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Getting Beneath the Veil of Effective Schools: Evidence From New York City†

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In this paper, we collect data on the inner-workings of 39 charter schools and correlate these data with school effectiveness. We find that traditionally collected input measures—class size, per-pupil expenditure, teacher certification, and teacher training—are not correlated with school effectiveness. In stark contrast, we show that an index of five policies suggested by qualitative research—frequent teacher feedback, the use of data to guide instruction, high-dosage tutoring, increased instructional time, and high expectations—explains approximately 45 percent of the variation in school effectiveness. The same index provides similar results in a separate sample of charter schools. (*JEL* H75, I21, I28)

Improving the efficiency of public education in America is of great importance. The United States spends $10,768 per pupil on primary and secondary education, ranking it fourth among OECD countries (Aud et al. 2011). Yet, among these same countries, American 15-year-olds rank twenty-fifth in math achievement, seventeenth in science, and fourteenth in reading (Fleischman et al. 2010). Traditionally, there have been two approaches to increasing educational efficiency: to expand the scope of available educational options in the hope that the market will drive out ineffective schools, or directly to manipulate inputs to the educational production function.[1]

Evidence of the efficacy of both approaches is mixed. Market-based reforms, such as school choice or school vouchers, have, at best, a modest impact on student achievement (Hoxby 1994; Rouse 1998; Hoxby 2000, 2003; Krueger and Zhu 2004; Carnoy et al. 2007; Chakrabarti 2008; Wolf et al. 2010; Card, Dooley, and Payne 2010; Winters 2012). This suggests that competition alone is unlikely to significantly increase the efficiency of the public school system.

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[1] Increasing standards and accountability reflect a third approach to education reform. There is evidence that increased accountability via the No Child Left Behind Act had a positive impact on math test scores, but not reading test scores (Dee and Jacob 2011).

Similarly, efforts to manipulate key educational inputs have been hampered by an inability to identify school inputs that predict student achievement (Hanushek 1997).[2] This is due, at least in part, to a paucity of detailed data on the strategies and operations of schools, little variability in potentially important inputs (e.g., instructional time), and the use of noncausal estimates of school effectiveness. For instance, the vast majority of quantitative analyses only account for inputs such as class size, per pupil expenditure, or the fraction of teachers with an advanced degree. Measures of teacher development, data driven instruction, school culture, and student expectations have never been collected systematically, despite decades of qualitative research suggesting their importance (see reviews in Edmonds 1979, 1982).

In this paper, we provide new evidence on the determinants of school effectiveness by collecting data on the inner workings of 39 charter schools in New York City and correlating these data with credible estimates of each school's effectiveness. We collected information on school practices from a variety of sources. Principal interviews asked about teacher development, instructional time, data driven instruction, parent outreach, and school culture. Teacher interviews asked about professional development, school policies, school culture, and student assessment. Student interviews asked about school environment, school disciplinary policy, and future aspirations. Lesson plans were collected to measure curricular rigor. Videotaped classroom observations were used to calculate the fraction of students on task throughout the school day.

School effectiveness is estimated using two empirical models. The first exploits the fact that oversubscribed charter schools in New York City are required to admit students via random lottery. In this scenario, the treatment group is composed of students who are lottery winners and the control group consists of students who are lottery losers. An important caveat to our lottery analysis is that oversubscribed lottery admissions records are only available for 29 of our 39 schools. To get an estimate of school effectiveness for schools in our sample that do not have valid lottery data or are not oversubscribed, our second empirical strategy uses a combination of matching and regression estimators to control for observed differences between students attending different types of schools. The observational estimates compare demographically similar students zoned to the same school and in the same age cohort, who nevertheless spend different amounts of time in charter schools.

Schools in our sample employ a wide variety of educational strategies and philosophies, providing dramatic variability in school inputs. For instance, the Bronx Charter School for the Arts believes that participation in the arts is a catalyst for academic and social success. The school integrates art into almost every aspect of the classroom, prompting students to use art as a language to express their thoughts and ideas. At the other end of the spectrum are a number of so-called "No Excuses" schools, such as KIPP Infinity, the HCZ Promise Academies, and the Democracy Prep Charter School. These "No Excuses" schools emphasize frequent testing,

[2] Krueger (2003) argues that resources are systematically related to student achievement when the studies in Hanushek (1997) are given equal weight. It is only when each estimate is counted separately, as in Hanushek (1997), that the relationship between resources and achievement is not significant. There is some evidence that instructional time is associated with increased test scores (Pischke 2007).

dramatically increased instructional time, parental pledges of involvement, aggressive human capital strategies, a "broken windows" theory of discipline, and a relentless focus on math and reading achievement (Carter 2000; Thernstrom and Thernstrom 2004; Whitman 2008). This variability, combined with rich measures of school inputs and credible estimates of each school's impact on student achievement, provides an ideal opportunity to understand which inputs best explain school effectiveness.

In our empirical analysis, we find that input measures associated with a traditional resource-based model of education—class size, per pupil expenditure, the fraction of teachers with no teaching certification, and the fraction of teachers with an advanced degree—are not correlated with school effectiveness in our sample. Indeed, our data suggest that increasing resource-based inputs may actually lower school effectiveness. Using observational estimates of school effectiveness, we find that schools with more certified teachers have annual math gains that are 0.041 (0.023) standard deviations *lower* than other schools. Schools with more teachers with a masters degree have annual ELA gains that are 0.032 (0.020) standard deviations *lower*. An index of class size, per pupil expenditure, the fraction of teachers with no teaching certification, and the fraction of teachers with an advanced degree, explains about 15 percent of the variance in charter school effectiveness, but in the unexpected direction.

In stark contrast, an index of 5 policies suggested by 40 years of qualitative case studies—frequent teacher feedback, data driven instruction, high-dosage tutoring, increased instructional time, and a relentless focus on academic achievement—explains roughly half of the variation in school effectiveness. Using observational estimates of school effectiveness, we find that a 1 standard deviation (σ) increase in the index is associated with a 0.053σ (0.010) increase in annual math gains and a 0.039σ (0.008) increase in annual ELA gains. Moreover, four out of the five school policies in our index make a statistically significant contribution controlling for an index of the other four, suggesting that each policy conveys some relevant information. Controlling for the other 4 inputs, schools that give formal or informal feedback 10 or more times per semester have annual math gains that are 0.048σ (0.023) higher and annual ELA gains that are 0.044σ (0.014) higher than other schools. Schools that tutor students at least 4 days a week in groups of 6 or less have annual ELA gains that are 0.040σ (0.020) higher. Schools that add 25 percent or more instructional time have annual gains that are 0.050σ (0.013) higher in math. Schools that have high academic and behavioral expectations have annual math gains that are 0.044σ (0.023) higher and ELA gains that are 0.030σ (0.015) higher.

We conclude our analysis by exploring the robustness of our results across two dimensions. First, we show that our main results are qualitatively similar in a larger sample of charter schools in New York City, using less detailed administrative data from site visits, state accountability reports, and school websites. Second, we show that the results are unaffected if we control for an index of 37 other control variables collected for the purposes of this research.

Our analysis has two important caveats. First, our estimates of the relationship between school inputs and school effectiveness are unlikely to be causal given the lack of experimental variation in school inputs. Unobserved factors, such as principal skill, student selection into lotteries, or the endogeneity of school inputs, could drive the correlations reported in the paper. Second, our estimates come from a subset of charter schools in New York City. Although participating schools are similar to other urban charter schools, they could differ in important ways that limit our ability to generalize our results. Moreover, there may be inputs common to almost all of the schools in our sample (e.g., a nonunionized staff) that have important interactions with other inputs. An important next step is to inject the strategies identified here into a set of traditional public schools. Fryer (2011) reports results from an ongoing experiment implementing similar practices in nine low-performing traditional public schools in Houston. The intervention appears to have led to substantial test score gains, suggesting that these strategies may be effective beyond the charter context.

The results reported in this paper contribute to a growing body of evidence using admissions lottery records to document the effectiveness of certain charter schools. Students attending an oversubscribed Boston-area charter school score approximately 0.4σ higher per year in math and 0.2σ higher per year in reading (Abdulkadiroğlu et al. 2011), with similar gains reported for students attending the Promise Academy charter school in the Harlem Children's Zone (Dobbie and Fryer 2011), the Knowledge is Power Program (KIPP) schools (Angrist et al. 2010, Tuttle et al. 2010), and the SEED urban boarding school in Washington DC (Curto and Fryer forthcoming). Dobbie and Fryer (2012) find that students attending the Promise Academy charter school also do better on a variety of medium-term outcomes, such as college enrollment and risky behaviors. The paper most closely related to ours is Angrist, Pathak, and Walters (2011), which argues that Massachusetts charters that adhere to a "No Excuses" model, defined as selective teacher hiring, extensive teacher feedback, increased instructional time, and a focus on discipline, are more effective at increasing test scores than other charter schools. These "No Excuses" practices are highly correlated with the effective practices identified in our analysis.

The paper is structured as follows. Section I provides a brief overview of the literature examining effective schools. Section II describes the data collected for our analysis. Section III details our empirical strategy to estimate a school's effectiveness and reports treatment effects for our sample of charter schools. Section IV provides a series of partial correlations of school inputs and school effectiveness. Section V concludes. There are three online appendices. Online Appendix A describes our sample and variable construction. Online Appendix B outlines our data collection process. Online Appendix C provides information on the lottery data from each charter school.

I. A Brief Review of the Literature

Qualitative researchers have amassed a large literature exploring the attributes of effective schools. In 1974, New York's Office of Education Performance Review analyzed two NYC public schools serving disadvantaged students, one highly effective, one not. The study concluded that differences in academic achievement were driven by differences in principal skill, expectations for students, and classroom instruction. Madden, Lawson, and Sweet (1976) examined 21 pairs of California elementary schools matched on pupil characteristics, but differing in student achievement. The more effective schools were more likely to provide teacher feedback, tutor their students, monitor student performance, and have classroom cultures more conducive to learning. Brookover and Lezotte (1979) found similar results for a set of schools in Michigan.

