Appendix D

Innovative Schools in Washington: What Lessons Can Be Learned?

Value-Added Estimation

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Data Constraints

A key question for policymakers is how the innovations discussed in this report affect student outcomes. For example, does attending a school focused on wraparound services cause test scores to increase? Unfortunately, because of the data available for this study, we are not able to answer these cause-and-effect questions. We can, however, describe the students who attend these schools as well as several dimensions of their performance. We can also assess whether the designated schools are "high-performing" given their student characteristics.

Assessment of student outcomes in the designated innovative schools is complicated by several factors. The schools differ in important ways including level (elementary, middle, and high school), socioeconomic status of students, and school admission policies. Several are option schools where students apply or opt in. Two of the schools were established in 2009, and we only have two years of student-level data for their assessment.

To identify the effect of an innovation, we must control for other factors that influence student outcomes—characteristics of the schools, teachers, students, and parents. Unfortunately, many of these factors are unobserved (e.g., student ability and motivation, teacher quality, and parental involvement). Suppose we observe relatively high test scores in an innovative school. These high scores could be due to the innovation or to other factors, such as a few exceptional teachers or a student body with above average motivation.

How could we control for the influence of unobserved factors? We would select a large number of schools, randomly assign the innovation to some of these schools (treatment) and not others (control), and then observe the change in outcomes in the treatment schools versus the control schools. This design effectively controls for observed and unobserved differences across the schools. We cannot do this.

A fundamental constraint is that there are too few schools in our analysis. Randomization controls for unobserved characteristics, but it can do so only if there are enough schools in the study. The ability to estimate a true effect of an innovation (statistical power) is determined by several factors—the magnitude of the effect (effect size), the degree to which students in schools are similar, the number of students in each school, and, importantly, the number of schools in the study. Power analysis allows us to determine the number of schools needed to achieve an "acceptable" level of statistical power (say 80% power at a 0.05 level of significance). Given the effect sizes we typically observe in education, the intra-school correlation in the Washington Assessment of Student Learning (WASL) scores, and average school sizes, we would want to include at least 40 schools with a specific innovation and another 40 without that innovation in the analysis. We have only 20 schools with student outcome data, and their innovations are different.[1] Only a handful of schools share a common innovation. Moreover, in most cases, we do not observe pre-implementation outcomes in these schools. The innovations were usually implemented when the school was established.

Another important issue is that the innovations were not randomly assigned across schools. Schools decided to adopt these innovations and, in several cases, students choose to enroll in these schools. Without randomization we typically cannot distinguish between the effects of the innovation and unobserved school and student characteristics. In some cases additional information permits the estimation of "treatment" effects without random assignment. Examples

[1] Among the designated innovative schools, we do not have student outcomes data for the Washington Youth Academy and Delta High School.

include the use of school lottery information, entrance exam thresholds supporting regression discontinuity analyses, and natural experiments that allow for instrumental variable techniques. We do not have these types of additional identifying information. A few of the innovative schools do have lotteries, but information from these was not available.

Given these constraints, we cannot identify how adopted innovations have affected student outcomes. Instead, we assess the extent to which the designated schools are high performing by estimating value-added models.

Value-Added Models

The Education Research and Data Center at the Office of Financial Management provided us with (de-identified) matched data for all Washington K-12 students over several years (2005 to 2011). The data include information on student characteristics, enrollment, and state assessment scores. We use these data to estimate value-added models of state assessment scores.

Value-added models help identify the contribution of schools to student learning.[2] These models partially control for unobserved student characteristics by examining the change in test scores for an individual over time. Controlling for prior student achievement is critical. The objective is to measure how schools encourage student progress, taking into account the achievement levels of incoming students. Prior scores are a very useful measure of student ability; adding them to regression models substantially increases our ability to explain variation in scores.[3]

We estimate variations of the following general model. This example is for math scores, which are assumed to be determined by prior math and reading scores, student characteristics, school fixed effects and random factors. Test scores are standardized within a year and subject (mean=0, standard deviation=1). Standardized scores measure where a student falls within the distribution of results for a given exam.

$$A^{m}_{igt} = \delta A^{m}_{i(g-1)(t-1)} + \lambda A^{r}_{i(g-1)(t-1)} + \beta\,'X_{it} + \alpha'\Phi_{ist} + Y'G + \xi'T + \epsilon_{igt}$$

- A^{m}_{igt} is the standardized math score for student i, in grade g, during year t;
- $A^{m}_{i(g-1)(t-1)}$ is the prior year's standardized math score for student I;
- $A^{r}_{i(g-1)(t-1)}$ is the prior year's standardized reading score for student I;
- X_{it} is a set of observed student characteristics;
- Φ_{ist} are school indicator variables that identify where student i was enrolled during the test year. α are the estimated school effects;
- G and T are grade and test year indicators. Estimated models also include interactions between grade, test year and prior test scores; and
- The error term (ϵ_{igt}) represents the effects of other unobserved factors.

