. Thus, while the Bergman and Hill (2015) results suggest parents care about value-added, our results indicate the utility gained from moving students to high value-added schools is very small relative to the gain from moving to schools with high achieving peers as indicated by Figlio and Lucas (2004), other literature using boundary fixed-effects estimates, and our own estimates of boundary fixed-effects impacts of API in Los Angeles.

Finally, such a finding is consistent with prior literature on parental preferences that suggest parents mainly care about factors other than value-added. Jacob, Cullen and Levitt (2006) show that while students who win a school choice lottery in Chicago tend to attend schools with higher school value-added compared to lottery losers, that increase is small relative to the increase in peer mean achievement and the reduction in minority share in their new schools. Additionally, Hastings and Weinstein (2008) find that parents respond strongly to the provision of test score levels in the context of school choice in Charlotte-Mecklenburg. Admittedly, in neither of these cases were parents provided direct information on value-added, but they do suggest that parents care a lot about peer quality *levels*, and so it is not unreasonable for the valuation of levels to far outweigh the valuation of value-added.

As discussed above, our analysis takes place in a time period just after an historic housing market decline that was accompanied by significant rigidities in the housing market. It could be the case that such rigidities affect the capitalization of new information. If so, our estimates still would identify the effect of the LA Times and LAUSD information releases, but the external validity of our results would be more limited. We note that, to our knowledge, there currently is no evidence in the literature that capitalization is responsive to housing market rigidities. In addition, it is possible that when home prices decline, people become more sensitive to the characteristics of the home they are purchasing because concerns about resale value may be more salient.

Nonetheless, trends in home prices in LA suggest that the market was not especially rigid. First, we note that the most severe problems in the Southern California housing market were in the “Inland Empire” region far to the east of Los Angeles. Second, the Case-Shiller Home Price Index for Greater Los Angeles shows that housing prices in Los Angeles reached their trough in mid 2009 and had increased 9% by the time of the release in September 2010. Afterwards, prices remained roughly steady through our study period.³⁶ Further, news reports at the time indicated that the housing market was recovering.³⁷ We also have estimated models that include interactions between value-added rank and housing price changes from 2007 to 2009, which reflect the degree to which different areas in LAUSD were affected by the housing market downturn. We find no evidence of different effects by the size of price declines during the bust, which is inconsistent with housing market rigidities biasing our estimates.

Another important piece of evidence that our results are unlikely to be due to housing market rigidities is from the results in Table 3 that show API scores are highly valued by the housing market in this time period and that the magnitude of these effects is consistent with other research. So LA during our study period does not appear to be less responsive to school quality in general than has been found in prior research in other locations.

A further concern with our preferred interpretation of the results is that the value-added data are based off of historical information - the calculations published in the LA Times use data from 2002-2003 through 2008-2009. Using this longer time span of data has the benefit of making the value-added estimates more stable and reliable, but if schools are changing rapidly, then the yearly API scores might be a better contemporaneous measure of school quality than value-added. However, there is very little evidence that schools are changing rapidly over time, at least as measured by API scores. An ANOVA analysis shows the intra-school correlation in API rank to be 0.93, and the standard deviation within a school is only 9 percentiles (versus 32

³⁶These housing price data were retrieved from <http://www.nytimes.com/interactive/2011/05/31/business/economy/case-shiller-index.html>. Our own data confirm these reports and the Case-Shiller index. Online Appendix Figure 4 plots quarterly sales and median sale prices in LAUSD using LACAO sale price data. For sale prices we see that the peak occurs in 2007Q2 and the trough in 2009Q1. By the time of the VA release, sale prices had been stable for over a year, and by 2009Q2 they had recovered to pre-collapse levels. Thus, the entirety of our analysis period occurs after the housing market in LAUSD had stabilized.

³⁷See, for example, *Los Angeles Times* on May 19, 2010; *Orange County Register* on July 27, 2010; and *Los Angeles Times* on July 13, 2011.

percentiles overall). Even when the first and second LA Times value-added rankings disagree, there is no evidence that this is reflective of a trend in achievement. If we split schools into quartiles by the difference between their first and second LA Times value-added percentile, the trend in API scores across the quartiles from 2006 to 2010 are identical. Furthermore, our estimates of the impact of value-added information are very similar across these quartiles.³⁸ We also note that the LAUSD data are based off of one year change in student performance. While this feature makes them much more noisy, if the data lags associated with the LA Times estimates made them irrelevant for housing prices, there still should have been a capitalization effect of the LAUSD value-added information. Together, these pieces of evidence suggest that the lagged data used in the LA Times VA measures are not the reason the housing market does not respond to this information.³⁹

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

8 Conclusion

School districts across the country have begun to use value-added methodologies to evaluate teachers and schools. Although only a few large districts have released these results publicly, it is likely that more will in the future. Thus, it is important to understand whether and

³⁸These estimates are available upon request.