Summarizing the literature, Edmonds (1979) argued that effective schools tend to have a strong administrative leadership, high expectations for all children regardless of background, an atmosphere conducive to learning, a focus on academic achievement, and frequent monitoring of student progress. Purkey and Smith (1983) and Sammons, Hillman, and Mortimore (1995) argue this literature suggests that effective schools have organizational structures that empower school leaders, develop human capital, reach out to parents, create a positive school culture, and maximize learning time. Stedman (1985) argues that, in addition to the practices suggested by Edmonds (1979) and others, effective schools also focus on students' racial and ethnic background while not being overly regimented and fixated on testing.

A more recent branch of this literature focuses on the characteristics of so-called "No Excuses" schools, loosely defined as schools that emphasize strict discipline, extended time in school, and an intensive focus on building basic reading and math skills. Using observations from 21 high-poverty, high-performing schools, Carter (2000) argues that "No Excuses" schools succeed due to empowered principals, the use of interim assessments to measure student progress, frequent and effective professional development, aggressive parent outreach, and a relentless focus on achievement for all students regardless of background. Thernstrom and Thernstrom (2004) similarly argue that "No Excuses" schools are more effective due to more instructional time, a zero tolerance disciplinary code, high academic expectations for all students, and an emphasis on teaching basic math and reading skills (see Whitman 2008 for similar arguments).

II. Constructing a Database on the Inner Workings of Schools

The main data for this paper are gathered from two sources: school-specific data collected from principal, teacher, and student surveys, lesson plans, and videotaped observations of classroom lessons; and administrative data on student demographics and outcomes from the New York City Department of Education (NYCDOE). Below, we describe each data source.

A. *School Characteristics Data*

In the spring of 2010, we attempted to collect survey, lottery, and video data for all charter schools in New York City with students in grades 3–8. Eligible schools were invited to participate via e-mail and phone. We also hosted an informational event at the New York Charter Center to explain the project to interested schools. Schools were offered a $5,000 stipend to be received conditional on providing all of the appropriate materials. Of the 62 eligible charter elementary schools (entry grades of PK to fourth) and 37 eligible charter middle schools (entry grades of fifth to eighth), 26 elementary schools, and 13 middle schools chose to participate in the study. Within the set of participating schools, 19 elementary schools, and

Table 1—School Participation

	All charters (1)	Eligible sample (2)	Survey sample (3)	Lottery sample (4)
Elementary	68	62	26	19
Middle	38	37	13	10

Notes: This table reports the number of elementary and middle charter schools in New York City and their participation in the observational and lottery studies. Elementary schools include all schools that have their main admissions lottery in grades PK–4. Middle schools include all schools that have their main admissions lottery in grades 5–8. Eligible charters are defined as schools that serve a general student population with at least one tested grade in 2010–2011.

10 middle schools also provided admissions lottery data. The other ten schools were either undersubscribed or did not keep usable lottery records. Table 1 summarizes the selection process. Appendix Table 1 lists each participating school, along with the data that are available for each school.

A wide variety of information was collected from participating schools. A principal interview asked about teacher and staff development, instructional time, data driven instruction, parent outreach, and school culture. An hour-long follow up phone interview with each school leader provided additional details on each domain. Information on curricular rigor was coded from lesson plans collected for each testable grade level in both math and ELA. Finally, information on school culture and practices was gathered during full day visits to each school. These visits included videotaped classroom observations of at least one math and one reading class and interviews with four randomly chosen teachers and four randomly chosen students.

Below we describe the variables we code from this data—with an eye toward measuring the five inputs suggested most often by case studies of successful schools. effective human capital policies, the use of data in instructional practice, high-dosage tutoring, increased instructional time, and high expectations. We also code measures of parent engagement and the rigor of lesson plans to test alternative models of schooling. Within each domain, we code an indicator variable equal to one if a school has an above median level of that input, selecting the variable or combination of variables that best captures the variation described by the qualitative literature. Additional details on the data are available in online Appendix A. Full survey and interview scripts are available in online Appendix B.

Human Capital.—A school's human capital policies are captured through the number of times a teacher receives formal or informal feedback from classroom visits, how many hours teachers spend on instructional and noninstructional activities during a normal week, the highest teacher salary at the school, the fraction of teachers who leave involuntarily each year, and the number of nonnegotiables a school has when hiring a new teacher.

Our primary measure of a school's human capital policies is whether the school gives an above median amount of formal or informal feedback each semester. This measure is meant to capture the quality of a school's teacher development efforts, as emphasized by Madden, Lawson, and Sweet (1976); Brookover and Lezotte (1979); Carter (2000); among many others. Using all of the human capital data we collected, we also analyzed

Table 2—Characteristics of Charter Schools

	Elementary schools			Middle schools		
	Above median (1)	Below median (2)	*p*-value (3)	Above median (4)	Below median (5)	*p*-value (6)
Human capital						
Frequent teacher feedback	0.87	0.45	0.024	1.00	0.12	0.000
Teacher formal feedback	3.12	2.73	0.664	3.20	1.81	0.227
Teacher informal feedback	12.75	7.50	0.034	13.30	4.12	0.001
Nonnegotiables when hiring	1.46	1.45	0.989	1.00	1.29	0.572
Teacher tenure	3.29	3.77	0.470	4.12	3.81	0.818
Teachers leaving involuntarily	0.09	0.07	0.346	0.06	0.12	0.488
Total teacher hours	57.77	55.00	0.513	57.00	52.88	0.513
Teacher noninstructional hours	1.83	1.95	0.867	3.60	3.94	0.850
Teacher responsibilities	2.13	2.55	0.519	2.60	2.62	0.982
Max teacher pay (in $10k)	7.80	7.94	0.786	9.16	8.16	0.331
Data driven instruction						
Data driven instruction	0.70	0.43	0.292	1.00	0.50	0.495
Uses interim assessments	1.00	0.90	0.245	0.80	1.00	0.220
Number of interim assessments	3.50	2.69	0.340	4.25	2.16	0.094
Number of differentiation strategies	4.36	3.12	0.234	5.00	4.00	0.704
Number of teacher reports	4.14	4.27	0.901	2.60	3.12	0.603
Data plan in place	0.45	0.25	0.390	0.50	0.25	0.633
Tracking using data	0.36	0.20	0.426	0.40	0.75	0.241
Parent engagement						
Academic feedback	6.61	5.25	0.590	13.40	8.18	0.305
Behavior feedback	19.69	10.60	0.335	24.30	15.50	0.463
Regular feedback	7.75	7.22	0.919	15.12	4.04	0.293
Tutoring						
High quality tutoring	0.27	0.18	0.912	0.20	0.00	0.220
Any tutoring	0.92	0.82	0.461	0.80	0.75	0.851
Small group tutoring	0.50	0.56	0.813	0.25	0.17	0.779
Frequent tutoring	0.42	0.20	0.300	0.75	0.33	0.242
Instructional time						
+25% increase in time	0.57	0.09	0.012	0.80	0.50	0.319
Instructional hours	8.01	7.57	0.089	8.20	7.88	0.395
Instructional days	189.93	183.73	0.079	195.20	185.00	0.040
Daily time on math	76.92	69.00	0.369	81.20	80.23	0.947
Daily time on ELA	136.88	124.38	0.568	131.00	92.68	0.266
Culture						
High expectations priority rank	0.60	0.10	0.011	0.80	0.25	0.059
School-wide discipline ten-item measure	0.33	0.09	0.159	0.40	0.38	0.935
Schools	15	11		5	8	

(*Continued*)

the first principal component for the entire domain. Our teacher feedback measure has the largest loadings (element of the associated eigenvector) of any of the nine human capital variables considered. This is consistent with the frequent teacher feedback variable containing most of the variance in human capital policies more generally.

Summary statistics for our human capital data are displayed in Table 2. We split our sample into more and less effective schools based on estimates described in Section IV. Specifically, we separate the sample at the median using the average of each school's estimated impact on math and ELA scores. Consistent with

Table 2—Characteristics of Charter Schools (*Continued*)

	Elementary schools			Middle schools		
	Above median (1)	Below median (2)	*p*-value (3)	Above median (4)	Below median (5)	*p*-value (6)
Lesson plans						
Blooms taxonomy score	0.09	0.25	0.376	0.00	0.14	0.545
Objective standard	0.73	0.88	0.464	0.67	1.00	0.133
Number of differentiation strategies	0.64	0.75	0.623	0.67	0.57	0.807
Thoroughness index	4.73	5.25	0.687	5.00	6.86	0.308
Frequently measured inputs						
Small classes	0.20	0.45	0.178	0.50	0.83	0.312
High expenditures	0.50	0.33	0.531	0.67	0.60	0.875
High teachers with MA	0.33	0.45	0.549	0.50	0.83	0.312
Low teachers without certification	0.53	0.64	0.616	0.00	0.67	0.035
Other controls						
Part of CMO	0.60	0.18	0.034	0.60	0.38	0.471
Schools	15	11		5	8	

Notes: This table reports results from a survey of New York City charter schools with entry in elementary school (PK–fourth grade) or middle school (fifth to eighth) grades. The survey sample excludes schools without a tested grade in 2010–2011. The sample includes schools both with and without lottery admissions data. The sample is split based on the impact of attending the school on math and ELA test scores. Each impact is estimated controlling for match cell, race, sex, free lunch eligibility, grade, and year. Middle school specifications also include baseline test scores. Data-driven instruction, number of differentiation strategies, and data plan in place are from the principal interview. Lesson plan variables are from school lesson plans. Small classes, high expenditures, teachers with MA, and teachers with certification are from publicly available administrative data. All other variables are from the written principal survey. See the data Appendix for additional details.

