Peer Effects in Sexual Initiation:
Separating Demand from Supply*

Seth Richards-Shubik†
Carnegie Mellon University

December 15, 2010

Abstract

Most work on social interactions studies a single, composite effect of interactions within a group. Yet in the case of sexual initiation, there are two distinct social mechanisms—peer-group norms and partner availability—with separate effects and different potential interventions. Here I develop an equilibrium search and matching model for first sexual encounters that specifies distinct roles for these two mechanisms as part of demand and supply. I estimate the model using a national sample of high school students, with data over time on individual virginity status. The results indicate that peer-group norms have a large effect on the timing of sexual initiation for both boys and girls. Changes in opposite-gender search behavior (i.e., partner availability) also have a large impact on initiation rates for boys, but not for girls. The existence of a composite effect of social interactions is also confirmed using a standard method: instrumental variables estimation of linear regressions.

*I thank my thesis advisors for their dedication, support, and hours of their time: Kenneth I. Wolpin, David M. Cutler, Elena Krasnokutskaya, and Áureo de Paula. I am also grateful to John Cawley, Guy David, Sara Markowitz, Ellen R. Meara, and Nirav Mehta for helpful comments, and to the National Bureau of Economic Research for computer facilities. This research uses data from Add Health, a program project designed by J. Richard Udry, Peter S. Bearman, and Kathleen Mullan Harris, and funded by a grant P01-HD31921 from the Eunice Kennedy Shriver National Institute of Child Health and Human Development, with cooperative funding from 17 other agencies. Special acknowledgment is due Ronald R. Rindfuss and Barbara Entwisle for assistance in the original design. Persons interested in obtaining data files from Add Health should contact Add Health, Carolina Population Center, 123 W. Franklin Street, Chapel Hill, NC 27516-2524 (addhealth@unc.edu). No direct support was received from grant P01-HD31921 for this analysis.
†Email: sethrs@andrew.cmu.edu

1 Introduction

About one-half of the students in grades nine through twelve in the United States are sexually experienced (CDC 2008a). The prevalence of sexual activity among adolescents raises substantial concerns, largely because of associated risks such as unplanned pregnancy and sexually transmitted disease. And as with many youth risk behaviors, peers are often pointed to as a major influence on the decisions adolescents make about sex.

A growing body of research in economics examines peer effects. However, existing empirical work in this area typically focuses on the demand side of whatever "market" is under consideration, without attention to potential changes in supply that might occur in equilibrium. By ignoring separate effects on supply and demand, these studies measure a *composite* effect of social interactions. This is defined simply as the change in the probability of an outcome for an individual caused by a change in the distribution of that outcome (usually the mean) among some reference group. Clearly such an effect can result from many underlying mechanisms, but the effectiveness of any potential intervention against the behavior depends on the importance of the particular mechanism it targets.

In the case of adolescent sexual behavior, the equilibrium effects of changes in demand or supply are relevant because partners are found within a localized market, often at school. Thus any change in local demand is likely to affect the local supply of partners as well. Moreover, demand and supply correspond to different social mechanisms with distinct policies aimed at them. Some interventions designed to delay sexual initiation include an educational program against group norms that promote sex (Manlove, Romano-Papillo, and Ikramullah, 2004). Such programs target a peer effect on the demand for sexual partners. An alternative policy is to restrict the supply of partners. Single-sex schools represent one way to do this, but a less drastic option is to isolate the ninth grade from the older grades in high school, as in some districts where the ninth grade is in middle school.

To understand these policies, we need a way to disentangle the effects of the two relevant mechanisms, social norms among peers and the supply of partners at school. In this paper, I estimate an equilibrium model of sexual initiation in order to measure the separate effects of peer norms on the demand side and partner availability on the supply side. This draws on suggestions from Manski (2000), writing on social interactions, and Gruber (2001), writing on youth risk behaviors, to integrate formal economic models more closely with empirical work in these areas in order to clarify mechanisms.

The starting point for my model is to consider a market for sexual partners defined within the student body at a high school. The demand from each individual depends on the expected costs and benefits of sex, which is influenced by the share of same-gender peers who are nonvirgins. This is the effect of peer norms.[1] The model uses a search and matching framework, in which individual demand appears as the decision to search for a sexual partner. The probability of finding a partner then depends on the search decisions of others. Thus the effect of partner availability at school comes from changes in the probability of finding a match due to changes in the search behavior among the opposite gender.

The empirical analysis has two complementary components. First I estimate the composite effect of social interactions at school using an instrumental variables (IV) method that is standard in the literature on peer effects. Instruments for group nonvirginity rates are means of person-specific characteristics such as sibling structure and age of menarche, and the regressions include *school-by-grade* fixed effects (a relatively conservative approach). Then, having established the presence of a composite effect in my data using standard methods, I structurally estimate the search and matching model to measure the separate effects of peer norms and partner availability. This estimation uses maximum simulated likelihood. Here I control for the endogeneity of peer behavior by defining the norm effect as a function

[1] To be exact, "norms" is a reasonable interpretation for the influence of peer-group nonvirginity rates on individual preferences. See section 2 for evidence on norms from the sociology literature.

of lagged peer outcomes, including a random effect that is correlated within schools, and using exogenous peer characteristics as supply shifters.

The data come from the National Longitudinal Study of Adolescent Health (Add Health), which provides a nationally representative sample of U.S. high school students in the mid-1990s. I follow 14,300 students over two years using retrospective sexual histories taken in two rounds of interviews. The observation of virginity status over time allows the search and matching model to be estimated as a dynamic process, and it makes possible an innovative combination of econometric strategies to identify the endogenous effects of social interactions.

The results indicate that peer norms have a large effect on the timing of sexual initiation for both boys and girls. In a counterfactual simulation that removes the peer influence on search decisions, the share of individuals who initiate sex during the ninth or tenth grade falls by 0.07 for both boys and girls (a 41% decline for boys and 31% for girls). Changes in the availability of partners at school also impact the initiation rate for boys, but are not statistically significant for girls. The effect on boys is large: for example, for tenth grade boys a one-standard-deviation increase in the share of girls searching for a sexual partner raises the probability of finding a partner each period by 18 percent. Overall, these results are consistent with the IV estimates which show large composite effects for boys and girls. Previous studies also find large composite effects of social interactions in adolescent risk behaviors, including sexual initiation (Fletcher, 2007), as well as criminal activity, high school completion, substance abuse, and obesity (Case and Katz, 1991; Gaviria and Raphael, 2001; Lundborg, 2006; Clark and Lohéac, 2007; Trogdon, Nonnemaker, and Pais, 2008).

Policy simulations from the estimated model indicate that educational interventions reducing the effect of peer norms could have a larger impact than isolating the ninth grade from older grades to restrict the supply of partners. While the complete elimination of peer influence among adolescents seems unattainable (and perhaps undesirable), partially reducing the peer effect on demand would still have a substantial impact. On the other hand, removing the ninth grade from high school would decrease initiation in that year by about 13 percent for both boys and girls, but the effect dissipates over time. Other simulations examine the effect of separating virgins and nonvirgins into different schools at the beginning of high school, and the potential spillover effect of "virginity pledges" on non-pledgers.

Beyond the interest in measuring separate effects of peer norms and partner availability in adolescent sexual initiation, this work relates to a broad empirical literature on social interactions where the endogeneity of peer behavior is a central problem for estimation. In an overview of this literature, Moffit (2001) describes three conceptually distinct sources of endogeneity bias: the simultaneity of observed actions, which Manski (1993) calls the "reflection" problem; the correlation of omitted variables among peers; and selection into peer groups.

The most common strategy to address these problems is to use instrumental variables to provide exogenous variation in peer behavior.[2] Typically, instruments are person-specific characteristics hypothesized not to have a direct effect on the outcomes of others. However, the exclusion restrictions assumed for identification are violated if the distribution of these characteristics among peers has a direct effect on the individual, sometimes called a "contextual" effect (Manski, 1993; Brock and Durlauf, 2001a). This can occur if, for example, peers are defined spatially, and mean peer characteristics (especially socioeconomic attributes) relate to local factors that are unobserved. The use of school-by-grade fixed effects in my IV estimation is thus important to remove any such contextual effects that are time-invariant.

Apart from IV methods, several recent papers use longitudinal data to address the multiple sources of endogeneity.[3] De Paula (2009) presents a nonparametric test for social in-

[2]For example, among the econometric papers on adolescent risk behaviors referenced earlier, all use IV except for Clark and Lohéac (2007).

[3]The literature includes other methods that do not rely on longitudinal data. Evans, Oates, and Schwab (1992) and Krauth (2006) assume a multivariate normal distribution for the errors and use this to correct for selection or to allow for correlated unobservables (with additional assumptions). Glaeser, Sacerdote, and Scheinkman (1996) assume a specific network structure for individual interactions, which allows them to recover a peer effect from excess variance in aggregate outcomes. Sacerdote (2001) and Katz, Kling, and

teractions based on the simultaneous occurrence of outcomes among peers. Alternatively, if social interactions take time to affect individual behavior, the use of lagged peer outcomes is a potential strategy to circumvent the simultaneity problem (Manski, 1993). However unlike standard models, serial correlation in the individual errors would lead to biased estimates in social interactions models. This is because lagged peer outcomes are themselves affected by the individual's behavior in an earlier period.[4] To account for this and the other sources of endogeneity, some recent papers take advantage of data where individuals appear in multiple peer groups by including individual fixed effects (Hanushek et al., 2003; Mas and Moretti, 2009; Arcidiacono, Foster, and Kinsler, 2009; Jackson and Bruegmann, 2009). This strategy removes any permanent component of the unobservable, which addresses endogeneity bias due to both serial correlation in the individual errors and any common omitted variables among peers—assuming these factors are time-invariant.

In my structural estimation, I use similar strategies based on longitudinal data. First, I specify the peer influence on preferences to be a function of lagged peer outcomes. This avoids the problem of simultaneity, and it is consistent with the development of social norms over time.[5] To account for serial correlation in the individual errors, the model includes a random effect as a permanent component of preferences. The distribution of this random effect depends on individual characteristics, and on the nonvirginity rates by gender at the time when the individual enters high school (to capture initial conditions). This produces a correlation in the unobservable among peers, which addresses correlated omitted variables that are time-invariant. The combination of these two strategies—the use of lagged peer outcomes and a random effect that is correlated among peers—enables me to exploit time-series variation in data where individuals do not appear in multiple peer groups.[6]

Liebman (2001) use random assignment to peer groups.

[4]Clark and Lohéac (2007) do not address serial correlation, but they argue that it is not important in their setting.

[5]However, as Manski (1993) points out, the use of lags is not a simple panacea. One problem is that the choice of lag length is essentially arbitrary.

[6]Sirakaya (2006) estimates a duration model with social interactions, as do I, but uses time-invariant

There are two further strategies that do not rely on longitudinal data. Person-specific characteristics among the opposite gender play a role similar to IV. They affect preferences, so they function as exogenous predictors of search behavior (i.e., supply shifters). And finally, I use the grade in school to define peers, rather than an endogenous social group like sport teams or nominated friends, in order to avoid the problem of peer group selection.[7]

Apart from the methods used to address endogeneity bias, another innovation in this work relates to how I solve for equilibrium behavior. To determine optimal search decisions, agents need beliefs about the nonvirginity rates by gender and grade in future periods because these affect future payoffs and arrival rates. In order to construct equilibrium beliefs, I apply an insight from recent work on the estimation of discrete dynamic games which uses observed outcome probabilities directly for rational beliefs (Bajari, Benkard, and Levin, 2007; Pakes, Ostrovsky, and Berry, 2007).[8] I adapt this technique to be feasible in my context, where the large (but finite) number of agents produces a complicated distribution of outcomes, by approximating the evolution of nonvirginity rates as an autoregressive process. Obtaining beliefs directly from the data in this way greatly simplifies and speeds the estimation procedure because there is no need to solve for a new equilibrium with each set of candidate parameters.

The rest of this paper is organized as follows. The next section gives further background on teenage sexual activity and summarizes existing evidence on peer and other influences in this behavior. Section 3 presents the model. Section 4 describes the data, and section 5 contains the IV analysis that demonstrates a composite effect of social interactions. Section 6 describes the structural estimation procedure and provides the details on how the endogeneity of peer behavior is addressed in that approach. Section 7 gives the results from the search

explanatory variables. Identification in that work draws on the nonlinearity inherent to a duration model.

[7]The selection of school districts is another concern in this literature, but in my model this would be captured by the permanent component of preferences that is correlated within schools.

[8]These papers build on the method originally developed for individual dynamic models by Hotz and Miller (1993).

and matching model that measures separate effects for peer norms and partner availability, and section 8 presents policy simulations and other counterfactual experiments.

