Peer Effects, Take-Up, and Usage of Subsidized Goods:
A Structural Model of the Multi-Stage Dynamic Game*

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Abstract

When a good is provided for free or at subsidized prices, issues of take-up and usage may arise. This paper examines peer effects in the take-up and subsequent usage of a subsidized good. We develop a structural econometric model of a multi-stage dynamic game in which the first stage is the take-up (or ownership) decision and, conditional on ownership, the second stage is the usage decision. We apply our model to a health promotion program that provides free eyeglasses and training to myopic students in rural China. We find that while students might be more likely to own glasses if the glasses are provided for free, students who own glasses that were given to them for free may be less inclined to use the glasses. Our results also show that the decrease in the payoff from glasses usage resulting from the glasses being provided for free can be offset, however, by an increase in the fraction of the student's peers who own and/or use glasses. Peer effects can therefore help mitigate the issue with some social or public programs that, when a good is provided for free or at subsidized prices, individuals may not use the goods provided.

Keywords: structural model, dynamic game, subsidized goods, China

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1. Introduction

When a good is provided for free or at subsidized prices, several issues may arise. One issue is that, as with many social or public programs, participation or take-up may be low (Currie, 2006; Finkelstein and Notowidigdo, 2019; Carneiro et al., 2020): only a subset of individuals may actually take up and acquire the good being provided for free or at subsidized prices. A second issue is that the usage of a good that was provided for free or at subsidized prices may be low: even if individuals take up and acquire the good, only a subset of the individuals who acquire the good may actually use it (Sylvia et al., 2020).

The issue of low or attenuated usage may compromise the effectiveness and cost-effectiveness of programs that provide goods for free or at subsidized prices, and is particularly problematic for goods that require active use in order for their benefits to be realized (Sylvia et al., 2020). Examples of goods that need to be actively used in order to generate the intended benefits include insecticide-treated mosquito nets (Hoffman, Barrett and Just, 2009; Cohen and Dupas, 2010), water purification technologies (Ashraf, Berry and Shapiro, 2010; Dupas, 2014), improved cookstoves (Miller and Mobarak, 2013), preventive health products (Dupas et al., 2016), agricultural technologies (Oliva et al., 2020), and eyeglasses (Glewwe, Park and Zhao, 2016).

Ordeal mechanisms attempt to mitigate issues of low take-up and/or low usage by encouraging targeted individuals to self-select into programs by requiring that applicants undergo an ordeal, such as a time-consuming application procedure or traveling to redeem a voucher (Nichols, Smolensky and Tideman, 1971; Nichols and Zeckhauser, 1982; Besley and Coate, 1992; Globus-Harris, 2020; Sylvia et al., 2020). Ordeal mechanisms do not necessarily have the desired targeting effect, however (Bertrand, Mullainathan, and Shafir, 2004; Mani et al., 2013; Mullainathan and Shafir, 2013; Finkelstein and Notowidigdo, 2019).

In this paper, we examine peer effects in the take-up and subsequent usage of a subsidized good. Peer effects are often viewed as the key to understanding many social problems and opportunities (Sacerdote, 2014), and may lead to a multiplier effect that can potentially improve program participation and take-up (de Paula, 2017; Beaman et al., 2018; Carneiro et al., 2020). We examine if peer effects can potentially help with subsequent usage as well.

We use data from a large-scale field experiment in China that provides free eyeglasses and training to 3,177 myopic students in 485 classes from 252 primary schools. The field experiment is a randomized controlled trial we designed and used in Sylvia et al. (2020) to test whether ordeal mechanisms and/or information campaigns improve the cost-effectiveness of a program distributing free eyeglasses to myopic students in rural China. We find in Sylvia et al. (2020) that requiring recipients to undergo an ordeal better targeted eyeglasses to those who used them without reducing usage relative to free delivery. We also find in Sylvia et al. (2020) that an information campaign increased usage when eyeglasses were freely delivered, but not under an ordeal.

We use data from this health promotion program to study the effect of peers on the decisions of myopic students in rural primary schools of China of whether to own eyeglasses and whether to use eyeglasses. There are several possible reasons why students may be more likely to decide to own and use glasses if their peers own and use glasses. One source of a positive peer effect is that students may imitate the behaviors of their peers, perhaps to "keep up with the Joneses" (Luttmer, 2005; Fliessbach et al., 2007; Card et al., 2012) or as a result of social pressure (Bursztyn and Jensen, 2017): myopic students may mimic their peers' glasses ownership and usage decisions without really understanding the benefits and costs of owning and using a pair of eyeglasses. A second source of a positive peer effect is a positive learning effect wherein myopic students may decide to own and use eyeglasses because they learn from their peers that owning and using eyeglasses yields net benefits. Benefits of glasses that students can learn from their peers include better vision, better classroom performance, and perhaps also the potential aesthetic benefits of wearing glasses, if they think glasses look good on their peers. On the other hand, a negative peer effect, wherein students may be less likely to own and use glasses if their peers own and use glasses, may arise from a negative learning effect: myopic students may learn from their peers that owning and using eyeglasses yields net costs, including the potential aesthetic costs of wearing glasses, if they think glasses look bad on their peers.

While examining peer effects was not the purpose of the randomized control trial we designed and used in Sylvia et al. (2020), the data we collect in our field experiment provides an ideal context in which to examine peer effects in glasses ownership and usage. In rural China, students are enrolled in the primary school that is located in the town seat in which their village is a subdistrict, and household residences are linked to the location of their farmland; it therefore is not possible for parents to choose places to live in order to enroll their children in better schools. Even if there is some potential unobserved self-selection in the formation of classes, there is little evidence that self-selection would be based on the students' myopia and their attitudes toward wearing eyeglasses.

We use the data from our field experiment to estimate a structural econometric model of a multi-stage dynamic game of glasses ownership (take-up) and usage among students in the same classroom. In our multi-stage dynamic game, the first stage is the decision to own glasses and, conditional on deciding to own, the second stage is the decision to use glasses. This multi-stage model enables us to explicitly model each of the stages in the dynamic decision-making problem faced by myopic students, and to link the decisions made in each stage together in one integrated model that recognizes that the ownership decisions made in the first stage depend on the value of usage in the second stage (Lin, 2013).

There are several advantages to our dynamic structural approach. First, our structural model explicitly models the dynamic nature of decisions by students and their parents regarding glasses ownership and usage. These ownership and usage decisions can be viewed as decisions of investment under uncertainty (Dixit and Pindyck, 1994), since they are at least partially irreversible, and since their payoffs may depend on the ownership and usage decisions of classmates, which may be uncertain and evolve stochastically over time. Moreover, ownership and usage decisions are dynamic because they are sequential: one must first decide to own glasses before one is able to decide whether to use them.

A second advantage of our structural approach is that it enables us to estimate the effect of each state variable on the expected payoffs from deciding to own and use glasses. A student (and his or her parents) will decide for the student to own a pair of glasses if the payoff from owning exceeds the discounted continuation value from waiting. Likewise, a student (and his or her parents) will decide for the student to start using a pair of glasses if the payoff from using exceeds the discounted continuation value from waiting. With our dynamic structural model we are able to estimate parameters in the payoffs from the ownership (take-up) and usage decisions, since we are able to structurally model how the continuation value from waiting relates to these payoffs.

A third advantage of a structural approach is that it enables us to better estimate the strategic (social) interaction between classmates. While we use data that was collected in a field experiment we designed and used in Sylvia et al. (2020), identification of the peer effects does not come from the randomized controlled trials or any experimental variation in the experiment, as the experiment was designed for a different purpose. Instead, identification of the peer effects comes from our structural econometric model in conjunction with the institutional details of schools in rural China. In our dynamic structural econometric model of glasses ownership and usage, students (and their parents) base their decisions in part on expectations of the future, including their expectations of what fraction of their classmates will own by next year and their expectations of what fraction of their classmates will use by the next year.

We make several contributions to the existing literature on peer effects. First, our structural model enables us to distinguish between endogenous peer effects arising from peers' behavior and exogenous peer effects arising from peers' exogenous characteristics. Second, our multi-stage model adds a sequential decision-making component to the existing structural modeling literature. Third, the structural parameters we estimate enable us to compare the effects of peers with the effects of information and subsidies, which are two common and important interventions considered in development economics, health economics, and public economics that were implemented in our field experiment.

Our structural model of the multi-stage take-up and usage game also contributes to the burgeoning literature using structural models in development economics. While most of the dynamic structural econometric models in development economics model single-agent dynamic decision-making (see e.g., Todd and Wolpin, 2010; Duflo, Hanna and Ryan, 2012; Lessem, 2018; Oliva et al., 2020; Mahajan, Michel and Tarozzi, 2020), our structural model of a dynamic game between decision-makers allows for both dynamic and strategic decision-making.

The results of our structural model of the multi-stage game show that, while students might be more likely to own glasses if the glasses are provided for free, students who received glasses that were given to them for free may be less inclined to use the glasses. Our results also show that the decrease in the payoff from glasses usage resulting from the glasses being provided for free can be offset, however, by an increase in the fraction of the student's peers who own and/or use glasses. Peer effects can therefore help mitigate the issue with some social or public programs that, when a good is provided for free or at subsidized prices, individuals may not use the goods provided. Our research has important implications for the effective and cost-effective design of programs that provide goods and services for free or at subsidized prices.

The rest of paper proceeds as following. We review the related literature in Section 2. Section 3 describes the research setting and data. Section 4 describes our structural econometric model of the multi-stage dynamic game. Section 5 presents the results. Section 6 concludes.

2. Literature Review

Peer effects are often viewed as the key to understanding many social problems and opportunities (Sacerdote, 2014). In the economics literature, studies have examined peer effects in a variety of contexts, including education (Calvó-Armengol, Patacchini and Zenou, 2009; Lalive and Cattaneo, 2009; Kremer, Duflo and Dupas, 2011; Epple and Romano, 2011; Duflo, Dupas and Kremer, 2011; Hong and Lee, 2017; Dasgupta et al., 2020), agriculture (Foster and Rosenzweig, 1995; Munshi, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010; Maertens, 2017), welfare program participation (Carneiro et al., 2020), health (Oster and Thornton, 2012), adolescent and youth behavior (Gaviria and Raphael, 2001; Kling, Liebman and Lawrence, 2007; Kremer and Levy, 2008; Battaglini, Díaz and Patacchini, 2017), commuting to work (Morrison and Lin Lawell, 2016), worker productivity (Cornelissen, Dustmann and Schönberg, 2017), residential segregation (Graham, 2018), migration (Rojas Valdés, Lin Lawell and Taylor, 2020b), financial decisions (Bursztyn et al., 2014; Kleiner, Stoffman and Yonker, 2020), oil drilling (Lin, 2009), deforestation (Robalino and Pfaff, 2012), group lending (Li, Liu and Deininger, 2013), groundwater (Pfeiffer and Lin, 2012; Sears, Lim and Lin Lawell, 2019; Sampson and Perry, 2019; Sears et al., 2020), conservation (Beattie, Han and La Nauze, 2019; Bollinger, Burkhardt and Gillingham, 2020), business practices (Bisztray, Koren and Szeidl, 2018), and occupational choice (Guerra and Mohnen, 2020).

