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Approximating the Equilibrium Effects of Informed School Choice

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Abstract

This paper studies the potential small and large scale effects of a policy designed to produce more informed consumers in the market for primary education. We develop and test a personalized information provision intervention that targets families of public Pre-K students entering elementary schools in Chile. Using a randomized control trial, we find that the intervention shifts parents' choices toward schools with higher average test scores, higher value added, higher prices, and schools that tend to be further from their homes. Tracking students with administrative data, we find that student academic achievement on test scores was approximately 0.2 standard deviations higher among treated families five years after the intervention. To quantitatively gauge how average treatment effects might vary in a scaled up version of this policy, we embed the randomized control trial within a structural model of school choice and competition where price and quality are chosen endogenously and schools face capacity constraints. We use the estimated model of demand and supply to simulate policy effects under different assumptions about equilibrium constraints. In counterfactual simulations, we find that capacity constraints play an important role mitigating the policy effect but in several scenarios, the supply-side response increases quality, which contributes to an overall positive average treatment effect. Finally, we show how the estimated model can inform the design of a large scale experiment such that reduced form estimates can capture equilibrium effects and spillovers.

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1 Introduction

The lack of information about product quality can affect consumer behavior and have important effects on equilibrium market outcomes (Akerlof, 1970). In markets for educational services, information and its effects on consumer behavior can have important effects on equilibrium levels of school quality (Andrabi et al., 2017). In addition, lack of information can have distributional effects, given that families from less educated socioeconomic backgrounds may be particularly misinformed and have more difficulty acquiring information (Hastings and Weinstein, 2008; Elacqua and Martínez, 2016).[1] Additionally, poorer families may not have accurate information about the returns to many investments, including underestimating the return to human capital investments (Jensen, 2010; Banerjee and Duflo, 2011). This combination can lead poor families in developing countries to under-invest in human capital by spending less time and energy searching for and acquiring information about what school to choose for their children. In the aggregate, a lower interest in school quality could also lead to an equilibrium with a lower quality schools than would be expected in a market with full information. These concepts are supported by empirical evidence and an emerging consensus that information and marketing interventions in education settings can shift individual choices, although specific effects depend on context, implementation, and design details (Lavecchia et al., 2016). However, with the notable exception of Andrabi et al. (2017), evidence regarding the equilibrium policy effects of large scale interventions are much less common, and evidence of what mechanisms are at play is even scarcer.

In this paper we explore the equilibrium implications of a government policy that provides information to the parents of Pre-K students in Chile. We develop a scalable, policy relevant intervention that consists of a video and a report card. Both provide personalized information about characteristics of nearby schools and a broad message emphasizing the feasibility and importance of searching for a school carefully. The intervention adapts ideas from previous work in other settings and the design accounts for local policy constraints.[2] We use a small-scale randomized control trial to evaluate the impact of our policy intervention on individual household school choices and later academic outcomes. The results from the randomized control trial show that household school choice decisions shift toward schools with higher test scores and higher prices on average. We use administrative data to track students over a five year period and find that the treated group had higher test scores on average, suggesting the intervention increased academic achievement, at least partly due to changes in school choice.

[1] There is ample empirical evidence of an information-socioeconomic gradient. See Hastings and Weinstein (2008) for evidence of parents in the USA lacking information about schools and their characteristics, and Elacqua and Martínez (2016); Hastings et al. (2016) for additional evidence from Chile.

[2] For example, relevant prior interventions with successful impacts include work by Hastings and Weinstein (2008), and Andrabi et al. (2017), which both provide a report card with school test scores. Jensen (2010) provides middle school children in the Dominican Republic, information on how earnings change by level of education, and Dinkelman and Martinez (2014) show evidence of the effects of providing information about financial aid through videos in Chile.

We quantify the way the policy modifies families' behavior by explicitly incorporating incomplete information into the empirical model of school choice developed in Neilson (2013). The framework directly accommodates evidence from a randomized control trial and administrative data on the choices of teh entire student population. Using the estimated empirical model of school choice, we explore how average policy effects change when the policy is implemented nationally, specifically taking into account capacity constraints and heterogeneous market structure across neighborhoods. when capacity constraints are taken into account, the average effect of the policy is still positive, but only half as large, as increased demand for higher quality schools in disadvantaged neighborhoods crowds itself out.

We next study the potential for the policy to generate equilibrium supply side effects in the medium run. We take advantage of recent variation in voucher funding policy together with detailed panel data on the population of schools to estimate a static model of school competition among current providers in the spirit of work in empirical industrial organization such as Berry et al. (1995) and Wollmann (2018). We use the estimated parameters of the cost structure to evaluate the effects that a national policy would have on schools incentives to provide quality and set prices. We then study the resulting equilibrium distribution of school characteristics induced by the new policy when schools can only adjust prices and quality. We find that the new equilibrium featues higher prices and higher quality schools on average. The increase in quality is found to more than compensate for the increased congestion and lack of capacity at higher quality schools. In our preffered model specifications, the effects of the policy on the achievment gap are found to be positive and even higher than the average treatment effects found in the small-scale randomized control trial.

The results from the randomized control trial and the modeling of demand and supply complement each other to provide a policy recommendation. The small-scale randomized control trial shows there is scope for simple information intervention to change behavior. The different simulations of an at-scale implementation highlight the importance of equilibrium considerations such as capacity constraints and the supply side reaction to invest in quality, raise prices, or expand capacity. Taken together, the simulations imply a range of results indicating that low SES test scores would increase, and the SES achievement gap would decrease.

Our paper makes two main contributions. First, we provide evidence on the role of a policy relevant information and marketing intervention in education markets at both the micro and macro level. This distinction is relevant because the difference between partial and equilibrium effects can be important in education contexts as has been noted in Heckman et al. (1998). At the same time, aggregate level ex-ante policy evaluation is difficult, if not impossible in many cases. Building evidence solely on randomized control trials will take time and significant resources to implement at scale evaluations in many applications. These considerations make it difficult to provide quantitative policy advice in a timely way. This is unsurprising since shifting behavior of many individuals is likely to have nontrivial general equilibrium effects that are difficult to account for in a randomized control trial. One important exception is recent work by Andrabi et al. (2017), which has shown that in Pakistan, providing school report cards in small village markets increased academic achievement without significant student sorting, suggesting that information on school quality and price can lead to changes in the aggregate and that the supply side reactions to information is a relevant margin to consider. While this experimental evidence is a rigorous proof of concept, it is hard to generalize the findings and make policy recommendations in other settings. In fact, some policies that generate signals of quality and are similar in spirit have not provided the same results. One important example is Mizala and Urquiola (2013), where a policy that provided a signal of school quality in Chile seems to not had any effect on school choice. Taken together, the empirical evidence to date indicates that information interventions do have the potential to change behavior but that policy details can matter quite a lot. The evidence presented in this paper shows that the specific policy intervention tested influences how families choose schools. Without an at-scale randomized control trial, we approximate the equilibrium implications of a national policy considering sorting, capacity constraints and schools supply side reaction to the policy. The results point toward a positive partial equilibrium policy effect that is dampened by capacity constraints. However, the equilibrium effects including schools reactions suggest large positive effects across a spectrum of potential assumptions.

Our second main contribution is to present an empirical framework that builds on a small-scale experiment to then approximate the effects of a large scale implementation of the policy. We use both theory and data to build on evidence from a randomzied control trial to provide estimates that can be used to consider implementing the policy or whether to proceed and plan for an at-scale experiment to gather more evidence. By explicitly modeling the consequences of changing individual choices on both the demand and the supply side, this empirical framework allows the researcher to quantify the poilicy implications and provide counterfactual analysis. This approach is one way to provide quantitative policy recommendations when implementing randomized control trials at-scale is infeasible, expensive or just not timely.

The empirical methods used add to a growing body of research that takes advantage of the variation created by RCTs and other credibly exogenous sources of variation. Some papers have used randomized control trials to estimate key parameters or to validate the predictions of a structural model. For example, this approach was famously used to evaluate PROGRESA in seminal work by Todd and Wolpin (2006). Our paper is different because the randomized control trial is not used to validate the model, nor is the structural model used to quantify the effects of changing different features of the policy. In Attanasio et al. (2011), the experimental data both provide variation at scale and a way to identify new parameters associated with the effect of the policy. However, our main objective is to extrapolate the effects of the policy to individuals beyond the experiment and extimate the equilibrium supply side reaction when we do not observe aggregate policy effects.

In this way, our equilibrium analysis is closer to policy evaluations of potential mergers, where estimating equilibrium responses to changes in demand and supply play a key role in evaluating the impacts of counterfactual policies that could be implemented. This allows the researcher to provide insight on the behavior of families who face different choice sets beyond the experimental sample. We can also explore the consequences of aggregate effects on demand when there are capacity constraints, and then on supply side considerations such as the choice of quality.[3]

Our paper also contributes to the line of work developing structural models of education markets by explicitly adding experimental variation to the modeling of supply and demand. While empirical models of market equilibrium are commonly used to evaluate policy in empirical industrial organization research, these types of models have rarely been applied to education markets and do not usually incorporate experimental variation.[4] In this paper, we argue that using a coherent economic framework to follow the logical implications of changing individual behavior expands the set of questions that researchers can ask. Our framework allows for a range of policy relevant predictions that can be useful for translating evidence and research into policy recommendations in education settings.

2 Data and Institutional Setting

We use several data sources for this project. First, we use administrative data on preschools from *Integra*, a preschool education provider, which includes information on the preschool location, enrollment, attendance, socio-economic level (measured as mothers schooling), income, and poverty[5]. Second, we use self-collected data through the baseline and follow up surveys in the preschools included in our experiment, which we discuss in detail in Section 4. These data include contact information, individual identifiers, location of the family, and questions regarding the application process. Then, we match this information with administrative data from the Ministry of Education.

The first source of administrative data are student-by-year matriculation records from the Ministry of Education of Chile (MINEDUC), along with information on grades and some basic demographic information. This also includes individual-level eligibility for the *Subvencion Escolar*

[3]One interesting application of similar ideas is Lise et al. (2015). They evaluate employment programs taking advantage of experimental variation and their treatment of equilibrium considerations is similar in spirit to what we look to achieve in our paper, although applied to the context of job training and employment.

[4]Some exceptions on work on school choice in education markets include work by Neilson (2013); Dinerstein and Smith (2015); Walters (2018). The model of school choice and competition in this paper builds on prior work in this space by Neilson (2013), and earlier work on school choice in Chile by Gallego and Hernando (2008) and Chumacero et al. (2011).

[5]See Section O-1 in the online appendix for further description of provision of preschool education in Chile.

Preferencial (SEP) targeted voucher. The second source of administrative data from MINEDUC is related to students test scores from the SIMCE test and an accompanying survey of the population of 2nd, 4th and 8th grade students. The survey contains detailed information about the household composition, demographics, and income. This data is complemented with data from the Ministry of Health which include all births in the country after 1992 and contains information on the health conditions of a child at birth such as birth weight, length, and gestation. It also contains information regarding the mother and father, such as education level and marital status.[6]

A third source of data available from the Ministry of Education consist of the administrative records on all schools in the country. This source lists each schools's type, matriculation rate by grade level, address, and other school characteristics, such as religious affiliation and tuition. Data on all transfers to schools is also available monthly since 2005[7]. All yearly school expenditures are available since 2014[8]. We associate each school with the markets defined by Neilson (2013) using census track information. We also add data on all the transfers made by the Ministry of Education to public and private voucher schools. We complement this school panel with data on teachers and principals from (Calle et al., 2018). In that paper, college entrance exam scores are matched to each teacher registered by the Ministry of Education.

Our study is focused on urban schooling markets. We use the proceedure to define urban schooling markets described in Neilson (2013) and leverages administrative data from the 2002 and 2012 Census with block level shapefiles and geocoded microdata on the population. This data is used to to produce the boundries of urban schooling markets as well as a detailed description of the distribution of the students and schools within markets.[9] After excluding very small markets (with less than five schools), we focus on 74 distinct urban markets that in 2012 contain 3937 schools, 181,000 students which represents 90% of urban students in first grade.

Using the data on students and schools in our sample of interest, we estimate measures of test score value-added at the school level as a proxy of school quality. The data available provide a rich set of characteristics to condition on and in some years, students prior test scores can be used as controls as well. We find that these measures of value added are very correlated with teacher quality as measured by teacher college entrance exams and that controling for prior test scores provides similar results to not having prior scores when ranking schools by measure of quality. These calculations are presented in the online appendix.

We are interested in studying the differences in choices and access across socioeconomic groups.

[6] Most of these datasets are described in detail in the online appendix of Neilson (2013), so we refer the reader there for more details.

[7] See Section O-6.1 in the online appendix.

[8] See Section O-6.2 in the online appendix.

[9] We present further details in the online appendix and refer the reader to Neilson (2013).

We divide the population of students into three groups, those whose mother had not completed high school at the time of birth (labeled No HS Mom, 15% of the population), those who had completed only high school (labeled HS Mom, 60% of the population) and those who completed more than a high school education (labeled College Mom, 25% of the population). We divide schools into quintiles of the socioeconomic status of the people who live within 1km of the school. Specifically, we calculate the percent of students who live within 1km that are poor enough to be elegible for a targeted voucher (intended for the 40% poorest students).

In Chile, most students enter primary school in Kindergarten at the age of 5. Prior to entering primary schools, the vast majority of children attend Pre-K institutions where net enrollment rates at ages 3 and 4 are 55% and 87%, respectively (OECD, 2016). Children can attend public or private centers. The two main providers of free public Pre-K are Junji and Fundación Integra, which administer approximately 3,000 and 1,000 centers respectively, and are explicitly tasked with providing access to Pre-K educational services for students all over the country. Of the 3 and 4 year old students enrolled in preschools in 2016, 42% were in Junji, and 18% in Integra.[10] The majority of these students live in urban markets (88% of those enrolled in Junji and Integra) and families tend to send their children to Pre-Ks very close to their homes.[11] We implement our information experiment among Integra centers.

Transiting from a Pre-K institution to a primary school requires parents to apply and sign up for school at some point before the start of the academic year. Until 2016 (i.e., during the our experiment), this process was decentralized and the timing of the application and matriculation process was heterogeneous. In 2016, a pilot version of a centralized application system started working in the southernmost region of the country. In 2017, the system was extended to 5 regions, and it will be implemented in the whole country in 2019.

Primary schools in Chile are either free public schools, private voucher schools or private non-voucher schools. The system features a high degree of choice and a large private sector. In 2016, the market share for first-grade students was 36% for public schools, 55% for voucher schools, and 8% for private schools. Private voucher schools can charge an additional out-of-pocket fee beyond the voucher, but there are some caps and discounts that limit the fee for schools that receive government funds. In 2016, 63% of voucher schools in urban areas are free and 86% have a fee lower than 70 USD (15% of the minimum wage). In addition, several policy changes have modified the transfers schools get per student. In particular, a large change ocurred in 2008 when the government introduced a larger voucher for the poorest 40% of students in schools that signed up for the policy. This policy required schools to not charge eligible students any out-of-pocket

[10] We calculated these numbers by taking the number of enrolled 3 to 4-year-old students (according to the OECD) and then calculating the share of students that are in Junji and Integra centers based on their administrative records. There are few official sources of information on private Pre-K centers. Some of these centers receive public funding and others charge tuition, which is out-of-reach for most lower income families as the ones included in our sample.