Edmonds (1979, 1982), high achieving schools have more intensive human capital policies than other schools. The typical teacher at a high-achieving elementary school receives feedback 15.89 times per semester, compared to 10.23 times at other charter schools. The typical teacher at a high-achieving middle school receives feedback 16.50 times per semester, over twice as much as teachers at other charter schools. Teachers at high-achieving schools also work longer hours than teachers at other charter schools, an additional 2.77 hours per week at the elementary level and 4.12 hours per week at the middle school level. Despite this higher workload, the maximum salary of teachers at high achieving schools is the same or somewhat lower than other charter schools.

The Use of Data in Instructional Practice.—We attempt to understand how schools use data through the frequency of interim assessments, whether teachers meet with a school leader to discuss student data, how often teachers receive reports on student results, and how often data from interim assessments are used to adjust tutoring groups, assign remediation, modify instruction, or create individualized student goals.

Our primary measure of data use is an indicator for a school having an above median number of interim assessments and an above median number of differentiation strategies. This interacted measure is meant to indicate when schools both collect and use data to inform instruction in the way suggested by Madden, Lawson, and Sweet (1976); Lezotte (1977); Carter (2000); among many others. Using all of the information on data we collected, we also analyzed the first principal component for the domain. A number of other variables have virtually identical loadings, including whether a school has an above median number of differentiation strategies and whether a school has a data plan in place. Results are similar using these alternative measures of data driven instruction.

Summary statistics for our data driven instruction variables are displayed in Table 2. High-achieving schools use data more intensely than other charter schools in our sample. High-achieving elementary schools test students 3.50 times per semester, compared to 2.69 times at other charter schools. Higher achieving middle schools test students 4.25 times, compared to 2.16 times at other charter middle schools in our sample. Higher achieving schools are also somewhat more likely to track students using data and utilize more differentiation strategies compared to low achieving schools.

Parental Engagement.—Parent outreach variables capture how often schools communicate with parents regarding academic performance, regarding behavioral issues, or to simply provide feedback.

Summary statistics in Table 2 suggest that high-achieving elementary and middle schools provide more feedback of all types to parents. Higher achieving elementary schools provide academic feedback 1.36 more times per semester than other schools, behavioral feedback 9.09 more times per semester, and general feedback to parents 0.53 more times per semester. Higher achieving middle schools provide academic feedback 5.22 more times per semester than other schools, behavioral feedback 8.80 more times per semester, and general feedback to parents 11.08 more times per semester.

High-Dosage Tutoring.—Tutoring variables measure how often students are tutored and how large the groups are. We code a school as offering small group tutoring if the typical group is six or fewer students. Schools are coded as offering frequent tutoring if groups typically meet four or more times per week. Schools are coded as having high-dosage tutoring if the typical group is six or fewer students (the below median number) and those groups meet four or more times per week (the above median number). This high-dosage variable corresponds closely to the tutoring described by Madden, Lawson, and Sweet (1976). The high-dosage variable also has the largest loadings in the first principal component compared to our other tutoring variables.

While almost all charter schools in our sample offer some sort of tutoring, high achieving charter schools in our sample are far more likely to offer high-dosage tutoring. Twenty-seven percent of high achieving elementary schools offer high-dosage tutoring compared to 18 percent of low-achieving schools. Twenty percent of high achieving middle schools offer high-dosage tutoring, while none of the low achieving schools do.

Instructional Time.—Instructional time is measured through the number of instructional days, the length of the typical school day, and the number of minutes typically spent on math and ELA in each school. Our measure of instructional time is an indicator variable for having an above median number of total instructional hours in an academic year. Unsurprisingly, this indicator for having an above median number of instructional hours has the largest loadings in the first principal component of instructional time.

High-achieving charter schools in our sample have a longer instructional year and day than other charter schools. The typical high-achieving elementary school has 189.93 instructional days and an instructional day of 8.01 hours, compared to 183.73 instructional days and 7.57 instructional hours at other charter schools. The typical high-achieving middle school meets for 195.20 instructional days, with a typical instructional day lasting 8.20 hours. Other charter middle schools in our sample meet for only 185.00 instructional days with an average day of 7.88 hours. In other words, high-achieving charter schools provide about 26.20 percent more instructional hours per year than a typical NYC schools, while low achieving schools provide about 16.8 percent more.[3]

Culture and Expectations.—School culture is measured through two sets of questions written for the purposes of this study by a "No Excuses" school founder. The first set of questions asks leaders to rank ten school priorities. We code a school as having high academic and behavioral expectations if an administrator ranks "a relentless focus on academic goals and having students meet them" and "very high expectations for student behavior and discipline" as her top two priorities (in either order). Other potential priorities include "a comprehensive approach to the social and emotional needs of the whole child," "building a student's self-esteem through positive reinforcement," and "prioritizing each child's interests and passions in designing a project-based unit."

The second set of culture questions consists of ten multiple choice questions. The questions ask about whether rules are schoolwide or classroom specific, how students learn school culture, whether students wait for the teacher to dismiss the class, desk and backpack rules, hallway order, classroom activities, and whether students track teachers with their eyes. We create a dichotomous variable for each question equal to one if a school leader indicates a more strict disciplinary policy. Our measure of a school's disciplinary policy is the standardized sum of the ten dichotomous variables.

Analysis of the first principal component shows that both culture measures have identical loadings, and results are robust to using either measure. We choose the "high expectations" variable as our primary measure in order to best capture the high-academic expectations discussed in effective schools by the qualitative literature (e.g., Edmonds 1979, 1982).

Consistent with past research (e.g., Edmonds 1979, 1982; Carter 2000; Thernstrom and Thernstrom 2004), Table 2 shows that high-achieving charter schools are more likely to have higher academic and behavioral expectations compared to other charter schools and are more likely to have schoolwide disciplinary policies.

[3] Traditional public schools in New York City meet for 180 instructional days and 6.0 to 7.5 instructional hours each day. We assume a 6.75 hour instructional day when calculating changes in instructional time.

Lesson Plans.—The rigor of a school's curriculum is coded from lesson plans collected from each testable grade level and subject area in a school. We code whether the most advanced objective for each lesson is at or above grade level using New York State standards for the associated subject and grade. Lesson plan complexity is coded using the cognitive domain of Bloom's taxonomy, which indicates the level of higher-order thinking required to complete the objective. In the case where a lesson has more than one objective, the most complex objective is chosen. We also code the number of differentiation strategies present in each lesson plan and the number of checks for understanding. Finally, we create an aggregate thoroughness measure that captures whether a lesson plan includes an objective, an essential question, a do-now, key words section, materials section, introduction section, main learning activity, a check for understanding, an assessment, a closing activity, time needed for each section, homework section, teacher reflection section, and if the lesson plan follows a standardized format. The inclusion of each element increases the thoroughness measure by one, which is then standardized to have a mean of zero and a standard deviation of one.

Surprisingly, lesson plans at high-achieving charter schools are not more likely to be at or above grade level and do not have higher Bloom's Taxonomy scores. Higher achieving charter schools also appear no more likely to have more differentiated lesson plans and appear to have less thorough lesson plans than lower achieving charter schools. Above median elementary schools have an average of 4.73 items on our lesson plan thoroughness measure, while lower achieving schools have 5.25. The gap between above and below median middle schools is even larger, with above median schools having 5.00 items and below median schools averaging 6.86 items.

B. *Administrative Data*

Our second data source consists of administrative data on student demographics and outcomes from the New York City Department of Education (NYCDOE). The data include information on student race, gender, free and reduced-price lunch eligibility, behavior, attendance, and state math and ELA test scores for students in grades 3–8. The NYCDOE data span the 2003–2004 to 2010–2011 school years.

The state math and ELA tests, developed by McGraw-Hill, are high-stakes exams conducted in the spring semester of third through eighth grade. The math test includes questions on number sense and operations, algebra, geometry, measurement, and statistics. Tests in the earlier grades emphasize more basic content such as number sense and operations, while later tests focus on advanced topics such as algebra and geometry. The ELA test is designed to assess students on their literary response and expression, information and understanding, and critical analysis and evaluation. The ELA test includes multiple-choice and short-response questions based on a reading and listening section, as well as a brief editing task.

All public school students, including those attending charters, are required to take the math and ELA tests unless they are medically excused or have a severe disability. Students with moderate disabilities or who are English Language Learners must take both tests, but may be granted special accommodations (additional time, translation services, and so on) at the discretion of school or state administrators. In

Table 3—Student Summary Statistics

	NYC (1)	Eligible charters (2)	Survey charters (3)	Lottery charters (4)	Lottery applicants: Winners (5)	Lottery applicants: Losers (6)	Lottery applicants: Difference (7)
Panel A. Elementary schools (grades 3–5)							
Male	0.51	0.49	0.49	0.51	0.51	0.53	−0.00
White	0.14	0.03	0.02	0.01	0.01	0.02	−0.00
Black	0.32	0.66	0.62	0.70	0.69	0.62	0.02
Hispanic	0.39	0.29	0.34	0.29	0.28	0.34	−0.02
Asian	0.14	0.02	0.02	0.01	0.01	0.01	0.00
Free lunch	0.85	0.83	0.86	0.84	0.87	0.89	−0.02**
Special education	0.11	0.06	0.08	0.08	0.10	0.12	−0.00
Limited English proficiency	0.12	0.05	0.05	0.04	0.05	0.08	−0.01
Years in charter	0.08	2.31	1.92	2.77	2.10	1.06	0.77***
School free lunch	0.85	0.85	0.87	0.85	0.87	0.89	−0.03***
Joint *F*-test							[0.19]
Observations	706,663	23,986	11,091	3,067	2,534	5,346	
Panel B. Middle schools (grades 5–8)							
Male	0.51	0.50	0.49	0.50	0.49	0.51	−0.01
White	0.14	0.03	0.03	0.01	0.03	0.02	−0.00
Black	0.33	0.64	0.59	0.68	0.62	0.62	0.03*
Hispanic	0.39	0.30	0.35	0.29	0.31	0.32	−0.02
Asian	0.14	0.02	0.02	0.01	0.03	0.03	−0.01
Free lunch	0.85	0.84	0.86	0.86	0.88	0.87	0.01
Special education	0.11	0.09	0.10	0.12	0.12	0.13	0.00
Limited English proficiency	0.10	0.05	0.05	0.05	0.05	0.06	−0.01**
Baseline math	0.02	−0.06	−0.16	−0.29	−0.25	−0.21	−0.05*
Baseline ELA	0.01	−0.07	−0.12	−0.22	−0.16	−0.15	−0.01
Years in charter	0.07	2.58	2.19	2.04	1.37	0.73	0.34***
School free lunch	0.84	0.84	0.87	0.88	0.88	0.88	−0.00
School baseline math	0.01	−0.04	−0.14	−0.25	−0.20	−0.20	−0.01
School baseline ELA	−0.01	−0.06	−0.12	−0.23	−0.19	−0.19	−0.01
Joint *F*-test							[0.13]
Observations	773,620	22,147	9,237	2,152	1,955	3,760	