Measuring peer effects is difficult owing to two sources of endogeneity. One source is the simultaneity of the peer effect: if individual i is affected by her peer j, then individual j is affected by his peer i. The other arises from correlated unobservable variables (Manski, 1993; Manski, 1995; Brock and Durlauf, 2001; Conley and Topa, 2002; Glaeser, Sacerdote and Scheinkman, 1996; Moffitt, 2001; Lin, 2009; Bramoullé, Djebbari and Fortin, 2009; Blume et al., 2011; Robalino and Pfaff, 2012; Pfeiffer and Lin, 2012; Morrison and Lin Lawell, 2016; Rojas Valdés, Lin Lawell and Taylor, 2020b).

A recent growing strand of policy evaluation studies employs field experiments or quasi-natural experiments to identify peer effects. Many do so by adding exogenous peer compositions or changing the fraction of peers treated. These studies include those that add cohort-to-cohort variations in the gender mix of schools (Hoxby, 2000), randomly assign college roommates (Carrell, Fullerton and West, 2009; Shue, 2013), or take advantage of the migration of hurricane refugees into new schools (Imberman, Kugler and Sacerdote, 2012; Damm and Dustman, 2014). Another type of study assumes that the friends of one's friends only affect oneself via one's friends' behavior, and then instruments for peers' behavior using the peers' characteristics (De Giorgi, Pellizzari and Redaelli, 2010). Other studies identify peer effects via the partial population approach (Moffitt, 2001), wherein an intervention is only administered to a random portion of the individuals in a group, so that the effect of the treatment on the control group only comes through the outcomes of treated and control peers (Bobonis and Finan, 2009; Dahl, Løken and Mogstad 2014; Joensen and Nielsen, 2018).

We make several contributions to the existing literature on peer effects. First, our structural model enables us to distinguish between endogenous peer effects arising from peers' behavior and exogenous peer effects arising from peers' exogenous characteristics. Second, our multi-stage model adds a sequential decision-making component to the existing structural modeling literature. Third, the structural parameters we estimate enable us to compare the effects of peers with the effects of information and subsidies, which are two common and important interventions considered in development economics, health economics, and public economics that were implemented in our field experiment.

A related literature examines how information about networks and spillovers can be leveraged to better target policies (Ballester, Calvó-Armengol and Zenou, 2006; Banerjee et al., 2013; Galeotti and Rogers, 2013; de Paula, 2017; Demange, 2017; Galeotti, Golub and Goyal, 2020); and whether networks and peer effects can be leveraged to improve adoption, participation, and take-up (Beaman et al., 2018; Carneiro et al., 2020). We build on this literature by examining if peer effects can also help with subsequent usage.

We also build on the literature on dynamic structural econometric modeling. Rust's (1987, 1988) seminal papers develop a dynamic structural econometric model using nested fixed point maximum likelihood estimation. Hotz et al. (1994) develop a conditional choice simulation estimator for dynamic models of discrete choice. Dynamic structural econometric models have been adapted for many applications, including bus engine replacement (Rust, 1987), nuclear power plant shutdown (Rothwell and Rust, 1997), water management (Timmins, 2002), rural labor supply (Duflo, Hanna and Ryan, 2012), air conditioner purchase behavior (Rapson, 2014), wind turbine shutdowns and upgrades (Cook and Lin Lawell, 2020), copper mining decisions (Aguirregabiria and Luengo, 2016), migration (Lessem, 2018; Morten, 2019), long-term and short-term decision-making for disease control (Carroll et al., 2020b), insecticide treated nets (Mahajan, Michel and Tarozzi, 2020), the adoption of rooftop solar photovoltaics (Feger et al., 2020; Langer and Lemoine, 2018), supply chain externalities (Carroll et al., 2020b), agriculture (Scott, 2013), vehicle scrappage programs (Li and Wei, 2013), vehicle ownership and usage (Gillingham et al., 2016), agricultural productivity (Carroll et al., 2019), environmental regulations (Blundell, Gowrisankaran and Langer, 2020), organ transplant decisions (Agarwal et al., 2020), hunting permits (Reeling, Verdier and Lupi, 2020), agroforestry trees (Oliva et al., 2020), and the spraying of pesticides (Yeh, Gómez and Lin Lawell, 2020; Sambucci, Lin Lawell and Lybbert, 2020).

While most of the dynamic structural econometric models in development economics model single-agent dynamic decision-making (see e.g., Todd and Wolpin, 2010; Duflo, Hanna and Ryan, 2012; Lessem, 2018; Oliva et al., 2020; Mahajan, Michel and Tarozzi, 2020), our structural model of a dynamic game between decision-makers allows for both dynamic and strategic decision-making. The literature on structural econometric models of dynamic games includes a model developed by Aguirregabiria and Mira (2007), which has been applied to oligopoly retail markets (Aguirregabiria, Mira and Roman, 2007); a model developed by Bajari, Benkard and Levin (2007), which has been applied to the cement industry (Ryan, 2012; Fowlie, Reguant and Ryan, 2016), the ethanol industry (Yi, Lin Lawell and Thome, 2020), migration decisions (Rojas Valdés, Lin Lawell and Taylor, 2020a), calorie consumption (Uetake and Yang, 2018), the global market for solar panels (Gerarden, 2019), groundwater management (Sears, Lin Lawell and Walter, 2020), the digitization of consumer goods (Leyden, 2019), the world petroleum market (Kheiravar, Lin Lawell and Jaffe, 2020), and climate change policy (Zakerinia and Lin Lawell, 2020); a model developed by Bajari et al. (2015), which has been applied to ethanol investment (Yi and Lin Lawell 2020a; Yi and Lin Lawell, 2020b); and models developed by Pesendorfer and Schmidt-Dengler (2008), de Paula (2009), Aguirregabiria and Mira (2010), Srisuma and Linton (2012), and Dearing and Blevins (2019). Structural econometric models of dynamic games have also been applied to fisheries (Huang and Smith, 2014), dynamic natural monopoly regulation (Lim and Yurukoglu, 2018), Chinese shipbuilding (Kalouptsidi, 2018), industrial policy (Barwick, Kalouptsidi and Zahur, 2020), preemption (Fang and Yang, 2020), and coal procurement (Jha, 2019).

The structural econometric model of a dynamic game we use builds on a model developed by Pakes, Ostrovsky and Berry (2007), which has been applied to the multi-stage investment timing game in offshore petroleum production (Lin, 2013) and to ethanol investment decisions (Thome and Lin Lawell, 2020).

3. Research Setting and Data

Half of all disabilities among children in the developing world are due to poor vision (Congdon et al., 2008). The leading and most readily treated cause of poor vision among children is myopia, affecting 12.8 million 5- to 15-year-old children worldwide, half of whom live in China (Resnikoff et al., 2008). Wearing eyeglasses has been proven to be the most cost-effective solution to correct myopia (Ma et al., 2014). In the context of primary schools in China, several studies have documented that teaching materials are primarily presented on the blackboard and children with uncorrected myopia have lower scores on a variety of tests (Yi et al., 2014; Ma et al., 2014). Wearing eyeglasses improves students' academic performance (Ma et al., 2014; Glewwe, Park and Zhao, 2016). In the developing world, however, only as few as one in six myopic children who need eyeglasses have them (Yi et al., 2014; He et al., 2004, 2007). Meanwhile, the prevalence of myopia has been increasing among Chinese children, afflicting about one in four children in primary schools (Yi et al., 2014; He et al., 2004, 2007). The welfare loss due to uncorrected myopia in the developing world is therefore potentially quite large.

In this paper, we use data from a randomized controlled trial that we designed and used in Sylvia et al. (2020) to test whether ordeal mechanisms and/or information campaigns improve the cost-effectiveness of a program distributing free eyeglasses to myopic students in rural China. A detailed description of our experimental design and data collection are provided in Ma et al. (2014) and Sylvia et al. (2020).

3.1. Sampling

Our experiment took place in two adjoining provinces of western China: Shaanxi and Gansu.[1] In each of the provinces, one prefecture was included in the study. A map of these regions is provided in Figure 1. From each prefecture, a list of all rural primary schools was obtained. To

[1] Shaanxi's GDP per capita of USD 6108 was ranked 14th among China's 31 provincial administrative regions in 2012, and was very similar to that for the country as a whole (USD 6091) in the same year, while Gansu was the second-poorest province in the country, with a GDP per capita of USD 3100 (China National Statistics Bureau, 2012).

minimize the possibility of inter-school contamination, we first randomly selected townships and then randomly selected one school per township for inclusion in the experiment. Within the schools, our data collection efforts (summarized briefly below and discussed in detail in Ma et al. (2014) and Sylvia et al. (2020)), focused on 4th and 5th grade students. From each grade, one class was randomly selected and surveys and visual acuity examinations were given to all students in these classes.

3.2. Experimental Design

Following the baseline survey and vision tests, schools were randomly assigned to one of the six cells in the 3 by 2 experimental design shown in Figure 2. Schools were first randomized into one of three *provision* groups (free distribution, ordeal, and control). Half of the schools assigned to each provision group were then assigned to receive a training program. To improve power, we stratified the randomization by county and by the number of students in the school found to need eyeglasses. In total, this yielded a total of 42 strata. Our analysis takes this randomization procedure into account (Bruhn and McKenzie, 2009).

The three experimental provision groups are as follows:

Free distribution: In this group, each student diagnosed with myopia[2] was given a free pair of eyeglasses as well as a letter to their parents informing them of their child's prescription. The child was permitted to select a pair of frames, which were then fit to the proper prescription and delivered to the hands of students at schools by a team of one optometrist and two enumerators.