³⁹A related issue is that school zones themselves may be changing too frequently for school quality information to be capitalized. Using school zone maps for 2002-03 constructed by the LA County Emergency Operations Center (available at <http://egis3.lacounty.gov/dataportal/2011/11/30/elementary-middle-and-high-school-attendance-areas-2002/>) we check how often a given property sold in our data would have been in a different elementary school had that property been sold in the 2002-03 school-year. Between 2002-03 and 2011-12, less than 5% of properties changed school zones. If we separate these rates by the 2011-12 school's LA Times VA quintile, we see little difference: the switch rates range from 2% to 6%.

how this information is valued by local residents. This is particularly important because recent evidence suggests parents *should* value this information, as value-added has large positive effects on future student outcomes (Chetty, Friedman and Rockoff, 2014b). Furthermore, value-added measures provide information about school quality that is less correlated with the school demographic makeup than are test score levels. Identifying how value-added information in particular is capitalized into housing prices therefore can lend new insight into the valuation of school quality that research focusing on test score levels as a school quality measure cannot.

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

Unique to our study in the school valuation literature is the ability to examine home price effects based on teacher quality information. Similar to the school-level results, though, we find that property values are unresponsive to the within-school variance in teacher value-added. Nonetheless, we do find suggestive evidence of a positive response to higher value-added scores in low SES neighborhoods, but we caution that since this is the only positive estimate found and it is not consistently significant across measures of SES, this result could be spurious.

Our estimates differ substantially from previous work on school valuation that use test score levels as a measure of school quality. This literature typically has found an effect on the order of 2 to 5 percent higher housing prices for each standard deviation increase in test scores (Black, 1999; Bayer, Ferreira and McMillan, 2007; Gibbons, Machin and Silva, 2009). Nonetheless,

previous work examining how property values respond to researcher-calculated school value-added or changes in school test scores have findings similar to our own (Black and Machin, 2011), but those studies are distinct from ours as they implicitly assume that home buyers make the same calculations from available data. The fact that property values do not respond to these school quality measures could be due to a lack of awareness of this information.

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

That we find no effect of school or teacher value-added information on home prices suggests these school quality measures as they are currently constructed are not highly valued by local residents, at least on the margin. While our research design identifies the effect of value-added information on home prices, it is not as well designed to allow us to understand *why* parents do not value this information. It might be the case that the contentious context in which this information was released and the difficulty in understanding the complex underlying statistical models affected how people valued it. If so, future value-added releases could have different impacts on property values if they are done in a more collaborative environment or if they are paired with educational campaigns. However, we argue our results are most consistent with parents not valuing the aspect of school quality related to the ability of schools and teachers to increase test scores sufficiently to impact housing prices. While we cannot fully disentangle these two mechanisms for the lack of capitalization of value-added information in this study, doing so is a fruitful area for future research.

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Figure 1: Example of Information Displayed in LA Times Database

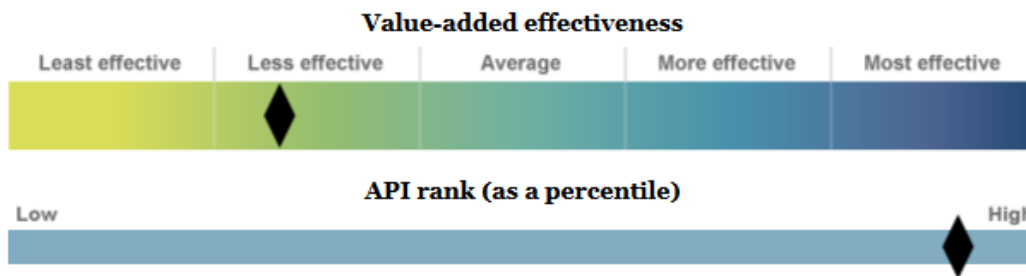
Los Angeles Teacher Ratings

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:

2010



2009



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

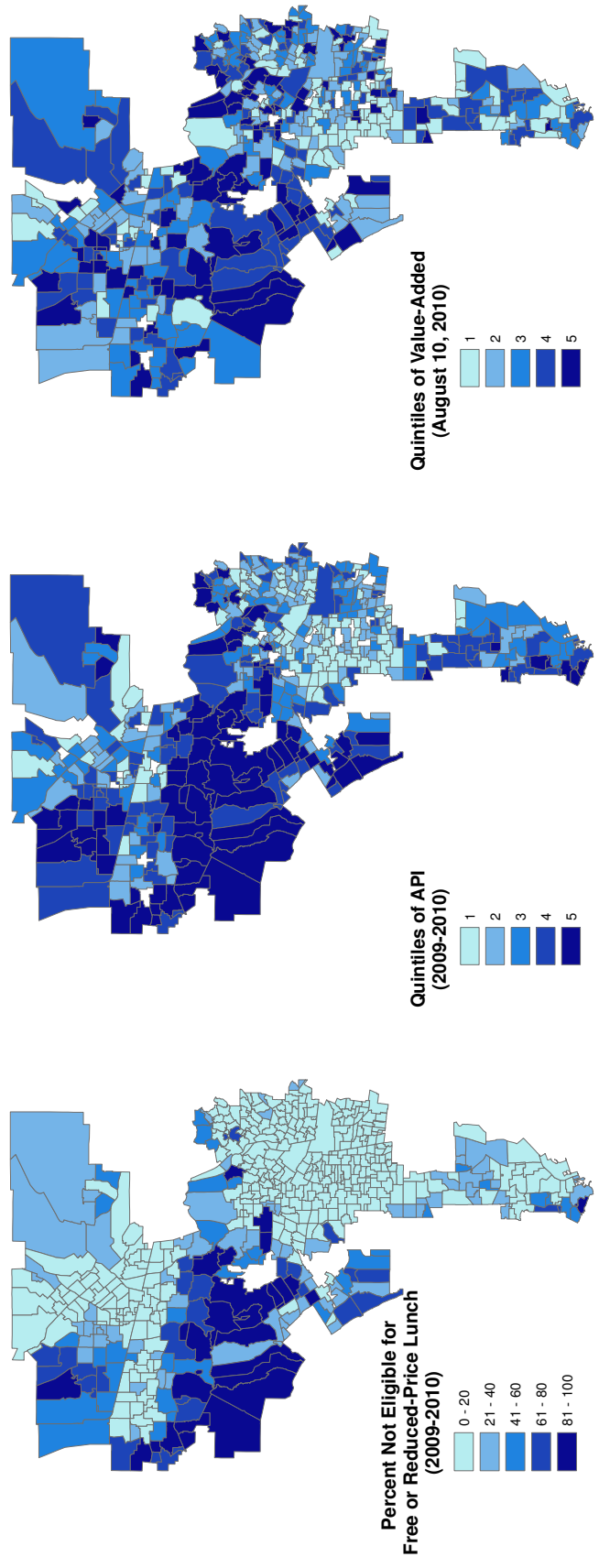