Notes: This table reports descriptive statistics for the sample of public school students, the sample of students in eligible charter schools, the sample of students in charter schools in the survey study, and the sample of students in the lottery study. The sample is restricted to students in grades 3–8 between 2003–2004 and 2010–2011 with at least one follow up test score. For the lottery applicants columns, a single student may be counted multiple times as the level of observation is the student-application level. The final column reports coefficients from regressions of an indicator variable equal to one if the student won an admissions lottery on the variable indicated in each row and lottery risk sets.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

our analysis, the test scores are normalized to have a mean of zero and a standard deviation of one for each grade and year across the entire New York City sample.

Student-level summary statistics for the variables that we use in our core specifications are displayed in Table 3. Charter students are more likely to be black and less likely to be English language learners or participate in special education compared to the typical NYC student. Charter students receive free or reduced-price lunch at similar rates as other NYC students. Charter middle school students score 0.08σ lower in fifth grade math and 0.08σ lower in fifth grade ELA compared to the typical NYC student.

Students in our sample of charter schools are approximately as likely to be black, Hispanic, eligible for free or reduced-price lunch, English language learners, or to participate in special education as students in a typical NYC charter. Students in our sample of charter middle schools score 0.10σ lower in math and 0.08σ lower in ELA in fifth grade compared to the typical charter student in NYC, suggesting that schools in our sample are negatively selected on test scores relative to other charter schools. Students in our lottery sample score an additional 0.12σ lower in math and 0.08σ lower in ELA in fifth grade compared to our survey sample.[4]

III. The Impact of Attending a NYC Charter School

To estimate the causal impact of each school in our sample, we use two empirical models. The first exploits the fact that oversubscribed charter schools in NYC are required to admit students via random lottery. The second statistical model uses a combination of matching and regression analysis to partially control for selection into charter schools.

Following Hoxby and Muraka (2009), Abdulkadiroğlu et al. (2011), and Dobbie and Fryer (2011), we model the effect of a charter school on student achievement as a linear function of the number of years spent at the school.

$$achievement_{igt} = \alpha_t + \lambda_g + \beta \mathbf{X}_{igt} + \rho Charter_{igt} + \varepsilon_{igt}, \tag{1}$$

where α_t and λ_g are year and grade of test effects, respectively; and $\mathbf{X}_{igt}$ is a vector of demographic controls including gender, race, free lunch status, and baseline test scores. ε_{igt} is an error term that captures random variation in test scores.

The causal effect of attending a charter school is ρ. If the number of years a student spends at a charter was randomly assigned, ordinary least squares (OLS) estimates of equation (1) would capture the average causal effect of years spent at the school. Because students and parents selectively choose whether to enroll at a charter school, however, OLS estimates are likely to be biased by correlation between school choice and unobserved characteristics related to student ability, motivation, or background.

To identify ρ we use an instrumental variables (IV) strategy that exploits the fact that New York law dictates that oversubscribed charter schools allocate enrollment offers via a random lottery.

The first-stage equations for IV estimation take the form

$$Charter_{igt} = \mu_t + \kappa_g + \gamma \mathbf{X}_{igt} + \pi Z_i + \sum_j \nu_j Lottery_{ij} + \eta_{igt}, \tag{2}$$

where π captures the effect of the lottery offer Z_i on the number of years a student spends at a charter school. The lottery indicators $Lottery_{ij}$ are lottery fixed effects for each of the school's j lotteries. We also control for whether the student had a sibling in a lottery that year to account for the different odds of admissions among sibling

[4] Appendix Table 2 presents summary statistics separately for above and below median schools as defined in Table 2. In our survey sample, elementary students in above median schools are 9 percentage points more likely to be black than students in below median schools. Middle school students in above median schools are 43 percentage points more likely to be black, but have comparable test scores as students in below median schools.

pairs. We estimate the impact of each school separately within the pool of lottery applicants. We stack test scores and cluster standard errors at the student level.

Our lottery sample is drawn from each lottery that took place between 2003 and 2009 at our sample schools. We make three sample restrictions. First, applicants with a sibling already at a school are excluded, as they are automatically admitted. Second, we drop applicants who either had no chance of winning the lottery or were automatically granted admission due to within-district preference introduced in 2008. Finally, we include only the first application of students who apply to a school more than once. These restrictions leave us with a sample of 16,179 lottery students in lotteries at 29 schools. Appendix C describes the lottery data from each school in more detail.

Columns 5 and 6 of Table 3 present summary statistics for lottery applicants in our lottery sample. As a measure of lottery quality, Table 3 also tests for balance on baseline characteristics. Specifically, we regress an indicator for winning the lottery on pretreatment characteristics and lottery fixed effects. Elementary lottery winners are 0.02 percentage points less likely to be eligible for free and reduced-price lunch compared to elementary lottery losers. Middle school lottery winners are 0.01 percentage points less likely to be English language learners. There are no other significant differences between lottery winners and lottery losers. This suggests that the lottery is balanced and that selection bias should not unduly affect our lottery estimates.

An important caveat to our lottery analysis is that lottery admissions records are only available for 29 of our 39 schools. Moreover, four schools in our lottery sample have very few lottery losers, with another four having admissions records for only one cohort with valid test scores. As a result, our lottery estimates for these schools are relatively imprecise.

To get an estimate of school effectiveness for schools in our sample that do not have valid lottery data or are not oversubscribed, and more precise estimates for schools in our sample with limited lottery records, our second empirical strategy computes observational estimates. Following Angrist et. al (2011), we use a combination of matching and regression estimators to control for observed differences between students attending different types of schools. First, we match students attending sample charters to a control sample of traditional public school students using the school a student is originally zoned to, cohort, sex, race, limited English proficiency status, and free and reduced-price lunch eligibility. Charter students are included in the observational estimates if they are matched to at least one regular public school student. Traditional school students are included if they are matched to at least one charter student. This procedure yields matches for 94.3 percent of students in charter schools in our sample.

Within the group of matched charter and traditional public school students, we estimate equation (1) controlling for baseline test scores and fixed effects for the cells constructed in the matching procedure. Specifically, the observational estimates were constructed by fitting.

$$(3)\qquad achievement_{igtc} = \sigma_t + \tau_g + \iota_c + \varphi \mathbf{X}_{igt} + \theta_s \mathbf{Charter}_{igts} + \zeta_{igts},$$

where σ_t and τ_g are year and grade of test effects, respectively; $\mathbf{X}_{igt}$ is a vector of demographic controls including baseline test scores; ι_c are match cell fixed effects;

Table 4—Effect of Attending a Charter School on Test Scores

Level	Subject	Reduced form (1)	First stage (2)	TSLS (3)	Lottery sample OLS (4)	Survey sample OLS (5)
Elementary	Math	0.108***	0.957***	0.113***	0.064***	0.052***
		(0.024)	(0.052)	(0.024)	(0.003)	(0.003)
Observations		15,439	15,439	15,439	454,563	770,109
Elementary	ELA	0.056***	0.957***	0.058***	0.048***	0.037***
		(0.022)	(0.052)	(0.023)	(0.003)	(0.003)
Observations		15,439	15,439	15,439	454,563	770,109
Middle	Math	0.055***	0.435***	0.126***	0.051***	0.028***
		(0.014)	(0.023)	(0.032)	(0.004)	(0.002)
Observations		16,340	16,340	16,340	669,360	1,171,465
Middle	ELA	0.021	0.436***	0.048	0.009***	0.015***
		(0.014)	(0.023)	(0.032)	(0.003)	(0.002)
Observations		16,340	16,340	16,340	669,360	1,171,465

Notes: This table reports reduced-form, first-stage, and two-stage least squares results for the lottery sample (columns 1–3), observational estimates for the lottery sample (column 4), and observational estimates for the survey sample (column 5). The lottery sample is restricted to students in an elementary or middle school charter school lottery, excluding students with sibling preference. The survey sample is restricted to students in a charter elementary or middle school that participated in our surveys. A single student may be counted multiple times as the level of observation is the student-year level. All lottery specifications control for lottery risk set, race, sex, free lunch eligibility, grade, and year. All observational specifications include match cell, race, sex, free lunch eligibility, grade, and year. Middle school specifications also include baseline test scores. All specifications cluster standard errors at the student level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

and $\mathbf{Charter}_{igts}$ is a vector of the number of years spent in each charter in our sample. We also control for the number of years enrolled in charters not in our sample. The observational estimates therefore compare demographically similar students zoned to the same school and in the same age cohort, who spend different amounts of time in charter schools. We stack student observations for all schools in our sample, and cluster standard errors at the student level.

Table 4 reports a series of results on the impact of attending charter schools on student achievement in our sample. We report reduced-form (column 1), first-stage (column 2), and instrumental variable estimates from our lottery sample (column 3), a nonexperimental estimate of our lottery sample (column 4), and a nonexperimental estimate that includes schools without oversubscribed lotteries (column 5). We estimate effects for elementary and middle schools separately. All regressions control for grade and year effects, gender, race, free lunch status, lottery cohort, and previous test scores in the same subject.