Ordeal: In this group, each student diagnosed with myopia was given a voucher as well as a letter to their parents informing them of their child's prescription. Their prescription was also printed in the voucher. This voucher was redeemable for one pair of free glasses at an optical store that was in the county seat. To a large extent, the ordeal of voucher redemption is simply the cost (in transportation fare, if needed, and time) associated with travel to this optical shop. The distance from each student's home and the county seat varied a great deal within our sample, ranging from 1 kilometer to 105 kilometers with the mean distance of 33 kilometers. The vouchers were non-transferable. The student's information, including name, school, and county, was printed on each voucher, and students were required to present their identification in person to redeem the voucher.

[2] More than 95% of poor vision is due to myopia. The rest is due to hyperopia and astigmatism. For simplicity, we will use myopia to refer to vision problems more generally.

Control: Students in the control group were given only a letter addressed to their parents informing them of their child's myopia status and prescription.

In each of these three provision groups, half of the schools were assigned to receive a training program:

Training program: The training program included three components. First, a short documentary-type film was shown to students in class. Second, students were given a set of cartoon-based pamphlets in class. Finally, parents and teachers were invited to a lecture in which they were shown the film and additional handouts were distributed. Each component of the training addresses the importance of wearing glasses and provides information meant to correct common misconceptions that lead to inflated perceptions of usage costs and that contribute to low adoption rates. For example, the training program specifically addressed the common misperceptions that wearing glasses deteriorates vision and that eye exercises can cure myopia.

3.3. Data Collection

Three rounds of data were collected by our enumeration team, which we denote as t = 0, 1, 2. See Figure 3 for the project timeline. A baseline survey was conducted in September 2012. The baseline survey (denoted as t = 0) collected detailed information on students' eyeglasses ownership and usage as well as their individual and household characteristics. As shown in Table 1, which shows the results of regressing each of the baseline characteristics on a vector of indicators for the other treatment arms and indicators for randomization strata, we cannot reject the null hypothesis that these coefficients are jointly zero. Only three of the 55 coefficients tested are significantly different from zero and none of the joint tests are rejected at conventional levels, which provides evidence that the baseline characteristics are well-balanced across the treatment and control groups. At the same time as the school survey, a two-step eye examination[3] was administered to all students in all sample classes of project schools. In total, 19,934 students in 252 schools were

[3] First, a team of two trained staff administered visual acuity screenings using Early Treatment Diabetic Retinopathy Study (ETDRS) eye charts (ETDRS charts are accepted as the worldwide standard for accurate visual acuity measurement (Camparini et al., 2001). Students who failed the visual acuity screening test (cutoff is defined by VA of either eye less than or equal to 6/12, or 20/40) were enrolled in a second vision test that was carried out at each school 1-2 days after the first test. This second vision test was conducted by a team of one optometrist, one nurse, and one assistant staff, and involved cycloplegic automated refracon with subjective refinement to determine prescriptions for students needing glasses. A cycloplegic refraction is a procedure used to determine a person's degree of myopia (or refractive error) by temporarily paralyzing the muscles that aid in focusing the eye. It is often used for testing the vision of children who sometimes make the results of visual acuity screening tests invalid by subconsciously accommodating their eyes during the eye examination.

surveyed and given eye examinations at baseline, of which 3,177 (16%) students among 485 classes[4] were found to be myopic. We include only these myopic students and their classmates in the analysis sample.

Free and vouchers for free eyeglasses and training interventions were implemented and completed one month after the baseline survey (October 2012). The first follow-up was conducted immediately after the interventions were completed (denoted as $t = 1$). A second follow-up was conducted by the end of the school year in May 2013 (denoted as $t = 2$). The overall attrition rate was less than four percent between period $t = 0$ and period $t = 2$.

3.4. Ownership and Usage of Eyeglasses

Our analysis focuses on two key variables: eyeglass ownership and eyeglass usage. Ownership is defined by a dummy variable which is equal to 1 if a student owns a pair of eyeglasses. Usage is defined by whether a student wears his or her glasses; in this paper, we use the terms *use* and *wear* interchangeably. Both ownership and usage are self-reported during the three rounds of data collection.

4. Structural Econometric Model

We define *peers* as classmates in the same classroom; in this paper, we use the terms *peers* and *classmates* interchangeably. For decisions regarding glasses ownership and usage by myopic students in rural primary schools of China, the decision-maker is likely a combination of the student and his or her parents, particularly for the glasses ownership decision. Thus, while we often refer to the "student" as the decision-maker, this "student" decision-maker in our model and analysis represents the student and his or her parents.

We estimate three structural econometric models: a dynamic ownership game; a dynamic usage game; and a multi-stage game in which the first stage is the decision to own glasses and, conditional on deciding to own, the second stage is the decision to use glasses. Our structural econometric models build on a structural econometric model of a dynamic game developed by

[4] There are 19 classes (504 minus 485) with zero myopic students diagnosed.

Pakes, Ostrovsky and Berry (2007), as well as on its extension and application to the multi-stage investment timing game in offshore petroleum production by Lin (2013).

4.1. Dynamic Ownership Game

In our structural econometric model of the dynamic ownership game, the action variable for each student *i* in class *k* is the ownership decision I_{ikt}^{o}, which is a dummy variable that is equal to 1 for student *i* in class *k* at time *t* if the student owns glasses for the first time at time *t*, and 0 if the student does not yet own glasses at time *t*. I_{ikt}^{o} is coded as missing for student *i* in class *k* at time *t* if the student already owned glasses in the previous period *t*-1, since then he or she no longer has an ownership decision to make.

For each class *k*, the state of the class at time *t* is given by a vector $\Omega_{kt}^{o} = (N_{kt}^{o}, X_{kt}^{o})$ of discrete and finite-valued state variables that are observed by all the students in the class *k* as well as by the econometrician. These state variables include endogenous state variables N_{kt}^{o} and exogenous state variables X_{kt}^{o}. The decision of student *i* in class *k* of whether to own glasses in year *t* depends on the publicly observable state of the class $\Omega_{kt}^{o} = (N_{kt}^{o}, X_{kt}^{o})$. The state variables $\Omega_{kt}^{o} = (N_{kt}^{o}, X_{kt}^{o})$ evolve according to a first-order Markov process and summarize the direct effect of the past on the current environment.

The endogenous state variables N_{kt}^{o} capture the strategic components of the ownership decision. In our model of the dynamic ownership game, the endogenous state variables N_{kt}^{o} include the fraction of all classmates in class *k* who own glasses by time *t* and the fraction of myopic classmates in class *k* who own glasses by time *t*.

The exogenous state variables X_{kt}^{o} include the six treatment dummies which indicate student *i*'s school type of random treatment assignment (pure control; training only; ordeal only; ordeal and training; free only; or free and training); baseline class size; class average of baseline awareness of myopia status; class average of baseline misinformation; and class average of baseline myopia severity.

We discretize the two endogenous state variables N_{kt}^{o} into 10 bins each (1=lowest to 10=highest). In particular, we discretize the fraction of myopic peers who own eyeglasses by time

t into 10 equally spaced bins from 0.0 (lowest bin) to 1.0 (highest bin), with an increment of 0.1 between each bin. We discretize the fraction of all peers who own eyeglasses by time t into 10 equally spaced bins from 0.0 (lowest bin) to 0.50 (highest bin), with an increment of 0.05 between each bin. We discretize the baseline class size; class average of baseline awareness of myopia status; class average of baseline misinformation; and class average of baseline myopia severity variables into 2 bins each (1=low or 2=high) with the cutoff defined as the median of each variable.

In addition to the publicly observable state variables $\Omega_{kt}^o = (N_{kt}^o, X_{kt}^o)$, the decision of a student i in class k of whether to own glasses in year t also depends on a shock ε_{ikt}^o, which is private information to the student and is not observed by either other classmates or by the econometrician. The shock ε_{ikt}^o to the student's utility (or payoff) from owning a pair of eyeglasses at time t, which is observed only by a student who does not yet own eyeglasses, may represent his or her aesthetic feeling for how glasses look. The shock may also include any private shocks to a student's costs or benefits of owning glasses. We assume the shock ε_{ikt}^o is independently and identically distributed exponentially with parameter σ^o, which is among the parameters to be estimated.

The payoff $\pi(N_{kt}^o, X_{kt}^o, \varepsilon_{ikt}^o; \theta)$ from deciding to own glasses in class k in time t can be separated into a deterministic component and a stochastic component as follows:

$$\pi(N_{kt}^o, X_{kt}^o, \varepsilon_{ikt}^o; \theta) = \pi_o(N_{kt}^o, X_{kt}^o; \theta) + \varepsilon_{ikt}^o, \tag{1}$$

where the deterministic component $\pi_0(\cdot)$ is linear in the state variables:

$$\pi_o(N_{kt}^o, X_{kt}^o; \theta) = N_{kt}^{o\prime}\gamma_N + X_{kt}^{o\prime}\gamma_X, \tag{2}$$

and where $\theta = (\gamma_N, \gamma_X, \sigma^o)$ denotes the parameters to be estimated. The coefficients γ_N and γ_X measure the effects of the state variables N_{kt}^o and X_{kt}^o, respectively, on the payoff from deciding to own glasses.

The coefficients γ_N on the fraction of classmates in class k who own glasses by time t and the fraction of myopic classmates in class k who own glasses by time t measure the net endogenous peer effects arising peers' behavior. A positive coefficient γ_N would indicate that a student is more likely to decide to own glasses if his or her peers own and/or use glasses. A negative value for γ_N would indicate that a student is less likely to decide to own glasses if his or her peers own and/or use glasses. The coefficients γ_X on baseline class size; class average of baseline awareness of myopia status, class average of baseline misinformation, and class average of baseline myopia severity capture exogenous peer effects arising from peers' exogenous characteristics.

The equilibrium concept used in the model is that of a Markov perfect equilibrium. Each student is assumed to play a Markov "state-space" strategy: the past influences current play only through its effect on the state variables. A student's dynamically optimal ownership policy is then the Markov strategy that he or she plays in the Markov perfect equilibrium, which is a profile of Markov strategies that yields a Nash equilibrium in every proper subgame (Fudenberg and Tirole, 1998).

While the time-*t* ownership decision of each student (and his or her parents) depends on both the publicly available endogenous and exogenous state variables $\Omega^o_{kt} = (N^o_{kt}, X^o_{kt})$ as well as the private information ε^o_{ikt} of the student (and his or her parents), the perception of each student (and his or her parents) of her peers' time-*t* ownership decisions depend only on the publicly observable state variables $\Omega^o_{kt} = (N^o_{kt}, X^o_{kt})$. This is because, owing to the above assumptions on the observable state variables and on the unobservable shocks, students (and their parents) can take expectations over their peers' private information.[5] In equilibrium, the perceptions of students (and their parents) of their peers' ownership investment probabilities should be consistent with those that are actually realized (Starr and Ho, 1969).