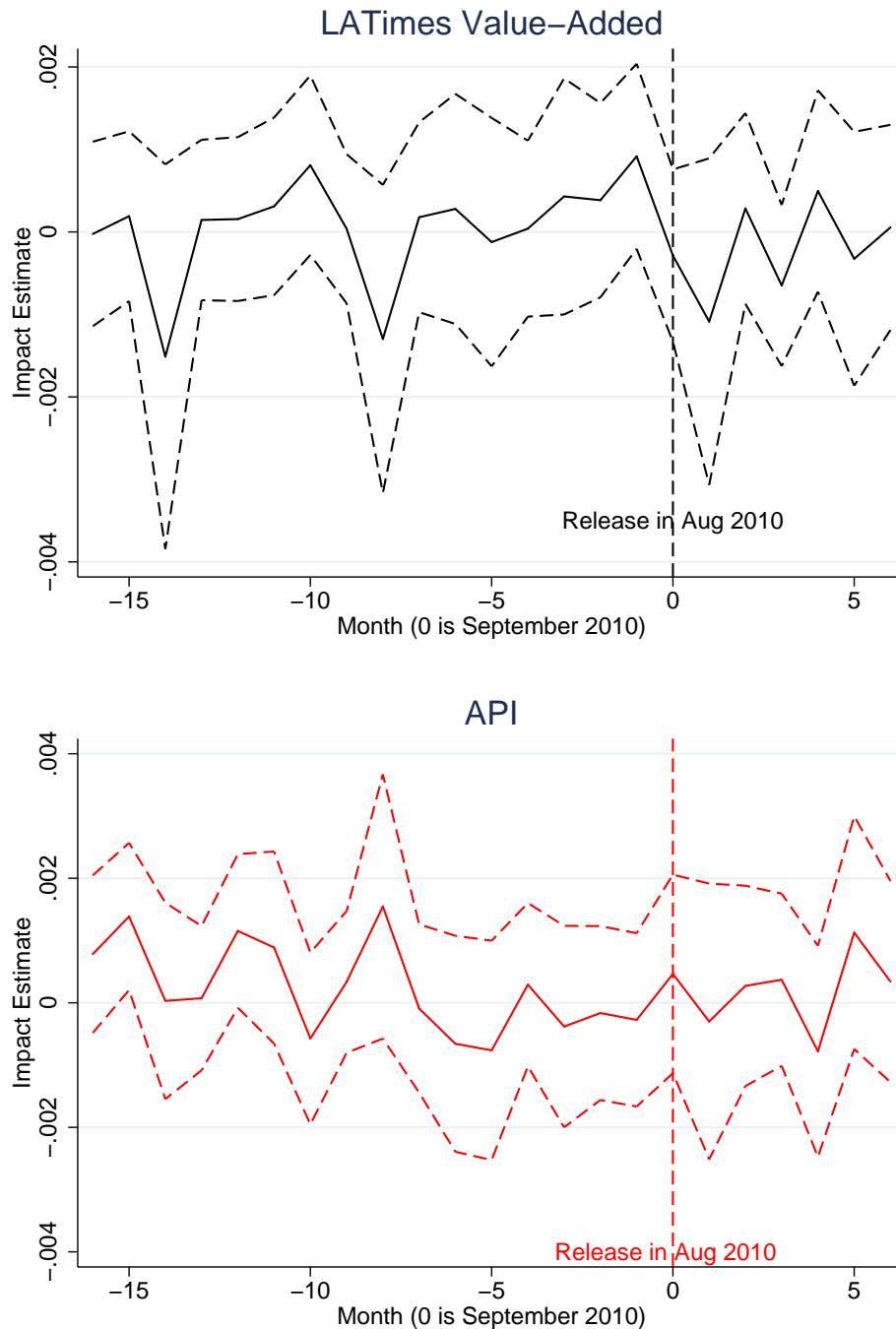
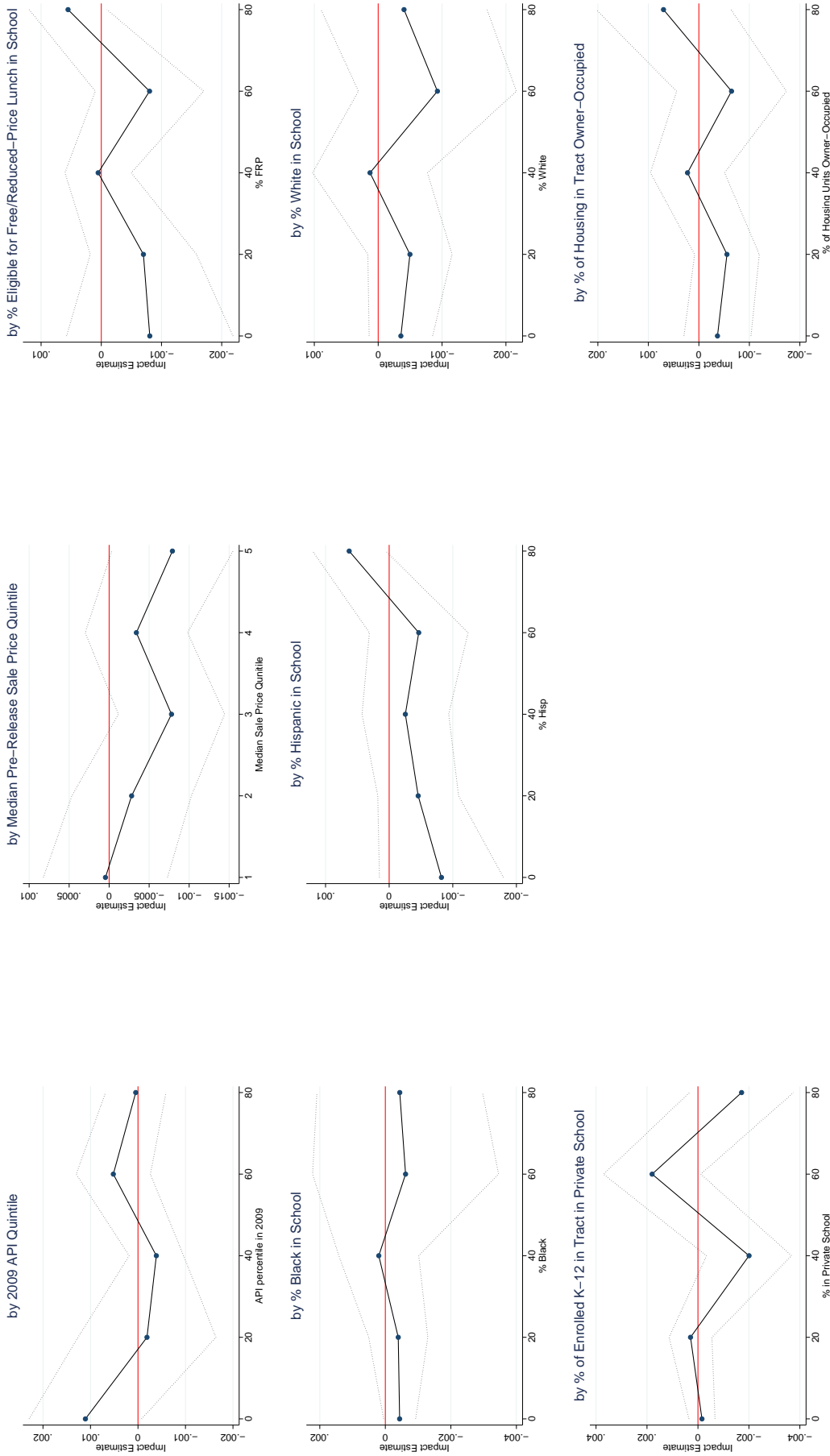