Elementary school lottery winners outscore lottery losers by 0.108σ (0.024) in math and 0.056σ (0.022) in ELA. Middle school lottery winners outscore lottery losers by 0.055σ (0.014) in math and 0.021σ (0.014) in ELA. The lottery first-stage coefficient is 0.957 (0.052) for elementary school, and 0.435 (0.023) for middle school. In other words, by the time they were tested, elementary school lottery winners had spent an average of 0.966 more years at a charter school than lottery losers, and middle school lottery winners had spent 0.452 more years at a charter school. This first stage is similar to lottery winners at other urban charter schools (Abdulkadiroğlu et al. 2011, Angrist et al. 2010). The two-stage least squares (2SLS) estimate, which captures the causal effect of attending a charter school for one year, is 0.113σ (0.024) in math and 0.058σ (0.023) in ELA for elementary schools, and 0.126σ (0.032) in math and 0.048σ (0.032) in ELA for middle schools. The magnitude of these results is similar, if slightly larger than the average charter in New York (Hoxby and Muraka 2009). The larger estimates could be due to an increase in school effectiveness since the Hoxby and Muraka study, or to schools with higher effectiveness selecting into our sample.

Column 4 of Table 4 presents observational results for our lottery charter schools. Our observational estimates imply that elementary charter students score 0.064σ (0.003) higher in math for each year they attend a charter school, and 0.048σ (0.003) in ELA. Middle school charter students gain 0.051σ (0.004) in math and 0.009σ (0.003) in ELA for each year they attend a charter. The observational estimates are qualitatively similar to the lottery estimates, though smaller in magnitude. This suggests that while matching and regression control for some of the selection into charter schools, observational estimates are still downward biased relative to the true impact of charter schools. Observational estimates for the full sample of charters are somewhat lower compared to the lottery sample.

Figure 1 plots lottery and observational estimates for the 29 schools in our lottery sample. Regressing each school's lottery estimate on that school's observational estimate results in a coefficient of 0.946 (0.325) for math and 0.842 (0.373) for ELA, suggesting that our observational estimates at least partially control for selection bias. With that said, Figure 1 also suggests that our observational estimates are somewhat biased downward and have less variance than the corresponding lottery estimates. For instance, the school level lottery estimates for math have a standard deviation of 0.308, while the observational school level estimates have a standard deviation of 0.099. Estimates for ELA reveal a similar pattern.

IV. Getting Beneath the Veil of Effective Schools

A. *Main Results*

In this section, we present a series of partial correlations between strategies and policies that describe the inner workings of schools and each school's effectiveness at increasing student test scores. The specifications estimated are of the form

$$(4) \qquad \theta_s = constant + \varphi MS_s + \vartheta \mathbf{P}_s + \xi_s,$$

where θ_s is an estimate of the effect of charter school s, MS_s is an indicator for being a middle school, and $\mathbf{P}_s$ is a vector of school policies and school characteristics measured in our survey and video observations. The estimates of equation (4) are weighted by the inverse of the standard error of the estimate treatment effect θ_s.

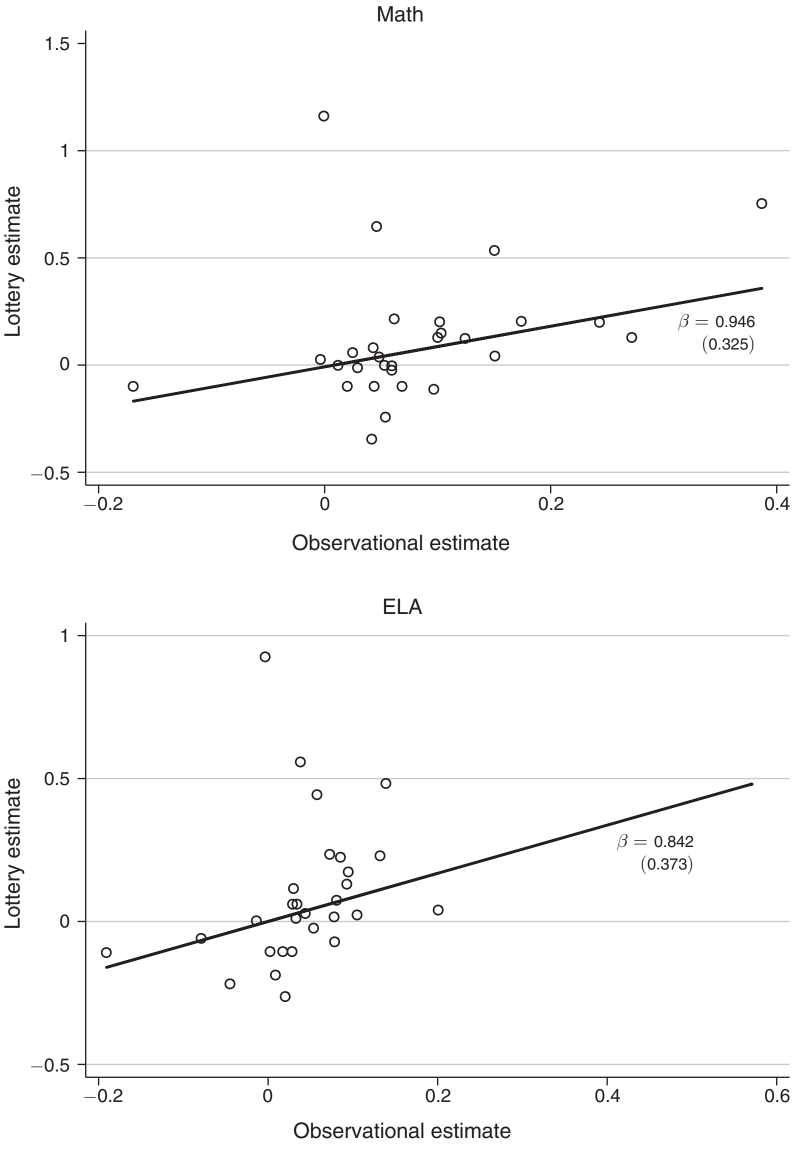

FIGURE 1. LOTTERY AND OBSERVATIONAL ESTIMATES

Notes: This figure reports school-specific treatment estimates using the lottery and observational designs. The lottery sample is restricted to students in an elementary or middle school charter school lottery, excluding students with sibling preference. All lottery specifications control for lottery risk set, race, sex, free lunch eligibility, grade, and year. All observational specifications include match cell, race, sex, free lunch eligibility, grade, and year. Middle school specifications also include baseline test scores.

Standard errors are clustered at the school level to account for correlation between elementary and middle school campuses. Unless otherwise noted, we use observational estimates of θ_s, which increases our sample size from 29 to 39. Our main results are qualitatively unchanged using lottery estimates, though the estimates are less precise (see Appendix Tables 3–6).

The parameter of interest is ϑ, which measures the partial correlation of a given school characteristic on effectiveness. Recall, our estimates are not likely to be causal in nature. Unobserved factors, such as principal ability or parental involvement, could drive the correlation between our measures and school effectiveness.

As mentioned in Section II, there is a voluminous literature relating school inputs to average test scores. The typical dataset includes variables such as class size, per pupil expenditure, and teacher credentials. With the notable exception of a number of quasi-experimental studies finding a positive impact of class size on test scores, previous research has found little evidence linking these inputs to achievement (see reviews in Hanushek 1997 and Krueger 2003).

Table 5 presents results using several of the traditionally collected school inputs—class size, per pupil expenditure, the fraction of teachers with no certification, and the fraction of teachers with a masters degree—as explanatory variables for school effectiveness. For each measure we create an indicator variable equal to one if a school is above the median in that measure. Consistent with Hanushek (1997), we find that these measures are either statistically unrelated to school effectiveness or are significant in an unexpected direction. For instance, schools where at least 89 percent of teachers are certified have annual math gains that are 0.041σ (0.023) *lower* and ELA gains that are 0.029σ (0.017) *lower*. An index of the four dichotomous measures explains 14.0 to 22.8 percent of the variance in charter school effectiveness but in the unexpected direction.[5]

In stark contrast, Table 6 demonstrates that the five policies suggested most often by the qualitative literature on successful schools (Edmonds 1979, 1982)—teacher feedback, the use of data to guide instruction, tutoring, instructional time, and a culture of high expectations—explain around 45 percent of the variance in charter school outcomes. Schools that give formal or informal feedback 10 or more times per semester have annual math gains that are 0.080σ (0.021) higher and annual ELA gains that are 0.066σ (0.015) higher than other schools. Schools that give 5 or more interim assessments during the school year and that have 4 or more differentiation strategies have annual math and ELA gains that are 0.050σ (0.039) and 0.034σ (0.029) higher, respectively. Schools that tutor students at least 4 days a week in groups of 6 or fewer have 0.051σ (0.033) higher math scores and 0.054σ (0.028) higher ELA scores. Schools that add 25 percent or more instructional time compared to traditional public schools have annual gains that are 0.080σ (0.022) higher in math and 0.048σ (0.022) higher in ELA. Whether or not a school prioritizes high academic and behavioral expectations for all students is associated with math gains that are 0.081σ (0.030) higher than other schools and ELA gains that are 0.059σ (0.020) higher per year. The last column of Table 6 reports results for an index of all five variables. We construct the index variable (and all other index variables in this paper) by taking the sum of each dichotomous variable, then standardizing that sum to have a mean

[5] One concern is that charter schools do not use resource-based inputs at the same rate as traditional public schools. This does not appear to be the case, though it's possible. According to the NYCDOE, for example, charter elementary schools have class sizes that range from 18 to 26 students per class and charter middle schools have class sizes ranging from 22 to 29 students. In 2010–2011, the average class size in a traditional elementary school in NYC was 23.7 students and the average class size in a traditional middle school was 26.6 to 27.1 students, depending on the subject.