[2] For further discussion of value-added models, see: Todd, P. and Wolpin, K. (2007). The Production of Cognitive Achievement in Children: Home, School, and Racial Test Score Gaps. *Journal of Human Capital*, 1(1): 91-136; see also Hanushek, E. (2008). Education Production Functions. In Steven N. Durlauf and Lawrence E. Blume (eds.), The New Palgrave

[3] R-squared statistic more than double when prior scores are added to the models we estimated.

The regressions control for the following student characteristics:

- free or reduced-price meal eligibility (prior eligibility is also included for high school students);
- English language status;
- special education status;
- homeless youth;
- disability status;
- gender;
- race/ethnicity; and
- mobility (measured by enrollment in the same school during the prior year, when appropriate).

There are potential caveats associated with value-added models including the following:

- The models are unlikely to fully address student self-selection into schools, limiting our ability to identify a school's effect on learning. Non-random assignment of students can bias value-added estimates because unobserved student characteristics could be distributed differently across schools. We can infer the likely direction of the bias. In schools that attract highly capable, motivated students (e.g., STEM schools) the models are likely to over-estimate school effects. Among schools that attract students with substantial (unmeasured) barriers to achievement (e.g., alternative schools serving at-risk students) the models are likely to under-estimate school effects.
- School value-added estimates may be imprecise, limiting our ability to identify differences across schools.
- A school's performance on assessments can vary substantially from year to year, nudging estimated school effects up or down. We attempted to address this by pooling data across years.
- Available student-level data is rich but not complete. For example, we have no information on parent characteristics.
- Prior test scores for students enrolling in some of the innovative schools are extremely high, and the estimates for these schools could be constrained by "ceiling effects." When prior test scores are high, there is little room for improving a student's relative position in the distribution of assessment results.

Model Estimation

We estimate the value-added models separately by subject (math, reading) and school level (elementary, middle, high). Models are run for individual years and, when possible, for pooled years.

The school indicator variable coefficients provide estimates for school effects. We mean center the effects, so that the average school has an estimate of 0. Estimates above 0 indicate higher than average performance, after controlling for student characteristics and prior test scores.

School effects are estimated with uncertainty, and the degree of uncertainty varies across schools. In order to take this into account, we "shrink" estimates of school effects based on the imprecision (standard error) of the estimate.[4] The shrinkage is greater for estimates with higher standard errors.

We use generalized linear models to estimate robust standard errors, which take student clustering within schools into account.[5] The confidence intervals reported for school effects (in Appendix C) reflect these robust standard errors.

We estimate models with and without race and ethnicity indicators. The estimated school effects are not very sensitive to including or excluding these variables. We also estimate models that exclude alternative schools. Again, the estimated school effects are not sensitive to this exclusion.

The models produce effect estimates for most of the public schools in Washington. We exclude schools that have fewer than 50 total students. We also require at least 15 test score observations for each school-year-grade combination when estimating value-added models. We also exclude on-line schools, institutions, juvenile detention centers, and special education schools.

The estimated effects for each designated innovative school are summarized in the main report overview, and detailed estimates are presented in the school summaries (Appendix C).

Exhibit D1 lists the variables used in the value-added analyses.[6]

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[4] We apply the procedure used by Aaronson, D., Barrow, L., & Sander, W. (2007). Teachers and Student Achievement in the Chicago Public High Schools. *Journal of Labor Economics* 25(1): 95-135. Mean-centered estimates are shrunk by the factor $\sigma^2/(\sigma^2+\sigma_s^2)$. The "signal variance" (σ^2) is calculated as the variance of the mean-centered school effects minus the mean of the variances of the individual school effect estimates.
$\sigma^2 = [1/(k-1)]\Sigma\tilde{\alpha}_s^2 - (1/k)\Sigma\sigma_s^2$; where k is the number of schools, $\tilde{\alpha}_s$ is the mean-centered effect for school s, and σ_s^2 is the squared OLS standard error of the estimate for school s.
[5] We use the PROC GENMOD routine in SAS.
[6] We also attempt to include teacher experience in the models. The only measure available to us was a school-level average years of teacher experience. This variable was not statistically significant and was highly collinear with the school indicator variables.