[11] In our sample of 1800 students, the average distance from their home to the Pre-K is 1.2 kilometers.

tuition fees in exchange for a larger transfer from the government. In practice, this resulted in zero out-of-pocket fees for poor students at all the public schools and the vast majority of the voucher schools (over 80% in 2016). Additional reforms implemented in 2016 froze the prices charged by vouchers schools and implemented a gradual plan to completely eliminate fees in voucher schools.[12]

Both public and voucher schools receive the same subsidy per student, and a large portion of private voucher schools have traditionally operated as for-profit.[13] However, it is reasonable to assume that while many private schools maximize profit, public schools face different incentives and different constraints. On one hand, public schools may behave like firms in a competitive market trying to increase revenue, which is proportional to the number of students the school attracts. On the other hand, public schools are administrated at the municipality level where the same administration controls a set of schools, potentially pooling funds across them. As a result, an individual public school can receive additional transfers and cross transfers from the municipality to cover their expenses, independent of their enrollment.[14] Public schools also have less flexibility in how they can spend their money and hire staff because public teacher contracts are highly regulated.

In spite of the variety of schools and choices available, students from poorer families tend to go to schools with lower outcomes in terms of test scores, and lower inputs in terms of teacher quality and overall resources. A series of policy changes have tried to reduce this stratification. Recent changes include implementing larger vouchers targeted for the poor which is studied in Neilson (2013); Mizala and Torche (2013); Elacqua and Santos (2013), among others. The steady increase in the baseline voucher and additional trasfers to schools for the poorest students has lead to a doubling of the average per pupil government transfer to schools and the differences in resources available to schools with higher and lower socioeconomic backgrounds has all but vanished. The recent introduction of centralized school applications, further expansions of voucher amounts, price caps, and gradual elimination of fees in voucher schools, all seek to increase access to high-quality education for disadvantaged students. While these reforms seem to have helped, the distribution of school inputs and outputs conditional on family socioeconomic status continue to be very different. Figure 1 shows the distribution of estimated school value added for students entering first grade. The figure shows how the type of school chosen differs by socioeconomic status using students mothers' level of education as a simple proxy because it is available for all

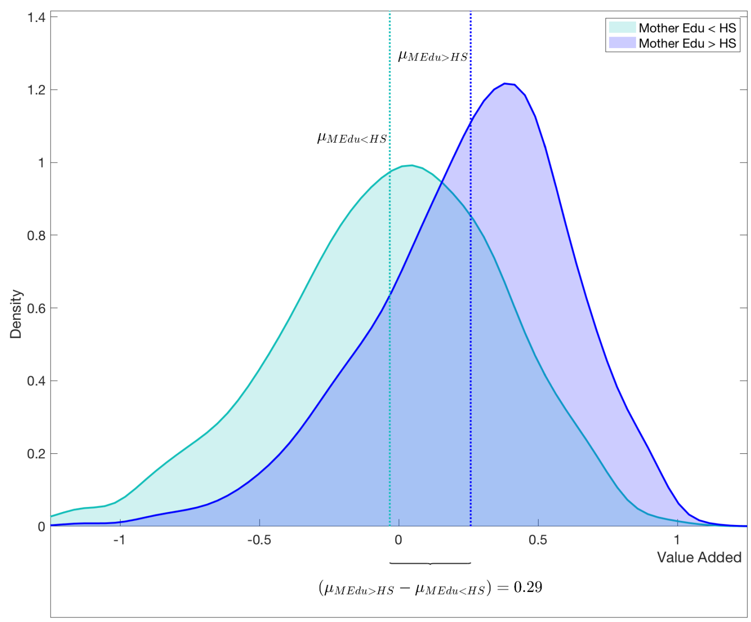
[12]The online appendix describes in detail the sources of income schools have and how they have changed since 2005.

[13]Voucher schools are operated by both for-profit firms and not-for-profit organizations. Aedo (1998) argues that not-for-profit schools behave similarly to for-profit schools as they raise additional funds for operating the school in a relatively competitive market for donations.

[14]Gallego (2013) argues that the fact that public schools receive other transfers different from the voucher implies that they operate under soft budget constraints, where they only partially react to the incentives created by the voucher system.

students from birth records.[15]

Figure 1: Inequality of School Quality Across SES



Note: This figure shows the distribution of school value added in 2012 conditional on the students' mothers' education. The population of students is divided into three groups, those whose mother had not completed high school at the time of birth (labeled No HS Mom, 15% of the population), those who had completed only high school (not shown, 60% of the population) and those who completed more than a high school education (labeled College Mom, 25% of the population). The term $\mu_C - \mu_{NoHS}$ corresponds to the difference in the average school quality for each type presented in Equation 3. Similar graphs showing the distribution of school average teacher quality are presented in the appendix in Figure O-8.

One reason that can explain the lack of convergence across groups even after important investments in access, is that poor families may not know the importance of choosing a high-quality school for very young children. In addition, it is possible that families with less experience with higher equality educational institutions may find it more difficult to accurately assess school quality. These hypotheses would lead poor families to put more weight on the school's proximity or other characteristics when deciding what option to choose. Note that if this is true, even in the case of total equality of access, we can expect differences across SES groups.

Policy makers in Chile have been trying to promote the production and dissemination of in-

[15]The online appendix presents similar information showing differences in the teacher quality at the schools attended by different types of students. Spending on teachers is show to representing over 70% of total school expenditures (Tables O-11 and O-10). It is also highly correlated with estimated school value added.

formation for many years. Standardized tests have been universally administered since 1987, and government web sites have posted school test scores for many years. For instance, in 2010 the government of Chile pushed an agenda called *"Mas Informacion, Mejor Educacion"* (More information, Better Education) showing interest in the idea of providing information[16]. Evidence from other countries and contexts such as the US and Pakistan suggests that there may be scope for an information provision policy to improve outcomes (see eg., Hastings and Weinstein (2008), and Andrabi et al. (2017) for a discussion on this issue in two different contexts) .

This paper builds on a project that began in 2009, and the randomized control trial was implemented in the second half of 2010. The objective was to study the effects of increasing information provision through government policy, so our research design and intervention were shaped by concerns of policy feasibility. The goal of the design was to accommodate scalability and policy feasibility, while rigorously evaluating effectiveness at a small scale, eventually arriving at a quantitative recommendation relevant for policymakers.

3 Conceptual Framework

3.1 Framework for Policy Analysis

In this section we provide a general framework to analyze the effects of an information provision policy. We are interested in how this policy might change individual behavior and specifically how it might change the quality of the schools chosen. We are also interested in how applying the policy at-scale might result in different effects in the short and long run (when firms can adjust their quality). The challenge is to incorporate enough institutional background into our empirical model so that we can make sense of the data while keeping it simple enough to be tractable.

Our model specifies the behavior of families and schools together with a notion of equilibrium. Each make choices to maximize their objective function subject to financial and other regulatory constraints.[17] A notion of short and long run determine what variables are under the control of schools.

[16]"Ms Informacin, Mejor Educacin" or MIME it's a platform where families and students can find relevant information about any school on the country. Among other things, they can find schools general description, educational programs, standarized tests scores, teachers evaluation, information about selection processes and geographic location.

[17]Several papers have studied school demand systems in the context of Chile, notably Gallego and Hernando (2008) and (Neilson, 2013). Very few studies include supply side considerations in education context. One recent exception is Sanchez (2017), which takes the supply side seriously and models the extensive margin of voucher program participation of schools in Chile.

3.2 Families

When a student $i \in \{1, ..., N\}$ is entering school, the family must choose a school $j \in J_i^m$ where $J_i^m \subset J^m$ is the set of schools that are available to student i and J^m is the set of all schools in a market with $\#J^m = N_J$ the number of schools in market m. Families might differ in the set of schools that are available to them so that J_i^m is not the same for all i. Families can also differ by their socioeconomic status $\text{type}_i \in \{1, ..., T\}$ and location node n_i across an urban market m. Families can have heterogeneous preferences for school characteristics such as out of pocket price p_j, quality q_j and distance to their location d_{ij}. Government voucher policy v_{ij} determines the out-of-pocket expenses for different families i at potentially different schools j.

The value the family gets by choosing j is given by $U_{ij}(\omega)$ where $\omega \in \Omega$ is a state of the world indicating the price, quality and distance of all schools as well as government policy and how important school quality is for future outcomes of the children. Families have an information set $\mathcal{I}_i \in \mathcal{I}$ so that, at the time of choosing a school, the perceived value of a school, given the information set the family has, is given by Equation 1.

$$U_{ij}^{\mathcal{E}}(\mathcal{I}_i) = \mathcal{E}\left(U_{ij}(\omega) | \mathcal{I}_i\right) \tag{1}$$

We further assume that families choose the school that provides the highest perceived value conditional on their information set so that $j_i^* = \text{argmax}_{j \in J_i^m} U_{ij}^{\mathcal{E}}(\mathcal{I}_i)$. Having defined the latter, we can sum over all such choices to write the share of families of each SES type that choose school j as in Equation 2. The average school quality for each type can be written as the weighted average in Equation 3.

$$s_j^{\text{type}}(U, \mathcal{I}, J^m) = \frac{1}{N_{\text{type}}} \sum_{i=1}^{N_{\text{type}}} 1(j = j_i^* | U_{ij}^{\mathcal{E}}(\mathcal{I}_i), J_i^m) \tag{2}$$

$$\mu_q^{\text{type}} = \sum_{j=1}^{N_J} q_j \cdot s_j^{\text{type}}(U, \mathcal{I}, J^m) \tag{3}$$

With this very basic framework we can conceptually decompose the differences in school quality attended by students of low and high socioeconomic status as a composite of several forces. Part of the difference can be due to heterogeneity in the schools available. This could be driven by differences across markets or due to selection on the part of schools that make some options unfeasible to some families. Differences in location of a family within a market also changes the value of the available options due to preferences for distance. Another reason is differences in choices can be driven by heterogeneity in preferences for school characteristics. Finally differences could arise due to differences in the information sets available to different types of families, which lead them to make different choices due to different beliefs about school characteristics and also how important school quality can be.

3.3 Schools

An elementary school $j \in J^m$ can be public or private and is located at a node n_j in an urban market m. The school can potentially choose to make investments and exert effort to adjust their quality[18], q_j, and over time, their capacity k_j as well. Private schools can also choose a price p_j, subject to restrictions given by policy. Schools can also differ in their ability to mix inputs to generate quality so that their cost structure is heterogeneous $C_j(q)$. This could reflect that some schools may be run more or less efficiently or they can have access to cheaper inputs. This would allow schools to differ in the cost of providing a given level of quality and capacity. Schools receive a student-level transfer v_{ij} that is potentially different for different students at different schools.

Given the choice of individual families described above,it follows that the demand a school can expect to get given the government policy, quality, price and location of other schools also depends on the information structure that partially determines decisions of families and thus can influence quality and prices.

$$s_j(U, \mathcal{I}, J^m) = \frac{1}{N} \sum_{\text{type}=1}^{T} N_{\text{type}} \cdot s_j^{\text{type}}(U, \mathcal{I}, J^m) \tag{4}$$

Schools maximize some combination of profit and quality weighted average, subject to a set of financial and technological constraints. Thus, conditional on capacity, quality and price are chosen endogenously as a function of government policy, own costs/productivity, objectives and local market conditions.

$$(q_j^*, p_j^*) = \text{argmax}_{(p,q)} \Pi(C_j(q), v_j, s_j(U, \mathcal{I}, J^m)) \tag{5}$$

This setup highlights that schools quality, price and other valued attributes are endogenous to a series of environmental factors. The heterogeneity in school quality in a particular market can be due to government policy, differences in costs, differences in objectives and differences in market structure and competitive pressure. Importantly for this paper, the quality and price chosen by schools can also depend on the information structure of local families given that this can affect the demand (Ns_j) faced by schools.

[18]For simplicity, note that quality is assumed to be the same for all students at the school and, while potentially chosen with some uncertainty, it is not a function of which students attend. This rules out peer effects and other more complicated school-student match effects.

3.4 Equilibrium and Potential Policy Effects

In equilibrium, schools will have chosen quality and prices, and families have chosen what school to attend, such that there is no excess demand for any particular school given school capacities. Due to fixed costs and the zero lower bound on prices, there may exist excess capacity at some schools. Schools can expand capacity, and raise or reduce quality over the medium term.

Given the above, the average school quality chosen by different types of family defined by Equation 3 is due to demand, supply, and government policy. The model can be used to decompose the factors that define that average and the gap between any particular groups such as rich and poor. The policy of providing information takes an aim at shifting the information set families use when making school choices. At the individual family level, such a policy directly affects the optimal school choice, assuming the choice set J_i^m and the characteristics of all schools in that set are unchanged. A small scale randomized control trial is an approximation to this situation and helps identify the effect of the policy on families' optimal school choice. Given that the treatment changes the information set to $\mathcal{I}'$, and defining $\Delta_{(\cdot)}(\cdot)$ as a conditional post-treatment difference operator, such that $\Delta_{\mathcal{A}} x := x|_{\mathcal{A}'} - x|_{\mathcal{A}}$ for any x and $\mathcal{A}$, then

$$\Delta_{\text{Treat}} \mu_{q,\text{ small}}^{\text{type}} \approx \sum_{j=1}^{N_J} q_j^* \cdot \Delta_{\mathcal{I}} s_j^{\text{type}} \tag{6}$$

A larger, scaled version of the policy could induce additional reactions that could affect the average quality chosen. To simplify, assume the policy is implemented to all families in the short run, but schools are unable to adjust prices, quality or capacity. We would have that average quality that a particular type of family chooses is now affected by the changing information set, but also due to a change in the schools available. Unexpected shifts in demand could lead to excess demand at some schools and crowd out some of the families' demand.

$$\Delta_{\text{Treat}} \mu_{q,\text{ scale, sr}}^{\text{type}} \approx \sum_{j=1}^{N_J} q_j^* \cdot \left(\Delta_{\mathcal{I}} s_j^{\text{type}} + \Delta_{J^m} s_j^{\text{type}} \right) \tag{7}$$

In the medium term, a large scale policy that shifts demand for schools by shifting information sets could have additional effects through the supply side, as schools may adjust their quality and price as a function of changing demand.

$$\Delta_{\text{Treat}} \mu_{q,\text{ scale, mr}}^{\text{type}} \approx \sum_{j=1}^{N_J} \left[\frac{\partial q_j^*}{\partial s_j} \cdot \Delta_{\text{Treat}} s_j \cdot s_j^{\text{type}} + q_j^* \cdot \left(\Delta_{\mathcal{I}} s_j^{\text{type}} + \Delta_{J^m} s_j^{\text{type}} \right) \right] \tag{8}$$

In the long run, schools are expected to adjust capacity and re-optimize price and quality to maximize their objective function, given local market conditions. Entry and exit margins are likely to be relevant and a series of dynamics can be of interest as well. Without going into further details, this framework suggests that there could be meaningful adjustments on both the demand and the supply side once equilibrium constraints are imposed on the policy effects. The relevance of these adjustments depends on the quantitative importance of particular mechanisms. The first is that the policy affects individual decisions in a meaningful way. Secondly, the changing demand could make capacity constraints binding and limit the adjustments in demand in the short run. The third important aspect that links supply side reactions is whether schools change their behavior as a function of changing demand and local market conditions. These three aspects and their implications are explored quantitatively in the following sections.