2 Background on Adolescent Sexual Behavior in the U.S.

Data from the Youth Risk Behavior Survey, a national survey of high school students, shows that the fraction individuals in grades nine through twelve who were sexually experienced declined from 54 percent in 1991 to 46 percent in 2001 and then increased (not statistically significantly) to 48 percent in 2007.[9] The National Survey of Family Growth (NSFG) provides further trends by gender and age for the noninstitutionalized population. From 1995 to 2002, nonvirginity rates among (never married) 15 to 17 year-olds decreased from 38 to 30 percent for girls and from 43 to 31 percent for boys. The rate among 18 and 19 year-olds remained statistically unchanged at 68-69 percent for girls, while it dropped from 75 to 64 percent for boys (Abma et al., 2004).

Sexual activity is highly persistent among teenagers. Only 9 percent of sexually experienced teenage boys and girls report having had sex only once, compared with 69 (76) percent of nonvirgin boys (girls) who report having sex in the past three months and 87 (91) percent in the past year.[10] This persistence indicates the importance of initiation, which Arcidiacono, Khwaja, and Ouyang (2009) measure explicitly as a large fixed-cost-like term in preferences. Similarly, the decrease in sexual *experience* from 1995 to 2002 noted above almost completely accounts for a related decrease in sexual *activity* over that period.[11] The rates of activity and experience fell by the same relative amounts, meaning that the prob-

[9] CDC fact sheet on "Trends in the Prevalence of Sexual Behaviors, National YRBS: 1991-2007," `http://www.cdc.gov/HealthyYouth/yrbs/pdf/yrbs07_us_sexual_behaviors_trend.pdf`, accessed 4/28/09.

[10] These figures and those that follow are calculated from data published in Abma et al. (2004).

[11] Sexual activity is typically defined as intercourse within the past three months.

ability of being sexually active conditional on being sexually experienced was unchanged.[12] Thus changes in initiation appear to drive changes in the amount of sexual activity among teenagers.

While sexual initiation is a normal part of human development, most of the policy interest in adolescent sexual activity focuses on the risks associated with sex. Among these risks, unplanned pregnancy receives the most attention. In perhaps the most noteworthy example, President Bill Clinton declared the "epidemic" of teenage pregnancy and out-of-wedlock childbearing to be "our most serious social problem" in his 1995 State of the Union address.[13] Teenage childbearing is associated with negative outcomes for both the mothers and their children. For example, teenage mothers have lower educational attainment, and their sons are more likely to be incarcerated at some point in their lives (Hoffman, 2006). There are also large public expenditures on the children of teenage mothers, such as an estimated \$1.9 billion for medical care and \$2.3 billion in foster care per year (Hoffman, 2006). The rate of childbearing among women aged 15-19 in the U.S. peaked at 61.8 per 1,000 in 1991 and then declined to 40.5 per 1,000 in 2005, followed by a small increase (Hamilton, Martin, and Ventura, 2009). These rates are substantially higher than in other developed nations. An analysis of the decline in teenage pregnancy from 1995 to 2002 finds that it resulted from both increased contraceptive use and decreased sexual activity (Santelli et al., 2007). The impact of changes in sexual activity was primarily among younger teens, which corresponds with the trends in nonvirginity rates by age for girls. Among girls aged 15 to 17, reductions in sexual activity accounted for 23 percent of the decrease in childbearing over that period (Santelli et al., 2007).

Another risk associated with sexual activity is sexually transmitted disease (STD). Teenagers

[12] For boys, the rates of sexual experience and sexual activity both fell by 17%; for girls, the rate of sexual experience fell by 8% and the rate of sexual activity fell by 9%. Calculated from Abma et al. (2004).

[13] Transcript from "The American Presidency Project" website, `http://www.presidency.ucsb.edu/ws/index.php?pid=51634`, accessed 11/10/09.

and 20-24 year-olds have the highest prevalence of STDs of any age groups. For the two most common and well-reported STDs, chlamydia and gonorrhea, there were nearly 480,000 cases reported among teenagers in 2007 (CDC, 2008b). Considering these and six other major STDs, Chesson et al. (2004) estimate that the lifetime medical cost of treating the STDs acquired over one year by 15 to 24 year-olds totals $6.5 billion. Finally, there is work indicating possible direct effects of early sexual initiation on psychological well-being and academic performance. Sabia (2007) and Sabia and Rees (2008) estimate that boys who initiate sex before age 16 then have decreased GPAs and girls who initiate before age 17 are then more likely to have symptoms of depression, controlling for individual fixed effects.

A number of individual-based factors have been studied in relation to sexual initiation or sexual activity among adolescents. The National Research Council (NRC) Panel on Adolescent Pregnancy and Childbearing (1987, chapter 4) provides a useful overview of characteristics that predict early initiation. These include black race and low socioeconomic status meaured by parental education and family income, although some recent research finds the association with race is mainly for boys (Levine, 2001; Michael and Bickert, 2001). Early onset of puberty is another strong and plausibly exogenous predictor, which is well measured in girls as the age of menarche (NRC Panel, 1987; Miller et al., 1997). Several authors have studied the relationship between substance use and sexual behavior, with mixed evidence about the effect of alcohol or drug use on sexual activity (Rees, Argys, and Averett, 2001; Sen, 2002; Markowitz, Kaestner, and Grossman, 2005). Levine (2001) considers the indirect costs of sex that arise from state employment rates, welfare benefits, or the prevalence of AIDS. He finds that each of these is associated with changes in rates of sexual experience or activity among teenagers. Finally, Oettinger (1999) shows theoretically how sex education could either increase or decrease the propensity to initiate sex by changing expected payoffs and risk probabilities, and he presents evidence that sex education increases the hazard rate for initiation among girls.

The role of peer norms in sexual initiation has been documented primarily by work in psychology and sociology. Kinsman et al. (1998), Santelli et al. (2004), and Sieving et al. (2006) measure peer norms through self-reported perceptions about the level of sexual activity among peers, peer attitudes toward sex, or the social gains for becoming sexually active. All three studies find that norms defined this way have a significant association with the probability of initiating sex. In addition, earlier work surveyed by the NRC Panel (1987) indicates that peer norms regarding sexual behavior are established within gender for adolescents. As for econometric work, Fletcher (2007) is the only analysis estimating a social multiplier on sexual behavior per se, although Case and Katz (1991) and Evans, Oates, and Schwab (1992) estimate social effects on teenage childbearing.

In addition to peers defined as friends, other work has examined the roles of siblings and romantic partners. Rodgers et al. (1992), Widmer (1997), and Argys et al. (2006) give evidence that individuals with older siblings tend to initiate sex earlier. Kaestle, Morisky, and Wiley (2002) find that girls with romantic partners who are much older have a higher probability of initiating sex.

Given the evidence on peer influence, interventions to delay sexual initiation often target peer norms. Two examples are "Safer Choices," first implemented in 1993 with 2,000 ninth and tenth grade students in ten high schools in California and Texas, and "Draw the Line/Respect the Line" (DL/RL), first implemented in 1997 with 1,500 middle school students in California (Manlove, Romano-Papillo, and Ikramullah, 2004). These programs consist of about 20 classroom sessions spaced out over two or three school years, with some sessions devoted to learning about social norms and practicing communication skills. To give a flavor of how this works, Session 2 in Safer Choices is described as

> *The Safest Choice: Deciding Not to Have Sex.* Students learn about "social norms." They discuss perceptions of how many of their peers have had sex and how these perceptions compare to actual statistics. Using role-playing, students also learn refusal skills. (p. 31)

Similarly, Session 5 in DL/RL "discusses the role that friends play in respecting the line. Role play scenarios are used to practice showing respect for another person's limits" (p. 21).[14] Programs such as these demonstrate a specific policy interest in the effect of peer norms, as distinct from the composite effect of social interactions.

3 A Search and Matching Model for First Sex

The model describes a discrete-time dynamic process leading to sexual initiation. Each period, virgins decide whether or not to search for their first sexual partners. For those who search, there is a probability of finding a partner per period which depends on the search behavior among virgins and nonvirgins of the opposite gender. Equilibrium is defined within a local market for partners, which is the student body at a high school. There is also an external market, which appears through an exogenous probability of finding a partner from outside the school.

The model abstracts from certain aspects of adolescent sexual behavior that would add complications without greatly enhancing the analysis of social influences in sexual initiation per se. First, there is no constraint on the number of partners per period. Although a single partner per period is the most common, multiple partners (observed as overlapping relationships) also appear in the data. To incorporate this in the model, I would need to specify multiple types of relationships (exclusive and nonexclusive) and include a dissolution rate for exclusive relationships. Then the arrival rate of partners would depend in part on the share of exclusive relationships, and agents would need to keep track of this aspect of the market, which would greatly expand the state space.

Second, payoffs relate directly to virginity status. All the costs and benefits of sexual

[14] These programs were evaluated by comparing outcomes across schools that were randomly assigned into treatment or control groups. The results found that DL/RL reduced sexual initiation among boys by one third but Safer Choices did not have an effect on the population as a whole, although there was a decrease in initiation among Latinos (Manlove et al., 2004).

activity, such as the risk of pregnancy or the frequency of sex, are embedded in the expected utility of nonvirginity. In connection to this, subsequent decisions related to sexual activity are suppressed (e.g., contraceptive use and abortion).[15] Further decisions and additional structure in the payoffs are not necessary for my analysis because, for a virgin, it is the overall expected utility of novirginity that determines whether he or she wants to become sexually active.

Third, nonvirgins are assumed to stay in the market and continually search for new partners. This allows individuals to have more than one partner during high school, which is true for a large portion of the population. And again, it avoids the decisions to have multiple partners or end a relationship.

Finally, the match probabilities among individuals do not depend on own or partner characteristics. Including them would introduce sorting behavior, which is not the purpose of this research. Thus the arrival rate in the model averages over any individual heterogeneity and any differences related to the characteristics of opposite-gender searchers. To the extent that arrival rates are in fact heterogeneous, the model misassigns the effect of such characteristics to the search decision. However, the typical characteristics one would think to use to add heterogeneity to the arrival rate or match probabilities are permanent attributes. In contrast, the primary objects of interest—the effects of peer norms and partner availability—are identified from changes in nonvirginity rates over time, not permanent attributes.

3.1 Model Specification

The model applies to individuals, i, located in a local market for partners, m, who have a gender, $\tau \in \{b, g\}$.[16] Virginity status at the start of a period is denoted $y_{i,t-1}$, with 0

[15] Also, there is no decision to accept a match offer. This is not needed because all matches produce the same payoff for an individual.

[16] The model pertains to heterosexual sex, so a partner must be of the opposite gender.

meaning virginity. Each period virgins make a search decision $d_{it} \in \{0, 1\}$, and for those who search there is a probability of finding a partner and thereby initiating sex. Nonvirgins always search.

Age, a, is defined socially as quarter within grade in high school. The model covers the fall of ninth grade ($a = 1$) through the spring of twelfth grade ($a = 15 \equiv A$). Time, t, is also measured in quarters, and is needed separately from age to track multiple cohorts at once. However in the exposition, the model is presented from the perspective of a reference cohort for which time and age are equal ($a_{it} = t$). Also, all functions are gender-specific, but gender subscripts are suppressed unless needed for clarity.

The probability of finding a partner each period is expressed by the arrival rate, λ_{it}, which is a function of the proportion of searchers among the opposite gender at the school.[17] This proportion is denoted N_{it}, and it includes the behavior of both virgins and nonvirgins. The arrival rate does not depend on search behavior within the same gender because there is no constraint on the number of partners, so there is no competition between same-gender individuals. Also, because there is also an external market for partners, the arrival rate is positive even if there are zero searchers at school.

The arrival rate is given by a gender and age specific function, which is specified as a logit:

$$\lambda_{it} = \lambda_{a_{it}}(N_{it}) \equiv \frac{\exp(\lambda_{0a_{it}} + \lambda_1 N_{it})}{1 + \exp(\lambda_{0a_{it}} + \lambda_1 N_{it})} \tag{1}$$

(with subscripts τ_i suppressed). The main reason to allow the parameters λ_{0a} to vary with age is to capture changes in the amount of contact with the external market as students progress to older grades. The key parameter of interest in (1) is λ_1, which captures the effect of partner availability at school.

Individuals derive utility from their virginity status. The per-period payoff for being

[17] An advantage of using the proportion rather than the number of searchers is that it normalizes for population size, which is helpful in the estimation. Also, using the proportion allows the measure to be treated as a sample estimate rather than exact behavior. See Manski (1993) for a discussion of this distinction.

sexually experienced is a linear combination of age, the proportion of peers who are already nonvirgins, denoted $Y_{i,t-1}$, a permanent individual component, ω_i, and an iid mean-zero preference shock, ϵ_{it}. Peers are individuals of the same gender in the same grade as i. The per-period utility for a nonvirigin is then expressed as

$$u(a_{it}, Y_{i,t-1}, \omega_i, \epsilon_{it}) \equiv \overbrace{\alpha a_{it} + \gamma Y_{i,t-1}}^{u_{it}} + \omega_i + \epsilon_{it}. \tag{2}$$

The per-period utility for a virgin is normalized to zero.