Exhibit D1
Value-Added Model Variables

Variable	Description
Dependent Variables	
math score	scale score transformed into a standardized score (mean=0, standard deviation=1)
reading score	scale score transformed into a standardized score (mean=0, standard deviation=1)
Independent Variables	
prior math	prior score for student, transformed into a standardized score
prior reading	prior score for student, transformed into a standardized score
same school	=1 if student enrolled in same school during the prior year; 0 otherwise
American Indian	=1 if yes; 0 otherwise
Asian	=1 if yes; 0 otherwise
Black	=1 if yes; 0 otherwise
Pacific Islander	=1 if yes; 0 otherwise
multiracial	=1 if yes; 0 otherwise
Hispanic	ethnicity indicator variable
male	=1 if yes; 0 otherwise
bilingual	=1 if enrolled in Transitional Bilingual Instruction Program; 0 otherwise
disability	=1 if yes; 0 otherwise
free/reduced price meals	=1 if yes; 0 otherwise
ever free/reduce meals	=1 if student ever eligible for free/reduced price meals; 0 otherwise
homeless	=1 if yes; 0 otherwise
special education	=1 if yes; 0 otherwise
grade5	=1 if in grade 5 during exam; 0 otherwise
grade6	=1 if in grade 6 during exam; 0 otherwise
grade7	=1 if in grade 7 during exam; 0 otherwise
grade10	=1 if in grade 10 during exam; 0 otherwise
grade11	=1 if in grade 11 during exam; 0 otherwise
year2008	=1 if score is from 2008; 0 otherwise
year2009	=1 if score is from 2009; 0 otherwise

*Models also include school indicator variables that identify where a student was enrolled.

Exhibits D2 to D11 summarize estimates for the various models. In general, the estimates are consistent with expectations; coefficients have the expected signs. Coefficient estimates are stable across models estimated for different years.

Elementary School Estimates

We estimate elementary school models for three school years (2009-10, 2010-11, and 2011-12). Standardized test scores for grades 4 and 5 are regressed on prior scores, student characteristics, school indicator variables, and grade and year indicators.

Exhibit D2
Elementary School Value-Added Models

	Exam Year			
Model	**2011**	**2010**	**2009**	**2008**
2011 Results	grade 5	grade 4		
	grade 4	grade 3		
2010 Results		grade 5	grade 4	
		grade 4	grade 3	
2009 Results			grade 5	grade 4
			grade 4	grade 3
Assessment	MSP*	MSP	WASL**	WASL

*Measurement of Student Progress

**Washington Assessment of Student Learning

Exhibits D3 and D4 summarize estimates for models that pool data for all three school years. Estimated coefficients for the school-level variables are not presented given the large number of schools.

Exhibit D3
Elementary School Math Value-Added Estimates (2009, 2010, and 2011)

Variable	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
prior math	0.5127	0.0045	0.5039	0.5216	113.06	<.0001
prior reading	0.2308	0.0036	0.2237	0.2378	64.13	<.0001
prior math*year2009	0.0159	0.0051	0.0059	0.0259	3.13	0.0018
prior math*year2008	0.0251	0.0047	0.0158	0.0343	5.32	<.0001
prior reading*year2009	-0.0270	0.0045	-0.0358	-0.0182	-5.99	<.0001
prior reading*year2008	-0.0149	0.0042	-0.0231	-0.0067	-3.57	0.0004
grade5*prior math	0.0402	0.0045	0.0313	0.0491	8.88	<.0001
grade5*prior reading	-0.0279	0.0039	-0.0354	-0.0203	-7.2	<.0001
same school	0.0260	0.0070	0.0122	0.0398	3.7	0.0002
grade5	-0.0036	0.0084	-0.0200	0.0128	-0.43	0.6666
American Indian	-0.0802	0.0070	-0.0940	-0.0665	-11.45	<.0001
Asian	0.1158	0.0054	0.1051	0.1264	21.27	<.0001
Black	-0.1081	0.0051	-0.1181	-0.0980	-21.07	<.0001
Hispanic	-0.0501	0.0033	-0.0566	-0.0436	-15.03	<.0001
Pacific Islander	-0.0440	0.0101	-0.0637	-0.0242	-4.36	<.0001
multiracial	-0.0272	0.0057	-0.0385	-0.0160	-4.74	<.0001
male	0.0661	0.0021	0.0620	0.0702	31.76	<.0001
bilingual	-0.0695	0.0049	-0.0792	-0.0599	-14.1	<.0001
disability	-0.0812	0.0160	-0.1126	-0.0497	-5.06	<.0001
free/reduced price meals	-0.0937	0.0028	-0.0992	-0.0881	-32.98	<.0001
homeless	-0.0468	0.0085	-0.0635	-0.0301	-5.48	<.0001
special education	-0.0801	0.0164	-0.1122	-0.0480	-4.89	<.0001
year2008	-0.0122	0.0064	-0.0248	0.0003	-1.92	0.055
year2009	-0.0055	0.0063	-0.0178	0.0067	-0.88	0.3763