Table 5—The Correlation between Resource Inputs and School Effectiveness

	(1)	(2)	(3)	(4)	(5)
Panel A. Math results					
Class size	−0.041				
	(0.028)				
Per pupil expenditures		0.004			
		(0.027)			
Teachers with no certification			−0.041*		
			(0.023)		
Teachers with MA				−0.043	
				(0.027)	
Index					−0.030***
					(0.011)
R^2	0.064	0.006	0.073	0.074	0.140
Observations	39	39	39	39	39
	(6)	(7)	(8)	(9)	(10)
Panel B. ELA results					
Class size	−0.034				
	(0.021)				
Per pupil expenditures		−0.005			
		(0.020)			
Teachers with no certification			−0.029*		
			(0.017)		
Teachers with MA				−0.032	
				(0.020)	
Index					−0.025**
					(0.010)
R^2	0.133	0.069	0.126	0.132	0.228
Observations	39	39	39	39	39

Notes: This table reports regressions of school-specific treatment effects on school characteristics. The sample includes all schools with at least one tested grade that completed the charter survey. Each independent variable is an indicator for being above the median in that domain. Class size equals 1 if a school's pupil-teacher ratio is less than 13. Per pupil expenditure is equal to 1 if expenditures are greater than $15,000. Teachers with no certification is equal to 1 if more than 89 percent of teachers are uncertified. Teachers with MA is equal to 1 if more than 11 percent of teachers have an advanced degree. The index is a sum of the dichotomous measures standardized to have a mean of zero and standard deviation of one. The dependent variable is the school-specific impact estimated using OLS and controlling for match cells, race, sex, free lunch eligibility, grade, and year. Middle school specifications also include baseline test scores. Regressions weight by the inverse of the standard error of the estimated school impact. Standard errors are clustered at the school level.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

of zero and a standard deviation of one. A 1 standard deviation increase in this index of all 5 school practice inputs is associated with a 0.053σ (0.010) increase in annual math gains and a 0.039σ (0.008) increase in annual ELA gains.[6] These data are

[6] While the index variable is associated with large and statistically significant gains in the lottery sample, the measure only explains 6.9 percent of the variance in math effectiveness and 6.0 percent of the variation in ELA effectiveness in the lottery sample. The relatively low R^2 is most likely due to the imprecision of the lottery estimates of school effectiveness; only 7 of the 29 schools have statistically significant results in either subject when using our lottery estimation strategy. The reduction in sample size from 39 to 29 schools itself does not appear important,

Table 6—The Correlation Between School Practice Inputs and School Effectiveness

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Math results						
Teacher feedback	0.080***					
	(0.021)					
Data driven instruction		0.050				
		(0.039)				
High quality tutoring			0.051			
			(0.033)			
Instructional time				0.080***		
				(0.022)		
High expectations					0.081***	
					(0.030)	
Index						0.053***
						(0.010)
R^2	0.227	0.082	0.057	0.250	0.257	0.444
Observations	39	22	39	38	38	39
	(7)	(8)	(9)	(10)	(11)	(12)
Panel B. ELA results						
Teacher feedback	0.066***					
	(0.015)					
Data driven instruction		0.034				
		(0.029)				
High quality tutoring			0.054*			
			(0.028)			
Instructional time				0.048**		
				(0.022)		
High expectations					0.059***	
					(0.020)	
Index						0.039***
						(0.008)
R^2	0.318	0.171	0.166	0.210	0.295	0.475
Observations	39	22	39	38	38	39

Notes: This table reports regressions of school-specific treatment effects on school characteristics. The sample includes all schools with at least one tested grade that completed the relevant part of the charter survey for that domain. Each independent variable is an indicator variable. Teacher feedback equals one if a school gives formal or informal feedback ten or more times per semester. Data driven instruction equals one if a school gives five or more interim assessments during the school year and has four or more differentiation strategies. Tutoring equals one if a school tutors students at least four days a week in groups of six or fewer. Instructional time equals 1 if a school adds 25 percent or more instructional time compared to a traditional public school. High expectations equals one if a school says that it prioritizes high academic and behavioral expectations for all students. The index is a sum of the dichotomous measures standardized to have a mean of zero and standard deviation of one. The dependent variable is the school-specific impact estimated using OLS and controlling for match cells, race, sex, free lunch eligibility, grade, and year. Middle school specifications also include baseline test scores. Regressions weight by the inverse of the standard error of the estimated school impact.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

consistent with Angrist, Pathak, and Walters (2011), who argue that Massachusetts charters that adhere to a "No Excuses" model, defined as selective teacher hiring,

however. The index measure explains over 45 percent of the variation in both math and ELA effectiveness among the 29 lottery schools when using observational measures of effectiveness.

extensive teacher feedback, increased instructional time, and a focus on discipline, are more effective at increasing test scores than other charter schools.

Table 7 estimates the partial correlation of each of the five policies on school effectiveness, controlling for the other four. Each regression includes all schools in our survey sample, even if they did not provide information on a particular school practice. Surprisingly, four out of the five policy measures used in our index continue to be statistically significant in at least one subject, suggesting that each policy conveys some relevant information. Controlling for other school policies, schools that give formal or informal feedback 10 or more times per semester have annual math gains that are 0.048σ (0.023) higher and annual ELA gains that are 0.044σ (0.014) higher than other schools. Schools that add 25 percent or more instructional time compared to traditional public schools have annual gains that are 0.050σ (0.013) higher in math, though not in ELA. Controlling for other policies, schools that prioritize high-dosage tutoring have annual ELA gains that are 0.040σ (0.022) higher. Schools that have high academic and behavioral expectations have annual math gains that are 0.044σ (0.023) higher and annual ELA gains that are 0.030σ (0.015) higher than other schools.

B. *Robustness Checks*

In this subsection, we explore the robustness of our results by performing an out of sample test of our main index and accounting for a more diverse set of controls.

An Out of Sample Test.—Our first robustness check explores the association between the school inputs in our main index and school effectiveness in a set of schools that did not participate in our survey. To do this, we collected similar (though less detailed) publicly available data on human capital, data driven instruction, instructional time, and culture for every possible charter school in New York City. Despite an exhaustive search, we could not find any publicly available data on whether or how these schools tutored students. Thus, our index for this out of sample test will contain four out of the five variables.

Our data is drawn primarily from annual site visit reports provided by each school's chartering organization. New York City charter schools are either authorized by the New York City Department of Education (NYCDOE), the State University of New York (SUNY), or the New York State Department of Education (NYSDOE). The site visits are meant to "describe what the reviewers saw at the school—what life is like there" (NYCDOE 2011). The publicly available report identifies some of the strengths in a school, as well as areas where improvement is needed.[7] Thirty-one NYCDOE and 25 SUNY schools have both site visit reports and students in grades 3 to 8. For this set of schools, we complement the site visit data with publicly available data from New York State Accountability and Overview Reports, the Charter School Center, and each school's website. More information on each data

[7] Site visit reports chartered by the NYCDOE include quantitative rankings, from which we draw our measures. SUNY site visit reports are qualitative in nature. In the latter case, we code each variable directly from the text of the site visit report.

Table 7—The Partial Correlation of Each School Practice Input

	(1)	(2)	(3)	(4)	(5)
Panel A. Math results					
Teacher feedback	0.048**				
	(0.023)				
Data driven instruction		0.020			
		(0.024)			
High quality tutoring			0.029		
			(0.020)		
Instructional time				0.050***	
				(0.013)	
High expectations					0.044*
					(0.023)
Index	0.040***	0.055***	0.052***	0.038***	0.041***
	(0.010)	(0.011)	(0.011)	(0.009)	(0.012)
R^2	0.446	0.476	0.446	0.524	0.448
Observations	39	39	39	39	39
	(6)	(7)	(8)	(9)	(10)
Panel B. ELA results					
Teacher feedback	0.044***				
	(0.014)				
Data driven instruction		0.013			
		(0.019)			
High quality tutoring			0.040*		
			(0.022)		
Instructional time				0.020	
				(0.017)	
High expectations					0.030*
					(0.015)
Index	0.027***	0.039***	0.036***	0.033***	0.031***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)
R^2	0.486	0.489	0.478	0.535	0.479
Observations	39	39	39	39	39

Notes: This table reports regressions of school-specific treatment effects on school characteristics. The sample includes all schools with at least one tested grade that completed any part of the charter survey. Each independent variable is an indicator variable. Teacher feedback equals one if a school gives formal or informal feedback ten or more times per semester. Data driven instruction equals one if a school gives five or more interim assessments during the school year and has four or more differentiation strategies. Tutoring equals one if a school tutors students at least four days a week in groups of six or fewer. Instructional time equals 1 if a school adds 25 percent or more instructional time compared to a traditional public school. High expectations equals one if a school says that it prioritizes high academic and behavioral expectations for all students. The index is a sum of the remaining dichotomous measures standardized to have a mean of zero and standard deviation of one. The dependent variable is the school-specific impact estimated using OLS and controlling for match cells, race, sex, free lunch eligibility, grade, and year. Middle school specifications also include baseline test scores. Regressions weight by the inverse of the standard error of the estimated school impact.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

source and how we construct our variables to most closely match the variables collected in our survey is available in online Appendix A.[8]

[8] Appendix Table 7 presents summary statistics for schools that are in both the survey and out-of-sample regressions, and schools that are only in the out-of-sample group. Schools that did not take part in our survey, but have publicly available data, have math test score gains that are 0.039σ higher than schools in our survey sample, and

Table 8—Out of Sample Test of School Practice Inputs

	(1)	(2)	(3)	(4)	(5)
Panel A. Math results					
Teacher feedback	0.039*				
	(0.020)				
Differentiated instruction		0.004			
		(0.024)			
Instructional time			0.062***		
			(0.020)		
High expectations				0.063***	
				(0.022)	
Index					0.027***
					(0.009)
R^2	0.040	0.000	0.139	0.114	0.102
Observations	59	59	51	55	59
	(6)	(7)	(8)	(9)	(10)
Panel B. ELA results					
Teacher feedback	0.016				
	(0.013)				
Differentiated instruction		−0.001			
		(0.014)			
Instructional time			0.023		
			(0.014)		
High expectations				0.043***	
				(0.015)	
Index					0.013**
					(0.006)
R^2	0.018	0.000	0.049	0.129	0.061
Observations	59	59	51	55	59