The term $\gamma Y_{i,t-1}$ represents the effect of peer norms. This is a standard specification for a social component of utility, as in Brock and Durlauf (2001b). To be precise, the term relates lagged peer nonvirginity rates to the expected utility of sex, and I interpret this as an effect of social norms based on the evidence from sociological work on sexual initiation discussed in section 2.[18] The age term (αa_{it}) is intended to capture the individual maturation process, which is both biological and psychological. The permanent individual component (ω_i) reflects aspects of the potential costs and benefits of sexual activity that vary across individuals. For example, this captures differences in the desire for sex, as well as differences in the costs of pregnancy and STDs, or the perceptions of these risks.

Individuals are not myopic in the model and consider future payoffs with a discount rate β. This is supported by strong evidence of anticipation and intentionality in sexual initiation, found by Kinsman et al. (1998). Consequently, because the model ends with high school graduation but the payoff to virginity status continues, non-trivial terminal values are needed. For nonvirgins, I eliminate the peer influence on preferences after high school (there is no further data, anyway) and hold the age and permanent individual components constant for an infinite horizon. This yields a simple terminal value of $(\alpha A + \omega_i)/(1-\beta)$. For virgins, the terminal value is a free parameter $\nu(\omega_i)$. This is nonzero to allow virgins to

[18] Also, the use of *lagged* peer nonvirginity rates is supported by sociological work such as Kinsman et al. (1998) which specifically asks for perceptions about how many peers are *already* sexually experienced.

anticipate a payoff from sexual activity later in life.[19]

I express lifetime utility using the Bellman representation, with value functions denoted $V_a(y_{i,t-1}, Y_{t-1}, \omega_i, \epsilon_{it})$. The vector Y_{t-1} (8×1) contains the nonvirginity rates by gender in each of the four grades in high school; this is the aggregate state of the local market. The arguments of the value functions, along with the individual's gender and age, constitute the information set. $V_{a_{it}}(1, Y_{t-1}, \omega_i, \epsilon_{it})$ gives the expected lifetime utility for a nonvirgin, which has an analytical expression:

$$u_{it} + \omega_i + \epsilon_{it} + \sum_{s=1}^{A-a_{it}} \beta^s [\mathrm{E}_t u_{i,t+s} + \omega_i] + \beta^{(A-a_{it}+1)} \frac{\alpha A + \omega_i}{1-\beta}, \tag{3}$$

where u_{it} is defined in (2) and E_t denotes the individual's expectation given his or her information set.[20]

For a virgin, the value function is a more complicated object that incorporates the search decision and the arrival rate. It is expressed as

$$\begin{aligned} & V_{a_{it}}(0, Y_{t-1}, \omega_i, \epsilon_{it}) = \max_{d_{it}} \\ & d_{it}\ \mathrm{E}_t \Big[\lambda_{it} \cdot \Big(u_{it} + \omega_i + \epsilon_{it} + \beta V_{a_{it}+1}(1, Y_t, \omega_i, \epsilon_{i,t+1}) \Big) + (1-\lambda_{it}) \cdot \beta V_{a_{it}+1}(0, Y_t, \omega_i, \epsilon_{i,t+1}) \Big] \\ & + (1-d_{it})\ \beta \mathrm{E}_t V_{a_{it}+1}(0, Y_t, \omega_i, \epsilon_{i,t+1}). \end{aligned} \tag{4}$$

The second line above expresses that an individual who searches ($d_{it} = 1$) will become a nonvirgin with probability λ_{it} and will remain a virgin with probability $(1 - \lambda_{it})$. The third line is the value of not searching, in which case the individual advances to the next period still a virgin.

To form the expected values in (3) and (4), individuals need beliefs over the sequences

[19] Because only differences in payoffs are identified by choice behavior, the estimated $\nu(\omega)$ may capture omitted aspects of the terminal values for nonvirgins such as the expected value of any preference interactions in the future.

[20] To simplify the indexes, note that $a_{it} = t$ for the reference cohort.

of nonvirginity rates among peers $(Y_{it}, Y_{i,t+1}, \dots)$ and arrival rates $(\lambda_{it}, \lambda_{i,t+1}, \dots)$. In fact, beliefs over the evolution of the vector Y_t (the nonvirginity rates by gender and grade) are sufficient for both. This is because expected arrival rates can be derived based on the decision rules for the opposite gender. The search decisions among the opposite gender depend on their state variables $(a_{jt}, y_{j,t-1}, Y_{t-1}, \omega_j, \epsilon_{jt})$. Given Y_{t-1}, it is possible to integrate the decision rules over the distributions of ω_j and ϵ_{jt}, and the various possible assigments of individual virginity statuses $y_{j,t-1}$ that would correspond to the group nonvirginity rates in Y_{t-1}. This yields a distribution for N_{it}, the share of searchers, which in turn gives the distribution of λ_{it}. How I implement this is explained in sections 3.2 and A.1.

For the evolution of Y_t, I use an approximation to fully rational beliefs that is similar to Krusell and Smith (1998) and Lee and Wolpin (2006). In the approximation the distribution of Y_t given past values is Markovian, and its expected value is autoregressive with the following specification:

$$\mathrm{E}[Y_{kt}|Y_{k,t-1}] = \psi_{0k} + \psi_1 Y_{k,t-1} + \psi_2 Y_{k,t-1}^2 + \sum_{j \in s(k)} \psi_{3j} Y_{j,t-1}. \tag{5}$$

Here k indicates one element of the vector (i.e., one gender-grade group), and $s(k)$ collects the subscripts for the opposite-gender groups, which I refer to as "supply groups." The vector autoregression that stacks these elements is denoted $\psi(Y_{t-1})$. As in Krusell and Smith (1998) and Lee and Wolpin (2006), this first-order autoregression fits the true evolution of the aggregate state extremely well (see section 7). There are two details in the implementation of these beliefs. First, because school populations are finite in the model, the approximation incorporates the impact of an individual's choice and outcome on his or her own group's nonvirginity rate.[21] Second, because the aggregate state does not contain information on cohorts not yet in high school, the nonvirginity rates for each new cohort of ninth graders

[21] There is a straightforward modification to (5) to account for a known value of y_{it} in Y_{it}, in a group of given size n_i. The approximation ignores any impact on other groups.

are predicted based on the previous cohort.[22]

Finally, the expected costs and benefits of sexual activity embodied in the permanent individual term ω_i may relate to the probability of initiation prior to ninth grade. Because these initiation rates vary across schools, the model must account for initial conditions. To do this, I specify a distribution of ω_i for *virgins at the beginning of ninth grade* that is conditional on the vector Y_0, which includes the nonvirginity rates among rising ninth graders just before they enter high school.[23] There are two reasons to think that the distribution of ω_i among virgins might not be independent of the initial nonvirginity rates in Y_0. First, if ω is correlated among peers, then a high Y_{i0} (the proportion of nonvirgins in the peer group) indicates a higher ω_i for the individual. Second, if ω is uncorrelated but there are common opportunities to initiate sex prior to ninth grade, the distribution of ω_i among the remaining virgins is affected by selection.

In addition to Y_0, the conditional distribution of ω_i also depends on a vector of exogenous, permanent individual characteristics, x_i. This is for the empirical implementation, to incorporate observable attributes that relate to the expected costs and benefits of sex. I specify ω to have finite support, so that $\omega_i \in \{\omega^k\}_{k=1}^{\kappa}$, which assumes there are κ "types" when it comes to sexual initiation. The conditional distribution of ω_i, for virgins at the beginning of ninth grade, is specified as a multinomial logit:

$$\Pr(\omega_i = \omega^k \mid Y_0, x_i) = \pi_{k|Y_0,x_i} \equiv \frac{\exp(\pi_0^k + Y_0'\pi_1^k + x_i'\pi_2^k)}{1 + \sum_{l=2}^{\kappa} \exp(\pi_0^l + Y_0'\pi_1^l + x_i'\pi_2^l)}, \tag{6}$$

where the parameters for the first type are normalized to zero.

[22] I use the nonvirginity rate of one cohort in the summer after ninth grade (e.g., $t = 4$ for the reference cohort) to predict the rate for the new cohort in the same time period. I do this by inverting the following regression for the annual growth of nonvirginity rates during ninth grade: $\mathrm{E}Y_{k4} = \Pi_0 + \Pi_1 Y_{k0}$ (k denotes a gender-cohort group). The formula for the prediction is then $\widehat{Y}_{k'4} = Y_{k4}/\Pi_1 - \Pi_0/\Pi_1$, where k' denotes the new ninth-grade cohort.

[23] Of course, the vector Y_0 contains all grades because they are needed as part of the state space.

3.2 Individual Behavior and Equilibrium

Given beliefs about the evolution of Y_t, the individual decision problem solves much like a single-agent dynamic problem. This simplification occurs because the current period λ_{it} drops out from the decision rule, so there is no simultaneous game to be solved each period. To show this result, I rearrange (4) to

$$\begin{aligned}\max_{d_{it}} \ & d_{it} \cdot \mathrm{E}_t\lambda_{it} \cdot \Big(u_{it} + \omega_i + \epsilon_{it} + \beta\mathrm{E}_t V_{t+1}(1, Y_t, \omega_i, \epsilon_{i,t+1}) - \beta\mathrm{E}_t V_{t+1}(0, Y_t, \omega_i, \epsilon_{i,t+1})\Big) \\ & + \beta\mathrm{E}_t V_{t+1}(0, Y_t, \omega_i, \epsilon_{i,t+1}). \qquad (7)\end{aligned}$$

Because $\mathrm{E}_t\lambda_{it}$ is strictly positive, the decision rule is therefore

$$d_{it} = 1 \text{ iff } u_{it} + \omega_i + \epsilon_{it} + \beta\mathrm{E}_t V_{t+1}(1, Y_t, \omega_i, \epsilon_{i,t+1}) > \beta\mathrm{E}_t V_{t+1}(0, Y_t, \omega_i, \epsilon_{i,t+1}). \qquad (8)$$

Thus a virgin will search if and only if the value of becoming sexually active exceeds the value of remaining a virgin.[24] This is a standard result in a model with no search cost.

The age-specific value functions for virgins, given by (7), do not have analytical expressions, but they can be numerically constructed by backward recursion starting from the final period which has known terminal values. I use interpolation to approximate these functions (Keane and Wolpin, 1994) because the state space includes an 8-dimensional continuous vector (Y_{t-1}). This involves evaluating the functions on a set of points in the state space and then regressing these values on transformations of the state variables to create very close approximations to the true functions. To choose solution points that span the state space, I draw Y_{t-1} from a joint uniform distribution and ω_i from the set of values $\{\omega^k\}$, and sample x_i and the membership of the peer and supply groups from their joint empirical distribution.

[24]It is interesting to note that the criterion would be the same in a decision about accepting an offer to have sex. However the reason to model the decision as search rather than offer acceptance is that search behavior produces an endogenous supply of partners.

To evaluate the value functions for virgins at the solution points, I need to extend the standard procedure in order to account for the search decisions of opposite-gender virgins, which are embedded in the arrival rate (λ_{it}). An exact calculation for the expected arrival rate would use the decision rule in (8), and integrate over the unobserved values of ω_j and ϵ_{jt} among those virgins. However, the random values of Y_{t-1} drawn for the solution points do not correspond to the observed virginity statuses of the members of the supply groups, and there is no simple procedure to choose virgins and nonvirgins to match Y_{t-1}. This is because the probability of being a nonvirgin in the model depends on the individual characteristics that affect the distribution of ω and on the entire history of Y. Instead, I approximate the search decisions among the opposite gender as a function of Y_{t-1} and use this to approximate the expected arrival rate. This procedure is described in appendix A.1.

Then to solve for equilibrium, I need equilibrium beliefs about the evolution of Y_t. To construct these beliefs I estimate the autoregression ψ in (5) directly from the observed aggregate data, in a preliminary stage before the estimation of the structural parameters. As in Bajari, Benkard, and Levin (2007) and Pakes, Ostrovsky, and Berry (2007), this method assumes only one equilibrium is observed, and it assumes a steady state from one cohort to the next. Moreover because I use an approximation to rational beliefs, unlike these papers, I need to check that the estimated beliefs are consistent with the model. I do this post-estimation by re-estimating ψ on data simulated from the model and comparing the two estimates with each other. The results support the approximation (see section 7 and table 11). Also, because the autoregression fits the observed evolution of Y_t extremely well, with $R^2 > 0.95$, I use a degenerate distribution at the expected values for the beliefs in the approximation. This avoids the need to integrate over a distribution in each future period when solving for individual behavior.

An alternative to the two-step estimation procedure would be to solve for the approximation ψ as a fixed point along with the structural parameters, as in Lee and Wolpin (2006).