The model has at least one Markov perfect equilibrium, and each equilibrium generates a finite state Markov chain in Ω^o_{kt} tuples (Pakes, Ostraovsky and Berry, 2007).[6] Although model assumptions do not guarantee a unique equilibrium, they do insure that there is only one set of equilibrium policies that is consistent with the data generating process. It is thus possible to use the data itself to pick out the equilibrium that is played. For large enough samples, the data will pick out the correct equilibrium and the estimators for the parameters in the model will be consistent (Pakes, Ostrovsky and Berry, 2007).[7]

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[5] While each student plays a pure strategy, from the point of view of their peers, they appear to play mixed strategies. Thus, as with Harsanyi's (1973) purification theorem, a mixed distribution over actions is the result of unobserved payoff perturbations that sometimes lead students to have a strict preference for one action, and sometimes a strict preference for another.
[6] A Markov chain is a Markov process on a finite state space (Stokey, Lucas and Prescott, 1989).
[7] This assumes that the same equilibrium is played in each class *k*. If a mixed strategy equilibrium is played, then it is assumed that the same mixed strategy equilibrium is played in each class *k*.

The value function for a student i in class k who does not yet own glasses by period t can be written as:

$$V(N_{kt}^o, X_{kt}^o, \varepsilon_{ikt}^o;\theta) = \max\{\pi(N_{kt}^o, X_{kt}^o, \varepsilon_{ikt}^o;\theta), \beta V^c(N_{kt}^o, X_{kt}^o;\theta)\}. \tag{3}$$

The student (and his or her parents) will decide for the student to own glasses if and only if the payoff from deciding to own glasses exceeds β times the continuation value $V^c(\cdot)$ to waiting. The continuation value $V^c(\cdot)$ is the expected value of the next period's value function, conditional on not owning glasses in the current period, and is given by:

$$V^c(N_{kt}^o, X_{kt}^o;\theta) = E[V(N_{k,t+1}^o, X_{k,t+1}^o, \varepsilon_{ik,t+1}^o;\theta) \mid N_{kt}^o, X_{kt}^o, I_{ikt}^o = 0]. \tag{4}$$

Let $g(N_{kt}^o, X_{kt}^o;\theta)$ denote the probability of deciding to own glasses at time t, conditional on the publicly available information $\Omega_{kt}^o = (N_{kt}^o, X_{kt}^o)$ at time t, but not on the private information ε_{ikt}^o.

Using an exponential distribution for the ownership decision payoff shock ε_{ikt}^o, the continuation value $V^c(\cdot)$ reduces to:

$$V^c(N_{kt}^o, X_{kt}^o;\theta) = E[\beta V^c(N_{k,t+1}^o, X_{k,t+1}^o;\theta) + \sigma^o g(N_{k,t+1}^o, X_{k,t+1}^o;\theta) \mid N_{kt}^o, X_{kt}^o, I_{ikt}^o = 0], \tag{5}$$

and the ownership decision probability $g(\cdot)$ reduces to:

$$g(N_{kt}^o, X_{kt}^o;\theta) = \exp\left(-\frac{\beta V^c(N_{kt}^o, X_{kt}^o;\theta) - \pi_0(N_{kt}^o, X_{kt}^o;\theta)}{\sigma^o}\right), \tag{6}$$

as shown by Lin (2013).

The parameters to be estimated are $\theta = (\gamma_N, \gamma_X, \sigma^o)$, which includes the parameter σ^o in the exponential distribution of the private shock ε_{ikt}^o, and the coefficients γ_N and γ_X on the state variables N_{kt}^o and X_{kt}^o, respectively, in the ownership decision payoff function $\pi(\cdot)$.

The econometric estimation technique we use employ a two-step semi-parametric estimation procedure following Pakes, Ostrovsky and Berry (2007) and Lin (2013). In the first step, the continuation value is estimated non-parametrically and this estimate is used to compute the predicted probabilities of the ownership decision. In the second step, the parameters $\theta = (\gamma_N, \gamma_X, \sigma^o)$ are estimated by matching the predicted probabilities with the actual probabilities in the data using generalized method of moments (GMM).

For the first step in the estimation, we first estimate the transition matrix *M*, which describes the evolution of the state variables N_{kt}^{o} and X_{kt}^{o} over time conditional on not investing. In particular, the transition matrix *M* gives, for each combination of state variables this period, the probability of transitioning to each combination of state variables the next period conditional on not investing this period. The element in each row *r* and each column *c* of the transition matrix *M* is $M_{rc} = \Pr(\Omega_{k,t+1}^{o} = c \mid \Omega_{kt}^{o} = r, I_{ikt}^{o} = 0)$. We estimate *M* non-parametrically using empirical averages. We therefore assume rational expectations on the part of potential eyeglass owners, namely that their expectations about the evolution of state variables over the time period of our data set were consistent with the actual evolution realized.

Let $\overline{g}$ be the vectorized investment policy function, which is a vector whose length is the number of combination of state variables and whose value at each component is the ownership decision policy function $g(\cdot)$ evaluated at a particular combination of state variables. $\overline{g}$ gives the probability of deciding to own glasses for every tuple of state variables. We estimate $\overline{g}$ using empirical averages:

$$\overline{g}(N_{kt}^{o}, X_{kt}^{o}) = \Pr(I_{ikt}^{0} = 1 \mid N_{kt}^{o}, X_{kt}^{o}) \ . \tag{7}$$

From equation (5), the vectorized continuation value $\overline{V}^{c}$, which is a vector whose length is the number of combination of state variables and whose value at each component is the continuation value $V^{c}(\cdot)$ evaluated at a particular combination of state variables, can be specified in vector form as:

$$\overline{V}^{c} = M(\beta \overline{V}^{c} + \sigma^{o} \overline{g}) \ , \tag{8}$$

where *M* is the empirical transition matrix, β is the discount rate, and $\overline{g}$ is the vector of empirical ownership decision probabilities. Since this is an infinite horizon problem, we estimate the continuation value by solving for the fixed point $\hat{V}^{c}$, which, from Blackwell's Theorem, is unique. We then use this estimate $\hat{V}^{c}$ to form the predicted probability of deciding to own glasses, which from equation (6) can be specified in vector form as:

$$\hat{g}(N_{kt}^{o}, X_{kt}^{o}; \theta) = \exp\left(-\frac{\beta \hat{V}^{c} - N_{kt}^{o\prime} \gamma_{N} - X_{kt}^{o\prime} \gamma_{X}}{\sigma^{0}} \right) \ . \tag{9}$$

In the second step of the estimation procedure, we estimate the parameters $\theta = (\gamma_N, \gamma_X, \sigma^o)$ by finding the parameters that best match the ownership decision probability predicted by our model with the respective empirical ownership decision probabilities in the data using GMM. We use the following moment function:

$$\psi(N_{kt}^o, X_{kt}^o; \theta) = \left(\hat{g}(N_{kt}^o, X_{kt}^o; \theta) - \overline{g}(N_{kt}^o, X_{kt}^o) \right) n(N_{kt}^o, X_{kt}^o \mid I_{ik,t-1}^o = 0) \ , \qquad (10)$$

where $n(N_{kt}^o, X_{kt}^o \mid I_{ik,t-1}^o = 0)$ counts the number of times each state $\Omega_{kt}^o = (N_{kt}^o, X_{kt}^o)$ occurs where there is a student who has not yet decided to own glasses by time *t*. Thus, ψ is a vector where each row represents difference in the predicted and empirical probabilities of deciding to own glasses for each of the possible states of the world Ω_{kt}^o, and is weighted by the number of times that state occurs in the data. The population moment condition is that in expectation, ψ equals zero. Additional moments are constructed by interacting the above moments ψ with the state variables $\Omega_{kt}^o = (N_{kt}^o, X_{kt}^o)$.

The GMM estimator $\hat{\theta}$ is the solution to the problem:

$$\min_{\theta} \left(\frac{1}{n_{ikt}} \sum_{kt} \psi(N_{kt}^o, X_{kt}^o; \theta) \right)' W_n^{-1} \left(\frac{1}{n_{ikt}} \sum_{kt} \psi(N_{kt}^o, X_{kt}^o; \theta) \right) , \qquad (11)$$

where n_{ikt} is the number of student-time observations. Since the system is exactly identified, an identity matrix is used as the weight matrix W_n.

Standard errors are formed by a nonparametric bootstrap. Classes are randomly drawn from the data set with replacement to generate 100 independent panels of size equal to the actual sample size. The structural econometric model is run on each of the new panels. The standard error is then formed by taking the standard deviation of the estimates from each of the random samples.[8]

4.2. Dynamic Usage Game

For our model of the dynamic usage game, the action variable is the usage decision I_{ikt}^u, which is a dummy variable that is equal to 1 for student *i* in class *k* at time *t* if the student uses

[8] One challenge is determining whether the model has converged at a global or local minimum. We experimented with several combinations of starting values to initialize the parameters to be estimated. We found the model is robust to the starting value.

glasses for the first time at time t, and 0 if the student has not yet decided to use glasses at time t. I_{ikt}^{u} is coded as missing for student i in class k at time t if the student already used glasses in the previous period t-1, since then he or she no longer has a usage decision to make.

The publicly observable state variables $\Omega_{kt}^{u} = (N_{kt}^{u}, X_{kt}^{u})$ in the dynamic usage game can be decomposed into two endogenous state variables N_{kt}^{u} and 11 exogenous state variables X_{kt}^{u}. In our model of the dynamic usage game, the endogenous state variables N_{kt}^{u} include the fraction of all classmates in class k who use glasses by time t and the fraction of myopic classmates in class k who use glasses by time t. The exogenous state variables X_{kt}^{u} include the 10 exogenous state variables used in the dynamic ownership model and one additional variable: the fraction of classmates who own eyeglasses in the baseline.

We discretize the two endogenous state variables N_{kt}^{u} into 10 bins each (1=lowest to 10=highest). In particular, we discretize fraction of myopic peers who use eyeglasses by time t into 10 equally spaced bins from 0.0 (lowest bin) to 1.0 (highest bin), with an increment of 0.1 between each bin. We discretize the fraction of all peers who use eyeglasses by time t into 10 equally spaced bins from 0.0 (lowest bin) to 0.50 (highest bin), with an increment of 0.05 between each bin. We discretize the baseline class size; class average of baseline awareness of myopia status; class average of baseline misinformation; and class average of baseline myopia severity variables into 2 bins each (1=low or 2=high) as before. We also discretize the fraction of classmates who own eyeglasses in the baseline into 2 bins (1=low or 2=high), with the cutoff defined as the median.