We first quantify the effects of the policy on individual choices using a randomized control trial. We estimate average treatment effects on the characteristics of the schools chosen and students' later outcomes. Once we verify potential meaningful effects on individual choices, we lay out an estimation strategy to recover how the treatment changes the way families choose, even if the econometrician does not observe information sets. We then propose an empirical strategy to recover estimates of the schools' cost structures and how to use these to recover new equilibrium behavior of all schools.

4 The Policy and Randomized Control Trial

4.1 Design of the Randomized Control Trial

The main objective of the intervention was to encourage parents to invest in the process of choosing a school for their child. The intervention tried to increase the awareness of neighborhood schools characteristics and the perceived returns to school quality. The intervention was designed to have a low marginal cost and be easily scalable by government agencies that provide Pre-K services. We collaborated with the network of *Integra* preschools that provide Pre-K education to 25,229 students in the cohort of 3 to 4 years (30% of public Pre-K enrollment) to test the intervention. The information provision treatment consisted of a session during regular parent-teacher meetings. Parents were shown a video that emphasized the returns to investing in school quality and choosing a school carefully. The video urged parents to think about how their choice today could affect their child's future. One segment of the video asked parents to think about what kind of job their child might have and what opportunities higher education could provide them. The video then explained that higher education is associated with more job opportunities and higher earnings. The video placed a special emphasis on the idea that going to a good school can be very important in helping a child prepare for higher education and a good job.

Figure 2: Choosing a school carefully is important for your child's future

(a) Think about your child's future. **(b)** Think about your child's future education. **(c)** Think about your child's future job. **(d)** High average return to attending college.

To reinforce the idea that school choice is important for a child's future, the video included testimonials from students and parents. The video shows that there are good schools in poor neighborhoods and that going to these schools can improve future opportunities, showing real-life examples of two students and one parent from neighborhoods that are well-known to be low income.

Figure 3: Message Conveyed Through Relatable Role Model Testimonials

(a) Silvia searched carefully for a school that was good for her son. **(b)** Felix went to a good school and now is in college. **(c)** Rose Marie went to a good school and is now working at a bank.

The video explains that to get into higher education, students need to do well on standardized tests. So they should make sure to check how well students are doing on standardized tests when comparing schools. Parents received a report card that highlights test scores and prices of schools in the neighborhood. A discussion with parents provided space for asking questions about the school choice process. We refer the reader to the Online Appendix for more details on the treatment design. The overall message is reiterated with a plea for parents to invest in getting information and comparing options to be able to choose well.

Figure 4: To choose well, get information and compare options

We conducted our study in three of the largest regions of Chile: Valparaíso, Biobío, and Santiago. To be included in the sample, schools had to be located in urban areas (according to *Integra's* classification), in areas with at least 10 schools within 1.2 miles and with the ratio $(\text{primary schools}_m/\text{preschools}_m) \geq 2$.

We randomly assigned preschools to control (C) and treatment (T) arms, stratifying by region, number of grades the preschools offer, and a proxy of "school competition", given by the number of primary schools within 1.2 miles. The online appendix describes the design in detail. It is important to note that the initial design of the experiment included two subgroups within the information treatment arm. One subgroup was to receive the full treatment of both the video and report card, and the other was to receive only the report card. However, implementation difficulties led to imperfect tracking of which schools within the treatment arm received the more and less intense versions of the treatment. Our final research design looks at the effectiveness of an information provision policy that is a mix of report cards and video, both designed with the explicit goal of providing accurate information to parents. Pooling both versions of the treatment implies that we cannot identify which media (e.g. brochures vs. videos) are most effective.

The experiment was implemented between August and December 2010 by trained staff who participated in the parents' meeting scheduled by the preschools. In the 133 preschools that agreed to participate, a total of 1,832 parents signed the informed consent and answered a baseline survey. Parents took this survey before the staff handed out any information and it included contact information and questions regarding the application process. We asked parents whether they had decided to send their child to primary school in 2011, if they had already chosen a specific school, and whether they had already enrolled their child. Parents were also asked if they had any other children already enrolled in primary school. After the survey, parents in treatment schools received the school choice intervention (see the treatment description above). Parents did not know about the intervention before the meeting, to prevent self-selection due to a special interest in the enrollment process or preferences toward quality and demand for information. Most of the staff were hired by the surveying firm, and they had a similar background to the preschool parents.

Between May and July 2011, we conducted a follow-up survey asking parents about their enrollment decisions. Of the 1,832 who received information, we were able to survey 1,611 (87%). In addition, we were able to match 1,795 out of 1,832 (98%) in our original sample to administrative records using individual student identifiers.

The characteristics at the pre-school level come from *Integra's* administrative data and include total enrollment, mean attendance, and measures of SES proxied by mothers' education, income quintile and poverty status for children in each pre-school. We see no difference in the characteristics between the treatment and control pre-schools.[19] Family characteristics were self-reported in the baseline and follow-up surveys and also show no systematic differences across treatment and control groups for a host of characteristics, including SES characteristics (household size, possession of durable goods, whether the family owns the dwelling, whether the mother is the head of the household and measures of the mother's education), baseline information about the school (whether the child is already enrolled in a school or the parents have an older child that is already going to school), and an indicator for whether the child will start school in the following year (2011) or later.

The intervention was implemented during the time period that parents were enrolling their children into schools. The treatment should have a much smaller impact on school choice decisions for families who have already made their decisions prior to receiving the intervention. It is possible that the timing of matriculation could be correlated with the characteristics of the family.[20] Matriculating early does seem to be correlated with some observable characteristics associated with slightly higher SES (possession of durable goods), but we see no difference between groups in other SES family characteristics (except for a marginally higher probability of being born at a hospital) that can affect school choice, or with other background characteristics of the children that affect academic achievement (Almond and Currie, 2011; Bharadwaj et al., 2017). There are no systematic differences across treatment and control groups when we look at subsamples that either were enrolled or were not enrolled at baseline.[21] This is because treatment and control groups are balanced across time by design. We present results for the pooled sample as well as for the sample that has not yet matriculated.

The experiment is designed to compare the school choices of families in treated groups to the choices of control groups. In the short run, we look at the characteristics of schools that are chosen:

[19] Table A1 presents the coefficients and standard errors for regressions of each school characteristic on treatment status. Table O-2 shows the coefficients and standard errors for regressions of each characteristic of the families in our sample on treatment status.

[20] Table A2 shows the coefficients and standard errors for regressions of each characteristic of the families in our sample on enrollment status at baseline.

[21] See Table O-2

their price, distance, inputs, and outputs. In the long run, we look at students' standardized test scores in fourth grade and compare the treated students to the control students.

4.2 Results of the Randomized Control Trial

Table 1 shows a summary for the main results for the effect of the treatment on the characteristics of the schools that families chose. Table 2 includes the effect on student achievement five years after the experiment took place. The specifications include market characteristics such as the number of schools nearby, the average, the standard deviation and percentiles 25, 50 and 75 of test scores of schools nearby and municipality fixed effects. These are our most preferred specifications which include controls for randomization units. We present subsample analyses by matriculation status at the time of treatment.[22] The online appendix explores a series of alternative specifications with expanded controls, including a list of variables measuring family socioeconomic status and student health.

Table 1: Effects on Characteristics of Schools Chosen One Year After Treatment

	Distance	Positive Price	Lang 2nd	Lang 4th	Math 4th	V. Added
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full Sample						
Treatment	0.1371**	0.0438	0.0108	0.0107	0.0147	0.0274
	(0.0595)	(0.0354)	(0.0224)	(0.0275)	(0.0293)	(0.0273)
N obs.	1,378	1,775	1,758	1,752	1,752	1,752
Panel B: Already enrolled at the time of the PreK visit						
Treatment	-0.0843	0.0091	-0.0123	-0.0097	-0.0348	-0.0320
	(0.1234)	(0.0522)	(0.0430)	(0.0489)	(0.0570)	(0.0496)
N obs.	487	596	589	590	590	590
Panel C: Not enrolled at the time of the PreK visit						
Treatment	0.2390†	0.1198†	0.0591**	0.0377	0.0658*	0.0718**
	(0.0658)	(0.0399)	(0.0268)	(0.0323)	(0.0386)	(0.0345)
N obs.	780	975	967	961	961	962

Note: Randomization controls are used, which include market characteristics of schools (number and test scores mean, standard deviation and percentiles 25, 50 and 75.). † indicates significance at 0.01 confidence level, while $**$ and $*$ indicate 0.05 and 0.1 levels respectively.

Column 1 in Table 1 shows the impact of the treatment on the distance between treated families

[22]Note that from the original 1,832 students in our sample, we only have enrollment status at the time of the intervention for 1,612 students. That is why the number of observations in the pooled regression and the sum of the observations separated by enrollment do not coincide.

and their schools. If we look at the full sample in panel A, we see that treated families travel 0.14 additional kilometers (km) to attend school, a significant treatment effect of approximately 0.1 standard deviations. However, as we see in panel C, most of this effect comes from a significant and positive treatment effect for families that were not enrolled in the baseline, with a magnitude of 0.24 additional kilometers.[23]

Column 2 in Table 1 shows the impact of the treatment on whether the family went to a school that would charge them a positive price beyond the voucher. Treated students are slightly more likely to attend schools that charged additional out-of-pocket fees than students in the untreated group. Columns 3-5 show the impact of the treatment on the test scores of the schools chosen by families, measured using the mean math and language test scores for the school available at 2nd and 4th grade. If we look at the full sample, we see a significant increase in the math test scores of the schools chosen. Panel C shows larger and significant effects for students that had not enrolled at the time of the preK visit. Finally, column 6 shows similar results for the estimated value added of the schools chosen. These findings indicate that our intervention pushed parents to choose schools with higher academic achievment. It is interesting to note that the test scores are correlated with value-added measures and other proxies for quality such as teacher quality and parents satisfaction.[24]

[23] In this analysis we exclude families that appear to have moved. We determined this in two ways, a) if the administrative data indicates that the child lives in a different municipality than at the beginning of the study, or b) if the child's distance to the school is greater than 99th percentile distance (further than 4 km). As a robustness check, we look at the treatment effect on distance for several maximum distance restrictions in Figure O-6.

[24] See figures O-10 and O-9 for evidence that the value added measure used is significantly correlated with spending per student and with teacher quality. Figure O-11 shows the very close relationship between value added controling for a large vector of observables and when adding prior test scores. The Online Appendix for more descriptive evidence regarding the correlation between value added measures, test score outcomes, school inputs and parent satisfaction.

Table 2: Effects on Student Outcomes Five Years After Treatment

	Lang 4th	Math 4th
Panel A: Full Sample		
Treatment	0.0617	0.1298**
	(0.0612)	(0.0556)
N obs.	1,443	1,442
Panel B: Already enrolled		
Treatment	-0.1247	-0.0635
	(0.1211)	(0.1036)
N obs.	506	495
Panel C: Not enrolled		
Treatment	0.2163**	0.2210†
	(0.0898)	(0.0723)
N obs.	772	779

Note: Randomization controls are used, which include market characteristics of schools (number and test scores mean, standard deviation and percentiles 25, 50 and 75.). † indicates significance at 0.01 confidence level, while $**$ and $*$ indicate 0.05 and 0.1 levels respectively.

Table 2 presents the effects on individual tests scores in 4th grade, five years after the treatment took place. For students that were not enrolled before the treatment, we see positive and significant impacts in virtually all specifications.[25] This is an important result because it provides evidence that the policy changes not only behavior, but also outcomes.[26] It also shows that parents do have some margin to improve their choices and get access to better schools if they have more information about both the importance of carefully choosing a school and the relative quality of the schools. The results lend credibility to value added estimates as well, since the RCT results are consistent with the value-added predictions of which schools are more likely to improve students' test scores.

We study whether the more salient design features of the report card had behavioral effects on choices beyond simple information provision that should be taken account when mapping the intervention to a model of choice. To do this, we investigate whether information about options

[25]Families that reported having already enrolled at the time of the baseline survey were different from the group that had not previously enrolled. Relative to the unenrolled group, these families selected schools with higher test scores, they traveled about 0.14 km farther to their enrolled school and were more 25% more likely to choose schools with positive prices. This suggests that the unenrolled children at baseline may have faced more information frictions, which the intervention at least partially corrected.

[26]Table O-4 in the Appendix presents results for additional specifications.

raised awareness of the options on the report card, leading to increased likelihood of choice. We also study whether the color coding of red and green schools had any additional effects. Table 3 presents results showing evidence of several interesting additional insights that help interpret the effects of the intervention. In the first column we see that treated families were less likely to matriculate in a school nearby their PreK and thus on the report card. The second column shows that there is no evidence that green schools were more likley to be chosen over red schools overall. Both of these results provide evidence against many potential mechanisms where the report card raised awareness of specific schools or the color coding played an inordinate role in nudging parents towards certains schools. The results are consistent with the idea that the more salient feature of the treatment was to increase search and awareness of the importance of school quality and not to focus on specific design features of the report card. In anything, this suggests the video and salience of the choice seemed to be the more likely channels through which the intervention affected choices.

Table 3: Direct Effects of Report Card Design

	On Report Card		Green		Top 5	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full Sample						
Treatment	-0.118***	-0.112***	0.039	0.028	0.075*	0.064*
	(0.029)	(0.030)	(0.046)	(0.044)	(0.041)	(0.039)
N obs.	1775	1775	1136	1136	1136	1136
Panel B: Enrolled sample						
Treatment	-0.007	0.004	0.069	0.038	0.048	0.025
	(0.054)	(0.053)	(0.076)	(0.072)	(0.069)	(0.069)
N obs.	596	596	389	389	389	389
Panel C: Not enrolled sample						
Treatment	-0.172***	-0.159***	0.019	0.036	0.076*	0.090**
	(0.032)	(0.033)	(0.059)	(0.060)	(0.041)	(0.041)
N obs.	975	975	639	639	639	639
Randomization controls	×		×		×	
Expanded controls		×		×		×

Note: Randomization controls include market characteristics of schools (number and test scores mean, standard deviation and percentiles 25, 50 and 75.). Expanded controls include Mother's education, household information (size, durable goods, owned house), baseline school choice information.