In that paper part of the aggregate state is unobserved to the econometrician (there is an aggregate productivity shock), so it is not possible to estimate an approximation to rational beliefs directly from the data. Given that the aggregate state for my model *is* observed, the advantage of recovering beliefs directly from the data is that it avoids the iteration needed to solve a fixed point for each candidate set of structural paremeters. This greatly reduces the computational burden of estimation.

4 Data and Descriptive Statistics

The data come from Waves I and II of the National Longitudinal Study of Adolescent Health (Add Health). The study contains a nationally representative sample of students in grades 7-12 during the 1994-95 school year, when the first wave was conducted. The second round of interviews (Wave II) followed up with respondents one year later in April through August of 1996. Add Health features a highly clustered sample drawn from 80 high schools plus additional middle schools that feed students into the sample high schools (one middle school per high school, unless the sample high school already includes grades seven and eight).

Add Health collects detailed retrospective histories on sexual activity and romantic relationships. To enhance the sense of privacy, these questions were administered in a self-directed portion of the survey on a laptop computer at respondents' homes. Included in these questions, respondents are asked if they have ever had sexual intercourse which is defined explicitly.[25] Those who say yes are then asked to report the month of first sex. Both rounds of interviews ask these questions of all respondents, and to minimize the loss of observations due to missing data I use the earliest month reported in either round. From these observations I construct a quarterly series on virginity status for each individual, starting in the

[25] The question reads: "Have you ever had sexual intercourse? When we say sexual intercourse, we mean when a male inserts his penis into a female's vagina." (Wave I Adolescent In-Home Questionnaire Code Book, section 24, page 1.)

summer of 1994 and ending in the spring of 1996.

The estimation sample uses individuals observed in grades 9-12 in either the 1994-95 or 1995-96 school years, who were selected for in-home interviews.[26] Add Health contains 17,657 such individuals, who are in grades 8 through 12 during the first round of interviews in 1994-95. I use the grade in that academic year to refer to separate "cohorts." I exclude 2,635 individuals who drop out of the second round of interviews (except for the twelfth grade cohort, which was not reinterviewed). I also exclude 69 individuals from an all-boys school, 98 in schools with small samples that do not have both genders in some grades, and 318 who report homosexual sex. After dropping observations without information on key identifying variables (school, grade cohort, and gender), the final extimation sample contains 14,294 individuals in 78 schools.

Figure 1 presents the nonvirginity rates for this sample by quarter in high school (i.e., "age"). Each cohort, which is observed for one or two years, is shown as a separate line positioned over the appropriate ages. The black line then averages among all individuals observed at a given age, to produce a complete path through high school for a synthetic cohort. I exclude the twelfth grade cohort from the synthetic cohort because they are interviewed only once, so they have a higher rate of missing data on the month of first sex. This makes their retrospective nonvirginity rates fall below the trend constructed from the younger cohorts. These graphs show that a large portion of individuals initiate sex during high school. The share of nonvirgins among boys increases from just over 26 percent at the beginning of ninth grade to just under 64 percent at the end of twelfth grade, and among girls it increases from 20 percent to 62 percent. Thus about 40 percent of the population initiates sex during the four years of high school.

Data on individual or family characteristics come from Wave I. In the structural estimation of the search and matching model, I use indicators for black race, parental education,

[26]Add Health also administered an in-school questionnaire to all students in the sampled schools.

and sibling status as the characteristics (x_i) that affect the distribution of the individual preference term (ω_i). The education variable indicates whether one parent has 16 years of education (i.e., is a four-year college graduate). The sibling variables are two dummies that indicate whether the individual is a younger sibling or is an only child. I use these variables because they are predetermined characteristics that have been shown to predict early sexual initiation in other work, and they have clear relationships with the expected costs or benefits of sexual activity. For example, race and parental education relate to expected labor market outcomes, which affect the relative cost of a pregnancy. Younger siblings may learn from older siblings about the benefits of sex or how to reduce the costs (e.g., through birth control). In the IV estimation of the composite effect of social interactions I use additional exogenous characteristics to improve the power of the instruments, because the computational burden of additional coefficients is negligible. These variables are indicators for: Hispanic ethnicity; mother currently married; a foreign-born parent; relatively high household income, defined as above \$50,000; and early menarche for girls, defined as before the median age of 12.

The shares of individuals with each of these characteristics are shown in table 1. The table presents both the unweighted and weighted shares, and these figures are similar except for black race, Hispanic ethnicity, and a foreign-born parent, which reflect oversamples in the sample design. Table 1 also shows the shares of individuals in urban school districts and in districts where the ninth grade is in a separate location from the rest of the high school. The weighted and unweighted values for the latter are quite different because a large number of individuals are sampled in one high school that only has grades 10 through 12.[27] Either way, however, the vast majority of ninth graders go to school with older students.

Table 2 shows the raw correlation between individual virginity status and the nonvirginity rates for each gender and grade at the same school, assessed in the last observation period (the

[27]In 16 of the sampled high schools, in-home interviews were conducted with nearly all students. One of these is a large, urban high school with only grades 10-12, which is the cause of the discrepancy between the weighted and unweighted figures.

spring quarter of the second year). Under random sampling, these correlations are equivalent to correlations in virginity status between two individuals, one from each specified group.[28] The bolded numbers along the diagonal give the correlations within peer groups, which are somewhat higher than the correlations with other grades of the same gender (except for girls in the tenth and twelfth grades, who have slightly higher correlations with some other grade). This provides support for the definition of peer groups by grade. Overall, table 2 shows there are large correlations in virginity status within schools, about 0.2 in magnitude. This would produce substantial variation in nonvirginity rates across schools, which is a notable consequence of social interactions, although it can also result from unobserved factors.

For the endogenous supply of partners, only certain grades of the opposite gender are used in the empirical implementation. These grades are shown in bold in table 2: for boys, they are girls in the same grade, the grade below, and the grade above; and for girls, they are boys in the same grade and the next two older grades.[29] These were chosen because, in the sexual histories, more partners are reported from these grades than any others. The purpose of these restrictions is to incorporate the low probability of matches between certain grades, and to create variation within schools in the shares of nonvirgins and searchers on the supply side of the market. Partners from outside these groups, such as an eleventh grade girl for a ninth grade boy or vice versa, are considered to be exogenous, which treats them as part of the external market. Thus in the estimation, the grade-specific constant term in the arrival function (λ_{0a}) captures the probability of finding a partner either from outside school or in one of these other grades. With a few exceptions, the correlations between individuals and their supply groups as used for estimation are larger than the correlations with the excluded grades of the opposite gender (table 2).

[28]The individual is excluded from the nonvirginity rate for his or her own peer group.

[29]The supply groups do not need to be symmetric in the model or in reality because the lack of constraint on the number of partners makes it possible for a small number of individuals from one grade to match with a large number from another grade.

5 Instrumental Variables Analysis

For the first empirical analysis, I apply an IV method that is standard in the literature on peer effects. There are two purposes for this exercise. First, I am able to improve on estimates from previous work due to the richness of my data. I can estimate an effect of social interactions on virginity status at each grade because the clustered sample provides a sufficient number of individuals in each grade per school. In addition, because the data contain multiple cohorts that pass through each grade, I am able to include school-by-grade fixed effects. This controls for any correlated unobservables or contextual effects that are invariant over the observation period.

Other recent work on school-based social interactions in adolescent risk behaviors uses school fixed effects for this same purpose (Lundborg, 2006; Clark and Lohéac, 2007; Trogdon, Nonnemaker, and Pais 2008; Fletcher, 2009). However, except for Lundborg (2006), these papers have one fixed effect for all grades.[30] This removes a common effect on levels but does not address differences across schools in how risky behaviors increase with age. Yet because sexual initiation is a one-time transition, it is natural to think of a duration process and focus on how nonvirginity rates rise with age rather than just the levels. If unobserved school-wide factors affect the hazard rate, there will larger differences across schools at younger grades and smaller differences at older grades. These are not captured with a single school fixed effect.

The second purpose for the IV analysis is to demonstrate the presence of social interactions in my data using a standard method that has different identifying assumptions than the structural estimation of the model. As in Fletcher (2007), which uses a different dataset but from the same time period, the IV estimation here finds a large composite effect of social interactions on sexual initiation.

[30]Lundborg (2006) defines peer groups at the classroom level and uses variations across classrooms within grades, at a single point in time.

5.1 Regression Model

The empirical models in this analysis are linear regressions for virginity status at the spring quarter of each grade in high school. They are specified as

$$y_{imat} = \pi_{0at} + \pi_{1a}' x_i + \pi_{2a} \bar{y}_{(-i)mt} + w_{ma} + e_{imat}, \tag{9}$$

where m indexes schools, a is "age" at school (as in the model), and t is calendar time.[31] As the subscripts on the coefficients indicate, these regressions are estimated separately by grade (and by gender, with the subscripts suppressed as usual). The term π_{0at} is a time-specific intercept to capture differences in the average outcomes of each cohort. The variable $\bar{y}_{(-i)mt}$ contains the nonvirginity rate in the reference group, to be defined later, and w_{ma} is the school-by-grade fixed effect.

Estimation is via 2SLS. As is standard, I use means of the individual characteristics within the reference group ($\bar{x}_{(-i)m}$) to instrument for $\bar{y}_{(-i)mt}$. The identification strategy relies on the school-by-grade fixed effects (w_{ma}) to remove any violations of the exclusion restrictions for these instruments. This works under the assumption that any contextual effects related to the mean characteristics do not vary over a two-year period.[32] I test the exclusion restrictions with an overidentification test. This requires that at least one element of $\bar{x}_{(-i)m}$ can be excluded from (9), which is itself an untestable assumption.[33] Because all of the characteristics are predetermined, however, it seems reasonable that the exclusion should hold for at least one of them given that any violations must relate to *differences* in the instruments from one year to the next. With this strategy, the effect of social interactions

[31]Note that although individual outcomes are subscripted with t, an individual appears only once in the sample for each regression.

[32]It is also possible to include some elements of $\bar{x}_{(-i)m}$ in (9), but I exclude all in order to have as much "within" variation as possible for the first stage.

[33]The overidentification test also assumes that any potential violations of the specification do not perfectly cancel each other out in the test statistic, which is possible due to the loss of degrees of freedom that results from estimating the coefficients. See Hayashi (2000, p. 218).

is identified from differences between the mean characteristics of the two cohorts that are observed at each grade level in each school.

It is important to note that these regressions cannot be interpreted as approximations for the search and matching model. Seen in terms of the model, virginity status at a point in time is the cumulative result of a transition process over many periods. Because the per-period transition probabilities multiply out to produce the probability of being a nonvirgin at a point in time, there is no simple correspondence between the components of the transition process specified in the model and this cumulative outcome.[34] In addition, the search and matching model applies to individuals who are virgins at the beginning of high school, while the IV analysis does not condition on initial status (this is standard). Given these differences, the baseline specification uses *contemporaneous* peer outcomes in the regressions rather than lagged outcomes, because this is the standard formulation in the literature. Regressions using lagged outcomes produce similar results.

Another difference with the model is the use of a single reference group, whic also follows the literature. Thus the regressions do not attempt to distinguish between a within-gender effect and a cross-gender effect. Having separate effects in a static regression model would be misleading because both coefficients would reflect combinations of the peer influence on demand and the effect of partner availability. To see this, consider an exogenous increase in the share of (same gender) peers who are sexually experienced. This would directly increase an individual's demand for sex. However it would also indirectly increase the supply of partners in equilibrium. This is because the increase in the peer nonvirginity rate would raise the arrival rate experienced by the opposite gender, thereby increasing nonvirginity rates among the opposite gender, which in turn raises the arrival rate for the individual. This indirect effect becomes clear when followed over time: in period 1, the nonvirginity

[34]To see this, suppose that the per-period transition probability for individual i is P_{it}. Then the probability that i is nonvirgin at time t, conditional on being a virgin at time 0, is $1 - \prod_{s=1}^{t}(1 - P_{is})$.

rate among peers exogenously increases; the search behavior of these nonvirgins then raises the arrival rate of partners for the opposite gender, so in period 2 their nonvirginity rate increases as well; hence in period 3 both the individual's search probability (demand) and arrival rate (supply) are higher. In a static framework, these effects cannot be disentangled. This is different than a shock to supply that is common among peers, which can be addressed with proper instruments. The difference is that both the direct effect on demand and the indirect effect on supply are consequences of the exogenous increase in peer nonvirginity, due to the equilibrium nature of the model.

To explore different sources of variation in the data, I estimate the regressions with two alternative constructions of the reference group: one is the peer group as defined in the model, i.e., by gender and grade; the other pools the peer group with the opposite-gender supply groups described at the end of section 4. The regression coefficient for either construction combines the demand and supply effects contained in the model, but the exact combination will be different under the two constructions.