*Generalized linear model estimation with robust standard errors. The model also includes school indicator variable for all elementary schools. Ordinary least squares estimate of this model had an R-squared of 0.615.

Exhibit D4
Elementary School Reading Value-Added Estimates (2009, 2010, and 2011)

Variable	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
prior math	0.2459	0.0033	0.2395	0.2523	75.34	<.0001
prior reading	0.4741	0.0033	0.4676	0.4806	143.08	<.0001
prior math*year2009	0.0103	0.0041	0.0022	0.0185	2.5	0.0125
prior math*year2008	0.0386	0.0040	0.0307	0.0464	9.63	<.0001
prior reading*year2009	-0.0191	0.0040	-0.0270	-0.0111	-4.72	<.0001
prior reading*year2008	-0.0386	0.0040	-0.0464	-0.0307	-9.62	<.0001
grade5*prior math	0.0194	0.0034	0.0127	0.0261	5.65	<.0001
grade5*prior reading	-0.0136	0.0034	-0.0203	-0.0069	-3.98	<.0001
same school	0.0144	0.0051	0.0044	0.0245	2.81	0.0049
grade5	-0.0047	0.0058	-0.0161	0.0066	-0.82	0.4139
American Indian	-0.0849	0.0091	-0.1028	-0.0670	-9.3	<.0001
Asian	0.0210	0.0043	0.0126	0.0294	4.89	<.0001
Black	-0.0571	0.0058	-0.0684	-0.0458	-9.92	<.0001
Hispanic	-0.0448	0.0036	-0.0519	-0.0377	-12.35	<.0001
Pacific Islander	-0.0465	0.0114	-0.0688	-0.0241	-4.07	<.0001
multiracial	0.0001	0.0054	-0.0105	0.0107	0.02	0.9821
male	-0.0608	0.0022	-0.0651	-0.0565	-27.63	<.0001
bilingual	-0.2050	0.0050	-0.2149	-0.1952	-40.72	<.0001
disability	-0.1125	0.0164	-0.1446	-0.0803	-6.85	<.0001
free/reduced price meals	-0.1022	0.0029	-0.1079	-0.0964	-34.85	<.0001
homeless	-0.0473	0.0089	-0.0648	-0.0297	-5.29	<.0001
special education	-0.0941	0.0169	-0.1273	-0.0609	-5.56	<.0001
year2008	-0.0137	0.0051	-0.0236	-0.0037	-2.69	0.0072
year2009	-0.0067	0.0048	-0.0161	0.0028	-1.38	0.1661

*****Generalized linear model estimation with robust standard errors. Model also includes school indicator variables for all elementary schools. Ordinary least squares estimate of this model had an R-squared of 0.573.

Middle School Estimates

We also estimate middle school models for three school years (2009-10, 2010-11, and 2011-12). Standardized test scores for grades 6, 7, and 8 are regressed on prior scores, student characteristics, school indicator variables, and grade and year indicators. Exhibits D6 and D7 summarize estimates for pooled models using data for all three years.