The results presented in this section suggest that the intervention does indeed shift families' school choice towards better quality schools, in spite of the fact that they can be farther away and are more likely to charge out of pocket costs. The results on student test scores indicate the policy shifts students to schools that will help them learn more. The intervention is low cost and easy to scale-up, suggesting a policy expanding this intervention could make the education system more efficient and equitable by moving less privileged students to more productive schools.

5 Empirical Model for Policy Analysis

In this section, we present our empirical model in more detail, guided by the framework in section 3 3. Our starting point for the empirical analysis is a model of demand for schools based on each family making a discrete choice about what school to send their child to. We apply recent empirical work in industrial organization on demand estimates to education markets and draw on the framework developed in Neilson (2013). We model families as heterogeneous agents based on their geographic location within a market. We also let families have heterogenous preferences based on their observable and unobservable characteristics. We model schools as spatially differentiated firms that can choose price and quality. We abstract from explicitly modeling the firms' production function and input choices and instead choose a more parsimonious model where schools choose quality and price given capacity constraints. We explicitly allow families to have imperfect information about school attributes and avoid interpreting the weight they put on different school characteristics as a deep parameter associated with preferences.

This specification allows for rich heterogeneity among firm and consumer preferences and provides a realistic characterization of the choice set that each family faces. Viewing the experimental sample through this lens, we can describe in detail the set of schools and characteristics that each family faced when choosing a school. This allows us to rationalize the experimental results taking into account all the relevant dimensions of heterogeneity in both the choice set and across subjects in the experiment. We see this approach as a key contribution to uncovering the role of information in school choices since we explicitly model choice as a function of information.

5.1 Empirical Model of School Choice with Incomplete Information

We model the utility for family i from sending their children to school j in time t as a linear function of the school's observable and unobservable characteristics. To simplify notation, we drop the time subscript t from the demand model. The observable characteristics include quality, q_j, a measure of how much the school increases student's test scores. Another important observable characteristic is the out-of-pocket price op_{ij}, which is specific to family i due to different vouchers provided to different families at different schools. We approximate the distance between each school and each family with the linear distance d_{ij}. Other observable characteristics at the school level, x_j^r, are the school administration type (public, voucher or private), religious orientation, co-education and type of corporation (for-profit or not-for-profit). Families share a common preference for unobservable school characteristics, which we could think of as other dimensions of quality that do not translate into higher test scores, ξ_j. Finally, each family i has a random iid preference shock for school j, ϵ_{ij}. Preferences over quality, price and location are heterogeneous across family observable discrete type k that is given by the mothers education and income. With these definitions, we can describe family i's utility from sending their children to school j to be

$$U_{ij} = \beta_k q_j - \alpha_k op_{ij} + \lambda_k d_{ij} + \sum_r \eta_k^r x_j^r + \xi_j + \epsilon_{ij}. \tag{9}$$

We assume families have incomplete information about school quality, price and distance. This implies that families must choose a school based on their beliefs, which are given by potentially heterogeneous information sets $\mathcal{I}_i$. To operationalize this assumption, we assume that families know the true distribution of quality, $q_j \sim N(0, \sigma_q^2)$, but only observe a noisy signal for school. This signal corresponds to the true quality plus an error distributed $v(q)_{ij}^k \sim N(0, \sigma(q,\epsilon)_k^2)$. The expected quality would be: $q_{ij}^e = \rho_k^q (q_{ij} + v(q)_{ij}^k)$, where $\rho_k^q = \dfrac{\sigma_q^2}{\sigma_q^2 + \sigma(q,\epsilon)_k^2}$. Beliefs about prices and distance have a similar form with varying $\rho^o p_k$ and ρ_k^d given these attributes may be more or less easy to observable. For simplicity, we assume these signals are independant and unbiased, but these assumptions are not crucial. With these additional assumptions we have that expected utility from the families perspective is given by:

$$U_{ij}^{\mathcal{E}} = \phi_k^q q_j - \phi^{op}{}_k op_{ij} + \phi^d{}_k d_{ij} + \sum_r \eta_k^r x_j^r + \xi_j + \widetilde{\epsilon}_{ij} \tag{10}$$

The reduced form parameters ϕ represent the weight families place on the true quality, price and distance that are weighted by the precision of the signal. For example $\phi_k^{op} = \alpha_k \rho_k^{op}$ and $\phi_k^q = \beta_k \rho_k^q$. The residual terms derived from signals and idiosyncratic tastes are accumulated in the $\widetilde{\epsilon}_{ij} = \rho_k^q \cdot v(q)_{ij}^k + \rho_k^{op} \cdot v(p)_{ij}^k + \rho_k^d \cdot v(d)_{ij}^k + \epsilon_{ij}$.

The families choose school j to maximize their expected utility $U_{ij}^{\mathcal{E}}$ based on their information and their choice set J_m which we assume includes all schools in market m. Assuming $\widetilde{\epsilon}_{ij}$ follows an extreme value distribution, the following expression describes the share of families of type k who live at node n that will select school j as a function of observables and parameters, $(\mathbf{q}, \mathbf{op}, \theta)$ where $\theta = \{\eta, \xi, \phi, \sigma\}$ parameter vector θ:

$$s_j^{nk}(\mathbf{q}, \mathbf{op}, \theta) = \sum_{i=1}^{N_{v_i}} w_{v_i} \left(\frac{\exp(\phi_k^q q_j - \phi^{op}{}_k op_{ij} + \phi^d{}_k d_{ij} + \sum_r \eta_k^r x_j^r + \xi_j)}{\sum_{\ell \in J_m} \exp(\phi_k^q q_\ell - \phi^{op}{}_k op_{i\ell} + \phi^d{}_k d_{i\ell} + \sum_r \eta_k^r x_\ell^r + \xi_\ell)} \right) \tag{11}$$

It is important to note that the role of incomplete information in this setting is to modify the weight families place on school characteristics when choosing what option maximizes their expected utility. The more noise associated with the signals about a school characteristic, the lower the weight placed on that characteristic, $\frac{\partial \phi}{\partial \sigma_\epsilon^2} < 0$. This allows the model to accommodate differences in choice produced by systematic differences in the precision of the signals across socioeconomic groups. This, in turn, opens a role for the information treatment to play a part in shifting choices.

In practice, we define discrete family types based on: (i) their poverty status: poor or non poor, (ii) the mother's education level, which is divided into three groups: incomplete high school, complete high school or more than high school. The market definition joins all urban areas that are five kilometers apart or less at their closest point, and this union of areas will define one market. The assumption is that these areas are close enough for these students to feasibly travel within them. Each market is comprised of a total of N students living on the discrete set of N^m nodes. In order to get the market level shares, we need to aggregate over the distribution of students of each type across the nodes in the city and across the distribution of students across nodes. The distribution of students of type k across nodes is given by the vector w_k^m with $\sum_n^{N^m} w_{nk}^m = 1 \;\forall\; k$. The proportion of the students in the market who are of type k is given by π_k^m where $\sum_{k=1}^{K} \pi_k^m = 1$ so that average school quality for students k is given by Equation 13 and market shares for each school are given by Equation 12.

$$s_j(\mathbf{q}, \mathbf{op}, \theta) = \sum_k^K \left\{ \sum_n^{N_m} s_j^{nk}(\mathbf{q}, \mathbf{op}, \theta) \cdot w_{nk} \right\} \cdot \pi_k \tag{12}$$

$$\mu_q^{\text{type}}(\mathbf{q}, \mathbf{op}, \theta) = \sum_{j \in J^m} \sum_{n \in N^m} q_j \cdot s_j^{nk}(\mathbf{q}, \mathbf{op}, \theta) \cdot w_{nk} \tag{13}$$

5.1.1 Imbedding the RCT Effects into the Model

We incorporate the information treatment in the model of household behavior by shifting the weight families put on price, distance and quality. Given assumptions made above, this can ocurr either because treatment reduced the noise associated with the signal ($\rho \rightarrow 1$) or because the structural preference parameter changed due to the treatment. In our empirical setting, this distinction is not material but it is important to note we will recover only a reduced form parameter quantifying how families change their choices but not their welfare and this does limit the type of questions we can answer with this model. We allow treatment to affect ϕ^q, ϕ^{op}, and ϕ^d differentially and potentially in heterogeneous ways for each type k. To operationalize this idea, we expand the types described above to incorporate the families in the RCT and generate new *treated types*. Thus we add six parameters to the model that modify the weight given to each school characteristic $\left(\varphi_k^q, \varphi_k^{op}, \varphi_k^d\right)$ for $k = 1, 2, 3, 4$[27]. With this modified emprical framework, we can describe

[27]Note there are only four types that are affected by the policy because there are very few mothers with more than a high school education ($k = 5, 6$) in the sample of public PreK included in this study.

household choices for all families, with and without treatment.

$$\begin{aligned}
\widetilde{\phi}_i^{op} &= \sum_k \left(\phi_k^{op} + \psi_k^{op} \cdot \text{Treat}_i\right) \cdot \text{Type}_{ik} && (14)\\
\widetilde{\phi}_i^{d} &= \sum_k \left(\phi_k^{d} + \psi_k^{d} \cdot \text{Treat}_i\right) \cdot \text{Type}_{ik} && (15)\\
\widetilde{\phi}_i^{q} &= \sum_k \left(\phi_k^{q} + \psi_k^{q} \cdot \text{Treat}_i\right) \cdot \text{Type}_{ik} + \beta^U v_i^q && (16)
\end{aligned}$$

Now we describe the aggregate effects of the policy by mapping different levels of treatment penetration to market shares. Define τ_{nk} be the proportion of families of type k living in node n that are treated, and τ a vector that collects τ_{nk} for all (n,k). Augmenting the parameter vector $\vartheta = \{\theta, \psi\}$ we can now describe the share of students (n,k) that attend a school j as a function of other schools characteristics, estimated parameters and the proportion of students in the market that are treated:

$$s_j^{nk}(\mathbf{q}, \mathbf{op}, \vartheta) = \sum_{i=1}^{N_{v_i}} w_{v_i} \left(\frac{\exp(\delta_j + \widetilde{\phi}_k^q q_j - \widetilde{\phi}_k^{op} op_{ij} + \widetilde{\phi}_k^d d_{ij})}{\sum_{\ell \in J_m} \exp(\delta_k + \widetilde{\phi}_k^q q_\ell - \widetilde{\phi}_k^{op} op_{i\ell} + \widetilde{\phi}_k^d d_{i\ell})} \right). \tag{17}$$

We can then write the demand for school j, coming from node n, family type k, treatment intensity τ_{nk}, as,

$$s_j^{nk}(\mathbf{q}, \mathbf{op}, \vartheta, \tau) = \tau_{nk} \cdot s_j^{nk}(\mathbf{q}, \mathbf{op}, \vartheta) + (1 - \tau_{nk}) \cdot s_j^{nk}(\mathbf{q}, \mathbf{op}, \theta). \tag{18}$$

To get an expression for the market share of a school j for type k students, we aggregate over geographical nodes in the market taking into account the vector of treatment intensity at each node τ:

$$s_j^{k}(\mathbf{q}, \mathbf{op}, \vartheta, \tau) = \sum_{n}^{N_m} \left[\tau_{nk} \cdot s_j^{nk}(\mathbf{q}, \mathbf{op}, \vartheta) + (1 - \tau_{nk}) \cdot s_j^{nk}(\mathbf{q}, \mathbf{op}, \theta) \right] \cdot w_{nk}. \tag{19}$$

Finally, aggregate demand for a school j, with the treatment distribution τ, is given by

$$s_j(\mathbf{q}, \mathbf{op}, \vartheta, \tau) = \sum_{k}^{K} \left\{ \sum_{n}^{N_m} \left[\tau_{nk} \cdot s_j^{nk}(\mathbf{q}, \mathbf{op}, \vartheta) + (1 - \tau_{nk}) \cdot s_j^{nk}(\mathbf{q}, \mathbf{op}, \theta) \right] \cdot w_{nk} \right\} \cdot \pi_k. \tag{20}$$

The average school quality attended by type k with the treatment distribution τ, is given by

$$\mu_q^{\text{type}}(\mathbf{q}, \mathbf{op}, \vartheta, \tau) = \sum_{j \in J^m} \sum_{n \in N^m} q_j \cdot \left[\tau_{nk} \cdot s_j^{nk}(\mathbf{q}, \mathbf{op}, \vartheta) + (1 - \tau_{nk}) \cdot s_j^{nk}(\mathbf{q}, \mathbf{op}, \theta) \right] \cdot w_{nk}. \tag{21}$$

5.2 Supply side

We now present an empirical framework to model supply. We begin by assuming that privately owned, privately administered, for-profit schools will maximize profit. The profit function for a school j in a market with N students is given by aggregating revenue minus costs for each type of student. The school chooses a sticker price p_j and a school quality q_j, which is proxied by the school's ability to increase the student's test scores. Government voucher policy is described by the voucher schedule $v_j^k(p_j)$ which can vary by school depending on the school's characteristics and chosen price. Marginal revenue is thus described by $R_k(v_j^k, p_j)$ for each student as a function of the voucher schedule, the sticker price and the student type. Costs are given by fixed cost F_j and marginal costs which are a function of school quality and the student type $MC(q_j, k)$. We can then write the following expression for school profits:

$$\pi_j(\mathbf{q}, \mathbf{p}, \vartheta, \tau) = \sum_k^K s_j^k(\mathbf{q}, \mathbf{op}, \vartheta, \tau) \cdot \left[R(v_{jk}, p_j) - MC(q_j, k)\right] - F_j. \tag{22}$$

We make some simplifying assumptions before applying our model to the empirical setting. First, we focus on a static model where each school's capacity is given by $\bar{c}_j$ and schools can adjust their sticker prices p_j as well as inputs and effort to increase school quality q_j. We further assume that the marginal cost of providing a particular level of quality is linear conditional on a vector of school specific cost characteristics that are summarized in the vector w_j^l. In addition, we allow for a vector of unobservable cost shifters that add to the marginal cost of quality, ω_j.