5.2 Estimates of the Composite Effect of Social Interactions

Tables 3 and 4 present estimates of the composite effect of social interactions (also referred to as the "social effect") from the regression model in (9) using the alternative reference groups described above. Full results for each of these specifications are contained in appendix tables A1-A4. The coefficients reported in tables 3 and 4 give the effect of the nonvirginity rate in the reference group on the probability that an individual is sexually experienced by the spring quarter of the indicated grades. For example, in panel A, column 11, of tables 3 and 4, the point estimates imply that a 10 percentage-point increase in the share of nonvirgins among same-gender peers increases the probability of being sexually experienced by 7.4 percentage points for boys and 9.6 points for girls in the eleventh grade.

These results provide strong evidence of a school-based social effect on sexual initiation for both boys and girls. The use of school-by-grade fixed effects appears to be a successful strategy for removing any contextual effects that would otherwise invalidate the instruments. Although the overidentification tests indicate that the exclusion restrictions are violated without fixed effects (columns 1-4) the test statistics in columns 9-12 of tables 3 and 4 have high p-values, which indicates the instruments are properly excluded. As expected, the standard errors are much larger with the fixed effects, but there is still enough variation in the data to yield statistically signficant results in most grades when both constructions of the reference group are considered.[35] The instruments retain their predictive power when fixed effects are included, as indiciated by the first-stage F-statistics shown in tables A1-A4.

Although the fixed effects estimates are somewhat noisy, there are suggestive differences across grades and between boys and girls. For boys, the effect of nonvirginity rates among peers (i.e., same gender, same grade) appears strongest in grades 10 and 11. For girls there is no such difference across grades. When the reference group includes the opposite gender as well as the peer group, the fixed effects estimates indicate a larger social effect for boys than for girls, especially in grades 9 and 10. This is interesting in light of the structural estimates, which find an effect of opposite gender search behavior on the arrival rate for boys but not for girls.

Tables 5 and 6 show estimates of the social effect from fixed effects regressions that only contain the smaller set of variables (race, parental education, and sibling indicators) used in the structural estimation. Although there is no direct link between the coefficients in these regressions and the parameters of the model, these estimates demonstrate the robustness of the IV results using only the variation and controls provided by these limited characteristics. For comparison, columns 1-4 of these tables repeat the estimates from the full specifications (i.e., columns 9-12 of tables 3 and 4). Columns 5-8 show results with the

[35]The estimates are particularly noisy using the combined peer and supply group, which makes sense because the supply groups overlap for the two cohorts observed in each grade, so there is less "within" variation in the outcomes and characteristics of the reference groups.

smaller set of variables using contemporaneous group outcomes, and columns 9-12 show results using lagged outcomes. Both sets of estimates are noisier than the richer specification, but still the qualitative patterns are similar and so are the magnitudes in many cases.

For an additional robustness check, I estimated (9) using separate variables for the mean characteristics of boys and girls as instruments. As tables A1-A4 show, these characteristics have different associations with individual sexual initiation depending on gender, so one might want to allow for such differences in the first stage estimation. Appendix table A5 reports the estimated social effects from the combined peer and supply groups, using gender-specific mean characteristics as instruments. The results are similar to those in the baseline specification (panel B of tables 3 and 4). However there appears to be a multicollinearity problem because the mean characteristics of boys and girls at a school are highly correlated. In the first-state estimates (not shown), the gender-specific means often have opposite signs and relatively large magnitudes.

Finally, I conducted a falsification exercise similar to Cohen-Cole and Fletcher (2008) by estimating a social effect on height using the same specification as (9). The results (shown in tables A6 and A7) support the identification strategy for girls—when school-by-grade fixed effects are included, the coefficient on mean height in the peer group drops from 0.45 to a statistically insignificant 0.10 (table A7, columns 5 and 10). However for boys the coefficient remains large and statistically significant at about 0.6. Clearly this raises questions about the IV results for boys. One interpretation is that the additional instrument for girls, early menarche, provides crucial exogenous variation. However if the other peer-group means were invalid instruments, this should appear in the overidentification tests for girls, which it does not. Another possibility is that there truly is a social effect on *reported* height among boys, but not girls. In any case, it is important to note that the identification strategy for the structural estimation uses variation over time and does not rely on peer mean characteristics to identify the peer effect on demand.

6 Structural Estimation

I estimate the search and matching model via maximum simulated likelihood. The model generates a discrete-time duration to first sexual intercourse based on the per-period probability of the transition from virginity to nonvirginity. Because search decisions are unobserved, this transition probability is given by the product of the probabilities of searching and of finding a partner. So, to improve the estimation of the parameters for the arrival rate separately from those for the payoffs (which drive the search decision), I take advantage of data on the arrival of subsequent partners for nonvirgins. Thus the likelihood function includes individual contributions for both the duration to first sex and the arrival of subsequent partners.

6.1 Likelihood Function

The likelihood contributions for the durations to first sex take the form of a finite mixture, because the permanent component of preferences, ω, has a discrete distribution. Conditional on ω, the per-period transition probability is the product of the arrival rate and the probability that the decision rule in (8) is satisfied.[36] With ϵ distributed standard normal, its CDF denoted Φ, this product is

$$L_{it}(\omega) \equiv \Phi\left[u_{it} + \omega + \beta \mathrm{E}_t V_{a_{it}+1}(1, Y_t, \omega, \epsilon_{i,t+1}) - \beta \mathrm{E}_t V_{a_{it}+1}(0, Y_t, \omega, \epsilon_{i,t+1})\right] \cdot \int \lambda_{a_{it}}(N_{it})\, f(N_{it})\, \mathrm{d}N_{it}. \tag{10}$$

The solution to the model for a particular set of parameters provides the expected future values of virginity and nonvirginity inside Φ. Simulation is needed for the arrival rate (the second line above), in order to integrate over the unobserved search decisions of opposite-

[36]The transition probablity factors in this way because the remaining unobservable in the search decision is the iid preference shock ϵ_{it}.

gender virgins which generate N_{it}. The simulation procedure is described in appendix A.2.

For an individual who initiates sex in period t_i^*, the type-specific probability for the observed duration is

$$L_i(\omega) \equiv L_{it_i^*}(\omega) \cdot \prod_{s=1}^{t_i^*-1} [1 - L_{is}(\omega)]. \tag{11}$$

Then the individual likelihood contribution for the duration to first sex is the combination of these type-specific probabilities, weighted by the probability of each type given initial conditions:

$$\mathcal{L}_i \equiv \sum_{k=1}^{\kappa} \pi_{k|Y_{m0},x_i} L_i(\omega^k) \tag{12}$$

(note m indexes schools). For individuals who are not observed to initiate sex, there is a standard modification to (11).

In addition to the likelihood contributions for the durations to first sex, the likelihood function contains individual contributions from nonvirgins in order to improve the estimation of the arrival rate parameters λ_0 and λ_1. This draws on data from the sexual histories reporting when sex first occurred with each partner. The use of nonvirgins exploits the fact that, in the model, they search every period, so the arrival of subsequent sexual partners after the first one directly identifies the raw arrival rate.

To limit departures from model, specifically the assumption that partner arrival rates are the same for virgins and nonvirgins, I only use the arrival of second partners for this purpose. The estimated arrival parameters will be biased to the extent that arrival rates of second partners differ from arrival rates of first partners, and this bias could go in either direction. Exclusivity in relationships would reduce the arrival rate of second partners because individuals do not immediately continue to search once they have a first partner. On the other hand, learning how to meet partners would increase the arrival rate. Any bias is partially mitigated, however, because the arrival rate function also appears in the likelihood contributions for the durations to first sex.

The individual likelihood contribution for the arrival of a second partner is

$$\mathcal{A}_i \equiv \mathrm{E}[\lambda_{a_{it_i^{**}}}(N_{it_i^{**}})] \prod_{s=t_i^*}^{t_i^{**}-1} (1 - \mathrm{E}[\lambda_{a_{is}}(N_{is})]) \tag{13}$$

where t_i^{**} is the period when sex first occurred with the second partner and $\mathrm{E}[\lambda(N)]$ is the integral over the distribution of N, as in the second line of (10).[37] I restrict to individuals with $y_{i0} = 0$ (initial virgins) in order to observe the beginning of these spells.

Finally, because the arrival of each partner is assumed to be an independent event and to be independent of individual characteristics, the likelihood contributions in (13) simply multiply with the likelihood contributions in (12). Thus the complete log-likelihood function is $\sum_i \log(\mathcal{L}_i) + \sum_i \log(\mathcal{A}_i)$, using individuals who are virgins at $t = 0$.

For the standard errors, I use the asymptotic distribution of a standard maximum likelihood estimator. This assumes that the number of simulations for the expected arrival rates grows fast enough with the sample size (Gouriéroux and Monfort, 1996). The variance approximation is calculated via numerical differentiation of the individual likelihood contributions.[38]

6.2 The Endogeneity of Peer Behavior

In the structural estimation, the multiple potential sources of endogeneity of peer behavior are addressed as follows. First, the use of lagged peer outcomes in the search decision removes the simultaneity problem. This addresses simultaneity both among same-gender peers and between genders; for the latter, it is because the arrival rate is determined by opposite-gender search behavior, which is also a function of lagged outcomes. Second, the

[37]The first period when sex occurred with the first partner is included in the duration to the second partner because multiple partners are possible per period.

[38]The variance estimate ignores the first-stage estimation of the beliefs approximation. Murphy and Topel (2002) discuss this issue and propose an estimator, but it would be cumbersome to implement with a dynamic, structural model.

presence of a permanent unobservable (ω) addresses the problem with serial correlation in the unobservable that arises in a dynamic model of social interactions. Third, ω is correlated among peers because its distribution is a function of the initial nonvirginity rates, Y_{m0}. This controls for correlated omitted variables that are time invariant.[39] Finally, the definition of peer groups is intended to avoid selection bias. Peer groups are defined by grade, and it seems unlikely that individuals would systematically skip or repeat grades in order to affect their chances of sexual initiation. Overall, this identification strategy is innovative in that the use of lagged peer outcomes along with a permanent unobservable that is correlated among peers, while natural for a dynamic model, appears to be novel in the literature on peer effects.

Under this strategy, the variation used to identify a peer influence on search decisions comes from differences in Y_{it} across peer groups conditional on initial nonvirginity rates, Y_{m0}. Two groups with the same Y_0 would have the same distribution of ω for their members (controlling for individual characteristics), but then different values of Y_{it} in later periods would produce different search probabilities. Thus the strategy directly uses the kind of variation that motivates interest in social interactions—the magnification of small differences given similar initial conditions. This variation also identifies the effect of partner availability, because the arrival rate depends largely on the nonvirginity rates among the opposite gender (i.e., the opposite gender elements of the vector Y_{mt}).

6.3 Left-Censored Observations

Although the start of the duration period is known (i.e., birth), the presence of unobserved heterogeneity presents a problem when individuals are first observed after ninth grade. The problem is that individuals who are still virgins in later grades are more likely to have low values of ω compared with virgins at the beginning of high school. The estimation procedure

[39] Broadly, this assumes that Y_{m0} is a sufficient statistic for any correlated unobservables among peers.

needs to account for this, or else the duration dependence captured by the age parameter α would have a negative bias. Moreover, because the hazard rate is a function of time-varying arguments, there is not a simple way to integrate over the unobserved periods.

To update the distribution of ω for virgins in cohorts that are first observed after ninth grade, I use data from younger cohorts at the same school to create approximate, type-specific hazard rates. With these I can calculate the probability, for each type, of still being a virgin when the individuals are first observed, and then update the initial distribution of ω (for ninth graders) via Bayes Rule. The exact procedure is described in appendix A.3.

7 Results from the Search and Matching Model

The estimated model fits the observed patterns in sexual intiation, and it finds meaningful differences between the two mechanisms of peer norms and partner availability. Figure 2 compares the observed growth of nonvirginity rates for a synthetic cohort ("8-11 Observed") against predictions from the model. The predicted line ("9 Predicted") shows the ninth grade cohort projected through the end of twelfth grade. This prediction is formed by starting with observed virginity status in the initial time period (the summer before the ninth grade cohort entered high school, 1994Q3), and then simulating the outcomes for initial virgins in all cohorts going forward. Thus by the time the ninth grade cohort reaches the end of high school, the prediction is fifteen periods out from the observed data. This is an out-of-sample prediction in the sense that the ninth grade cohort is only observed through tenth grade, so their predicted outcomes in eleventh and twelfth grades are shown against the observed outcomes of older cohorts. The forward projection fits the observed growth of nonvirginity rates well, which indicates that the use of multiple, overlapping cohorts was a reasonable way to estimate a model of a complete path through high school.

The structural parameters and their standard errors are shown in table 7. The effect of lagged peer nonvirginity rates on expected utility, γ, is large and significant for both boys and girls. The age parameter, α, is twice as large for girls compared with boys, which suggests that girls are more influenced by individual development.