In addition to the publicly observable state variables $\Omega_{kt}^{u} = (N_{kt}^{u}, X_{kt}^{u})$, the decision of a student i in class k in year t of whether to use glasses also depends on a shock ε_{ikt}^{u}, which is private information to the student and unobserved by either other classmates or by the econometrician. The shock ε_{ikt}^{u} to the student's utility (or payoff) from wearing a pair of eyeglasses at time t, which is observed only by a student owning eyeglasses who has not yet used them, may represent his or her physical or aesthetic feeling about wearing eyeglasses. For example, some students might feel dizzy or uncomfortable the first time they try to wear eyeglasses. The shock may also include any private shocks to a student's costs or benefits of using glasses. We assume the shock ε_{ikt}^{u} is independently and identically distributed exponentially with parameter σ^u, which is among the parameters to be estimated.

The method of estimation for our dynamic usage game is the same as that used for our dynamic ownership game above.[9]

4.3. Multi-Stage Dynamic Game

In the third structural model, we expand our dynamic structural model to a multi-stage dynamic game. In the first stage, a student decides whether or not to own eyeglasses. In the second stage, conditional on owning eyeglasses, a student decides whether or not to use them. This model is our preferred model as it enables us to explicitly model each of the stages in the dynamic decision-making problem faced by myopic students. As a consequence, the analysis of strategic interactions in this multi-stage model is more complete than that of the previous models because it incorporates the second-stage usage decision along with the first-stage ownership decision, not only by allowing for strategic interactions in both stages but also by linking the decisions made in each stage together in one integrated, multi-stage model that recognizes that the ownership decisions made in the first stage depend on the value of usage in the second stage (Lin, 2013).

Similar to our previous two structural models, the publicly observable state variables $\Omega_{kt} = (N_{kt}, X_{kt})$ can be decomposed into 4 endogenous state variables N_{kt} and 11 exogenous state variables X_{kt}. The 4 endogenous state variables N_{kt} are the fraction of all classmates in class *k* who own glasses by time *t*, the fraction of myopic classmates in class *k* who own glasses by time *t*, the fraction of all classmates in class *k* who use glasses by time *t*, and the fraction of myopic classmates in class *k* who use glasses by time *t*. The 11 exogenous state variables X_{kt} are the same 11 exogenous state variables used in the dynamic usage model. As before, we discretize the 4 endogenous state variables N_{kt} into 10 bins each and the 11 exogenous state variables X_{kt} into 2 bins each (low or high), using the same bins as in both the dynamic ownership model and the dynamic usage model.

Our multi-stage model includes both types of shocks from the dynamic ownership model and the dynamic usage model that are private information to the students and unobserved by either

[9] One challenge is determining whether the model has converged at a global or local minimum. We experimented with several combinations of starting values to initialize the parameters to be estimated. We found the model is robust to the starting value.

other students or by the econometrician: an ownership decision payoff shock ε_{ikt}^{o}, which is independently and identically distributed exponentially with parameter σ^{o}; and a usage decision payoff shock ε_{ikt}^{u}, which is independently and identically distributed exponentially with parameter σ^{u}.

The sequential decision-making problem of each myopic student *i* in class *k* is a two-stage optimization problem and can be solved backward using dynamic programming (Dixit and Pindyck, 1994; Lin, 2013). In the second, or usage, stage a myopic student who owns a pair of eyeglasses but has not yet used it must decide whether and when to use it for the first time. Assume that the payoff $\pi^{u}(N_{kt}, X_{kt}, \varepsilon_{ikt}^{u};\theta)$ from deciding to use eyeglasses in class *k* in time *t* can be separated into a deterministic component and a stochastic component as follows:

$$\pi^{u}(N_{kt}, X_{kt}, \varepsilon_{ikt}^{u};\theta) = \pi_{0}^{u}(N_{kt}, X_{kt};\theta) + \varepsilon_{ikt}^{u} , \tag{12}$$

where the deterministic component $\pi_{0}^{u}(\cdot)$ is linear in the state variables:

$$\pi_{0}^{u}(N_{kt}, X_{kt};\theta) = N_{kt}{}'\gamma_{N} + X_{kt}{}'\gamma_{X} , \tag{13}$$

and where $\theta = (\gamma_{N}, \gamma_{X}, \sigma^{o}, \sigma^{u})$ denotes the parameters to be estimated.

The value function for a myopic student *i* in class *k* at time *t* who owns but has not used eyeglasses is given by:

$$V^{o}(N_{kt}, X_{kt}, \varepsilon_{ikt}^{u};\theta) = \max\{\pi^{u}(N_{kt}, X_{kt}, \varepsilon_{ikt}^{u};\theta), \beta V^{co}(N_{kt}, X_{kt};\theta)\} . \tag{14}$$

The student who already own eyeglasses will choose to use eyeglasses if and only if the payoff $\pi^{u}(N_{kt}, X_{kt}, \varepsilon_{ikt}^{u};\theta)$ from deciding to use glasses exceeds β times the continuation value $V^{co}(\cdot)$ to waiting. The continuation value $V^{co}(\cdot)$ is the expected value of the next period's value function, conditional on not yet using glasses this period, and is given by:

$$V^{co}(N_{kt}, X_{kt};\theta) = E[V^{o}(N_{k,t+1}, X_{k,t+1}, \varepsilon_{ik,t+1}^{u};\theta) \mid N_{kt}, X_{kt}, I_{ikt}^{u} = 0] . \tag{15}$$

Let $g^{u}(N_{kt}, X_{kt};\theta)$ denote the probability that a myopic student *i* in class *k* at time *t* who owns eyeglasses but has not used them by time *t* decides to use glasses, conditional on the publicly available information $\Omega_{kt} = (N_{kt}, X_{kt})$ at time *t*, but not on the private information ε_{ikt}^{u}.

Using an exponential distribution for the usage decision payoff shock ε_{ikt}^{u}, the continuation value $V^{co}(\cdot)$ reduces to:

$$V^{co}(N_{kt}, X_{kt}; \theta) = E[\beta V^{co}(N_{k,t+1}, X_{k,t+1}; \theta) + \sigma^u g^u(N_{k,t+1}, X_{k,t+1}; \theta) \mid N_{kt}, X_{kt}, I^u_{ikt} = 0], \quad (16)$$

and the usage decision probability $g^u(\cdot)$ reduces to:

$$g^u(N_{kt}, X_{kt}; \theta) = \exp\left(-\frac{\beta V^{co}(N_{kt}, X_{kt}; \theta) - \pi_0^u(N_{kt}, X_{kt}; \theta)}{\sigma^u} \right), \quad (17)$$

as shown by Lin (2013).

In the first, or ownership, stage a myopic student *i* in class *k* without eyeglasses must decide whether and when to own one pair of eyeglasses. The payoff $\pi^o(N_{kt}, X_{kt}, \varepsilon_{ikt}; \theta)$ from deciding to own glasses in class *k* in time *t* can be separated into a deterministic component and a stochastic component as follows:

$$\pi^o(N_{kt}, X_{kt}, \varepsilon^o_{ikt}; \theta) = \pi^o_0(N_{kt}, X_{kt}; \theta) + \varepsilon^o_{ikt}, \quad (18)$$

where the stochastic component ε^o_{ikt} represents student *i*'s aesthetic feeling before using the glasses regarding how the glasses look, as well as any private shocks to a student's costs or benefits of owning glasses, at time *t*.

Owing to the sequential nature of the two-stage decision-making process, the deterministic component of the payoff from deciding to own eyeglasses in the first stage is equal to the expected value of deciding to use glasses in the second stage, net the cost of owning glasses:

$$\pi^o_0(N_{kt}, X_{kt}; \theta) = E_{\varepsilon^u}[V^o(N_{kt}, X_{kt}, \varepsilon^u_{ikt}; \theta) \mid N_{kt}, X_{kt}] - c^o(X_{kt}; \theta), \quad (19)$$

where the cost $c^o(\cdot)$ of owning glasses is giving by the following linear function of the treatment dummies, since the student's treatment group determines his or her costs to owning glasses:

$$c^o(X_{kt}; \theta) = -X_{kt}{}'\alpha. \quad (20)$$

The value function for a myopic student *i* in class *k* at time *t* who does not yet own eyeglasses is given by:

$$V^n(N_{kt}, X_{kt}, \varepsilon^o_{ikt}; \theta) = \max\{\pi^o(N_{kt}, X_{kt}, \varepsilon^o_{ikt}; \theta), \beta V^{cn}(N_{kt}, X_{kt}; \theta)\}, \quad (15)$$

where $V^{cn}(\cdot)$ is the continuation value to waiting instead of deciding to own eyeglasses at time *t*. The continuation value to waiting is the expectation over the state variables and shocks of the next period's value function, conditional on not yet owning glasses this period:

$$V^{cn}(N_{kt}, X_{kt}; \theta) = E[V^n(N_{k,t+1}, X_{k,t+1}, \varepsilon^o_{ik,t+1}; \theta) \mid N_{kt}, X_{kt}, I^o_{ikt} = 0]. \quad (22)$$

Let $g^o(N_{kt}, X_{kt}; \theta)$ denote the probability that a myopic student i in class k who does not yet own eyeglasses at time t decides to own eyeglasses, conditional on publicly observable information $\Omega_{kt} = (N_{kt}, X_{kt})$, but not on the private information ε^o_{ikt}.

Using an exponential distribution for the ownership decision payoff shock ε^o_{ikt}, the continuation value $V^{cn}(\cdot)$ to waiting instead of deciding to own can be reduced to:

$$V^{cn}(N_{kt}, X_{kt}; \theta) = E[\beta V^{cn}(N_{k,t+1}, X_{k,t+1}; \theta) + \sigma^o g^o(N_{k,t+1}, X_{k,t+1}; \theta) \mid N_{kt}, X_{kt}, I^o_{ikt} = 0], \qquad (23)$$

and the ownership decision probability $g^o(\cdot)$ can be reduced to the following function of the continuation values, state variables, and parameters:

$$g^o(N_{kt}, X_{kt}; \theta) = \exp\left(-\frac{\beta V^{cn}(N_{kt}, X_{kt}; \theta) - \left(\beta V^{co}(N_{kt}, X_{kt}; \theta) + \sigma^u g^u(N_{kt}, X_{kt}; \theta)\right)}{\sigma^o} \right). \qquad (24)$$

Owing to the sequential nature of the two-stage decision-making process, the continuation value $V^{co}(\cdot)$ and the usage decision probability $g^u(\cdot)$ from the second-stage usage decision appear in the expression for the ownership decision probability $g^o(\cdot)$ in the first-stage ownership decision.