Given these assumptions, the marginal cost of school j can be expressed as

$$MC(q_j) = \sum_l \gamma_l w_j^l + (\gamma_q + \omega_j) \cdot q_j. \tag{23}$$

Another important simplifying assumption is to express revenue as $R(v_j, p_j, k) = p_j + v_b$ where v_b is the baseline voucher not considering any additional targeting by type k that might ocurr in the implementation of a policy $v_j(p, k)$. In practice the relationship between price and revenue is slightly more complicated because in some cases $v_k > p_j + v_b$ so $R(v_j, p_j, k) = \max(p_j + v_b, v_k)$. This more realistic version of the revenue function is described in detail in the appendix. We use the more realistic version in estimation but continue this section ignoring this deviation for the sake of exposition and intution. With these two assumptions on revenue and marginal costs, we can write the first order condition for the static problem as

$$\frac{\partial \pi_j(\mathbf{q}, \mathbf{p}, \vartheta, \tau)}{\partial q_j} = N \frac{\partial s_j(\mathbf{q}, \mathbf{p}, \vartheta, \tau)}{\partial q_j} \left(v_b + p_j - MC(q_j)\right) - N s_j(\mathbf{q}, \mathbf{p}, \vartheta, \tau) \cdot \frac{\partial MC(q_j)}{\partial q_j} = 0 \tag{24}$$

And the expression for the optimal level of quality as

$$q_j^* \quad = \underbrace{\left[\frac{v_b + p_j - \sum_l \gamma_l w_j^l}{\gamma_q + \omega_j}\right]}_{\text{Competitive Quality}} \underbrace{- s_j(\mathbf{q}, \mathbf{p}, \vartheta, \tau) \left[\frac{\partial s_j(\mathbf{q}, \mathbf{p}, \vartheta, \tau)}{\partial q_j}\right]^{-1}}_{\text{Quality Mark Down}}. \tag{25}$$

5.3 Estimation

We have to estimate three sets of parameters: the linear parameters in the utility function ($\theta_1 = \eta$), the non-linear parameters in the utility function ($\theta_2 = (\phi, \varphi)$) and the marginal cost function parameters ($\theta_3 = \gamma$), which also include the vector of school fixed effects for the marginal cost of quality ($\overline{\omega_j}$). Our estimation has three steps.[28]

5.3.1 *First Step: Demand Parameters Estimation*

In the first step, we estimate the parameters (θ_1, θ_2) following Berry (1994), Berry et al. (1995), Petrin (2002), Berry et al. (2004) and Neilson (2013). We combine aggregate moments to get the unobservable quality for each school, micro moments to approximate the heterogeneity in preferences across different types of families, and IV (demand) moments to deal with endogeneity.

First, we use *aggregate moments for the shares*. These moments make us choose the parameters such that for each year and school the model matches the predicted school market shares to observed shares, what will help us identifying the unobservable school quality (ξ) parameter. We can summarize them as: Where $s_{jt}(\theta_2)$ is the expression in Equation 12. These aggregate share calculations will not consider the treated types -we are assuming there are no general equilibrium effects. Then, the vector $\boldsymbol{\pi}^m$ will be such that $\sum_{k=1}^{6} \pi_k^m = 1$ and $\pi_j = 0, j = 7, 8, 9, 10$.

Second, we use *micro moments* as in Petrin (2002) and Berry et al. (2004). These moments help us choose parameters so that the expected characteristics of the chosen schools (in terms of quality, price and distance) match the true chosen characteristics.

These moments are particularly useful for identifying the heterogeneity of preferences for observed school characteristics by observed family types. From the micro-data we have N_m observations in market m of students identified as type k at time t and their choices. Then, we can use the empirical averages of quality, price and distance chosen by these families to approximate the expectations in the expressions above. We can obtain the expectation for each characteristic given

[28]See Appendix O-4 for additional estimation details and a discussion on how we calculate standard errors.

the model's parameters from the distributions of student of each type in each node across schools in the market.

Finally we include *IV-demand moments*. Noting that ξ_j is correlated with both q_j and p_j, we deal with the endogeneity problem using an IV strategy that follows Berry et al. (1995). We define instruments taking advantage of the variation of costs across markets and changes to the voucher policy over time. These moments express an orthogonality condition between the demand side unobservable ξ_j and the chosen instruments.

We need instruments that are related to price and quality but not related to the unobserved quality of the school. The instruments include cross-market cost shifters such as the baseline voucher, which varies across time. Finally, we use the variation in prices induced by the SEP policy. This policy effectively eliminated prices at a significant number of schools for almost half of all students. The change in prices induced by this policy affect equilibrium prices and quality for all students through schools' first order conditions. This equilibrium effect occurs differentially across neighborhoods that have more or less concentration of eligible students, so the timing of the policy is interacted with the concentration of eligible students around the school.

5.3.2 *Second Step: Estimation of Parameters for Treated Types*

We estimate the parameters in (φ) in a second step using a set of moments that we call the *RCT Moments*, conditional on the demand estimates obtained in the first step.

With this set of moments we exploit the random assignment of the treatments. The idea is that the additional parameters for the treated types should replicate the treatment effects that we find in the reduced form, in terms of the quality, price and distance of the schools chosen by treated and non treated families, conditional on their family type. In particular, the moments will match the difference of the characteristics chosen by the control and treated families. These moments are useful at identifying the effect of the treatments in preferences for specific attributes.

We have two moments for each characteristic (one for each family type given by mother's education, incomplete high school and complete high school):

$$G^4_{q,k}(\theta_2, \theta_2^T) = \quad \hat{\beta}_k - \hat{\beta}_k{}^{sim} = (X'M_D X)^{-1} X' M_D Q_k - (X'M_D X)^{-1} X' M_D Q_k{}^{sim} \tag{26}$$

$$G^4_{p,k}(\theta_2, \theta_2^T) = \quad \hat{\alpha}_k - \hat{\alpha}_k{}^{sim} = (X'M_D X)^{-1} X' M_D P_k - (X'M_D X)^{-1} X' M_D P_k{}^{sim} \tag{27}$$

$$G^4_{D,k}(\theta_2, \theta_2^T) = \quad \hat{\lambda}_k - \hat{\lambda}_k{}^{sim} = (X'M_D X)^{-1} X' M_D D_k - (X'M_D X)^{-1} X' M_D D_k{}^{sim} \tag{28}$$

where X is a vector with the treatment indicator, Q, Q^{sim} are the vector of true and simulated qualities for each experiment observation (analogous for price and distance). The matrix M_D transforms the data to include pre-school municipality fixed effects (the stratification in the original randomization).

5.3.3 *Third Step: Supply Parameters Estimation*

Finally, we estimate supply side parameters (θ_3) using *IV-Supply Moments* that exploit the orthogonality between unobserved costs and the instruments, together with the panel nature of the data.

We obtain an expression for the unobserved costs from the school first order conditions. As in the previous section, we will focus on the FOC for quality, as the pricing decision is more complicated because of the voucher. Voucher schools face some restrictions on how much they can charge, and many choose not to charge a fee on top of the voucher. The kink solutions generated by these restrictions and by the fact that some schools would even be willing to charge a negative price (given the voucher), which we cannot observe, complicates how we think about pricing decisions. Rearranging Equation 25 we get an expression for the unobservable shock that affects the marginal cost of rising quality:

$$\Delta\omega_{jt} = \frac{v + p_{jt} - \sum_l \gamma^l w^l_{jt}}{\left[q^*_{jt} + s_{jt}(\mathbf{q}, \mathbf{p}, \boldsymbol{\xi}) \left[\frac{\partial s_{jt}(\mathbf{q}, \mathbf{p}, \boldsymbol{\xi})}{\partial q_{jt}}\right]^{-1}\right]} - \gamma^q - \overline{\omega_j}. \tag{29}$$

For a description of how we estimate the school-specific fixed component of the cost, $\overline{\omega_j}$, see the Appendix O-4.

5.4 Parameter Estimates

5.4.1 *Demand*

Table 4 presents results for the estimated parameters for school choice ϕ and the policy parameters φ. The three first rows show preferences for quality by family characteristics[29]. We refer the reader to Neilson (2013) for a discussion of the demand parameters overall and focus on the new estimates associated with the policy parameters ψ.

The estimates for the policy parameters show that they seem to reduce the differences across types in the weight given to school characteristics. In particular we can see that the ψ for non high

[29]Using the estimated model parameters, we can show how well the model fits the empirical features we are interested in replicating. The distribution of school quality in aggregate fits perfectly given that the model must replicate the aggregate share of each school perfectly. The Online Appendix shows the fit of the model by the mothers' educational group, showing a relatively adequate fit given moments include only means across markets.

Table 4: Demand Model Estimates

φ_k^q - Weight on Quality	
Mother No HS	1.37†
Mother HS	1.57†
Mother College	1.89†
Poor Household	-0.58†
Treated Mother No HS	0.55†
Treated Mother hspace	0.34†
φ_k^p - Weight on Price	
Mother No HS	-9.89†
Mother HS	-2.84†
Mother College	-0.01†
Poor Household	-3.31†
Treated Mother No HS	9.26†
Treated Mother HS	2.80†
φ_k^d - Weight on Distance	
Mother No HS	-0.99†
Mother HS	-0.70†
Mother College	-0.38†
Poor Household	-0.21†
Treated Mother No HS	0.38†
Treated Mother HS	0.12†
σ - Quality	0.13†

Note: † indicates significance at 0.01 confidence level.

school educated mothers pushes down the weight out of pocket prices op and distance play in determining choices, and raising the importance of school quality q. The differences in weights between non high school mothers and more than high school mothers is reduced substantially. Note that more educated mothers are not being treated in this policy, both in the RCT as in the planned scale up.

5.4.2 Supply

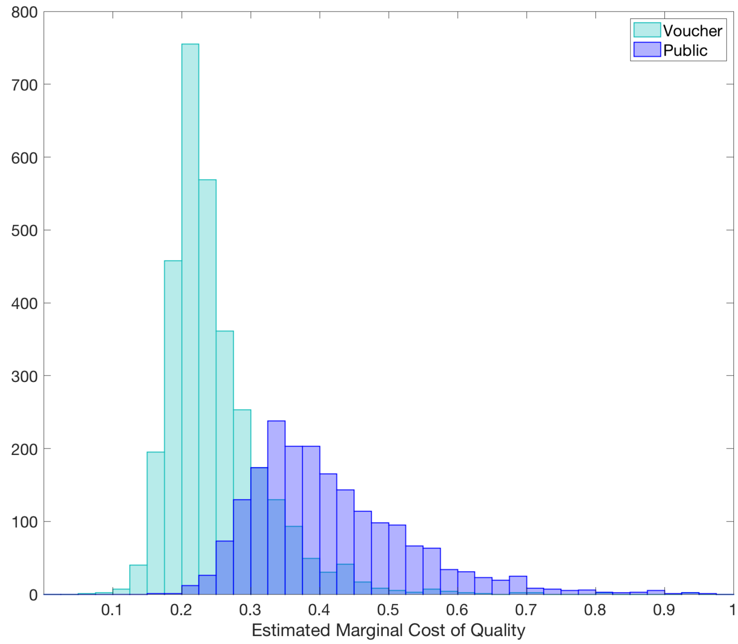
The estimated marginal cost fixed effect at the school level is presented in Table 5. It can be seen in Figure 5 that firm specific marginal costs of quality are larger for public schools. There are also systematic differences in costs faced by schools in different markets as we show in the appendix. Religious schools have lower costs and for profit schools face higher marginal costs. During estimation we have assumed profit maximization in the objective function which is likely to be at odds with the objective function of public schools and some nonprofit schools like religious schools. However it is interesting to note that public schools, should they use all their funds to product quality without regard to their market power, would look more efficient through the lens of the first order condition of a profit maximizing firm. The fact that they seem more inefficient in this estimation suggests this is a upper bound on their efficiency and raises the posibility that these schools are much less efficient. This is corroborated in external data on school spending. The data on all school expenditures is not used in estimation and is presented in **??** showing a significant difference across private and public schools. The left panel shows expenditure per student and school quality while the right panel shows expenditure per teacher and school quality. Both tend to show that higher levels of spending produce higher levels of value added amoung private schools but that relationship is much more muted among the public schools.

Table 5: Supply Model Estimates

γ_l - Marginal Cost	
Voucher	$0.12^{\dagger}$
Public	$0.65^{\dagger}$
For Profit	$0.25^{\dagger}$
Religious	$-0.10^{\dagger}$
Constant (Mean Market FE)	0.44
γ_q - Quality Marginal Cost FE	
Constant (Mean Firm FE)	0.31

Note: † indicates significance at 0.01 confidence level. Mean Market FE and Mean Firm Effects are show to give a sense of the magnitude.

Figure 5: Firm Level MgC(q)



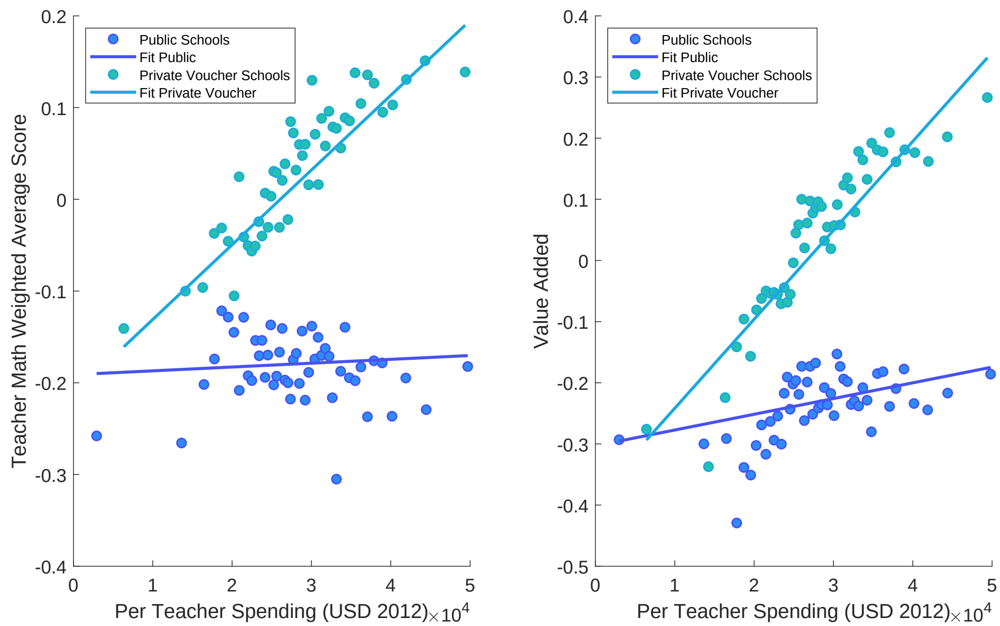
Note: This figure shows the distribution of $\overline{\omega_j}$ for public and private voucher schools. The distribution of the schools marginal cost of quality is shifted to the right for public schools suggesting that more resources are needed to produce the same level of value added. See Table 5 for other cost parameters.

Specifying the school cost structure with a school specific marginal cost of quality is important because we will consider counterfactual policy where we want to predict the schools reaction to changing demand.

To explore whether the estimated marginal costs are reasonable we compare them with out of sample data of two types. The first comparison is to look at the correlation between spending on teachers and school quality. The main proxies for the productivity of teachers and teaching staff are test scores of teachers (a performance proxy) and the value added of the school. Figure O-26 shows the correlations between per teacher spending and these two measures. Per-teacher spending accounts for spending on labor resources divided by the number of teachers in the school. Teachers' math weighted average score represents the average of teachers' scores in the school weighted by their teaching hours. The math test is the test for entering college or tertiary education, at the end of high school. On the other hand, value added is a measure of the quality of the school (more details on the Value Added Section). The main takeaway from Figure O-26 is that private voucher schools have a positive relationship between their labor expenditures and their quality. Public schools seem to see no relationship between spending on teachers and quality.

Thse findings are consistent with the structural estimation that finds public sector providers to be less efficient.