Exhibit D5
Middle School Value-Added Models

	Exam Year			
Model	**2011**	**2010**	**2009**	**2008**
2011 Results	grade 8 grade 7 grade 6	grade 7 grade 6 grade 5		
2010 Results		grade 8 grade 7 grade 6	grade 7 grade 6 grade 5	
2009 Results			grade 8 grade 7 grade 6	grade 7 grade 6 grade 5
Assessment	MSP	MSP	WASL	WASL

Exhibit D6
Middle School Math Value-Added Estimates (2009, 2010, and 2011)

Variable	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
prior math	0.6509	0.0044	0.6423	0.6596	147.65	<.0001
prior reading	0.1617	0.0031	0.1556	0.1679	51.74	<.0001
prior math*year2009	0.0371	0.0045	0.0283	0.0458	8.31	<.0001
prior math*year2008	0.0883	0.0042	0.08	0.0966	20.84	<.0001
prior reading*year2009	-0.0469	0.0034	-0.0535	-0.0403	-13.89	<.0001
prior reading*year2008	-0.0644	0.0033	-0.0709	-0.0579	-19.41	<.0001
grade6*prior math	-0.0824	0.0045	-0.0913	-0.0735	-18.17	<.0001
grade6*prior reading	0.0621	0.0035	0.0552	0.069	17.61	<.0001
grade7*prior math	-0.0114	0.0046	-0.0204	-0.0024	-2.48	0.0133
grade7*prior reading	0.0191	0.0035	0.0122	0.026	5.45	<.0001
grade6	-0.0646	0.0104	-0.085	-0.0442	-6.21	<.0001
grade7	-0.0094	0.008	-0.0251	0.0063	-1.18	0.239
year2008	-0.0096	0.0064	-0.0222	0.0029	-1.51	0.1308
year2009	-0.0045	0.0065	-0.0173	0.0083	-0.69	0.4901
American Indian	-0.0595	0.0052	-0.0697	-0.0492	-11.36	<.0001
Asian	0.1053	0.0058	0.0938	0.1168	18.01	<.0001
Black	-0.0935	0.0056	-0.1045	-0.0825	-16.62	<.0001
Hispanic	-0.0515	0.0027	-0.0568	-0.0462	-19.07	<.0001
Pacific Islander	-0.0408	0.0086	-0.0576	-0.024	-4.77	<.0001
multiracial	-0.0174	0.0045	-0.0262	-0.0086	-3.89	<.0001
male	0.0525	0.0017	0.0493	0.0558	31.78	<.0001
bilingual	-0.0173	0.0054	-0.0278	-0.0068	-3.22	0.0013
disability	-0.0469	0.0131	-0.0726	-0.0213	-3.59	0.0003
free/reduced price meals	-0.0756	0.0027	-0.0808	-0.0704	-28.48	<.0001
homeless	-0.0493	0.0071	-0.0633	-0.0354	-6.94	<.0001
special education	-0.1043	0.0135	-0.1308	-0.0777	-7.7	<.0001

*Generalized linear model estimation with robust standard errors. Model also includes school indicator variables for all middle schools. Ordinary least squares estimate of this model had an R-squared of 0.701.

Exhibit D7

Middle School Reading Value-Added Estimates (2009, 2010, and 2011)

Variable	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
prior math	0.2404	0.0039	0.2327	0.2481	61.05	<.0001
prior reading	0.4775	0.0045	0.4686	0.4864	105.16	<.0001
prior math*year2009	0.0428	0.0040	0.0349	0.0507	10.64	<.0001
prior math*year2008	0.0245	0.0040	0.0167	0.0323	6.17	<.0001
prior reading*year2009	-0.0499	0.0039	-0.0576	-0.0422	-12.71	<.0001
prior reading*year2008	-0.0341	0.0043	-0.0426	-0.0256	-7.85	<.0001
grade6*prior math	0.0285	0.0046	0.0195	0.0374	6.24	<.0001
grade6*prior reading	-0.0112	0.0046	-0.0202	-0.0022	-2.43	0.0149
grade7*prior math	0.0623	0.0043	0.0539	0.0707	14.51	<.0001
grade7*prior reading	-0.0235	0.0043	-0.0320	-0.0150	-5.42	<.0001
grade6	-0.0283	0.0091	-0.0461	-0.0106	-3.12	0.0018
grade7	-0.0037	0.0078	-0.0190	0.0116	-0.48	0.6323
year2008	-0.0106	0.0068	-0.0239	0.0028	-1.55	0.1211
year2009	-0.0044	0.0057	-0.0156	0.0069	-0.77	0.4443
American Indian	-0.0767	0.0087	-0.0937	-0.0597	-8.85	<.0001
Asian	0.0579	0.0039	0.0502	0.0656	14.77	<.0001
Black	0.0013	0.0050	-0.0086	0.0111	0.26	0.7973
Hispanic	-0.0034	0.0031	-0.0096	0.0027	-1.09	0.2771
Pacific Islander	-0.0522	0.0106	-0.0729	-0.0314	-4.93	<.0001
multiracial	0.0175	0.0051	0.0075	0.0275	3.44	0.0006
male	-0.1686	0.0021	-0.1727	-0.1645	-81.41	<.0001
bilingual	-0.2774	0.0069	-0.2908	-0.2639	-40.35	<.0001
disability	-0.0937	0.0173	-0.1276	-0.0599	-5.42	<.0001
free/reduced price meals	-0.0747	0.0030	-0.0805	-0.0688	-25.07	<.0001
homeless	-0.0646	0.0085	-0.0811	-0.0480	-7.63	<.0001
special education	-0.1786	0.0177	-0.2133	-0.1438	-10.06	<.0001