Notes: This table reports regressions of school-specific treatment effects on school characteristics. The sample includes all schools with at least one tested grade with available site visit data. Each independent variable is an indicator variable. Teacher feedback equals one if a school gives formal or informal feedback ten or more times per semester. Data driven instruction equals one if a school gives five or more interim assessments during the school year and has four or more differentiation strategies. Tutoring equals one if a school tutors students at least four days a week in groups of six or fewer. Instructional time equals 1 if a school adds 25 percent or more instructional time compared to a traditional public school. High expectations equals one if a school says that it prioritizes high academic and behavioral expectations for all students. The index is a sum of the remaining dichotomous measures standardized to have a mean of zero and standard deviation of one. The dependent variable is the school-specific impact estimated using OLS and controlling for match cells, race, sex, free lunch eligibility, grade, and year. Middle school specifications also include baseline test scores. Regressions weight by the inverse of the standard error of the estimated school impact.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 8 presents results using all eligible charter schools chartered with site visit data. The results of our out of sample test are similar to, though less precise than, the survey results. A 1 standard deviation increase in the case-study index is associated with a 0.027σ (0.009) increase in math scores and a 0.013σ (0.006) increase

ELA scores that are 0.026σ higher, although neither difference is statistically significant. Schools that did not take part in our survey, but have publicly available data, also are 48.5 percentage points more likely to give teacher feedback, 6.7 percentage points more likely to have a longer school year and day, and 46.2 percentage points more likely to have high expectations. These results suggest that our survey schools are somewhat negatively selected compared to other charter schools.

in ELA scores. However, the index explains less than 10 percent of the variation in math and ELA, likely reflecting measurement error in the data. Teacher feedback, instructional time, and high academic and behavioral expectations are significantly related to math achievement. High expectations are significantly related to ELA achievement, with the point estimates on teacher feedback and instructional time positive but not statistically significant.

Accounting for More Controls.—Our second robustness check simply accounts for every other measure of school inputs collected during the study that does not enter the main index. This control index is created by standardizing the sum of six indexes—human capital policies, data policies, parent engagement strategies, instructional time differences, culture and expectations, and curricular rigor—to have a mean of zero and a standard deviation of one. In total, the index captures variation in 37 measures, virtually all of the data we collected in the principal survey.

Table 9 presents results controlling for the aggregate index of 37 variables. A 1 standard deviation increase in this aggregate index is associated with a statistically insignificant 0.023σ (0.014) increase in annual math gains, and a statistically insignificant 0.010σ (0.008) increase in annual ELA gains. However, the control index is statistically indistinguishable from zero after controlling our main index. The coefficient on the main index is statistically indistinguishable from the specification with no controls from Table 6, suggesting that the other variables collected do not convey any more statistically relevant information in explaining charter school success.

V. Conclusion

Charter schools were created to serve as an escape hatch for students in failing schools and to use their relative freedom to incubate best practices to be infused into traditional public schools. Consistent with the second mission, charter schools employ a wide variety of educational strategies and operations, providing dramatic variability in school inputs. Taking advantage of this fact, we collected data on the inner workings of 39 charter schools in New York City to understand what inputs are most correlated with school effectiveness. Our data include a wealth of information collected from each school through principal, teacher, and student surveys, sample teacher evaluation forms, lesson plans, homework, and video observations.

We show that input measures associated with a traditional resource-based model of education—class size, per pupil expenditure, the fraction of teachers with no teaching certification, and the fraction of teachers with an advanced degree—are not positively correlated with school effectiveness. In stark contrast, an index of 5 policies suggested by 40 years of qualitative research—frequent teacher feedback, data driven instruction, high-dosage tutoring, increased instructional time, and a relentless focus on academic achievement—explains almost half of the variation in school effectiveness. Moreover, we show that these variables remain statistically important after accounting for a host of other explanatory variables,

Table 9—Robustness to Additional Controls

	Math results		ELA results	
	(1)	(2)	(3)	(4)
School practice index		0.056***		0.046***
		(0.013)		(0.010)
Control index	0.023	−0.005	0.010	−0.013
	(0.014)	(0.014)	(0.008)	(0.007)
R^2	0.077	0.446	0.094	0.509
Observations	39	39	39	39

Notes: This table reports regressions of school-specific treatment effects on school characteristics. The sample includes all schools with at least one tested grade that took the survey. The school practice index is a sum of the dichotomous measures from Table 6 standardized to have a mean of zero and standard deviation of one. The control index is the standardized sum of six indexes—human capital policies, data policies, parent engagement strategies, instructional time differences, culture and expectations, and curricular rigor—to have a mean of zero and a standard deviation of one. The dependent variable is the school-specific impact estimated using OLS and controlling for match cells, race, sex, free lunch eligibility, grade, and year. Middle school specifications also include baseline test scores. Regressions weight by the inverse of the standard error of the estimated school impact.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

and are predictive in a different sample of schools. These results align closely with those reported in Angrist, Pathak, and Walters (2011), who show that charter schools that employ a "No Excuses" model, defined by more selective teacher hiring, extensive teacher feedback, increased instructional time, and a focus on discipline and academic achievement, are more effective at increasing test scores. There is remarkable similarity between our findings and those reported in Angrist, Pathak, and Walters (2011) given two entirely different samples and ways of collecting data.

While there are important caveats to the conclusion that these five policies can explain significant variation in school effectiveness, our results suggest a model of schooling that may have general application. The key next step is to inject these strategies into traditional public schools and assess whether they have a causal effect on student achievement. Fryer (2011) reports on an ongoing experiment implementing similar practices in low-performing traditional public schools in Houston. This intervention appears to substantially increase achievement, suggesting that these five strategies may be effective more generally.

Appendix Tables

Table A1—Charter Schools in Survey Sample

	2010–2011 grades	Year opened	Years in lottery study	Survey	Video
Panel A. Elementary schools (3rd–5th grades)					
Amber Charter School	K–5	2000	2005–2006	Yes	Yes
Bronx Academy of Promise	K–4	2008		Yes	No
Bronx Charter School for Children	K–5	2004	2006-2010	Yes	Yes
Bronx Charter School for the Arts	K–6	2003	2007-2010	Yes	Yes
Brooklyn Ascend Charter School	K–4	2008	2008	Yes	Yes
Excellence Boys Charter School	K–8	2004	2003–2007	Yes	Yes
Explore Charter School	K–8	2000	2005–2007	Yes	Yes
Family Life Academy Charter School	K–8	2001		Yes	No
Future Leaders Institute Charter School	K–8	2005	2007-2009	No	Yes
Girls Preparatory Charter School	K–7	2005	2007-2009	Yes	Yes
Grand Concourse Academy Charter School	K–5	2004	2006-2009	Yes	Yes
Harbor Science and Arts Charter School	K–8	2002	2007	Yes	Yes
Harlem Children's Zone Promise Academy	K–5	2004	2004–2006	Yes	Yes
Harlem Children's Zone Promise Academy II	K–6	2005	2005–2006	Yes	Yes
Harlem Link Charter School	K–5	2005	2005–2009	Yes	Yes
Harlem Success Academy Charter School	K–5	2006	2006–2008	Yes	Yes
Hyde Leadership Charter School Bronx	K–5	2009	2006-2007	Yes	Yes
La Cima	K–3	2008	2009–2010	Yes	Yes
Manhattan Charter School	K–5	2005	2008	Yes	No
Mott Haven Academy	K–3	2008		Yes	No
Peninsula Preparatory Academy	K–5	2004	2009	Yes	Yes
Renaissance Charter School	K–5	2000		Yes	Yes
Sisulu-Walker Charter School of Harlem	K–5	1999	2007	Yes	Yes
South Bronx Classical Charter School	K–5	2006	2007	Yes	Yes
South Bronx Int. Cultures and the Arts	K–5	2005		Yes	No
VOICE	K–3	2008	2009-2010	Yes	Yes
Panel B. Middle schools (5th–8th grades)					
Bronx Preparatory Charter School	5–12	2000	2008–2009	Yes	Yes
Coney Island Preparatory Charter School	5–6	2009	2009–2010	Yes	Yes
Democracy Preparatory Charter School	6–10	2006	2006–2009	Yes	Yes
Equality Charter School	6–8	2009	2009–2010	Yes	Yes
Explore Charter School	6–8	2000		Yes	Yes
Harbor Science and Arts Charter School	K–8	2002	2007	Yes	Yes
Harlem Children's Zone Promise Academy	6–11	2004	2005–2008	Yes	Yes
Hyde Leadership Charter School Bronx	6–10	2009	2006–2009	Yes	Yes
KIPP Infinity	5–8	2005		Yes	No
Opportunity Charter School	6–12	2004	2008–2009	Yes	Yes
Renaissance Charter School	6–8	2000		Yes	Yes
St. HOPE Leadership Academy	5–8	2008		Yes	Yes
Summit Academy Charter School	6–7	2009	2009	Yes	Yes

Notes: This table lists all New York City charter schools participating in the survey study. Elementary schools include all schools that have their main admissions lottery in grades PK–4. Middle schools include all schools that have their main admissions lottery in grades 5–8. Eligible charters serve a general student population with at least one tested grade in 2010–2011.