The econometric estimation technique we use is similar to that used for our dynamic ownership game and our dynamic usage game above. In particular, the econometric estimation technique we use employ a two-step semi-parametric estimation procedure following Pakes, Ostrovsky and Berry (2007) and Lin (2013). In the first step, the continuation values for both the ownership and usage decisions are estimated non-parametrically and these estimates are used to compute the predicted probabilities of the ownership and usage decisions. In the second step, the parameters $\theta = (\gamma_N, \gamma_X, \sigma^o, \sigma^u)$ are estimated by matching the predicted probabilities with the actual probabilities in the data using generalized method of moments (GMM).[10]

4.4. Identification

Although we use data that was collected in a field experiment we designed and used in Sylvia et al. (2020), identification of the peer effects does not come from the randomized controlled

[10] One challenge is determining whether the model has converged at a global or local minimum. We experimented with several combinations of starting values to initialize the parameters to be estimated. We found the model is robust to the starting value.

trials or any experimental variation in the experiment in the experiment, as the experiment was designed for a different purpose. Instead, our structural econometric models, in conjunction with the institutional details of schools in rural China, are what enable us to identify the peer effects. In rural China, students are enrolled in the primary school that is located in the town seat in which their village is a subdistrict, and household residences are linked to the location of their farmland; it therefore is not possible for parents to choose places to live in order to enroll their children in better schools. Even if there is some potential unobserved self-selection in the formation of classes, there is little evidence that self-selection would be based on students' myopia and their attitudes toward wearing eyeglasses. In our dynamic structural econometric models of glasses ownership and usage, students (and their parents) base their decisions in part on expectations of the future, including their expectations of what fraction of their classmates will own by next year and their expectations of what fraction of their classmates will use by the next year.

Identification of the parameter σ^o governing the distribution of the private shock ε^o_{ikt} to a student's utility from owning a pair of eyeglasses is similar to the identification of the entry parameter in Pakes, Ostrovsky and Berry (2007): it comes from the realized ownership frequencies, and in particular the moments that match the predicted ownership probabilities with the actual ownership probabilities in the data. Similarly, identification of the parameter σ^u governing the distribution of the private shock ε^u_{ikt} to a student's utility from wearing a pair of eyeglasses comes from the realized usage frequencies, and in particular the moments that match the predicted usage probabilities with the actual usage probabilities in the data. Identification of the coefficients γ_N and γ_X on the endogenous state variables N_{kt} and exogenous state variables X_{kt}, respectively, comes from variation in the state variables, ownership decisions, and usage decisions across classrooms and time, and in particular the moments that match the predicted and actual ownership and usage probabilities when these probabilities are interacted with the state variables. Since our structural model only identifies relative values of the coefficients in the ownership and usage payoffs relative to the means σ^o and σ^u of the respective private shock, and does not separately identify the magnitudes of the coefficients in the payoffs and the means σ^o and σ^u of the private shocks, we focus on interpreting the signs, statistical significance, and relative magnitudes of the parameters, rather than their absolute magnitudes.

The problem of spatially correlated unobservables can be addressed by interpreting the payoffs in the model as the expected payoffs conditional on observables, where the expectation is taken over the correlated unobservables. In this case, the coefficients γ_N on the endogenous state variables N_{kt} measure the expected effect of the endogenous variables N_{kt}, where the expectation is taken over the correlated unobservables. Thus, the model is still able to separately identify the (expected) strategic interaction from the correlated unobservable. Lin (2013) conducts Monte Carlo experiments of the structural model of the multi-stage dynamic game to analyze the effect of a common shock that is observed by the decision-makers (in this case, students and their parents) when they make their decisions but unobservable to the econometrician, and finds that, for the structural model of the multi-stage dynamic game we use in this paper, the bias introduced by spatially correlated unobservables is small. Pakes, Ostrovsky and Berry (2007) similarly find that, for the structural econometric model of a dynamic game we use in this paper, the bias from serially correlated common shocks is small.

5. Results

The results of our dynamic ownership game, dynamic usage game, and multi-stage dynamic game are in Tables 2-4, respectively.[11] We focus our discussion primarily on the results of our multi-stage dynamic game, our preferred model. Since our structural model only identifies relative values of the coefficients in the ownership and usage payoffs relative to the means σ^o and σ^u of the respective private shock, and does not separately identify the magnitudes of the coefficients in the payoffs and the means σ^o and σ^u of the private shocks, we focus on interpreting the signs, statistical significance, and relative magnitudes of the parameters, rather than their absolute magnitudes.

As seen in the results of our ownership game in Table 2, we find the cost of obtaining eyeglasses plays an important role in the ownership decision, which suggests that liquidity constraints matter in the ownership decision. Specifically, being in schools where free eyeglasses were delivered in schools yields a higher payoff from deciding to own eyeglasses than does being

[11] For each model, we tried many different sets of initial guesses for the parameters, and report the results that minimize the weighted sum of squared moments.

in control schools without any subsidized eyeglasses or in schools in which students are expected to spend some non-monetary ordeal to redeem the voucher for a free pair of eyeglasses. Conditional on the cost of obtaining eyeglasses, we also find that providing information increases the payoffs from deciding to own eyeglasses.

We find in our dynamic usage game in Table 3 that relieving the liquidity constraint to ownership does not necessarily guarantee that myopic students will wear eyeglasses, and that providing information helps increase the payoff from deciding to use eyeglasses that are provided for free, as the coefficient on the dummy variable for the "free and training" group is positive and greater than the coefficient on the dummy variable for the "free only" group.

We focus our discussion on the results of our multi-stage dynamic game, our preferred model, in Table 4. We start by interpreting the coefficients in the ownership decision payoff function. We find that being in any of the treatment groups providing glasses for free ("free only"; "free and ordeal"; "free and training"; "free and ordeal and training") yields a higher payoff from deciding to own glasses than being in either group in which glasses are not provided for free ("pure control"; "training only"). These results make sense, as the costs to owning glasses are lower when the glasses are provided for free.

We then interpret the coefficients in the usage decision payoff function. We find that both the fraction of all peers who own glasses and the fraction of all peers who use glasses significantly increase the payoff to a myopic student (and possibly also her or her parents) from deciding for the student to use glasses at a 1 percent level. The fraction of myopic peers who own glasses and the fraction of myopic peers who own do not have an additional significant effect, perhaps because students do not know whether peers are myopic, and therefore respond to the behavior of all peers rather than the behavior of myopic peers.

We find that being in any of the treatment groups providing glasses for free ("free only"; "free and ordeal"; "free and training"; "free and ordeal and training") yields a lower payoff from deciding to use glasses than being in either group in which glasses are not provided for free ("pure control"; "training only"). Thus, while students might be more likely to own glasses if the glasses are provided for free, students who own glasses that were given to them for free may be less inclined to use the glasses.

Among the other parameters in the usage decision payoff function, we find that the larger the class size, the higher the payoffs to a myopic student (and possibly also her or her parents) from deciding for the student to use glasses. Thus, the benefits to a myopic student from using glasses is larger when the class size is larger, perhaps because it is harder to a myopic student to do well in a large class (e.g., because the blackboard is even harder to see when the class size is large). The class average of baseline misinformation about whether glasses harm vision is negatively and significantly associated with the payoff to a myopic student from deciding to use eyeglasses. Thus, the better informed the class is about whether glasses harm vision on average, the higher the payoff to a student (and possibly also her or her parents) from deciding for the student to use glasses. We also find that the baseline class average of myopic severity level is positively and significant associated with the payoff to a myopic student from deciding to use glasses. Thus, myopic students benefit more from using glasses when their peers are myopic as well.

As for the values of the parameters governing the distribution of private information, both the mean σ^o of the shock to the payoff from the ownership decision and the mean σ^u of the shock to the payoff from the usage decision are statistically significant, with the latter greater in magnitude than the former. In terms of economic significance, one way to interpret both the mean σ^o of the shock to the payoff from the ownership decision and the mean σ^u of the shock to the payoff from the usage decision is to compare them with the magnitudes of the dummies for treatment, such as free only or training only, in corresponding payoff function, following Lin (2013). For example, the ratio of the mean shock to the magnitude of the corresponding treatment dummy measures the importance of private information relative to the complete relief of any liquidity constraint and to the provision of the training program, respectively, in the decision-making of glasses ownership and usage. In both cases, a high value of the ratio indicates a high relative importance of private information.

In the ownership decision payoff function, the mean of the private information shock is roughly equal in magnitude to the dummies for being in any of the treatment groups providing glasses for free, with or without an ordeal, and with or without a training program. Thus, private information has roughly the same magnitude an effect on the payoff from deciding to own glasses as does not being provided glasses for free. The mean of the private information shock is roughly a third to a half the magnitude of the dummies for being in the control group or being provided the training program only.

In the usage decision payoff function, the mean of the private information shock is roughly twice the magnitude of the dummies for being in any of the treatment groups providing glasses either free, with or without an ordeal, and with or without a training program. Thus, private information has roughly twice the magnitude of being provided glasses for free. The mean of the private information shock is over six times the magnitude of the dummy for being provided the training program only.

In addition, we can also compare the magnitude of the parameters for the peer effects and the treatment dummies (which measure the effects of relieving liquidity constraints to ownership completely by providing free glasses or partially by providing an ordeal mechanism; and/or the the effects of providing a training program) to measure the relative importance of peer effects in the payoffs from the ownership and usage decisions. In the usage decision payoff function, the coefficients on the fraction of all peers who own glasses and on the fraction of all peers who use glasses both have a magnitude roughly comparable to that of the dummies for being in any of the treatment groups providing glasses for free ("free only"; "free and ordeal"; "free and training"; "free and ordeal and training"), but opposite in sign. Thus, the decrease in the payoff to glasses usage resulting from the glasses being provided for free can be offset by an increase in the fraction of all peers who own glasses of 0.05 (the bin size for the discretized fraction of all peers); an increase in the fraction of all peers who use glasses of 0.05 (the bin size for the discretized fraction of all peers); or, for example, an increase in both the fraction of all peers who own glasses and the fraction of all peers who use glasses of 0.025 each.

Thus, while the significant positive effects of being provided glasses for free on the ownership decision payoff are offset by its significant negative effects on the usage decision payoff, the decrease in the usage decision payoff resulting from being provided glasses for free can be offset by an increase in the fraction of all peers who own and/or use glasses. Peer effects can therefore help mitigate the issue that when goods are provided for free or at subsidized prices, individuals may not use the goods provided.