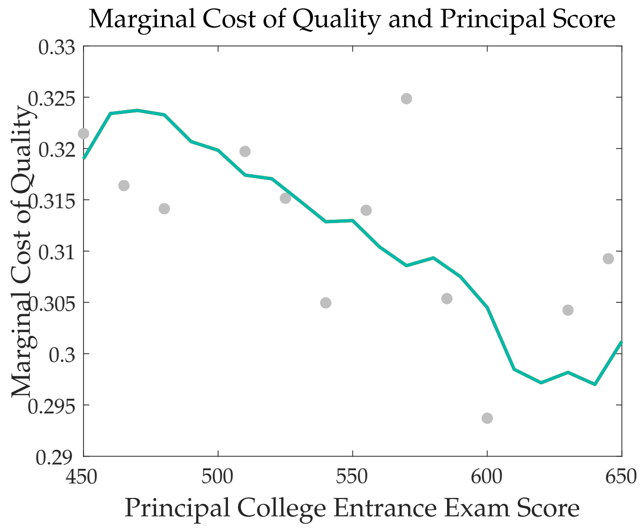
Figure 6: Share of Labor Spending over SEP Expenditure in 2012



Note: This figure shows the correlation between labor spending and the average weighted teachers' score of the school in the left subfigure; and the correlation between labor spending and the school value-added in the right subfigure. Both subfigures are differentiated by types of school, showing a positive relationship between labor spending and the productivity proxies for private voucher schools, while public schools show low or none relationship.

As a second out of sample test, we explor the relationship between firm specific marginal costs of quality and see if that is correlated with a measure of school administrator human capital. Specifically we merged digitalized public records of the college entrance exam for each school's principal as take that as a measure of their human capital and correlate that with the estimated school specific productivity. Figure 7 shows a binned scatter plot for the correlation between the estimated marginal costs of increasing quality by school and a measure of the school's principal ability given by their college entrance exam test average score. We find a negative correlation between these two variables, which is reasonable as we may expect more skilled administrators are more likely to be more efficient and be able to increase the quality of their school at a lower cost.

Figure 7: Correlation between MgC(q) and Principal's College Entrance Exam



Note: This figure shows the relationship between principals college entrance exams and the estimated school specific marginal cost of producing quality $\overline{\omega_j}$. The line plotted is the conditional mean for principals with scores within a window of 0.1σ of the distribution of principals math scores. This relationship suggests that principals human capital is associated with more efficient schools.

5.5 Simulation of Aggregate Policy Effects

We can use the estimated empirical model to evaluate the potential effects of the information policy under different counterfactuals. The empirical model described in the previous sections provides a rich environment where we can simulate policies at different locations and in different intensities. For brevity we start with polar cases where $\tau = 0$ or $\tau = 1$ for all families with mothers without high school education and with mothers with high school education. In practice, a realistic version fo the policy is implemented through the public preK network, so the detailed micro data on preK enrollment can be used to implement a more realistic version in which the porportion of families treated $\tau < 1$ varies to replicate the coverage and attendance of private preKs. We also run simulations with different supply side flexibility. The different counterfactuals allow us to evaluate short and long run effects of a policy implemented at scale taking into account both demand and supply side adjustments.

We begin with a counterfactual that assumes no supply side reaction and no capacity constraint. This simulation approximates the potential effects through students sorting to the existing schools and does not take into account any adjustments or institutional restrictions. While not realistic, this simulation is informative regarding the size and direction of the effects given the location and quality of schools currently available. If we expecte the supply side to not improve their quality, this can be considered an upper bound on the effects of the policy.

We then add more layers of complexity and simulate sorting with capacity constraints to approximate the effects of a more realistic at scale policy implementation and provide a quantitative measure of Equation 7. Specifically, in our second counterfactual, we take into account the fact that capacity constraints could bind once treatment shifts demand on aggregate. Using the estimated preferences, we generate a rank ordered list of the schools in the market for each student. We use the simulated applications to assign students to schools that have capacity constraints though a defered acceptance algorithm with lottery numbers to break ties, which is the system that is currently being used in Chile. This is useful for simulations of counterfactuals as it limits the ability for schools to change their admissions policy given potential changes in demand.

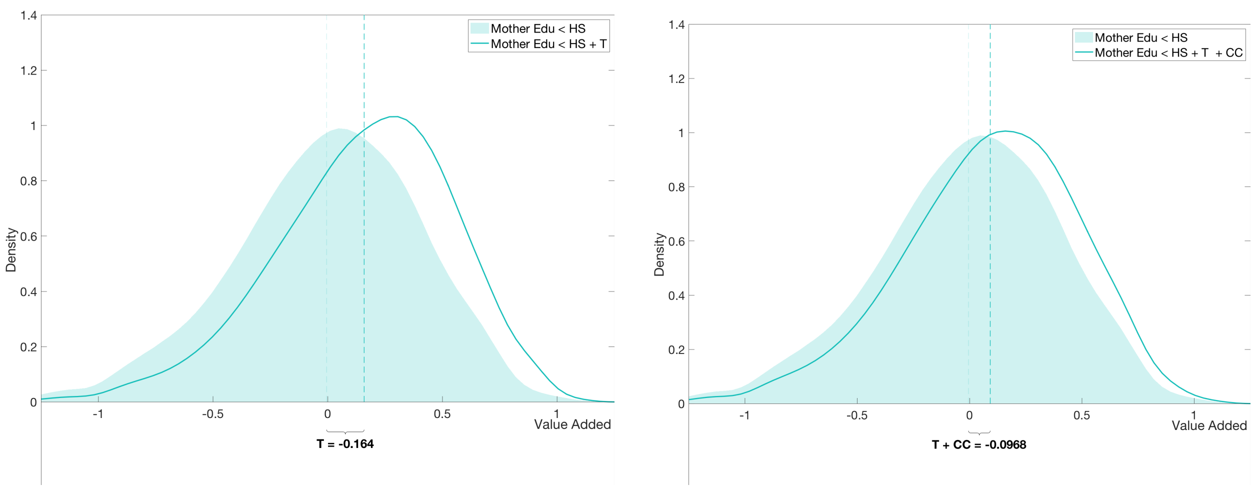
Then, we run a simulation that allows schools to choose quality and prices freely as a way to approximate a supply side reaction to the scale up version of the policy. This is a lower bound of what we can expect in a longer run equilibrium given by Equation 8.

In each simulation we report several statistics to summarize the new equilibrium and how it choices and alternatives have changed. The first is from Equation 6 and can be quantified by $\mu_q^{\text{No HS}}(\mathbf{q}, \mathbf{op}, \vartheta, \tau = 1) - \mu_q^{\text{No HS}}(\mathbf{q}, \mathbf{op}, \vartheta, \tau = 0)$. The second is to approximate the expression provided in Equation 21 where we recover the distribution of school value added across different SES groups under each counterfactual and use the difference in the average school quality as our main metric to compare outcomes under different scenarios.

5.5.1 *At Scale Implementation, Demand Side Responses*

In the very short run we can imagine schools will not be able to respond to an unpredicted demand shock. To implement this simulation, we will hold the set of schools and their quality and price fixed and apply the treatment to all students in the market so that $\tau = 1$ for all nodes in each market. We start with this assumption and simulate probabilities of going to each school for all the students in each market. We compute the implied distribution of value added for the low SES group with and without treatment as is shown in Figure 8. We see a substantial difference in the average quality of school attended by students of low SES when compared to the baseline. However, the implied distribution of demand over capacity shown by the third curve of Figure 8a suggests that the better schools in poor neighborhoods would have to grow their matriculation substantially to make space for additional students. This suggests capacity constraints may be an important factor in the short run.

Figure 8: Distribution of Quality - At Scale Policy - Capacity Constraints



(a) At Scale Implementation

(b) Capacity Constraints

Note: This figure shows the distribution of school value added conditional on the students' mothers' education. Panel A shows a simulation where low SES families are all treated ($\tau = 1 \ \forall \ n$) and schools cannot adjust prices or quality and there are no capacity constraints. This is the closest comparison to the small scale RCT given that the intervention and the change in behavior of families has no spillover effects on other families or schools. Panel B shows the change in the distribution of school value added conditional on the students' mothers' education in a simulation where low SES families are all treated ($\tau = 1 \ \forall \ n$) and schools cannot adjust prices or quality but schools do face actual capacity constraints. This approximates what could happen in the very short run when schools have yet to adjust and demand has moved away from the prior equilibrium.

In the next simulation, we include the role of capacity constraints explicitly because while they are expected to bind, we are unsure how important this constraint may be quantitatively. Figure 8b shows the impact on the distribution of school quality with fully saturated treatment,

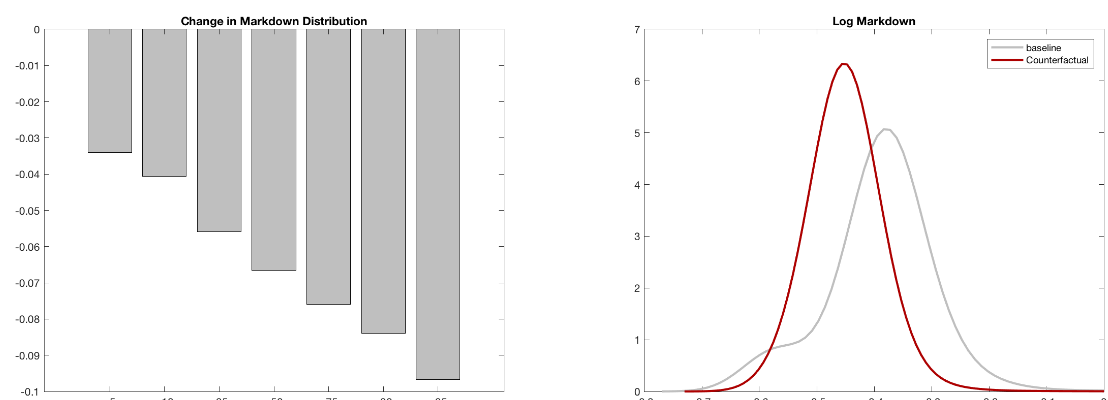
$\mu_q^{\text{No HS}}(\mathbf{q}, \mathbf{op}, \vartheta, \tau = 1)$, and without the policy $\mu_q^{\text{No HS}}(\mathbf{q}, \mathbf{op}, \vartheta, \tau = 0)$. We use simulation of preferences as well as assignment lottery numbers to produce allocations and summarize the result in Figure 8b. We can see that when capacity constraints are taken into account the effects of the policy are reduced dramatically. The plot shows the distribution of quality attended for families with mothers with less than a high school education. The mean effects are indicated in the figures but the notable result is that average treatment effects found in the randomized control trial are almost halved when the policy is scaled up and capacity constraints are active.

5.5.2 *At Scale Implementation, Demand and Supply Side Responses*

The simulations in the previous section show lower effects due to congestion when the policy is scaled up. This suggests that there could be meaningful effects on school incentives. To explore the extend to which school incentives changed on impact, we calculate quality markdowns from the FOC defined in Equation 25 and how they change when the policy is implemented. We plot the distribution of the markdowns with and without the policy on impact in Figure 9 where we can observe that incentives change but the policy seems to have a significant degree of heterogeneity, suggesting that some schools would face larger changes in incentives than others.

This evidence is consistent with recent research emphasizing supply side reactions in education markets (Neilson (2013); Dinerstein and Smith (2015); Andrabi et al. (2017)) and suggests exploring whether supply side reactions in the aggregate can be expected to change the effects of the policy simulations. In this context, schools have many more margins through which to adjust

Figure 9: Markdown Change on Impact



(a) Percentiles

(b) Distribution

Note: This figure shows the change in the distribution of school quality markdowns on impact when the policy is implemented at scale. No other schools adjustment is taken into account. This quantifies the change in incentives on impact of the policy. The graphs show significant heterogeneity across schools.

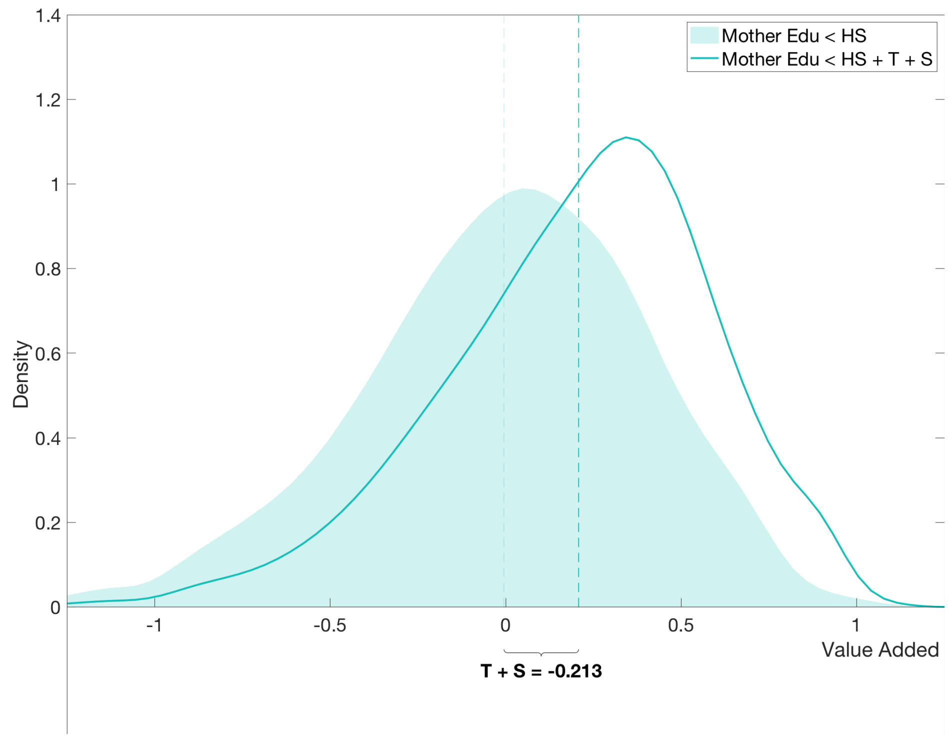
when considering a longer horizon. We focus on how the changing environment would lead to readjustment of the characteristics of the current schools and ignore other margins including entry, exit or investments in capacity. To explore the extent to which schools might readjust their characteristics once the policy is in place we conduct a simulation with a fully saturated policy again with $\tau = 1$ and allow school to adjust quality. Prices have now been frozen due to recent policy changes. We calculate the new equilibrium vector of quality when demand shifts in response to the policy implemented at scale. Capacity is held constant so this simulation could be interpreted as a medium run outcome where prices are fixed due to regulation, capacities are fixed due to slow adjustment in school size but schools can hire more and better inputs such as teachers and exert more effort.

To implement the simulation, we look for a local equilibrium allowing schools to iteratively adjust their FOC in small steps. One intuition for this type of procedure is based on Doraszelski et al. (2018), where it is assumed that schools have uncertainty about their rivals' costs but know the demand parameters. After a policy change, schools will not inmediately play the Nash equilibrium but will rather choose quality computing their first order conditions based on the demand they expect and their beliefs about their rivals' quality which can be heavily weighted on past observation in a context of a lot of uncertainty. Iterating over this adjustment process we find an equilibrium.[30]

Figure 10 shows the distribution of quality once the policy is expanded at scale and schools can adjust levels of quality. The effects are quite significant and the average treatment effects are similar if not bigger to the effects found in the randomized control trial. These simulations suggest the equilibrium effects will tend to be raised by increasing supply of school quality once families in poor neighborhoods are exposed to the policy and put more weight on school quality when choosing schools.