Figure 3: Effect of Value-Added Information on Log Sales Price by Month of Sale



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

Figure 4: Heterogeneity in the Estimated Effect of LA Times Value-Added on Log Sale Price



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

Table 1: Summary Statistics of Select Variables

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

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

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

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

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

Table 3: School-Zone Boundary Fixed Effects Estimates of the Impact of API on Ln(Sale Price) in the Pre-Release Period

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

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

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

Table 4: Effect of Value-Added Information on Log Sale Prices

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

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

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

	<i>Note: Estimates for all models except (3) are multiplied by 100 for ease of presentation.</i>				
	Include Std Dev of Current Teacher VA	Include % Teachers in VA Quintile	Include % Teachers in VA Quintile (No School VA)	Use Whether School in VA Quintile	Interact with # of Charters w/in 1 Mi
	(1)	(2)	(3)	(4)	(5)
LAT 1 st VA Pctl × Post Aug 2010	-0.029 (0.025)	-0.044 (0.031)			-0.052** (0.025)
API Pctl × Post Aug 2010	0.011 (0.048)	0.036 (0.045)	0.028 (0.043)	0.037 0.046	0.042 (0.045)
LAT Teacher VA Standard Deviation	0.007 (0.099)				
Teacher/School VA Quintile: 2 nd Quintile				2.4 (2.1)	
3 rd Quintile		1.0 (6.5)	0.1 (6.3)		
4 th Quintile		-0.0 (6.9)	-2.5 (6.5)	2.2 (2.4)	
5 th Quintile		1.1 (7.4)	-2.2 (6.9)	-1.9 (2.3)	
LAT 1 st VA × Charters w/in 1 Mi		1.3 (7.0)	-3.4 (5.7)	-0.9 (2.0)	0.008 (0.010)
Observations	50,365	50,365	50,365	51,514	51,514

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

Table 6: Effect of Value-Added Information Relative to Existing Information on Log Sale Prices

Note: Estimates for all models are multiplied by 100.