Table A2—Student Summary Statistics

	NYC (1)	Eligible charters (2)	Above median survey (3)	Below median survey (4)	Difference (5)	Above median lottery (6)	Below median lottery (7)	Difference (8)
Panel A. Elementary schools (3rd–5th grades)								
Male	0.51	0.49	0.48	0.47	0.01	0.53	0.49	0.05**
White	0.14	0.03	0.01	0.01	−0.00	0.00	0.02	−0.01***
Black	0.32	0.66	0.74	0.65	0.09***	0.77	0.55	0.22***
Hispanic	0.39	0.29	0.24	0.33	−0.08***	0.22	0.43	−0.21***
Asian	0.14	0.02	0.00	0.01	−0.00*	0.00	0.01	−0.00
Free lunch	0.85	0.83	0.85	0.85	−0.00	0.82	0.85	−0.03*
Special education	0.11	0.06	0.06	0.06	0.00	0.06	0.08	−0.02**
LEP	0.12	0.05	0.04	0.04	0.00	0.04	0.06	−0.02**
School free lunch	0.85	0.85	0.85	0.85	0.00	0.83	0.85	−0.02***
Observations	706,663	23,986	3,344	2,076		1,472	674	
Panel B. Middle schools (5th–8th grades)								
Male	0.51	0.50	0.50	0.49	0.01	0.48	0.47	0.01
White	0.14	0.03	0.00	0.00	0.00	0.00	0.00	0.00
Black	0.33	0.64	0.84	0.41	0.43***	0.89	0.42	0.47***
Hispanic	0.39	0.30	0.15	0.58	−0.43***	0.11	0.57	−0.46***
Asian	0.14	0.02	0.00	0.00	−0.00	0.00	0.01	−0.01*
Free lunch	0.85	0.84	0.88	0.94	−0.06***	0.90	0.94	−0.04*
Special education	0.11	0.09	0.06	0.04	0.02*	0.05	0.03	0.02
LEP	0.10	0.05	0.02	0.08	−0.06***	0.02	0.06	−0.04**
Baseline math	0.02	−0.06	−0.17	−0.11	−0.06	−0.33	−0.17	−0.16**
Baseline ELA	0.01	−0.07	−0.18	−0.15	−0.02	−0.26	−0.18	−0.08
School free lunch	0.84	0.84	0.89	0.95	−0.05***	0.90	0.94	−0.04***
School baseline math	0.01	−0.04	−0.22	−0.18	−0.04***	−0.32	−0.17	−0.15***
School baseline ELA	−0.01	−0.06	−0.20	−0.23	0.03***	−0.30	−0.22	−0.08***
Observations	773,620	22,147	900	455		382	270	

Notes: This table reports descriptive statistics for the sample of public school students, the sample of students in eligible charter schools, the sample of students in charter schools in the observational study, and the sample of students in the lottery study. The sample is restricted to students in grades 3–8 between 2003–2004 and 2010–2011 with at least one follow up test score. The final column reports coefficients from regressions of an indicator variable equal to one if the student won an admissions lottery on the variable indicated in each row and lottery risk sets.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A3—The Correlation between Traditional Resource Inputs and School Effectiveness: Lottery Estimates

	(1)	(2)	(3)	(4)	(5)
Panel A. Math results					
Class size	–0.095				
	(0.072)				
Per pupil expenditures		0.053			
		(0.065)			
Teachers with no certification			–0.105*		
			(0.060)		
Teachers with MA				0.025	
				(0.064)	
Index					–0.035
					(0.027)
R^2	0.064	0.026	0.093	0.006	0.035
Observations	29	29	29	29	29
	(6)	(7)	(8)	(9)	(10)
Panel B. ELA results					
Class size	–0.081				
	(0.062)				
Per pupil expenditures		0.012			
		(0.055)			
Teachers with no certification			–0.095*		
			(0.049)		
Teachers with MA				0.029	
				(0.054)	
Index					–0.041*
					(0.022)
R^2	0.076	0.017	0.121	0.024	0.079
Observations	29	29	29	29	29

Notes: This table lists all New York City charter schools participating in the survey study. Elementary schools include all schools that have their main admissions lottery in grades PK–4. Middle schools include all schools that have their main admissions lottery in grades 5–8. Eligible charters serve a general student population with at least one tested grade in 2010–2011.

Table A4—The Correlation between School Practices Inputs and School Effectiveness: Lottery Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Math results						
Teacher feedback	0.141**					
	(0.057)					
Data driven instruction		0.060				
		(0.089)				
High quality tutoring			0.062			
			(0.063)			
Instructional time				0.039		
				(0.042)		
High expectations					0.075	
					(0.060)	
Index						0.045**
						(0.020)
R^2	0.131	0.054	0.012	0.016	0.054	0.069
Observations	29	18	29	29	28	29
	(7)	(8)	(9)	(10)	(11)	(12)
Panel B. ELA results						
Teacher feedback	0.115**					
	(0.055)					
Data driven instruction		0.127				
		(0.088)				
High quality tutoring			0.051			
			(0.042)			
Instructional time				0.024		
				(0.039)		
High expectations					0.015	
					(0.049)	
Index						0.031
						(0.021)
R^2	0.137	0.108	0.025	0.023	0.019	0.060
Observations	29	18	29	29	28	29

Notes: This table reports regressions of school-specific treatment effects on school characteristics. The sample includes all schools with at least one tested grade that completed the charter survey. Each independent variable is an indicator variable. Teacher feedback equals one if a school gives formal or informal feedback ten or more times per semester. Data driven instruction equals one if a school gives five or more interim assessments during the school year and has four or more differentiation strategies. Tutoring equals one if a school tutors students at least four days a week in groups of six or fewer. Instructional time equals one if a school adds 25 percent or more instructional time compared to a traditional public school. High expectations equals one if a school says that it prioritizes high academic and behavioral expectations for all students. The index is a sum of the dichotomous measures standardized to have a mean of zero and standard deviation of one. The dependent variable is the school-specific impact estimated using lottery offer as an instrument of years of attendance at a school, controlling for lottery risk set, race, sex, free lunch eligibility, grade, and year. Middle school specifications also include baseline test scores. Regressions weight by the inverse of the standard error of the estimated school impact.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A5—The Partial Correlation of Each School Practices Input: Lottery Estimates

	(1)	(2)	(3)	(4)	(5)
Panel A. Math results					
Teacher feedback	0.134*				
	(0.067)				
Data driven instruction		0.043			
		(0.096)			
High quality tutoring			0.081*		
			(0.043)		
Instructional time				−0.040	
				(0.059)	
High expectations					0.052
					(0.080)
Index	0.008	0.036	0.052***	0.073**	0.028
	(0.026)	(0.022)	(0.020)	(0.036)	(0.037)
R^2	0.133	0.077	0.107	0.103	0.073
Observations	29	29	29	29	29
	(6)	(7)	(8)	(9)	(10)
Panel B. ELA results					
Teacher feedback	0.116*				
	(0.062)				
Data driven instruction		0.104			
		(0.092)			
High quality tutoring			0.062*		
			(0.032)		
Instructional time				−0.034	
				(0.060)	
High expectations					−0.023
					(0.052)
Index	−0.002	0.015	0.036*	0.054	0.044*
	(0.027)	(0.021)	(0.020)	(0.034)	(0.023)
R^2	0.137	0.092	0.088	0.088	0.085
Observations	29	29	29	29	29

Notes: This table reports regressions of school-specific treatment effects on school characteristics. The sample includes all schools with at least one tested grade that completed the charter survey. Each independent variable is an indicator variable. Teacher feedback equals one if a school gives formal or informal feedback ten or more times per semester. Data driven instruction equals one if a school gives five or more interim assessments during the school year and has four or more differentiation strategies. Tutoring equals one if a school tutors students at least four days a week in groups of six or fewer. Instructional time equals one if a school adds 25 percent or more instructional time compared to a traditional public school. High expectations equals one if a school says that it prioritizes high academic and behavioral expectations for all students. The index is a sum of the remaining dichotomous measures standardized to have a mean of zero and standard deviation of one. The dependent variable is the school-specific impact estimated using lottery offer as an instrument of years of attendance at a school, controlling for lottery risk set, race, sex, free lunch eligibility, grade, and year. Middle school specifications also include baseline test scores. Regressions weight by the inverse of the standard error of the estimated school impact.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A6—Robustness to Additional Controls: Lottery Estimates

	Math results		ELA results	
	(1)	(2)	(3)	(4)
School practices index		0.055*		0.033
		(0.030)		(0.027)
Control index	0.014	−0.016	0.014	−0.002
	(0.022)	(0.031)	(0.014)	(0.018)
R^2	0.009	0.076	0.032	0.060
Observations	29	29	29	29

Notes: This table reports regressions of school-specific treatment effects on school characteristics. The sample includes all schools with at least one tested grade that took the survey. The school practices index is a sum of the dichotomous measures from Table 6 standardized to have a mean of zero and standard deviation of one. The control index is the standardized sum of six indexes—human capital policies, data policies, parent engagement strategies, instructional time differences, culture and expectations, and curricular rigor—to have a mean of zero and a standard deviation of one. The dependent variable is the school-specific impact estimated using lottery offer as an instrument of years of attendance at a school, controlling for lottery risk set, race, sex, free lunch eligibility, grade, and year. Middle school specifications also include baseline test scores. Regressions weight by the inverse of the standard error of the estimated school impact.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table A7—Characteristics of Survey Schools and Schools with Publicly Available Data

	Survey and public (1)	Public only (2)	Difference (3)
Math test score gains	0.075	0.117	0.039
ELA test score gains	0.044	0.067	0.026
Teacher feedback	0.448	0.933	0.485***
Differentiated instruction	0.276	0.467	0.191
Instructional time	0.213	0.291	0.067*
High expectations	0.074	0.536	0.462***
Observations	29	30	

Notes: This table reports summary statistics for schools that are in both the survey and public sample and the sample of schools that only have publicly available data on school inputs. The survey and public sample excludes schools without a tested grade in 2010–2011 and schools without publicly available data on inputs. The survey and public sample does include schools with and without lottery data. The publicly available sample includes all schools with publicly available data from a chartering organization. All variables are school level measures and are taken from the administrative data. The difference between samples is reported in the last column. The number of observations in each sample is reported at the bottom of the table.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

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