The effect of opposite-gender search behavior on the arrival rate is shown by the parameters $\lambda_1 = (\lambda_{11}, \lambda_{12}, \lambda_{13})$. There is one parameter for each of the three grades that provide the endogenous supply of partners for an individual, as explained in section 4. These three parameters are jointly significant for boys (chi-square, 3 d.f. = 6.99, p-value = 0.072), but not for girls (chi-square, 3 d.f. = 2.32). For boys the estimated effect of opposite-gender search behavior is largest from girls in the same grade. For girls, it is interesting that the estimated effect from boys who are two years older is as large as from boys in the same grade, but this is not well measured.

Finally, two permanent types are sufficient to fit the observed growth of nonvirginity rates during high school, as well as differences in the age trends along various observable characteristics (not shown).[40] I refer to these as "low" and "high" types. Both types have negative values of ω, although the difference from zero is not statistically significant for the high type. The estimate values for each type are nearly the same for boys and girls, which indicates a similar distribution of the overall expected costs and benefits of sex across gender. And last, the type-specific terminal values for virgins, $\nu(\omega)$, are poorly measured, which is not surprising given the simple linear growth in nonvirginity rates.

To help interpret the key parameters, tables 8 and 9 present average search decisions and arrival rates by gender and grade, as well as the marginal effects of lagged peer nonvirginity rates on search probabilities (in table 8) and the marginal effects of current supply group search behavior on arrival rates (in table 9). Table 8 pertains to the search decisions by virgins. Among low-type boys and girls, the average probability of search is fairly small in

[40] Arcidiacono et al. (2009) also find that two types are sufficient in their work on adolescent sexual behavior.

ninth grade (under 0.2) but increases throughout high school to about 0.5 in twelfth grade. Among high-type boys and girls, the search probability is already at 0.45 or 0.65 in ninth grade, respectively, and it rises by about 0.2 more by twelfth grade. Thus high-type girls who are still virgins at the end of high school are very likely to be searching, according to the model. Averaging between the two types, weighted by the probability of each type, the search probability among virgins is between 4 and 10 percentage points higher for girls than for boys, depending on the grade. This fits with the faster growth in nonvirginity rates among girls during high school. The marginal effects of lagged peer nonvirginity rates are substantial in relation to the average search probabilities, especially for younger grades. In the ninth grade, they imply that a one-standard deviation increase in the nonvirginity rate among peers would increase the probability that a virgin decides to search by 0.055 for either boys or girls.[41] This is 17% (14%) of the average search probability for boys (girls).

Table 9 shows that the arrival rate of partners is similar for boys and girls and is fairly constant across grades. Because the constant term λ_0 varies by grade, the arrival rate does not automatically increase over time even though nonvirginity rates do. Also, not all grades have three supply groups available at school; for example, there are no older groups for twelfth graders. The average arrival rate is about 0.1, which corresponds to an expected wait of 10 periods or 2.5 years to find a partner. The marginal effects of search behavior among the opposite gender are listed for each of the supply groups present. Compared with the marginal effect of peer outcomes on search decisions, the raw marginal effects here are an order of magnitude smaller. Still, the combined effect of search behavior among the supply groups can be large for boys. For example, an increase of one standard deviation in the search behavior within each of the three supply groups raises the arrival rate of partners for a tenth grade boy by 0.02, or 18% of the average. For girls, the underlying parameters are not jointly significant so any apparent marginal effects may only reflect sampling noise.

[41] The standard deviations of peer nonvirginity rates are 0.17 for boys and 0.16 for girls in ninth grade.

Table 10 shows the average probability of being high type (among virgins at the beginning of ninth grade) and the average partial effects of individual characteristics that affect this probability. As explained, the type distribution applies to individuals who are virgins at the start of the model. Accordingly the reported estimates use individuals from the eighth and ninth grade cohorts who are virgins in the summer quarter before they enter ninth grade. Roughly half are high type, with a higher rate for boys than girls. The partial effects are calculated by averaging the individual-level effects of changing one variable from 0 to 1 while holding the other variables as observed. These partial effects are qualitiatively similar to the coefficients on these variables estimated in the IV analysis (shown in appendix tables A1-A4), including the fact that black race has an effect for boys but not girls.

Finally, table 11 shows the parameters of the approximation of equilibrium beliefs (equation 5) that was used to estimate the model (columns labeled "observed"). These are the coefficients from a regression of nonvirginity rates by gender and grade on their lagged rates and the lags from the relevant supply groups. After estimation of the structural parameters, I then re-estimated these regressions with data simulated from the structural model, in order to check that the approximation is consistent with the model. The results are generally quite close to the original approximation (columns labeled "simulated"). As a measure of distance between the two estimates, I compute a chi-squared statistic for their difference, using seemingly unrelated regressions. This accounts for basic sampling variation and the naıve correlation between the observed and simulated outcomes, but not any further variance or covariance in the coefficients due to the estimation of the structural parameters. The statistic is relatively small as reflected by its p-value of 0.75, which indicates the two regressions are close in some sense.

8 Policy Simulations and Other Counterfactuals

Figures 3 through 7 present the results of policy simulations and other counterfactuals that demonstrate features of the model. Each figure has two graphs, for boys and girls, and each graph shows two projections for the ninth grade cohort: the first uses the estimated model exactly as in figure 2 ("9 Predicted"); the second uses the model with some modification to produce the simulation ("9 Simulated"). For reference, the gray line in these graphs ("8-11 Observed") shows the observed nonvirginity rates for the synthetic cohort, but the relevant comparisons are between the estimated model and the simulations.

For each counterfactual, equilibrium beliefs must be revised in order to be consistent with the modified model. I do this by estimating the approximation ψ on data simulated from the modified model, and then simulating new data with the new beliefs. I repeat this process until the parameters in the beliefs approximation converge, which usually occurs in fewer than 10 iterations.

The counterfactuals in figures 3 and 4 function as decompositions, to demonstrate the overall impact of peer-group norms and partner availability on sexual initiation during high school. Figure 3 eliminates the effect of peer norms by setting $\gamma = 0$. The results indicate that peer norms have a large effect on the timing of sexual initiation, which is about the same for boys and girls. Without the multiplier on behavior due to these norms, the number of boys (girls) who become sexually active is reduced by 10 (9) percentage points, which is 26% (20%) of the total during high school. The relative impact is even larger in younger grades: in the simulation, the number of individuals who initiate sex in ninth or tenth grade falls by 41% for boys and 31% for girls.

Figure 4 eliminates the effect of opposite-gender search behavior on the arrival rate, by setting the vector $\lambda_1 = 0$. This is purely a decomposition, because individuals would likely compensate for the absence of available partners at school by increasing their search efforts elsewhere. The simulation shows that changes in the search behavior of boys at school have very little effect on the initiation rate for girls, while the availability of girls at school does impact boys. Without any girls at their schools who are looking for sexual partners (and without any compensating behavior), the share of boys who become sexually active during high school falls by 0.14 (37% of the total).

Figures 5 simulates isolating the ninth grade from the rest of high school. In the model, this is accomplished by setting the parameters for older supply groups in the arrival rate to zero for ninth graders (i.e., $\lambda_{g1,2}$, $\lambda_{g1,3}$, and $\lambda_{b1,3}$) and setting the parameter for the younger supply group to zero for tenth grade boys ($\lambda_{b1,2}$). This decreases initiation in the ninth grade by about 14% for both boys and girls, although the impact on girls is based on poorly measured parameters. The effect dissipates rapidly for girls but it persists somewhat for boys, perhaps due to the additional supply reduction for tenth-grade boys.

Figure 6 presents a simulation that removes all nonvirgins from high school (in all grades) at the point in time when the ninth grade cohort enters. This is intended to show the importance of initial conditions, both within a peer group and from the supply groups.[42] The results look similar to the elimination of peer norms in figure 3, although the effects are not as large. Indeed, the effect of removing nonvirgins appears to work mostly through the peer influence on demand, because simulations that remove only the nonvirgins of one gender (not shown) have little impact on the opposite gender. This is probably due to the fact that the arrival rate is a function of the fraction among the opposite gender who search, not the absolute number, and the fraction of virgins who search is reasonably large (see table 8). As with the simulation of no peer effect on demand, the relative impact of this simulation is larger in younger grades: initiation falls by 27% (17%) for boys (girls) in ninth and tenth grade, but by 15% (9%) throughout high school.

[42] The excluded nonvirgins are still counted toward the simulated nonvirginity rates presented in the graphs, so the basis for comparison is the same.

Figure 7 simulates the spillover effect of "virginity pledges" on non-pledgers.[43] This works by setting the value of ω^L (for low types) to a sufficiently negative value so that low-type virgins have a negligible probability of search.[44] These individuals represent the pledgers. The graphs show the nonvirginity rates among high-type individuals, who represent non-pledgers. The population in these graphs is restricted to individuals who are virgins at the start of high school, because total nonvirginity rates are not a good basis for comparison given that low-type individuals will not initiate sex.

The simulation shows little effect on high-type girls. This makes sense because they have a high probability of search (see table 8), and the supply of boys has little effect on their initiation rates (see figure 4). For high-type boys on the other hand, the amount of initiation during high school is reduced by 12%. This is an effect of both smaller nonvirginity rates among peers and a smaller share of searchers among girls at school. Of course, to the extent that pledgers and non-pledgers are not actually peers or potential partners for each other, this simulation overstates the spillover effects of virginity pledges.

9 Conclusion

In two separate analyses with different identifying assumptions, I find evidence that social interactions in high school have large effects on sexual initiation. This is in line with results from other work on peer effects in adolescent risk behaviors, including earlier evidence on sexual initiation. The magnitude of the composite effect of school-based social interactions is large: at some grade levels in high school, the estimated effect size is close to 1 or even above it. This means that an increase in the share of nonvirgins among an individual's reference group raises his or her probability of being nonvirgin by an equivalent amount,

[43] See Bearman and Bruckner (2001) or Rosenbaum (2009) for evidence on the outcomes of pledgers themselves.

[44] A value of -1 is sufficient to keep the search probability below 0.01 through the end of high school.

which represents a large multiplier individual behavior. Although this composite effect is estimated with linear regressions, this suggests the possibility of a nonlinear "tipping point," in which small changes in initial conditions or small shocks can lead to large differences across schools.

By applying an economic model of the underlying process, I am able to decompose the composite effect and provide an assessment of two distinct social mechanisms. This improves our understanding of adolescent sexual behavior, and it is useful for policy because the mechanisms—social norms among peers and the supply of partners at school—are susceptible to different interventions. The results indicate that programs counteracting peer norms that promote sexual activity have more potential to delay sexual initiation than do policies separating younger grades from older grades.

Future work in this area would benefit from data over time on subjective perceptions of peer sexual behavior and reported intentions to initiate sex.[45] The analysis in this paper assumes that individuals have accurate beliefs about nonvirginity rates at their schools; however, some survey evidence indicates that adolescents overestimate the share of peers who are sexually active (National Campaign to Prevent Teen Pregnancy, 2004). Thus it would be interesting to see how individual beliefs relate to the actual behavior of peers. As for reported intentions to initiate sex, if reliable they could be used as observed search decisions. This would remove the need to use subsequent partners to help estimate the arrival rate. Observing search decisions would also make it easier to include heterogeneity in the arrival rate, and to allow for possible competition for partners between individuals of the same gender.

[45] Add Health contains questions on the components of an ideal romantic relationship, which indicate whether the individual wants to become sexually active. However, these are assessed only at the time of the interviews, so they would not allow the identification strategies used in the estimation of the model.

Appendix A Approximations

Appendix A.1 Arrival Rate for Model Solution

As noted in section 3.2, it would be difficult to make an exact calculation for the expected arrival rate at randomly selected solution points, in order to construct the value functions in (4). Instead, I approximate the decision rules among the opposite gender and use this approximation to simulate an expected value for the arrival rate.

This procedure uses auxiliary regressions that relate the probability of search among both virgins and nonvirgins in a group to the lagged nonvirginity rate for that group. These regressions are made separately for each gender and quarterly "age" in high school. To construct the regression coefficients, I start with initial values which allow the model to be solved and thus generate search probabilties for the entire sample, and then iterate with regressions of these search probabilities on the observed lagged nonvirginity rates. This approach should well approximate the information structure specified in the model, because the state space does not include any information about the opposite gender apart from their lagged nonvirginity rates in Y_{t-1}.

To calculate the expected arrival rate ($\mathrm{E}_t\lambda_{it}$) to go into (4) or (7) with this approach, I first use the appropriate age-specific regression to assign a probability of search (not conditional on virginity status) to each person in the supply groups, based on the value of $Y_{k,t-1}$ for their group (k). Then I use a series of uniform draws to simulate their behavior several times, which gives a number of realizations for N_{it}. Finally I average over the resulting values of $\lambda(N_{it})$ to calculate an expected value for λ_{it}. The remainder of the solution algorithm for the individual problem is standard.