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

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

Table 7: Effect of Value-Added Information on Log Sale Prices - Specification Checks

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

	Add Census Tract FE (1)	Exclude Lagged API (2)	Use Sale Levels (3)	Limit to 0-2 Bedrooms (4)	Limit to 3+ Bedrooms (5)	Drop Imputed Sales (6)	Drop Properties w/ > 8 Bedrooms (7)	Drop Properties w/ > 5000 sf (8)	Drop Multi Unit (9)	3 Month Lead (10)	No API* Post (11)	Include High Sale Prices (12)
LAT 1 st VA Pctl × Post Aug 2010	-0.041* (0.024)	-0.028 (0.024)	-120.2 (82.3)	-0.010 (0.029)	0.005 (0.017)	-0.049** (0.025)	-0.027 (0.024)	-0.029 (0.024)	-0.017 (0.016)	-0.023 (0.030)	-0.029 (0.024)	0.078 (0.080)
API Pctl × Post Aug 2010	0.004 (0.040)	0.013 (0.036)	319.6* (193.1)	0.006 (0.049)	-0.018 (0.029)	0.046 (0.044)	-0.002 (0.044)	0.006 (0.044)	-0.003 (0.033)	0.045 (0.039)		0.082 (0.141)
Observations	51,514	51,514	51,514	19,191	30,189	47,926	51,044	50,959	45,575	51,514	51,514	54,188

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

Table 8: Effect of Value-Added Information on Log Sale Prices - Interactions Between VA Measures

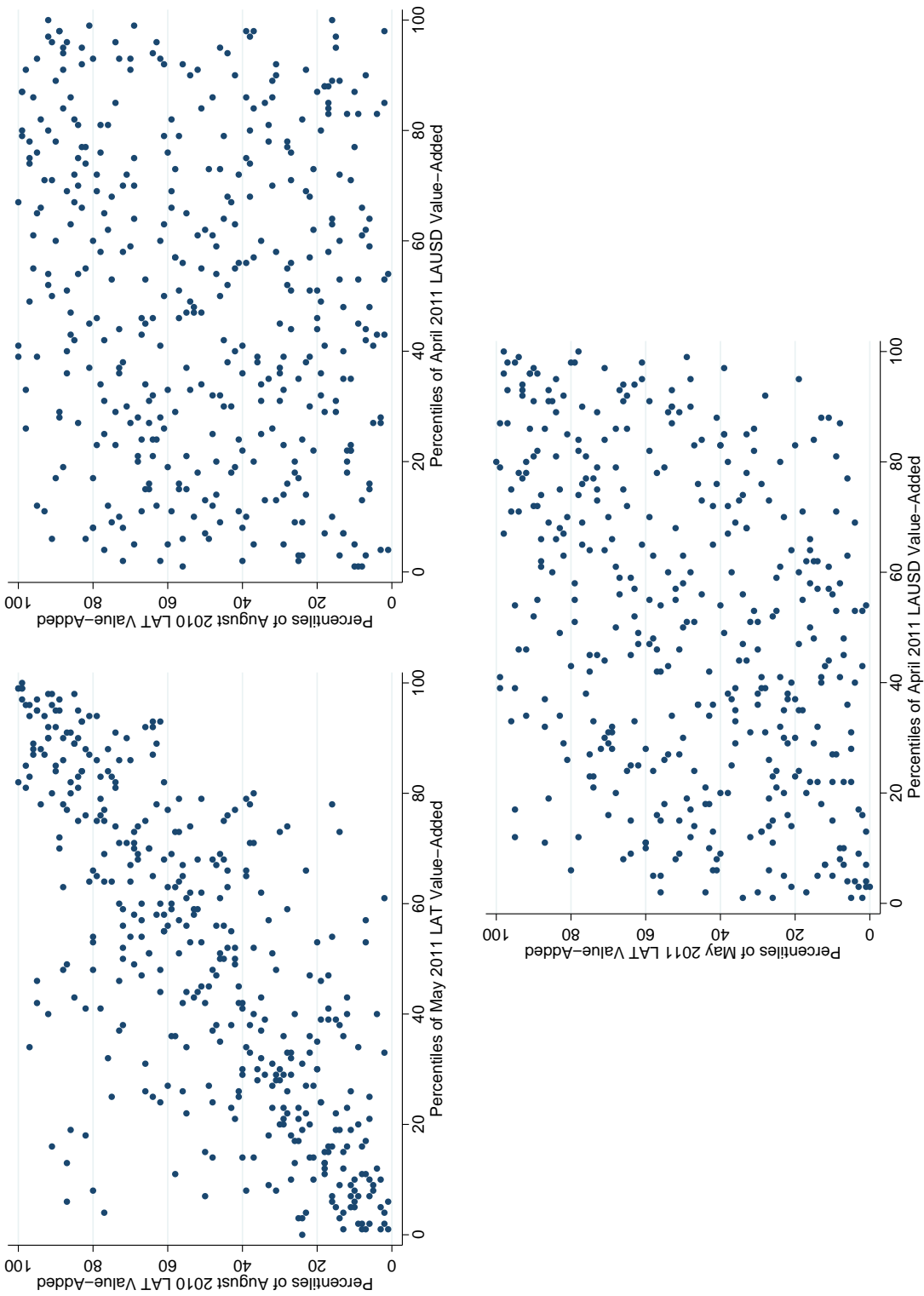
Note: Estimates for all models are multiplied by 100 for ease of presentation.