***** Generalized linear model estimation with robust standard errors. Model also includes school indicator variables for all middle schools. Ordinary least squares estimate of this model had an R-squared of 0.580.

High School Estimates

The high school math analysis was complicated by the change in state assessments in 2010-11, the most recent year of data. In 2010-11 Washington State began using 10th grade End of Course math exams. The EOC Math 1 (Algebra) and EOC Math 2 (Geometry) exams are typically taken by freshman and sophomore students. We estimate models analyzing the 10th grade assessments for 2009 and 2010. We also estimate models for the End of Course exams in 2011. The prior scores used in these regressions are from grade 8 assessments.

Exhibit D8
2011 End of Course Math 1 (Algebra) Value-Added Estimates

Variable	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
prior math	0.6504	0.0091	0.6326	0.6682	71.64	<.0001
prior reading	0.0900	0.0047	0.0807	0.0992	19.04	<.0001
grade10*prior math	0.0253	0.0114	0.0030	0.0475	2.22	0.0262
grade10*prior reading	0.0094	0.0066	-0.0036	0.0224	1.42	0.1569
grade10	-0.0126	0.0135	-0.0391	0.0139	-0.93	0.35
American Indian	-0.0475	0.0189	-0.0845	-0.0104	-2.51	0.012
Asian	0.1581	0.0120	0.1345	0.1817	13.12	<.0001
Black	-0.0391	0.0169	-0.0723	-0.0059	-2.31	0.0209
Hispanic	-0.0290	0.0081	-0.0449	-0.0131	-3.58	0.0003
Pacific Islander	0.0611	0.0244	0.0133	0.1089	2.5	0.0123
male	0.0431	0.0046	0.0341	0.0521	9.4	<.0001
disability	-0.0359	0.0273	-0.0894	0.0177	-1.31	0.189
homeless	-0.0814	0.0207	-0.1220	-0.0409	-3.94	<.0001
special education	-0.0099	0.0312	-0.0711	0.0513	-0.32	0.7509
ever free/reduced meals	-0.1280	0.0060	-0.1398	-0.1162	-21.21	<.0001

*Generalized linear model estimation with robust standard errors. Model also includes school indicator variables for all high schools. Ordinary least squares estimate of this model had an R-squared of 0.671.

Exhibit D9

2011 End of Course Math 2 (Geometry) Value-Added Estimates

Variable	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
prior math	0.5204	0.0084	0.5039	0.5370	61.71	<.0001
prior reading	0.1047	0.0064	0.0921	0.1173	16.26	<.0001
grade10*prior math	-0.0251	0.0109	-0.0465	-0.0037	-2.3	0.0214
grade10*prior reading	-0.0350	0.0091	-0.0528	-0.0172	-3.85	0.0001
grade10	0.0486	0.0167	0.0159	0.0813	2.91	0.0036
American Indian	-0.0625	0.0333	-0.1277	0.0028	-1.88	0.0606
Asian	0.1067	0.0140	0.0793	0.1341	7.63	<.0001
Black	-0.1532	0.0230	-0.1982	-0.1081	-6.66	<.0001
Hispanic	-0.0928	0.0127	-0.1177	-0.0679	-7.3	<.0001
Pacific Islander	-0.0489	0.0424	-0.1320	0.0342	-1.15	0.2487
male	0.0706	0.0076	0.0557	0.0855	9.29	<.0001
disability	-0.0155	0.0549	-0.1231	0.0921	-0.28	0.7774
homeless	-0.0977	0.0384	-0.1730	-0.0224	-2.54	0.011
special education	0.0177	0.0614	-0.1026	0.1380	0.29	0.7731
ever free/reduced meals	-0.0787	0.0089	-0.0961	-0.0613	-8.87	<.0001

*Generalized linear model estimation with robust standard errors. Model also includes school indicator variables for all high schools. Ordinary least squares estimate of this model had an R-squared of 0.476.