[30] The results in Doraszelski et al. (2018) support the idea that in stable environments, play of this sort will generally converge to a Nash equilibrium. In this application, iteration on small adjustments quickly find new equilibria in each counterfactual simulation.

Figure 10: Distribution of Quality - At Scale Policy - Medium Run Effects



(a) No High School Mother Type

Note: This figure shows the change in the distribution of school value added conditional on the students' mothers' education in a simulation where low SES families are all treated ($\tau = 1 \;\forall\; n$) and schools cannot adjust prices but can adjust quality and face actual capacity constraints. This approximates what could happen in the medium run when quality can adjust but prices are frozen as is the current policy in Chile.

5.6 Robustness and Discussion

It is expected that over time, investment in capacity or entry may play a bigger role. However, in prior work in the context of Chile, entry/exit margins were not found to be large drivers of change given current market structure and policy that seemingly has excess capacity (Neilson, 2013). Similar to the analysis in Wollmann (2018), this counterfactual focuses on the adjustment of product characteristic and is what we consider a lower bound on supply side effects over time. Capacity constraints and limiting entry both presumably dampen competition that is driving the change in incentives to invest in quality. This could also represent a medium run approximation to what could be expected to happen given the policy implementation.

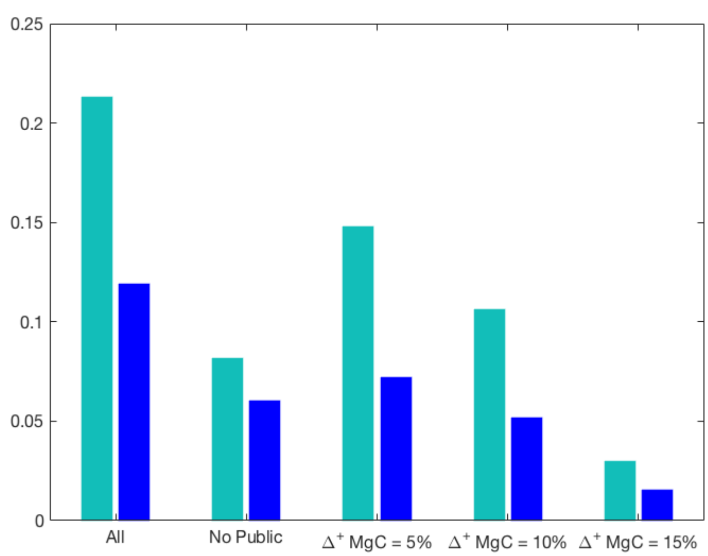
5.6.1 *Alternative Assumptions About Participation*

Additional simulations repeat the exercise with more realistic assumptions of supply responses. These results are presented in Figure 11. The first one is presented in the second column. For this exercise, we assume that public schools do not react at all, as they maximize quality given budget and ignore market conditions otherwise. We see that under this assumption low SES students are particularly affected.

5.6.2 *Potential Spillovers to Inputs Markets*

Policy changes that induce an increase in the provision of quality can put pressure on inputs markets. For example, schools may have to hire better teachers to increase their quality, increasing the demand and thus wages in teachers' labor markets. Schools' decisions could be different as they face higher marginal costs. In this simulation, we explore what might happen if increased demand for school quality inputs increased marginal costs across the board by 5%,10% and 20%. In all cases we find positive effects although increasing costs and limiting supply side reactions reduce the average policy effect relative to the benchmark in Figure 11.

Figure 11: Difference with the Baseline mean Quality



Note: This figure shows the change in the average policy effect when different assumptions are made about the slope of the marginal cost of quality curve. As marginal costs can increase with more demand for quality in the aggregate, we test how big would these increases need to be to eliminate the observed supply side effects. We find that an increase of 15% would eliminate most of the effects.

5.6.3 *Summary of Policy Simulation Exercises*

The results from the counterfactual analysis are summarized in Table 6. We find that capacity constraints play an important role in limiting the policy effects. We also find evidence that schools will have incentives to improve quality, especially in poor neighborhoods. In practice these aggregate effects imply students not affected directly by the policy (parents did not attend meetings for example) would find the set of schools available to them having higher quality.

Table 6: Summary of Policy Effect Simulations

	Experiment	Model						
	ATE	T	T+CC	T+CC+S (All)	T+CC+S (noPub)	$\Delta^{+}5\%$	$\Delta^{+}10\%$	$\Delta^{+}15\%$
All	-	0.076	0.041	0.104	0.0449	0.0770	0.0569	0.0193
No HS Mother	0.118	0.164	0.097	0.213	0.0817	0.1477	0.1061	0.0299
HS Mother	0.048	0.091	0.056	0.119	0.0600	0.0721	0.0518	0.0150
College Mother	-	0.000	-0.015	0.015	0.0126	0.0110	0.0080	0.0060

Note: This table summarizes the results of the policy simulations under different assumptions about constraints and the adjustments schools are allowed.

An important aspect to note is that in these counterfactuals simulations we are leaning on several current institutional aspects that could play a crucial role in the quantitative exercises. One is that applications to schools are processed in a centralized application system and the other is that prices have been fixed. These allow us to ignore potential changes to admissions policies when demand suddenly shifts due to the policy. Estimation is implemented in a stable environment where we assume excess demand is less of an issue as school have had time to adjust price and quality but this assumption seems less reasonable if a large policy change happened suddenly. The second policy fixing prices is also likely to play a role because this shuts down the ability for a high quality school with excess demand to raise prices, potentially dissuading poorer families that value quality more but are still more price sensitive that richer families. While this reduces incentives for high quality firms to increase quality it still leaves low quality schools to have incentives to increase their quality.

5.7 Leveraging the Estimated Model to Design a Large Scale RCT

The information provided in the simulations approximates the equilibrium outcomes of the implementation of the information policy at scale. Policy makers can use the evidence from the randomized control trial, together with this menu of quantitative results that consider equilibrium constraints of different types to help inform decision making. However, in some cases, the risk of making a mistake in the implementation of a policy can be too great and a policy maker might well be willing to invest in obtaining additional information about the effects of an at scale implementation of the policy. In this case, the RCT and the empirical model described in this paper can also help inform the design of an at scale.

The estimated empirical framework can be used to study the effects of different configurations of treatment and control neighborhoods. By controling the τ that is relevant for families in each node we can calculate the change in demand at the block level, $s_j^{nk}(\mathbf{q}, \mathbf{op}, \vartheta, \tau)$, once treatment is implemented by using Equation 18. Treating different sized clusters of blocks in an area will lead schools nearby to be exposed to different degrees of the policy treatment described by the vector τ and the demand they face $s_j^k(\mathbf{q}, \mathbf{op}, \vartheta, \tau)$ can be characterized by Equation 19. When enough blocks in the surrounding area are treated, a school will be full exposed to the change in demand but not necessarilly the equilibrium effect of the policy if not all competing schools in the area are also fully exposed. Using the estimated parameters that describe the substitution patterns of families and the degree of competition across schools, we can simulate the effects that we would obtain under different cluster designs.

We propose a generic design that consist in clusters defined by three areas. First, the core of the cluster, which size will be defined by an inner radius and is shown in solid colors in Figure 12. This will be our unit of observation for the simulated effects of the policy on school congestion and school quality. Then, we have an the intermediate zone, which contains the area defined by a bubble which radius is the sum of the inner and the outer radius, including the core. This will be our unit for policy implementation. In treated clusters, all the nodes that fall inside these intermediate zones will be assigned to the treatment for simulations. Finally, we define a buffer zone, which is defined by an outside buffer of the intermediate zone. This area between treated and control neighborhoods is needed to have a clean experiment. The smaller the buffer, the more likelly it is that there can be spillovers between treatment and control clusters.

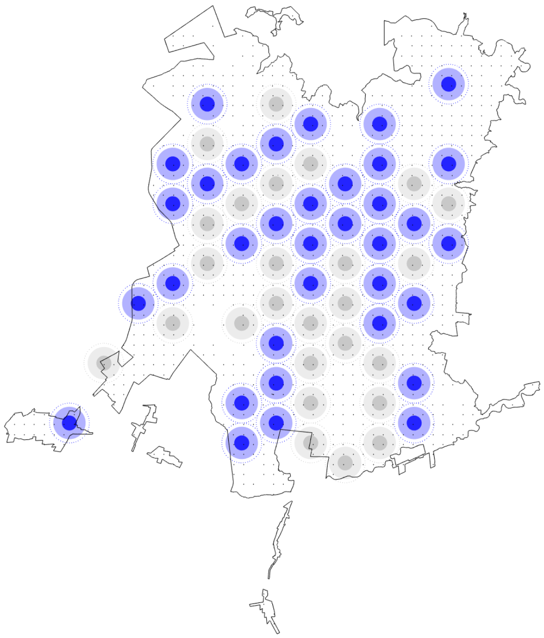
Figure 12 shows four different configurations of treatment and control clusters of blocks in Santiago. For simplicity, all clusters have the same buffer radius. Clusters A and B have the same total radius, but differ in the relative sizes of the inner and outer buffer. Same for clusters C and D, which both have a larger total radius than the first two. In all figures, the blue Then, we can use the estimated model and assign the treatment to the nodes cosimulate the demand and supply effects of the policy implemented only in treated groups. Spillover effects can be quantified and used to evaluate the properties of each experimental design.

Table 7 shows the results of running a regression on the simulated at scale RCT using Equation 30.

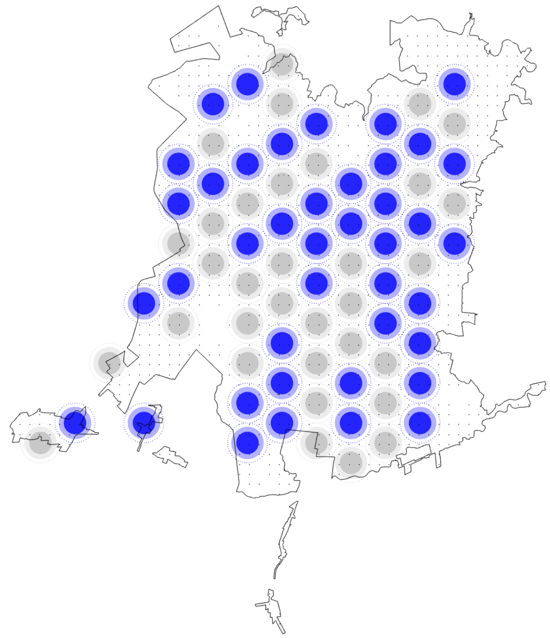
$$Y_{jt} = \alpha_m + \beta T_c + \gamma Y_{jt-1} + \epsilon_{jt} \tag{30}$$

Where m is the market and standard errors are clustered at the level of neighborhood c.

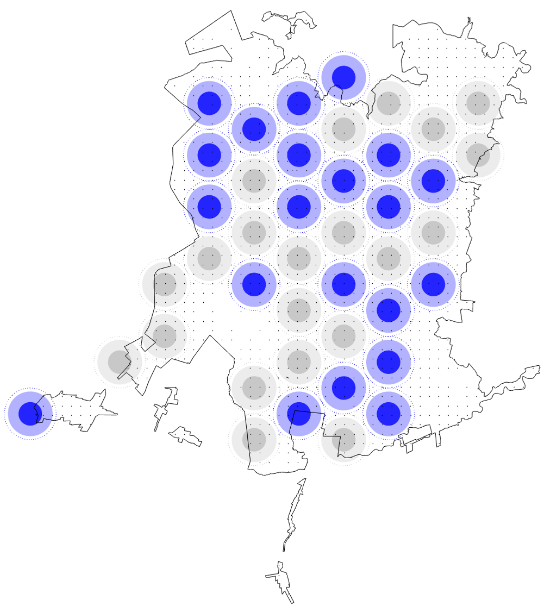
Figure 12: Effect of School Choices



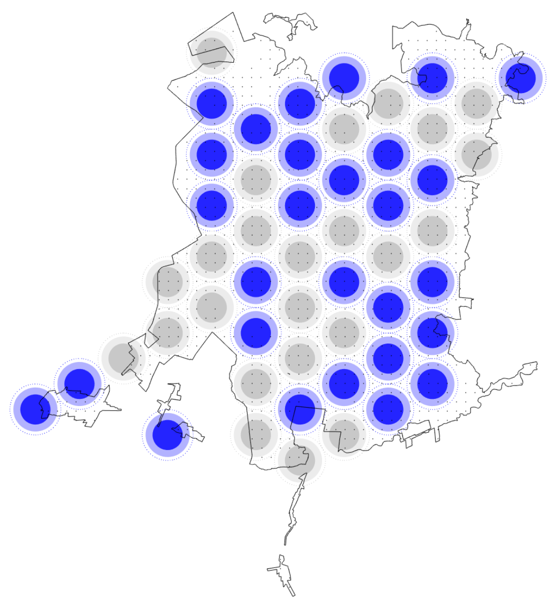
(a) I=0.6 km, O=0.7 km, B = 0.3 km



(b) I=0.9 km, O=0.4 km, B = 0.3 km



(c) I=1.0 km, O=0.9 km, B = 0.3 km



(d) I=1.3 km, O=0.6 km, B = 0.3 km

Note: This figure shows two different configurations of treatment and control clusters of blocks. The appropriate choice of inner bubble and buffer zone respond to the degree of spillovers and the substitution patterns found among families school choice when treated and not treated.

Table 7: Expected Impact of At Scale Policy RCT

	Design (Numbers of)			Radius (km)				Simulated Effects	
	Obs	Clusters	Nodes	Total	Inner	Outer	Buffer	Diff T-C	Control Mean
A	326	122	930	1.6	0.6	0.7	0.3	0.0537 (0.0231)	0.0018 (0.0007)
B	818	148	1088	1.6	0.9	0.4	0.3	0.0346** (0.0176)	0.0029 (0.0012)
C	932	84	1692	2.2	1.0	0.9	0.3	0.0543* (0.0285)	0.0024 (0.0011)
D	1258	104	1712	2.2	1.3	0.6	0.3	0.0379 (0.0117)	0.0017 (0.0009)

This procedure is meant to be used together with other budgetary and political considerations when designing a randomized control trial at scale. The estimated model can incorporate the treatment effects on individual behavior and in addition can be used to aggregate the behavior to describe what spillover effects can be expected from a partial at scale implementation of the policy. The hope is this can be useful when designing large and expensive RCTs that do not have prior knowledge of how big spill over effects will be when supply side reactions are incorporated.