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

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

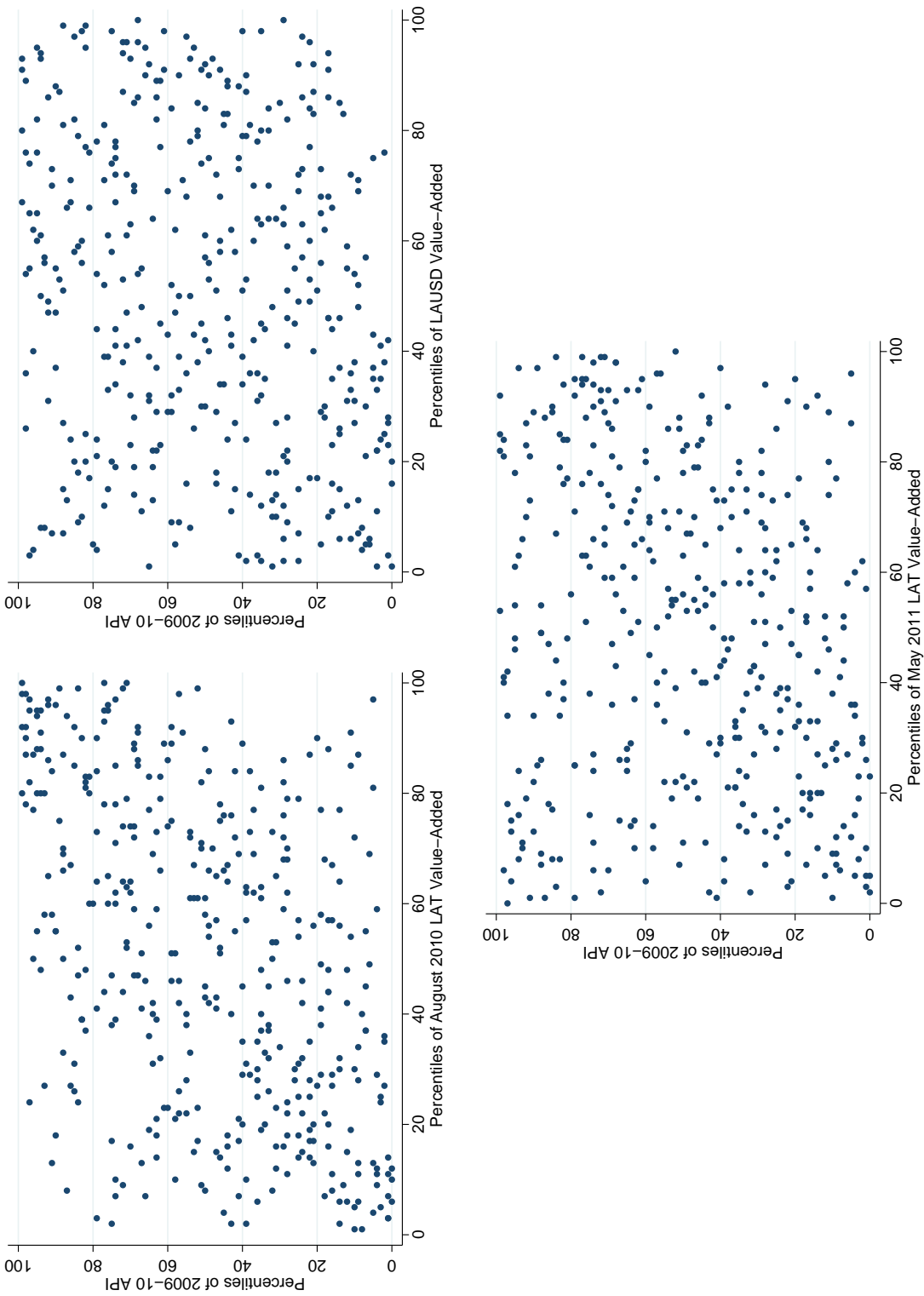
Online Appendix: Not for Publication

Figure A-1: Comparisons of the Three Value-Added Measures



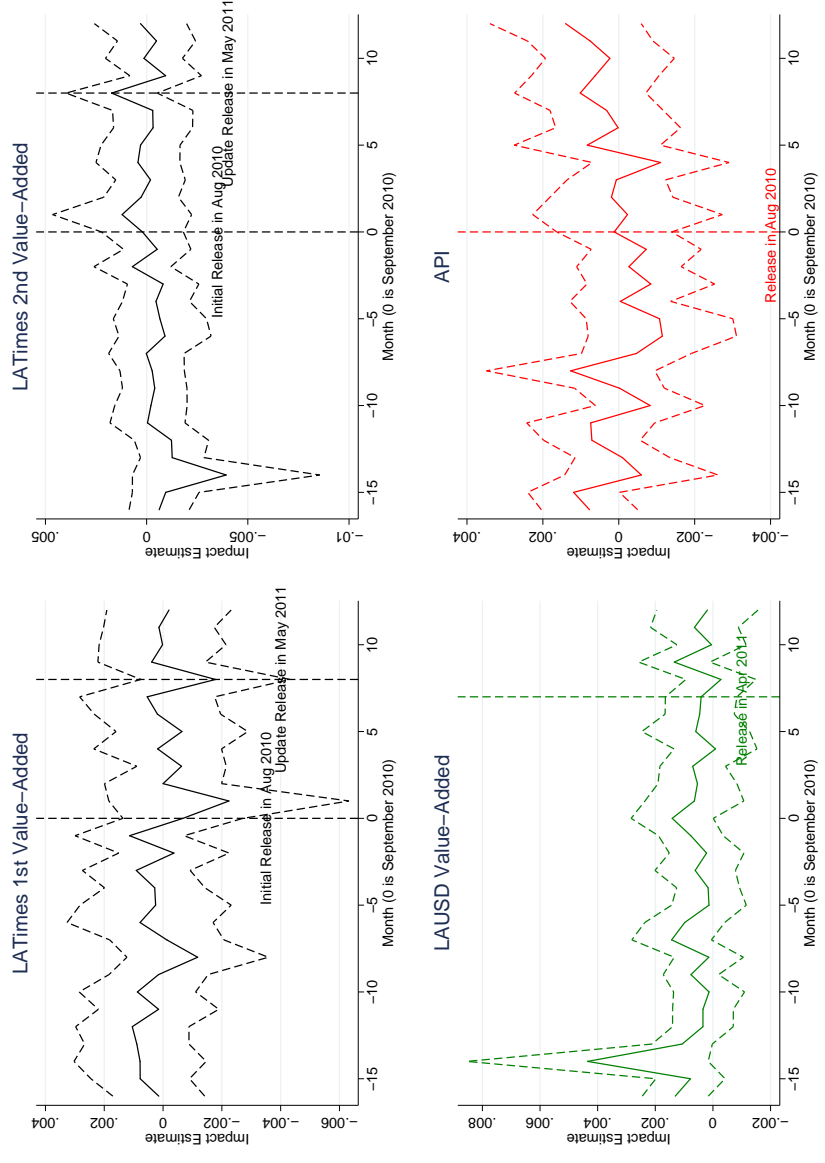
Percentile ranking amongst LAUSD elementary schools using the three value-added scores. Each dot is a single elementary school.

Figure A-2: API Percentile vs. Value-Added Percentile



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

Figure A-3: Effect of Value-Added Information on Log Sales Price by Month of Sale, Including All Value-Added Releases



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

Figure A-4: Quarterly Sales and Median Sale Price in LAUSD



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

Table A-1: Relationship Between Having Sale Price Imputed and Observable Characteristics of Property

	April 2009 to March 2011	April 2009 to September 2011	
	API Growth Percentile	0.00000 (0.00021)	0.00004 (0.00018)
	Share Black	0.00272** (0.00135)	0.00236** (0.00114)
	Share Hispanic	0.00234** (0.00110)	0.00191** (0.00091)
	Share API	0.00009 (0.00074)	0.00043 (0.00068)
	Share FRP	0.00037 (0.00055)	0.00066 (0.00047)
	Share Gifted	0.00092 (0.00073)	0.00057 (0.00061)
School Characteristics	Share ELL	-0.00183** (0.00078)	-0.00153** (0.00064)
	Share Speced	-0.00106 (0.00113)	-0.00054 (0.00096)
	Enrollment	-0.00006 (0.00007)	-0.00003 (0.00005)
	Share Parents HS Grad	-0.00016 (0.00105)	-0.00006 (0.00079)
	Share Parents Some Col	-0.00014 (0.00091)	-0.00018 (0.00074)
	Share Parents BA	0.00051 (0.00102)	0.00007 (0.00081)
	Share Parents Grad Schl	0.00112 (0.00137)	-0.00009 (0.00109)
	# Units	0.00458** (0.00227)	0.00676*** (0.00205)
	Year Built	-0.00010*** (0.00001)	-0.00009*** (0.00001)
Property Characteristics	# Bedrooms	0.00361** (0.00149)	0.00291** (0.00137)
	# Bathrooms	0.00321* (0.00177)	0.00361** (0.00160)
	Square Footage/1000	-0.00490** (0.00225)	-0.00664*** (0.00220)
	% Hispanic	0.01086 (0.02492)	0.01680 (0.02177)
	% Black	0.01673 (0.02281)	0.02355 (0.02174)
	% HS Grad	-0.01860 (0.02699)	-0.01880 (0.02548)
Census Block Characteristics	% Some College	-0.00903 (0.02505)	-0.01202 (0.02311)
	% College Grad	-0.01535 (0.02945)	-0.00566 (0.02706)
	% Female Head	-0.04305** (0.01820)	-0.03503** (0.01690)
	Median Income/1000	-0.00008 (0.00007)	-0.00007 (0.00006)
	Observations	51,514	63,122

The data cover April 2009 through September 2011. All regression control for month fixed effects and school zone fixed effects. Standard errors clustered at the school level are in parentheses. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table A-2: Effect of Value-Added on Demographic and Housing Characteristics