Exhibit D10

High School Math (2010 HSPE, 2009 WASL) Value-Added Estimates

Variable	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
prior math	0.7457	0.0042	0.7374	0.7540	176.45	<.0001
prior reading	0.0431	0.0036	0.0362	0.0501	12.11	<.0001
grade11*prior math	-0.0949	0.0080	-0.1105	-0.0793	-11.9	<.0001
grade11*prior reading	-0.0177	0.0071	-0.0317	-0.0038	-2.49	0.0127
prior math*year2008	-0.0089	0.0051	-0.0189	0.0010	-1.76	0.0778
prior reading*year2008	0.0435	0.0054	0.0330	0.0540	8.13	<.0001
same school	0.0684	0.0093	0.0502	0.0866	7.36	<.0001
grade11	0.0412	0.0072	0.0271	0.0553	5.73	<.0001
year2008	-0.0071	0.0063	-0.0194	0.0052	-1.13	0.2569
American Indian	-0.0670	0.0141	-0.0946	-0.0394	-4.76	<.0001
Asian	0.0767	0.0090	0.0590	0.0944	8.49	<.0001
Black	-0.0810	0.0103	-0.1012	-0.0608	-7.85	<.0001
Hispanic	-0.0491	0.0070	-0.0628	-0.0355	-7.05	<.0001
Pacific Islander	-0.0070	0.0224	-0.0508	0.0369	-0.31	0.7557
male	0.1225	0.0038	0.1150	0.1299	32.32	<.0001
homeless	-0.0884	0.0188	-0.1253	-0.0515	-4.69	<.0001
special education	-0.1152	0.0128	-0.1402	-0.0901	-9.02	<.0001
ever free/reduced meals	-0.0756	0.0045	-0.0845	-0.0667	-16.62	<.0001

*Generalized linear model estimation with robust standard errors. Model also includes school indicator variables for all high schools. Ordinary least squares estimate of this model had an R-squared of 0.684.

Exhibit D11
High School Reading (2011 HSPE, 2010 HSPE) Value-Added Estimates

Variable	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
prior reading	0.3376	0.0043	0.3292	0.3460	79.01	<.0001
prior math	0.3723	0.0049	0.3628	0.3819	76.31	<.0001
grade11*prior math	-0.0485	0.0114	-0.0709	-0.0262	-4.25	<.0001
grade11*prior reading	-0.0211	0.0110	-0.0426	0.0004	-1.93	0.0542
prior math*year2009	-0.0147	0.0062	-0.0269	-0.0026	-2.37	0.0176
prior reading*year2009	0.0035	0.0057	-0.0077	0.0147	0.61	0.5428
grade11	0.0920	0.0104	0.0715	0.1125	8.81	<.0001
year2009	-0.0127	0.0064	-0.0253	-0.0001	-1.98	0.048
American Indian	-0.0868	0.0178	-0.1216	-0.0520	-4.89	<.0001
Asian	-0.0934	0.0083	-0.1097	-0.0771	-11.22	<.0001
Black	-0.1007	0.0108	-0.1219	-0.0796	-9.34	<.0001
Hispanic	-0.1056	0.0086	-0.1224	-0.0888	-12.32	<.0001
Pacific Islander	-0.1865	0.0242	-0.2340	-0.1389	-7.69	<.0001
male	-0.0775	0.0049	-0.0870	-0.0679	-15.87	<.0001
disability	-0.1216	0.0292	-0.1788	-0.0644	-4.17	<.0001
homeless	-0.0905	0.0196	-0.1289	-0.0522	-4.62	<.0001
bilingual	-0.2832	0.0149	-0.3124	-0.2540	-18.98	<.0001
special education	-0.0353	0.0312	-0.0964	0.0259	-1.13	0.2581
ever free/reduced meals	-0.1017	0.0054	-0.1124	-0.0911	-18.7	<.0001

*Generalized linear model estimation with robust standard errors. Model also includes school indicator variables for all high schools. Ordinary least squares estimate of this model had an R-squared of 0.489.