Appendix A.2 Arrival Rate for Estimation

I use Monte Carlo integration to approximate the expected arrival rate in (10), because the search decisions of virgins in the supply groups $S(i)$ are unobserved and depend on their individual shocks. The procedure is as follows. For each simulation round, $r \in 1 \ldots R$, simulate a search decision, d^r_{jt}, for each virgin, j, in the three supply groups (to get $\{d^r_{jt} : j \in S(i),\ y_{j,t-1} = 0\}$). This proceeds by drawing ω^r_j from the appropriate distributions and then comparing the type-specific search probability for individual j, given by $\Phi[\ldots]$ in (10), against a pseudorandom uniform draw. Combining these simulated search decisions of virgins with the known search behavior of nonvirgins (i.e., they all search) yields N^r_{it}. Then averaging $\lambda_{a_{it}}(N^r_{it})$ across simulation rounds produces an approximation for the expected arrival rate.

Appendix A.3 Type Distribution for Virgins First Observed after Ninth Grade

As noted in section 6.3, I need to update the distribution of ω for cohorts that are first observed after ninth grade. To do this I create approximate, type-specific hazard rates, which combine to give the probability, for each type, of still being a virgin when the individuals are first observed. Then I can use Bayes Rule to update the initial distribution of ω (for ninth graders) to the appropriate grade.

The approximate, type-specific hazard rates are created with data from the younger cohorts at the individuals' schools, which relies on a steady state from one cohort to the next.[46] I regress the type-specific transition probabilties ($L_{it}(\omega)$) of the younger cohorts on their relevant state variables, which include the lagged nonvirginity rates by gender and grade ($Y_{m,t-1}$). I then use these regressions to predict type-specific hazard rates for the older

[46]The steady state assumption appears elsewhere, notably in the use of an aggregate law of motion estimated from current data to function as beliefs about the future.

cohorts before the observation period (i.e., when they were in earlier grades in high school). In these predictions, the current nonvirginity rates among younger cohorts substitute for the unobserved rates among older cohorts in previous years. The predicted hazard rates yield the probability of remaining a virgin for each type, and then I use Bayes Rule to update the initial distribution of ω for each individual in the older cohorts.

The exact procedure is:

i) Regress $L_{it}(\omega)$ on $Y_{m,t-1}$ and $\bar{x}_{s(i)}$, with separate approximations for each gender and age (i.e., quarter within grade).

ii) Project Y_{m0} forward using the approximation ψ, to create a sequence as long as the unobserved time span. For example, for someone first observed at the beginning of eleventh grade, Y_{m0} would be projected for two years (eight periods).

iii) Predict $\widehat{L}_{it}(\omega)$ for the unobserved periods using the regressions from step (i), and the generated sequence of $Y_{mt}, t < 1$, from step (ii).

iv) Define the approximate, type-specific probabilities of still being a virgin in the initial observation period as

$$\widehat{P}_i^0(\omega) \equiv \prod_{t=1-a_{i0}}^{0} [1 - \widehat{L}_{it}(\omega)].$$

v) Finally, update the individual's type distribution with

$$\Pr(\omega_i = \omega^k \mid Y_{m0}, x_i, a_{i0}, y_{i0} = 0) = \frac{\widehat{P}_i^0(\omega^k) \cdot \pi_{k|Y_{m0},x_i}}{\sum_{l=1}^{\kappa} \widehat{P}_i^0(\omega^l) \cdot \pi_{l|Y_{m0},x_i}}.$$

The circularity in this procedure is resolved by starting with some initial guess for the regressions that produce $\widehat{L}$ and then iterating. In practice, these approximations converge very quickly (within three iterations).

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Figure 1: Observed Nonvirginity Rates by Quarter within Grade in High School

Figure 1a.

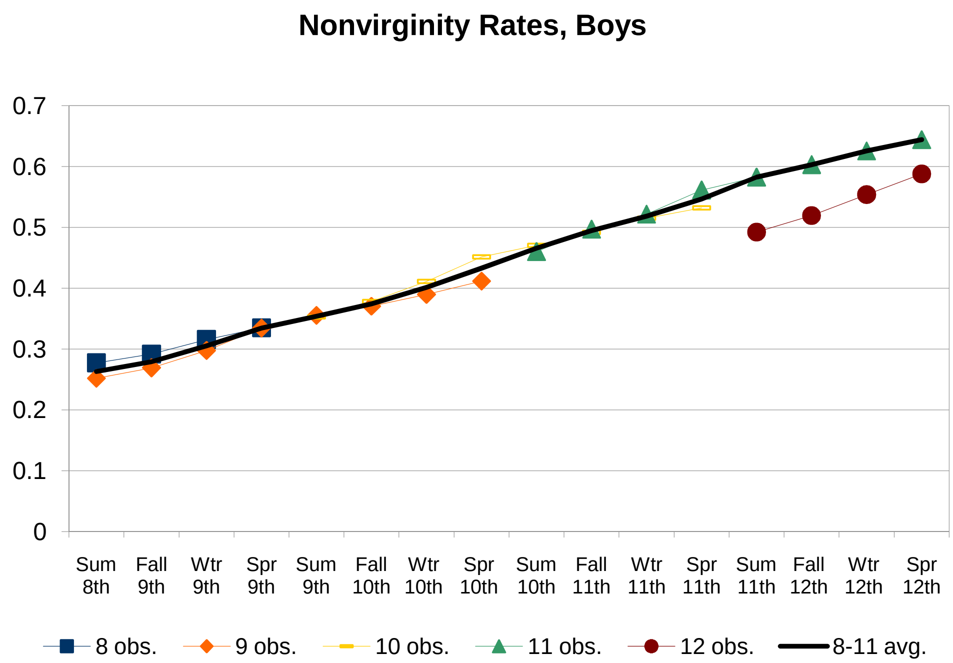
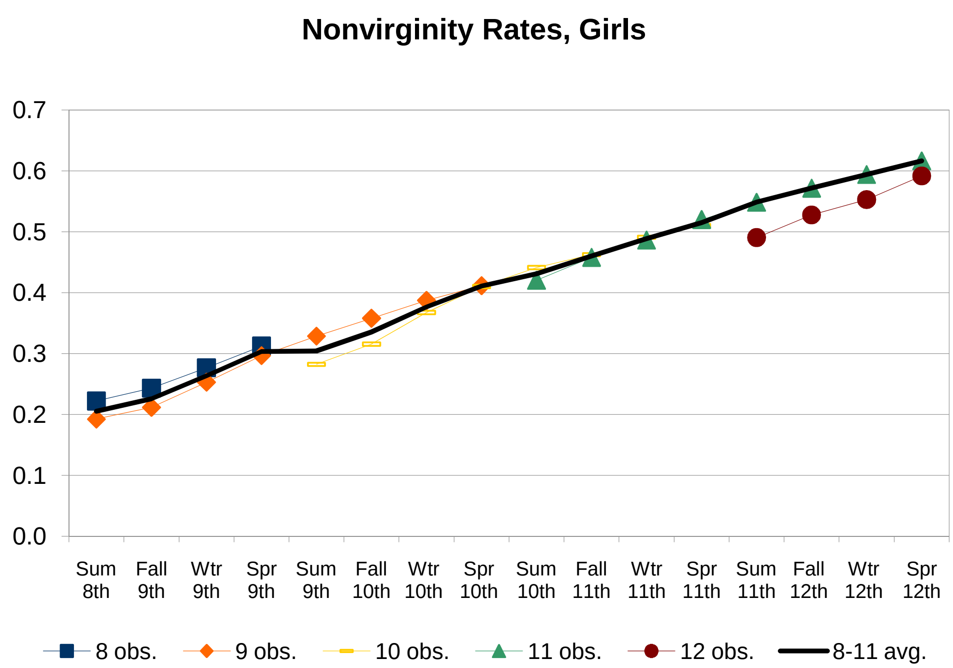


Figure 1b.



NOTES: Each line shows a different cohort, defined by grade in the 1994-95 school year. "8-11 avg." averages across cohorts, to make synthetic cohort.

Figure 2: Model Fit

Figure 2a.

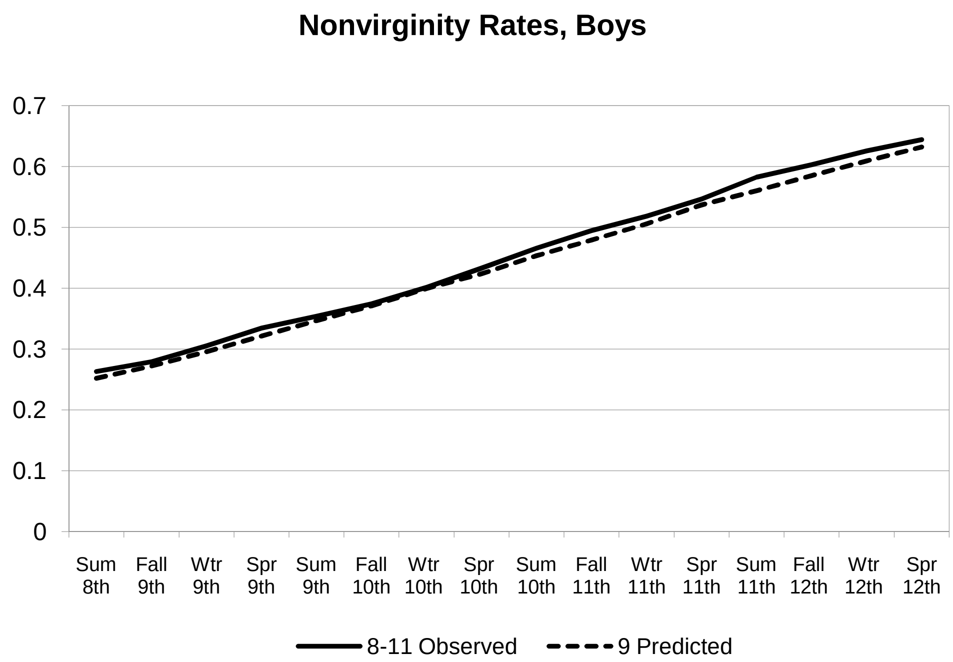
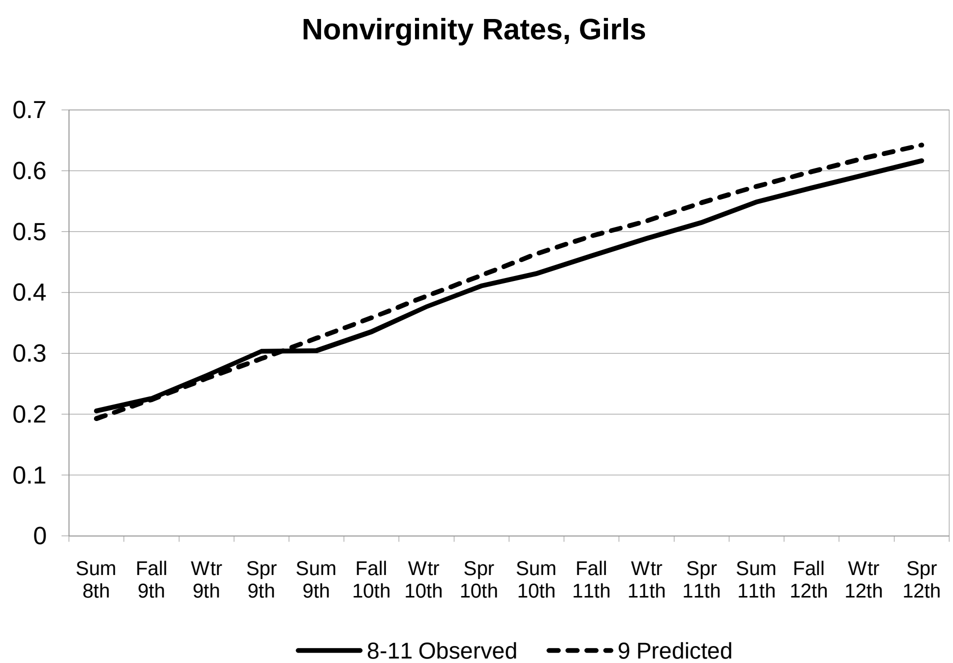


Figure 2b.



NOTES: "8-11 Observed" is the observed rates for the 8th-11th grade cohorts, combined into a synthetic cohort; "9 Predicted" is the prediction for the 9th grade cohort from the estimated model.

Figure 3: Eliminate Effect of Peer Norms on Search Decisions

Figure 3a.