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

<i>Panel A: Census Block Group Characteristics of Property</i>							
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Hisp	% Black	% No HS	% HS Grad	% Some Col	% BA+	% Fem Head	Med HH Inc
-1.03	0.18	-0.29	0.08	0.02	0.19	0.39	442
VA Pctl (0.67)	(0.40)	(0.46)	(0.35)	(0.33)	(0.56)	(0.34)	(1,278)
<i>Panel B: Census Tract Characteristics of Property</i>							
(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
% Children	% Senior	Median Age	% Institutionalized	% HH w/ Kids	% Single M w/ Kids	% Single F w/ Kids	% HH w Seniors
-0.01	0.25	0.07	0.40	-0.10	-0.01	-0.09	0.47*
(0.21)	(0.16)	(0.16)	(0.46)	(0.34)	(0.64)	(0.70)	(0.27)
(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
% Owner Occupied	% Male Married	% Fem Married	Fert Rate	% Veteran	% Same House 1Yr	% Born in USA	% English Speaker
-0.0106	0.44	-0.08	-0.0166	0.10	-0.49	-0.68**	-0.61
VA Pctl (0.81)	(0.32)	(0.36)	(0.0140)	(0.08)	(0.34)	(0.35)	(0.40)
(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
% Commute Public Trans	Mean Commute	% On Social Sec	% On SSI	% On Cash Assist	% On Food Stmp	Poverty Rate	(37)
-615	-0.53**	-0.17	0.11	0.45*	-0.06	-0.04	-0.03
VA Pctl (1929)	(0.23)	(0.41)	(0.15)	(0.26)	(0.13)	(0.10)	(0.17)
<i>Panel C: Property Characteristics</i>							
(38)	(39)	(40)	(41)	(42)	(43)	(44)	(45)
Mean # Units	Mean Age of Structure	Mean # Bedrooms	Mean # Bathrooms	Mean Sq Ft	Mean # Bedrooms	% Asian	% Hispanic
0.07	-2.5*	0.08	-0.04	44	0.08	-0.69*	0.09
VA Pctl (0.08)	(1.4)	(0.07)	(0.08)	(69)	(0.07)	(0.39)	(0.57)
<i>Panel D: School Characteristics</i>							
(43)	(44)	(45)	(46)	(47)	(48)	(49)	(50)
% Black	% Hisp	% Asian	% FRP Lunch	% Gifted	% ELL	% Spec Ed	Enroll
0.09	0.09	-0.69*	-0.12	0.22	-1.4	-0.35	8.9
VA Pctl (0.49)	(0.57)	(0.39)	(1.1)	(0.62)	(0.9)	(0.49)	(10.3)
(51)	(52)	(53)	(54)	(55)	(56)	(57)	(58)
% Parent HS Grad	% Parent Some Col	% Parent BA	% Parent HS Grad	% Parent Some Col	% Parent BA	% Parent HS Grad	% Parent Some Col
0.01	-0.20	-0.19	0.01	-0.20	-0.19	0.01	-0.20
(0.83)	(0.82)	(0.67)	(0.83)	(0.82)	(0.67)	(0.83)	(0.82)

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

Table A-3: Effect of Value-Added Information Using Quintiles of VA - All Releases

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

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

Table A-4: Effect of Value-Added Information Relative to Mean of Geographic and Ethnic Markets

Note: Estimates for all models are multiplied by 100.

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

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

Table A-5: Effect of Value-Added Information on Log Sale Prices - Specification Checks, All Releases

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

	Add Census Tract FE (1)	Exclude Lagged API (2)	Use Sale Levels (3)	Limit to 0-2 Bedrooms (4)	Limit to 3+ Bedrooms (5)	Drop Imputed VA (6)	Properties w/ > 8 Bedrooms (7)	Drop Properties w/ > 5000 sf (8)	Drop Multi Unit (9)	3 Month Lead (10)	No API* Post (11)	Include High Sale Prices (12)	Summer Only (13)
LAT 1 st VA Pctl	-0.026	-0.028	-110.3	-0.006	0.008	-0.030	-0.017	-0.018	-0.009	-0.011	-0.011	-0.062	-0.014
× Post Aug 2010	(0.021)	(0.022)	(73.3)	(0.026)	(0.017)	(0.023)	(0.022)	(0.021)	(0.016)	(0.022)	(0.022)	(0.146)	(0.058)
LAT 2 nd VA Pctl	0.021	0.024	55.0	0.046	0.006	0.031	0.023	0.026	0.031	0.003	0.025	0.080	0.028
× Post Apr 2011	(0.022)	(0.025)	(90.8)	(0.032)	(0.021)	(0.024)	(0.025)	(0.025)	(0.020)	(0.036)	(0.025)	(0.122)	(0.060)
LAUSD VA Pctl	-0.007	-0.014	-100.2	-0.029	0.024	-0.027	-0.019	-0.019	-0.022	-0.034	-0.019	-0.150	-0.042
× Post Mar 2011	(0.027)	(0.027)	(97.2)	(0.029)	(0.022)	(0.027)	(0.029)	(0.028)	(0.019)	(0.038)	(0.028)	(0.098)	(0.044)
API Pctl	0.023	0.048	457.8**	0.021	0.002	0.069*	0.035	0.035	0.011	0.081***	0.011	0.258*	0.173**
× Post Aug 2010	(0.032)	(0.031)	(197.0)	(0.044)	(0.025)	(0.041)	(0.041)	(0.041)	(0.032)	(0.029)	(0.032)	(0.152)	(0.074)
Observations	63,122	63,122	63,122	23,444	37,061	58,546	62,504	62,401	55,708	63,122	63,122	66,174	20,307

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