6. Conclusion

When a good is provided for free or at subsidized prices, issues of take-up and usage may arise. This paper examines peer effects in the take-up and subsequent usage of a subsidized good.

We develop a structural econometric model of a multi-stage dynamic game in which the first stage is the take-up (or ownership) decision and, conditional on ownership, the second stage is the usage decision. We apply our model to glasses ownership and usage data from a health promotion program that provides free eyeglasses and training to 3,177 myopic students in rural China.

The results of our structural model of the dynamic ownership game show that the cost of obtaining eyeglasses plays an important role in the ownership decision, which suggests that liquidity constraints matter in the ownership decision. The results of our structural model of the dynamic usage game show that relieving the liquidity constraint to ownership does not necessarily guarantee that myopic students will wear eyeglasses, however, since having the glasses offered for free has a negative effect on the payoff from deciding to use glasses.

According to the results of our structural model of the multi-stage dynamic game, our preferred model, we find that while being provided glasses for free has a significant positive effect on the payoff from deciding to own glasses, it also has a significant negative effect on the perceived or actual payoff from subsequently deciding to use glasses roughly equal or even greater in magnitude that offsets this positive effect. Thus, while students might be more likely to own glasses if the glasses are provided for free, students who own glasses that were given to them for free may be less inclined to use them. This attenuated usage may compromise the effectiveness and cost-effectiveness of programs that provide goods for free or at subsidized prices (Sylvia et al., 2020).

Our results also show the decrease in the payoff from glasses usage resulting from the glasses being provided for free can be offset, however, by an increase in the fraction of the student's peers who own and/or use glasses. Peer effects can therefore help mitigate the issue with some social or public programs that, when a good is provided for free or at subsidized prices, individuals may not use the goods provided.

Our results suggest that effectiveness and cost-effectiveness of providing goods and services for free or at subsidized prices can be enhanced by leveraging peer effects, which can help mitigate the issue with some social or public programs that, when a good is provided for free or at subsidized prices, individuals may not use the goods provided. In their analysis of policies to induce farmers to adopt a productive new agricultural technology in Malawi, Beaman et al. (2018) find that using network theory-based targeting to identify seed farmers to target and train on the new technology can out-perform traditional approaches to government extension, since most farmers need to learn from multiple people before they adopt themselves. Carneiro et al. (2020) estimate network effects on participation in social programs and similarly find that peer effects can enhance participation in a conditional cash transfer program for poor families in Chile. While Beaman et al. (2018) and Carneiro et al. (2020) find that networks and peer effects can be leveraged to improve adoption, participation, and take-up (which is analogous to the ownership decision in our model), we find a complementary result that peer effects can also help with subsequent usage.

Similarly, while Sylvia et al. (2020) find that ordeal mechanisms may better target eyeglasses to those who use them, and that an information campaign may increase use when eyeglasses are freely delivered but not under an ordeal, we find a complementary result that peer effects can also help with subsequent usage.

Our structural econometric model of the multi-stage dynamic game of take-up and subsequent usage yields the important insight that peer effects can help mitigate the issue with some social or public programs that, when a good is provided for free or at subsidized prices, individuals may not use the goods provided. Our research has important implications for the effective and cost-effective design of policies and programs that provide goods and services for free or at subsidized prices.