6 Discussion

Economist generally agree that an informed consumer demand is an important aspect of a well functioning market. A lack of information can lead individuals to make inefficient choices, and this could potentially have aggregate effects, decreasing efficiency. In the case of the market for education services, a growing body of evidence from different contexts suggests that providing information to individual families may indeed shift their school choice, and in some cases information provision can have aggregate effects. The prospect of a government policy based on this idea is very attractive since it has the potential to improve equity and efficiency at a very low cost. This is especially true in developing countries where private provision of services like education is common, but government supervision and regulation tend to be lax. In spite of this, when it comes to designing and implementing government policy, it is not clear how to extrapolate the existing evidence from different contexts. Design details, capacity constrainsts and supply side reactions can all make a particular intervention ineffective when it is implemented at scale.

In this paper, we employ a series of empirical tools and data to study the small- and large-scale effects of a particular policy that promotes information provision. We draw upon insights from prior research to develop an intervention that is low cost, scalable, and compatible with local political, institutional, and logistical restrictions. Using a small-scale randomized control trial, we evaluate whether this type of intervention can affect choice and later outcomes. The results provide evidence that an intervention of this type does indeed shift parents choices and raises student achievement several years later. To extrapolate to aggregate policy implications and evaluate equilibrium considerations, we embed the randomized control trial within a structural model of school choice and competition, estimating the parameters that describe how supply and demand would react to the policy intervention. We estimate the parameters of the supply and demand model, taking advantage of rich administrative and survey data, variation from recent policy changes, and the variation generated from the randomized control trial.

Using the empirical estimates from our structural model of school choice and competition, we evaluate the policy effects of an at-scale evaluation when students sort, capacity constraints bind but schools do not react. We then evaluate the effects of supply side reactions in equilibrium under different assumptions regarding how public and private schools react, and how costs may vary with the scale of the policy. We find positive effects of the policy that range from 50%-120% of the average treatment effect in the randomized trial, suggesting positive effects overall but potencially small short run effects due to capacity constraints. Depending on the assumptions used, the effects on average school quality attended by low socioeconomic families varies between $0.06\sigma - 0.22\sigma$.

These results add to prior work such as Andrabi et al. (2017) and suggest that this information intervention can be a cost-effective way to improve efficiency and equity in education markets with a large private sector, as is the case in many developing countries. Researchers can use our empirical strategy to study aggregate effects of new ways to provide information. For example, virtual assistants or chatbots leverage artificial intelligence to provide rich and dynamic personalization of information and are rapidly being deployed in many markets, such as retail and health care (Agrawal et al., 2018). Future research should study whether these new tools can have an impact on individual decisions and market efficiency in education contexts. Our empirical strategy combining evidence from a small scale randomized control trial together with an equilibrium model of supply and demand can provide a platform to study the market level effects of these and other new innovations in information provision.

Measuring school quality and retrieving causal estimates of value added are difficult, and testing students regularly is expensive and impractical in many contexts. The evidence presented in this paper suggests that governments in developing countries could have a high return on investing in systems to collect and disseminate basic information about schooling options. It is important to note that the intervention we studied did not focus exclusively on information about test scores, but also tried to persuade families that the return on investing in effort to search and choose a school carefully is high. This second aspect is complementary to the available informational structure and potentially less dependent on the quality of information available. Future research can help clarify the role of information provision in stimulating more search given that some very important aspects of education provision will remain fundamentally unobservable without some family effort.

Beyond the specific policy implications of this information intervention, we argue that the combination of randomized control trials and structural models of supply and demand can be useful for policy evaluation for several reasons. First, a randomized control trial implemented at scale is often politically or technically infeasible. Small-scale randomized control trials can be more cost effective for discovering what design details work best. The effects of the best version of the intervention can then be embedded into an empirical model that incorporates the main features governing supply and demand and researchers can use this model to evaluate impact before implementing a final and costly large-scale evaluation. In this sense, we would argue that in many cases, a small-scale randomized control trial combined with a structural model can be used to evaluate equilibrium considerations is a cost effective way of gaining further insight into the potential policy effects and aspects of design in practice. This could make small-scale experiments more appealing to governments, and be a relevant intermediate step to help guide funding institutions like USAID or DFID when allocating funding for expensive large at-scale evaluations.

Finally, it is important to mention that the methods implemented in this paper benefit from several unique policy changes, institutions and access to administrative data that may not be available in other settings. In particular, prior policy changes that shifted out of pocket prices and changed government transfers to schools are critital sources of instruments for key endogeous variables such as price and quality. The introduction of centralized assigment of students to schools make both estimation and simulation of counterfactuals much more realistic in this context as well. Access to administrative data on a large set of student characteristics as well as detailed data on school prices, capacities, revenue and expenditures also make ambitious empirical endevours more manageable and in our view, starting from a small scale RCT, allow the empirical application to get quite far in providing aggregate policy advice. These data and institutional frameworks may not be available in some context but the trend in data rich environments suggests that empirical structural modeling strategies that leverage big data and credible small scale RCT evidence will have increasinly more scope to inform policy in the future.

References

Aedo, Cristián, "Diferencias entre escuelas y rendimiento estudiantil en Chile," 1998.

Agrawal, Ajay, Joshua Gans, and Avi Goldfarb, *Prediction machines: the simple economics of artificial intelligence*, Harvard Business Press, 2018.

Aguirre, Josefa, "If you build it they will come: Evidence of the impact of a large expansion of childcare centers over attendance and maternal labor supply." PhD dissertation, Master's thesis, Pontificia Universidad Catolica de Chile 2011.

Akerlof, George A., "The Market for "Lemons": Quality Uncertainty and the Market Mechanism," *The Quarterly Journal of Economics*, 1970, *84* (3), 488–500.

Alfaro, Pablo, David K Evans, Peter Holland et al., "Extending the school day in Latin America and the Caribbean," *Policy Research working paper*, 2015, *7309.*

Almond, Douglas and Janet Currie, "Killing Me Softly: The Fetal Origins Hypothesis," *Journal of Economic Perspectives*, Summer 2011, *25* (3), 153–72.

Andrabi, Tahir, Jishnu Das, and Asim Ijaz Khwaja, "Report cards: The impact of providing school and child test scores on educational markets," *American Economic Review*, 2017, *107* (6), 1535–63.

Attanasio, Orazio P, Costas Meghir, and Ana Santiago, "Education choices in Mexico: using a structural model and a randomized experiment to evaluate Progresa," *The Review of Economic Studies*, 2011, *79* (1), 37–66.

Banerjee, Abhijit V and Esther Duflo, *Poor economics: A radical rethinking of the way to fight global poverty*, Public Affairs, 2011.

Berry, Steven, "Estimating Discrete-Choice Models of Product Differentiation," *The RAND Journal of Economics*, 1994, pp. 242–262.

_ , James Levinsohn, and Ariel Pakes, "Automobile Prices in Market Equilibrium," *Econometrica: Journal of the Econometric Society*, 1995, pp. 841–890.

_ , _ , and _ , "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Vehicle Market," *V Journal of Political Economy*, 2004, *112* (1), 68.

Bharadwaj, Prashant, Juan Eberhard, and Christopher A. Neilson, "Do initial endowments matter only initially? The persistent effect of birth weight on school achievement," 2017. Journal of Labor Economics.

Calle, Franco, Sebastian Gallegos, and Christopher A. Neilson, "What comes in must come out? Teacher Test Scores and Teacher Quality," December 2018. Manuscript.

Chumacero, Romulo A., Daniel Gomez, and Ricardo D. Paredes, "I would walk 500 miles (if it paid): Vouchers and School Choice in Chile," *Economics of Education Review*, 2011, *30* (5), 1103 – 1114.

Dinerstein, Michael and Troy Smith, "Quantifying the Supply Response of Private Schools to Public Policies," Technical Report, Stanford Institute for Economic Policy Research 2015.

Dinkelman, Taryn and Claudia Martinez, "Investing in Schooling in Chile: The Role of Information about Financial Aid for Higher Education," *Review of Economics and Statistics*, 2014, *96(2)*, 244–257.

Doraszelski, Ulrich, Gregory Lewis, and Ariel Pakes, "Just starting out: Learning and equilibrium in a new market," *American Economic Review*, 2018, *108* (3), 565–615.

Elacqua, G and M Martínez, "¿Padres incautos?: Análisis del comportamiento de elección escolar en Chile entre 2004 y 2009," *Mercado escolar y oportunidad educacional. Libertad, diversidad y desigualdad*, 2016, pp. 113–148.

Elacqua, Gregory and Humberto Santos, "Preferencias Reveladas de los proveedores de educacion privada en Chile," *Gestion y Politica Publica*, 2013, *22* (1), 85–129.

for Economic Co-operation, Organisation and Development, *Starting strong IV: Monitoring quality in early childhood education and care - Chile*, OECD Publishing, 2016.

Gallego, Francisco, "When Does Inter-School Competition Matter? Evidence from the Chilean "Voucher" System," *The BE Journal of Economic Analysis &; Policy*, 2013, *13* (2), 525–562.

_ **and Andres E. Hernando**, "On the Determinants and Implications of School Choice: Semi-Structural Stimulations for Chile," *Journal of LACEA Economia*, 2008.

Glewwe, Paul W., Eric A. Hanushek, Sarah D. Humpage, and Renato Ravina, "School Resources and Educational Outcomes in Developing Countries: A Review of the Literature from 1990 to 2010," Working Paper 17554, National Bureau of Economic Research October 2011.

Hansen, Lars Peter, "Large sample properties of generalized method of moments estimators," *Econometrica: Journal of the Econometric Society*, 1982, pp. 1029–1054.

Hastings, Justine S. and Jeffrey M. Weinstein, "Information, School Choice, and Academic Achievement: Evidence from Two Experiments," *Quarterly Journal of Economics*, 2008, *123(4)*, 1373–1414.

Hastings, Justine S, Christopher A Neilson, Anely Ramirez, and Seth D Zimmerman, "(Un) informed college and major choice: Evidence from linked survey and administrative data," *Economics of Education Review*, 2016, *51*, 136–151.

Heckman, James J, Lance Lochner, and Christopher Taber, "General-Equilibrium Treatment Effects: A Study of Tuition Policy," *American Economic Review*, May 1998, *88* (2), 381–386.

Jensen, Robert, "The (Perceived) Returns to Education and the Demand for Schooling," *The Quarterly Journal of Economics*, 2010, *125* (2), 515–548.

Lavecchia, Adam M, Heidi Liu, and Philip Oreopoulos, "Behavioral economics of education: Progress and possibilities," in "Handbook of the Economics of Education," Vol. 5, Elsevier, 2016, pp. 1–74.

Lise, Jeremy, Shannon Seitz, and Jeffrey Smith, "Evaluating search and matching models using experimental data," *IZA Journal of Labor Economics*, 2015, *4* (1), 16.

Mizala, Alejandra and Florencia Torche, "Bringing the Schools Back in: The Stratification of Educational Achievement in the Chilean Voucher System," *International Journal of Educational Development*, 2012, *32* (1), 132–144.

_ **and** _ , "Logra la subvencion escolar preferencial igualar los resultados educativos?," Technical Report, Espacio Publico Noviembre 2013.

_ **and Miguel Urquiola**, "School Markets: The Impact of Information Approximating Schools' Effectiveness," *Journal of Development Economics*, 2013.

Neilson, Christopher A., "Targeted Vouchers, Competition Among Schools, and the Academic Achievement of Poor Students," Job Market Paper, PhD Disseration, Yale University October 2013.

Nguyen, Trang, "Information, Role Models and Perceived Returns to Education: Experimental Evidence from Madagascar," 2008. Mimeo, MIT.

Petrin, Amil, "Quantifying the Benefits of New Products: The Case of the Minivan," *Journal of Political Economy*, 2002, *110* (4), pp. 705–729.

Sanchez, Cristian, "Understanding School Competition Under Voucher Regimes," Job Market Paper, PhD Disseration, ITAM October 2017.

Todd, Petra E. and Kenneth I. Wolpin, "Assessing the Impact of a School Subsidy Program in Mexico: Using a Social Experiment to Validate a Dynamic Behavioral Model of Child Schooling and Fertility," *American Economic Review*, December 2006, *96* (5), 1384–1417.

Walters, Christopher R., "The Demand for Effective Charter Schools," *Journal of Political Economy*, 2018, *126* (6), 2179–2223.

Wollmann, Thomas G., "Trucks without Bailouts: Equilibrium Product Characteristics for Commercial Vehicles," *American Economic Review*, June 2018, *108* (6), 1364–1406.

Appendix

A1 Appendix Tables and Figures

Table A1: Treatment Balance at the School Level

	Difference T-C		Control Group Mean	
	(1)		(2)	
Enrollment	-1.898	(3.248)	41.467	(2.530)
Mean attendance	-1.053	(2.430)	28.689	(1.903)
Mother HE	-0.643	(1.552)	9.495	(1.320)
Mother HS	-0.915	(2.195)	48.347	(1.652)
Mother NHS	0.760	(1.010)	7.309	(0.697)
Q1 Income	0.577	(2.996)	57.970	(2.348)
Q2 Income	0.288	(2.142)	31.365	(1.587)
Q3 Income	-1.136	(1.216)	8.752	(0.930)
Very Poor	0.637	(1.865)	14.947	(1.406)
Poor	0.083	(2.233)	40.619	(1.816)

Notes: Column 1 presents the coefficient and standard error for the difference between the treatment and control groups in a regression of each variable on treatment status. Column 2 presents the coefficient and standard error for the control group mean. * p-value<10% ** p-value<5% *** p-value<1%.

Table A2: Balance for Being Enrolled at Baseline

	Difference Enrolled - Non-Enrolled		Non-Enrolled Group Mean	
	(1)		(2)	
Panel A: SES characteristics				
Household size	-0.035	(0.108)	4.927	(0.081)
Durable goods	0.382***	(0.116)	4.461	(0.080)
Owns Dwelling	0.047	(0.031)	0.343	(0.019)
Mother head of hh	0.001	(0.030)	0.832	(0.014)
Mother NHS	-0.010	(0.022)	0.192	(0.016)
Mother HS	-0.039	(0.025)	0.391	(0.019)
Mother HE	0.007	(0.019)	0.836	(0.016)
Poor	-0.013	(0.016)	0.895	(0.011)
Another child in primary	0.010	(0.029)	0.405	(0.018)
Panel B: Birth characteristics				
Gestation Weeks	-0.019	(0.094)	38.751	(0.056)
Birth Weight	-3.982	(25.338)	3,342.137	(15.176)
Mother's Age	0.329	(0.364)	25.332	(0.232)
Father's Age	-1.646	(1.217)	36.472	(0.933)
Marital Status	-0.021	(0.023)	1.735	(0.014)
Doctor	-0.011	(0.024)	0.333	(0.015)
Hospital	0.014*	(0.008)	0.959	(0.006)
Number of Children	0.102	(0.087)	1.871	(0.035)

Notes: Column 1 presents the coefficient for the difference between households enrolled and non-enrolled at baseline in a regression of each variable on an indicator for being enrolled at baseline. Column 2 presents the coefficient and standard errors for the non-enrolled group mean. Regressions include the observations for which there is data on baseline enrollment (N=1,612). * p-value<10% ** p-value<5% *** p-value<1%.