Innovative Versus Other Schools

The value-added effects vary substantially across the designated innovative schools (see Appendix C). Two statistical tests were performed to examine whether or not the innovative schools, taken as a group, perform differently than other schools. Both tests rely on the value-added models. We find no evidence that the innovative schools perform differently from other schools. However, the power of these tests are limited by the small number of designated schools.

First, we estimate the value-added models adding an indicator variable for enrollment in a designated innovative school. The coefficient for this indicator variable measures the difference in average performance between innovative and other schools, controlling for student characteristics and prior test scores. Exhibit D12, for example, provides the estimates for elementary school math assessments. The coefficient is small and statistically insignificant, suggesting that there is no difference on average between the designated and other schools.

Exhibit D12

Elementary School Math Estimates (2009, 2010, 2011) with Innovative School Indicator

Variable	Estimate	Standard Error	95% Confidence Limits		Z	Pr > |Z|
Intercept	0.0205	0.0102	0.0005	0.0405	2.01	0.0444
prior math	0.5140	0.0045	0.5051	0.5229	113.65	<.0001
prior reading	0.2310	0.0036	0.2239	0.2381	64.02	<.0001
prior math*year2009	0.0155	0.0051	0.0055	0.0255	3.04	0.0024
prior math*year2008	0.0243	0.0047	0.0151	0.0336	5.17	<.0001
prior reading*year2009	-0.0268	0.0045	-0.0357	0.0180	-5.96	<.0001
prior reading*year2008	-0.0147	0.0042	-0.0229	0.0065	-3.51	0.0005
grade5*prior math	0.0411	0.0045	0.0323	0.0500	9.11	<.0001
grade5*prior reading	-0.0283	0.0039	-0.0359	0.0207	-7.31	<.0001
same school	0.0267	0.0070	0.0130	0.0404	3.83	0.0001
grade5	-0.0037	0.0084	-0.0201	0.0127	-0.44	0.6603
American Indian	-0.0839	0.0071	-0.0979	0.0699	-11.73	<.0001
Asian	0.1177	0.0055	0.1069	0.1285	21.33	<.0001
Black	-0.1076	0.0050	-0.1174	0.0977	-21.41	<.0001
Hispanic	-0.0511	0.0033	-0.0576	0.0447	-15.57	<.0001
Pacific Islander	-0.0419	0.0101	-0.0617	0.0221	-4.15	<.0001
multiracial	-0.0260	0.0057	-0.0373	0.0148	-4.53	<.0001
male	0.0660	0.0021	0.0619	0.0701	31.73	<.0001
bilingual	-0.0684	0.0049	-0.0780	0.0587	-13.91	<.0001
disability	-0.0797	0.0159	-0.1108	-0.045	-5.01	<.0001
free/reduced price meals	-0.0958	0.0028	-0.1014	0.0903	-33.77	<.0001
homeless	-0.0468	0.0085	-0.0635	0.0301	-5.5	<.0001
special education	-0.0799	0.0163	-0.1117	0.0480	-4.91	<.0001
year2008	-0.0124	0.0064	-0.0249	0.0002	-1.94	0.0529
year2009	-0.0056	0.0063	-0.0178	0.0067	-0.89	0.3733
innovative school	-0.0248	0.0397	-0.1026	0.0530	-0.63	0.5316

*Generalized linear model estimation with robust standard errors.

The second test uses a two-step approach. First, we estimate effects for all schools using the value-added models that include the full set of school indicator variables. Second, we regress the school effects on an innovative school indicator to test for a significant difference between designated and non-designated schools.[7] The indicator coefficient (-0.0215) in the elementary school math regression was not statistically significant.

We repeated these tests for math and reading assessments at all levels (elementary, middle, and high school). The results were similar. The innovative school indicator coefficients were insignificant.[8] We also repeated the tests excluding alternative schools; the inferences remain the same. Among the non-alternative schools, there is no evidence of significant difference between the designated and non-designated innovative schools in terms of state assessment scores.

[7] In the case of elementary schools, the value-added model provided effect estimates for 1,104 schools.
[8] The one exception was for the middle school math estimate from the student-level regression. In this case, the innovative school indicator was negative and significant. Note that in the two-step test for middle schools, however, the indicator was not significant.