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Figure 1. Study Region

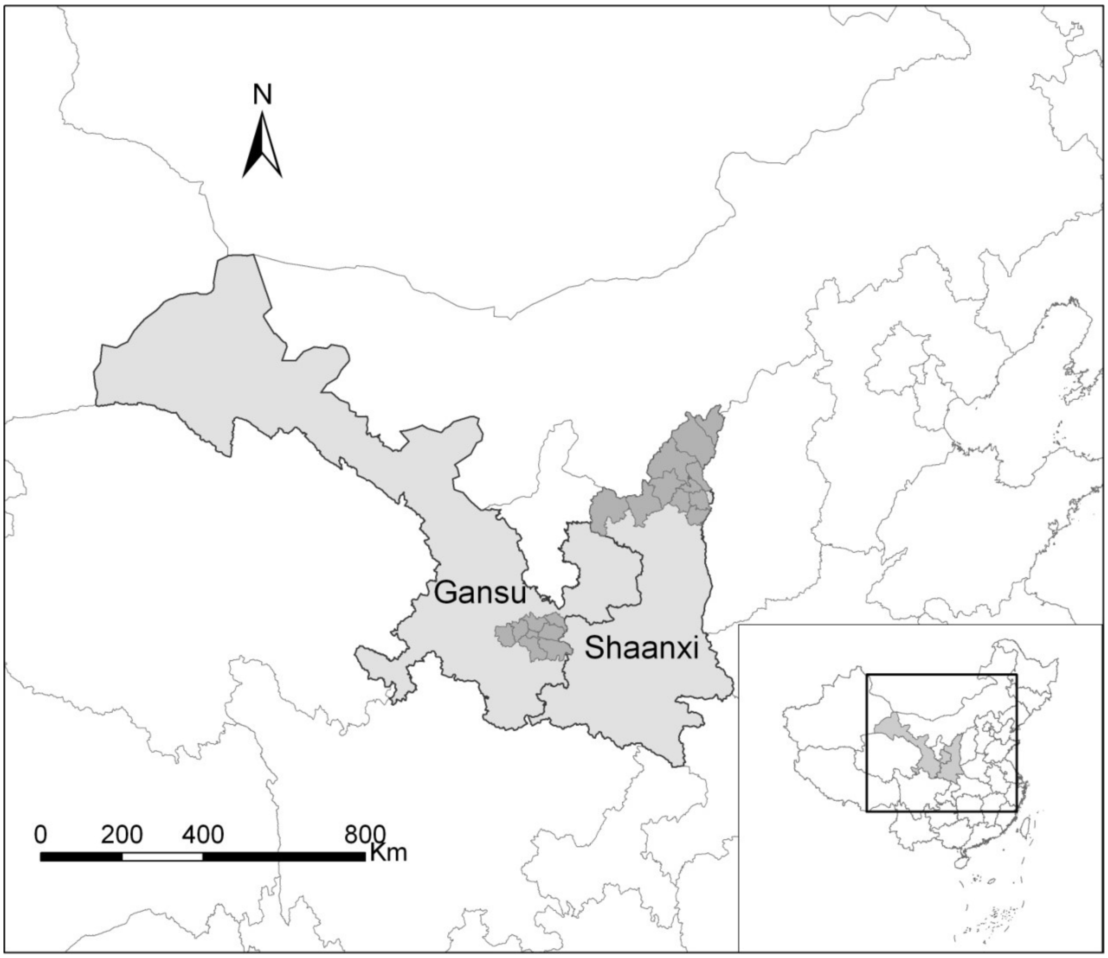

Figure 2: Experimental Design

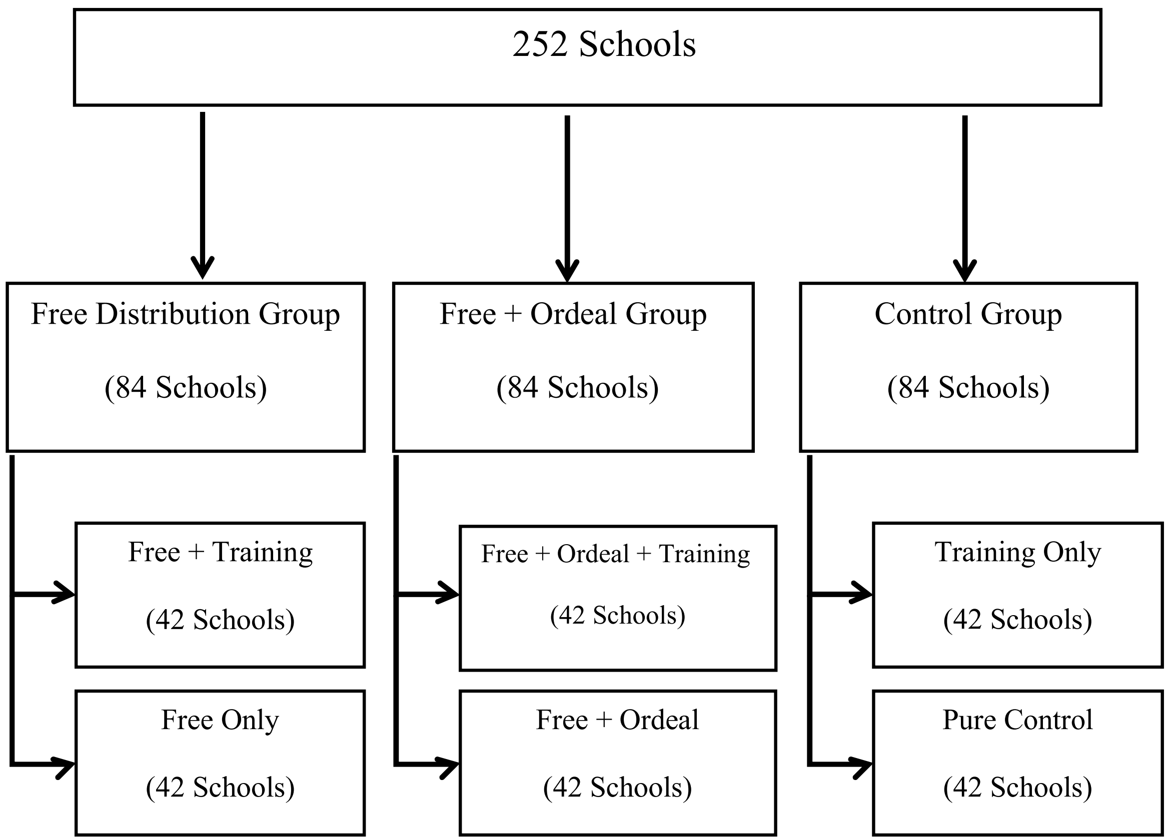

Figure 3: Data Collection and Intervention Timeline

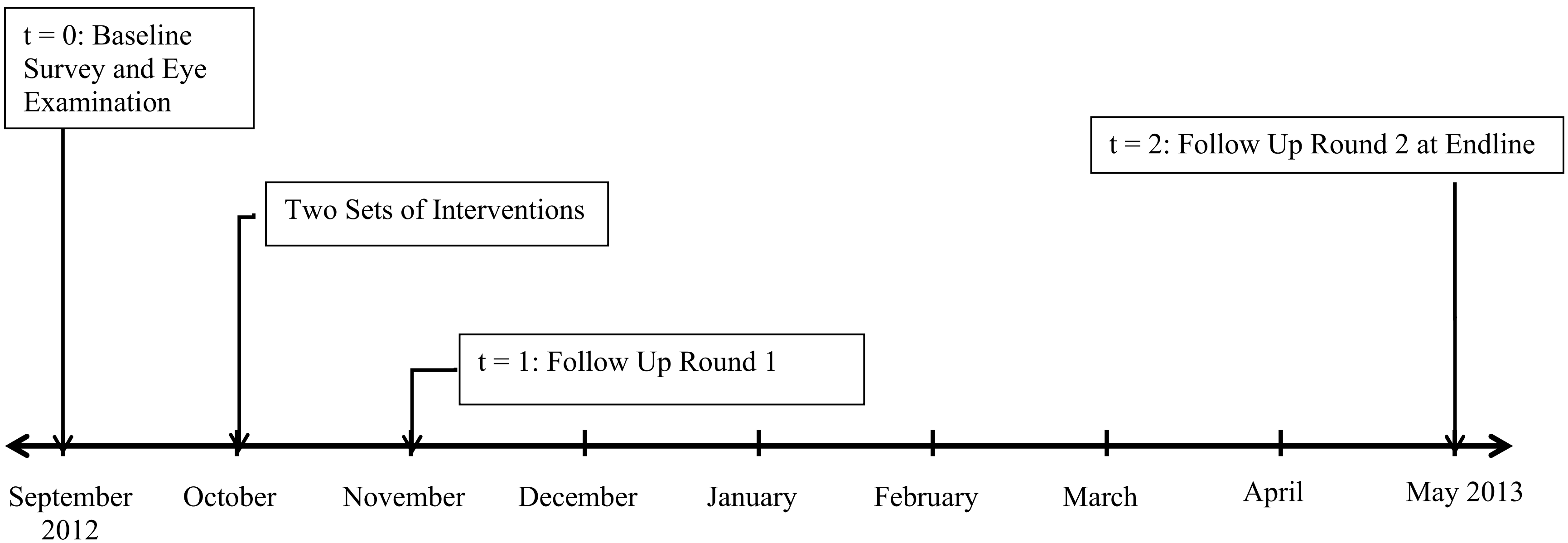

Table 1. Baseline Descriptive Statistics and Balance Check

	Free only		Coefficient (standard error) on:						
	Mean	SD	Free and Training	Free and Ordeal	Free and Ordeal and Training	Pure control	Training only	Joint test p-value	# Obs
Male (dummy)	0.480	0.500	0.005	0.010	-0.002	0.050	0.001	0.500	3177
			(0.029)	(0.029)	(0.028)	(0.031)	(0.031)		
Grade 5 (dummy)	0.611	0.488	-0.014	-0.002	-0.004	-0.005	-0.036	0.829	3177
			(0.031)	(0.034)	(0.030)	(0.032)	(0.031)		
At least one parent has high school education or above (dummy)	0.226	0.419	-0.005	-0.058*	-0.031	-0.017	-0.028	0.451	3163
			(0.025)	(0.031)	(0.028)	(0.027)	(0.030)		
Both parents migrate for work (dummy)	0.092	0.289	0.003	0.022	-0.003	0.009	0.016	0.653	3147
			(0.014)	(0.016)	(0.017)	(0.017)	(0.017)		
Household wealth (index)	-0.057	1.290	-0.104	-0.173*	-0.118	-0.127	-0.105	0.448	3032
			(0.086)	(0.088)	(0.101)	(0.082)	(0.089)		
Distance to county seat (km)	33.565	22.433	2.693	0.065	-1.991	5.184	-1.697	0.365	3177
			(4.109)	(4.419)	(4.602)	(3.558)	(4.080)		
Visual acuity of worse eye (LogMAR)	0.629	0.202	0.002	-0.005	-0.009	-0.003	0.041**	0.172	3177
			(0.016)	(0.021)	(0.016)	(0.016)	(0.019)		
Already owned glasses in baseline (t=0) (dummy)	0.188	0.391	0.014	0.025	-0.021	0.021	-0.016	0.169	3177
			(0.023)	(0.023)	(0.022)	(0.024)	(0.019)		
Believed at baseline (t=0) that he/she was myopic (dummy)	0.473	0.500	-0.015	0.014	-0.011	0.000	-0.025	0.894	3157
			(0.033)	(0.033)	(0.035)	(0.034)	(0.035)		
Parents believed at baseline (t=0) that wearing glasses harms vision (dummy)	0.747	0.435	-0.002	0.012	0.015	0.002	0.001	0.972	3011
			(0.027)	(0.029)	(0.027)	(0.030)	(0.031)		
Believed at baseline (t=0) that eye exercises treat myopia (dummy)	0.545	0.498	-0.015	-0.016	-0.033	0.017	-0.010	0.812	3177
			(0.035)	(0.038)	(0.036)	(0.039)	(0.036)		

Notes: Data source: baseline survey. The first and second columns show the mean and standard deviation of each baseline characteristic for myopic students in the free only group. Severity of myopia is measured by the LogMAR of the worse eye. LogMAR takes value from -0.3 (best vision) to 1.6 (worst vision), with an increment of 0.1 corresponding to a one line change on the vision chart; students with normal vision would have value less than or equal to 0.0. The household asset index was calculated using a list of 13 items and weighting by the first principal component. Distance is the distance from the school to the county seat. For each group aside from free only, we present coefficients and standard errors (in parentheses) from a regression of the characteristic on the other five treatment dummies, controlling for randomization strata. Standard errors are clustered at the school level. We also present the p-value from a Wald test that these coefficients are jointly zero. All tests account for clustering at the school level. Significance codes: * 10% level, ** 5% level, and *** 1% level.

Table 2. Results of Dynamic Ownership Game

	Dynamic Ownership Game (1)
σ^{o} parameter in exponential distribution of shock to payoff from ownership	32.06***
	(0.07)
Coefficient in the ownership decision payoff function on:	
Fraction of myopic peers who own glasses by time *t* (discretized)	-4.55***
	(0.59)
Fraction of all peers who own glasses by time *t* (discretized)	-1.02***
	(0.17)
Pure control (dummy)	-31.36***
	(0.14)
Training only (dummy)	-24.53***
	(0.18)
Free and ordeal (dummy)	-0.69***
	(0.05)
Free and ordeal and training (dummy)	7.71***
	(0.05)
Free only (dummy)	25.45***
	(0.03)
Free and training (dummy)	36.21***
	(0.01)
Class size (discretized)	-5.45***
	(0.51)
Baseline class average awareness of being myopic (discretized)	2.93***
	(0.45)
Baseline class average of believing wearing glasses harms vision (discretized)	1.24**
	(0.49)
Baseline class average of myopia severity level (discretized)	11.02***
	(0.48)

Notes: Standard errors calculated by bootstrap are reported in parentheses. Class averages are averaged over all classmates (including both myopic and non-myopic classmates). There are 970 observations spanning 485 classrooms. Significance codes: * 10% level, ** 5% level, and *** 1% level.

Table 3. Results of Dynamic Usage Game

	Dynamic Usage Game (2)
σ^u parameter in exponential distribution of shock to payoff from usage	25.01***
	(0.12)
Coefficient in the usage decision payoff function on:	
Fraction of myopic peers who use glasses by time *t* (discretized)	-3.33***
	(0.41)
Fraction of all peers who use glasses by time *t* (discretized)	2.29***
	(0.55)
Pure control (dummy)	-34.00***
	(0.16)
Training only (dummy)	-29.59***
	(0.14)
Free and ordeal (dummy)	-6.42***
	(0.16)
Free and ordeal and training (dummy)	-0.92***
	(0.15)
Free only (dummy)	-3.54***
	(0.27)
Free and training (dummy)	4.89***
	(0.33)
Class size (discretized)	2.65***
	(0.32)
Baseline class average awareness of being myopic (discretized)	8.66***
	(0.32)
Baseline class average of believing wearing glasses harms vision (discretized)	0.30***
	(0.27)
Baseline class average of myopia severity level (discretized)	12.11***
	(0.45)
Baseline fraction of all peers who own glasses (discretized)	-22.10***
	(0.18)

Notes: Standard errors calculated by bootstrap are reported in parentheses. Class averages are averaged over all classmates (including both myopic and non-myopic classmates). There are 970 observations spanning 485 classrooms. Significance codes: * 10% level, ** 5% level, and *** 1% level.

Table 4. Results of Multi-Stage Dynamic Game

	Multi-Stage Dynamic Game (3)
σ^o parameter in exponential distribution of shock to payoff from ownership	1.2475***
	(0.5534)
σ^u parameter in exponential distribution of shock to payoff from usage	2.4336***
	(0.4122)
Coefficient in the ownership decision payoff function on:	
Pure control (dummy)	-3.4412***
	(0.0429)
Training only (dummy)	-3.7583***
	(0.0392)
Free and ordeal (dummy)	1.2799***
	(0.0619)
Free and ordeal and training (dummy)	1.1065***
	(0.0602)
Free only (dummy)	0.7700***
	(0.0495)
Free and training (dummy)	1.2185***
	(0.0650)
Coefficient in the usage decision payoff function on:	
Fraction of myopic peers who own glasses by time *t* (discretized)	-0.0552
	(0.1131)
Fraction of all peers who own glasses by time *t* (discretized)	0.1471***
	(0.0111)
Fraction of myopic peers who use glasses by time *t* (discretized)	-0.0566
	(0.0652)
Fraction of all peers who use glasses by time *t* (discretized)	0.0901***
	(0.0139)
Pure control (dummy)	-0.1235
	(0.1082)
Training only (dummy)	-0.3620***
	(0.0722)
Free and ordeal only (dummy)	-1.2531***
	(0.0319)
Free and ordeal and training (dummy)	-0.9634***
	(0.0403)
Free only (dummy)	-1.0652***
	(0.0321)
Free and training (dummy)	-1.3163***
	(0.0589)
Class size (discretized)	0.1764*

	(0.0947)
Baseline class average awareness of being myopic (discretized)	0.0563
	(0.0559)
Baseline class average of believing wearing glasses harms vision (discretized)	-0.4253***
	(0.0225)
Baseline class average of myopia severity level (discretized)	0.1994***
	(0.0209)
Baseline fraction of peers who own glasses (discretized)	-0.1723***
	(0.0533)

Notes: Standard errors calculated by bootstrap are reported in parentheses. Class averages are averaged over all classmates (including both myopic and non-myopic classmates). There are 970 observations spanning 485 classrooms. Significance codes: * 10% level, ** 5% level, and *** 1% level.