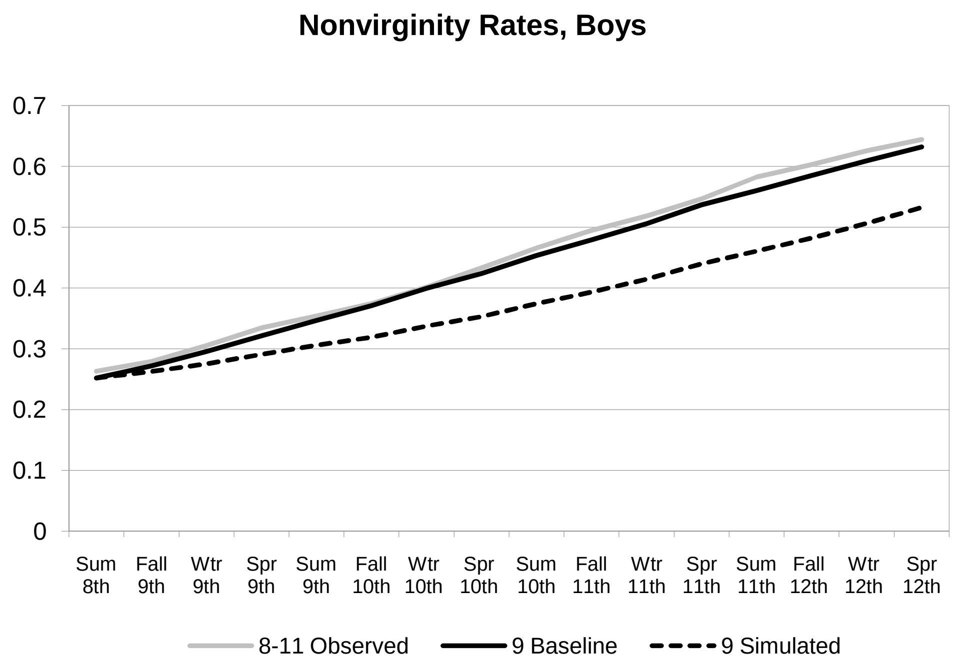
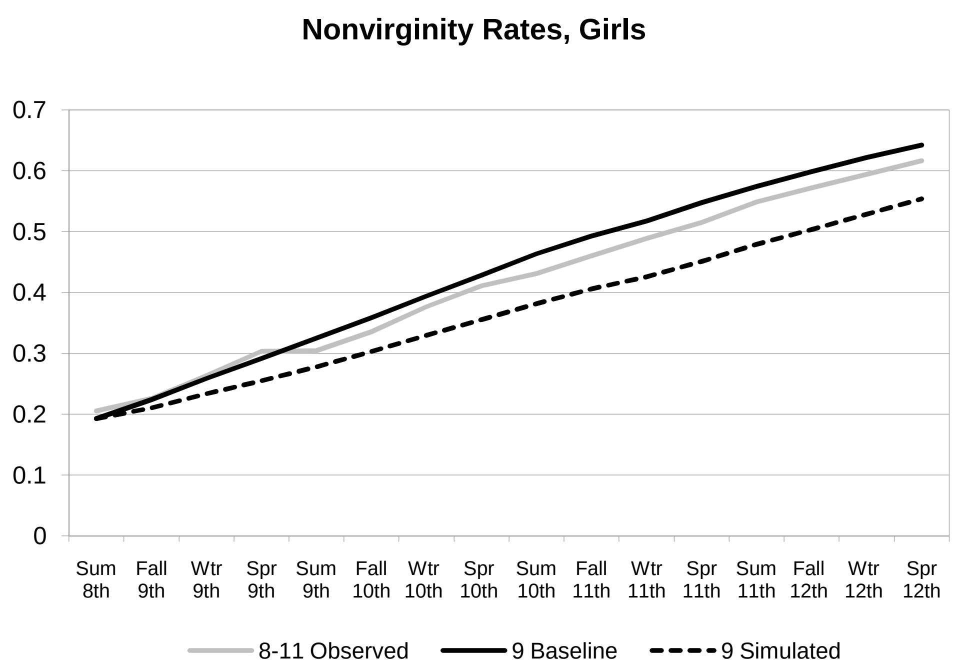


Figure 3b.



NOTES: "8-11 Observed" is 8th-11th grade cohorts, combined; "9 Baseline" is the prediction for the 9th grade cohort from estimated model; "9 Simulated" is the prediction from modified model.

Figure 4: Eliminate Effect of Opposite Gender Search Behavior on Arrival Rates

Figure 4a.

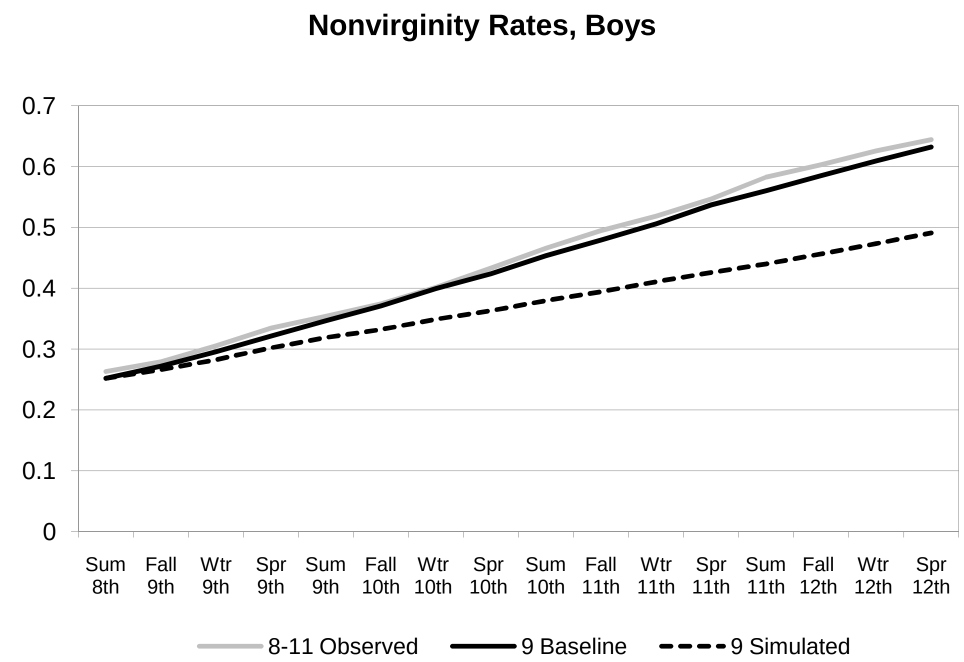
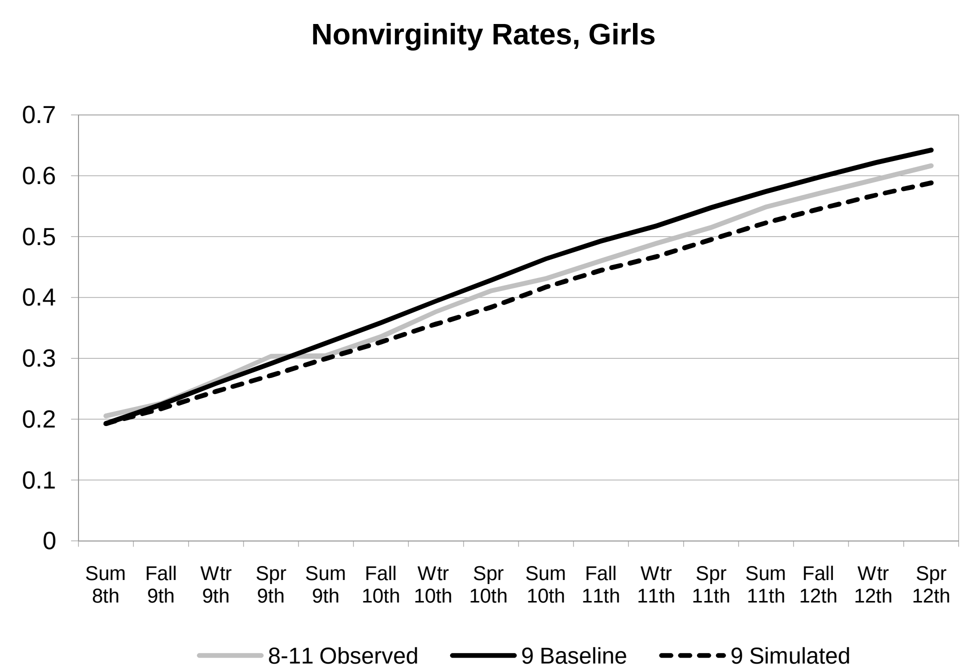


Figure 4b.



NOTES: "8-11 Observed" is 8th-11th grade cohorts, combined; "9 Baseline" is the prediction for the 9th grade cohort from estimated model; "9 Simulated" is the prediction from modified model.

Figure 5: Remove Ninth Grade from High School

Figure 5a.

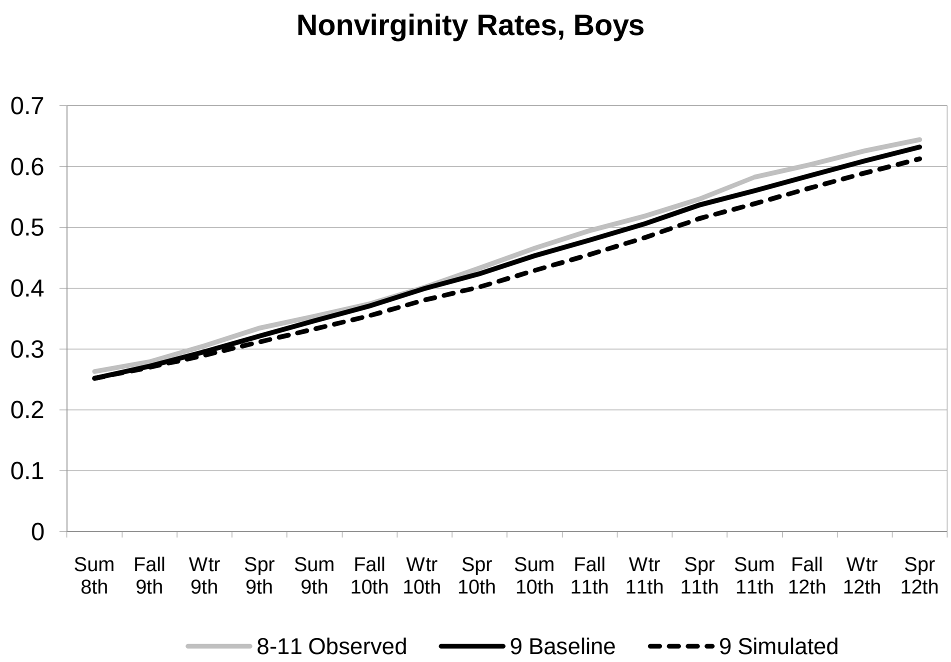
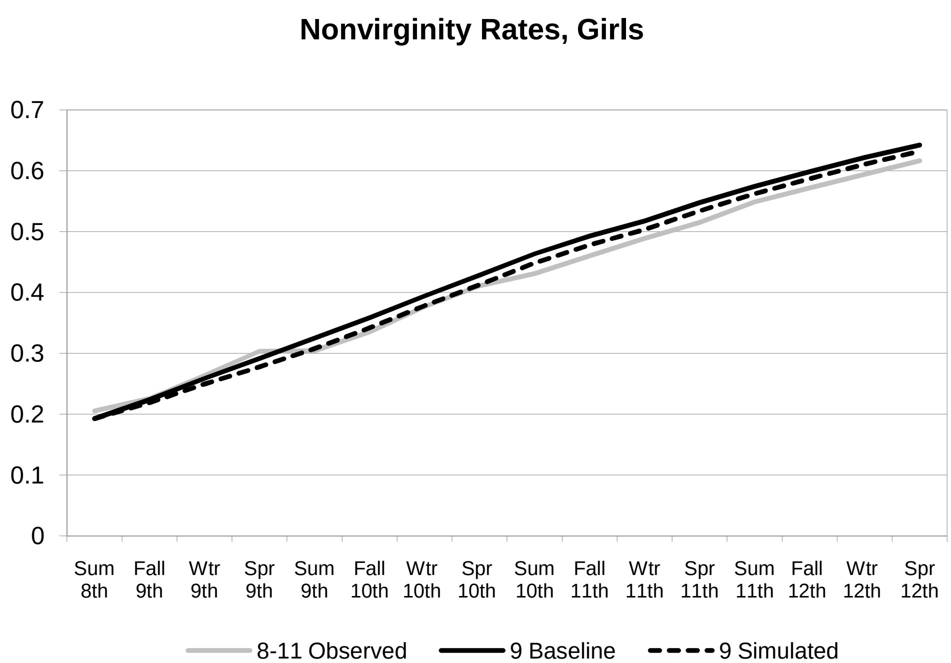


Figure 5b.



NOTES: "8-11 Observed" is 8th-11th grade cohorts, combined; "9 Baseline" is the prediction for the 9th grade cohort from estimated model; "9 Simulated" is the prediction from modified model.

Figure 6: Put Virgins and Nonvirgins in Different Schools at Initial Point in Time

Figure 6a.

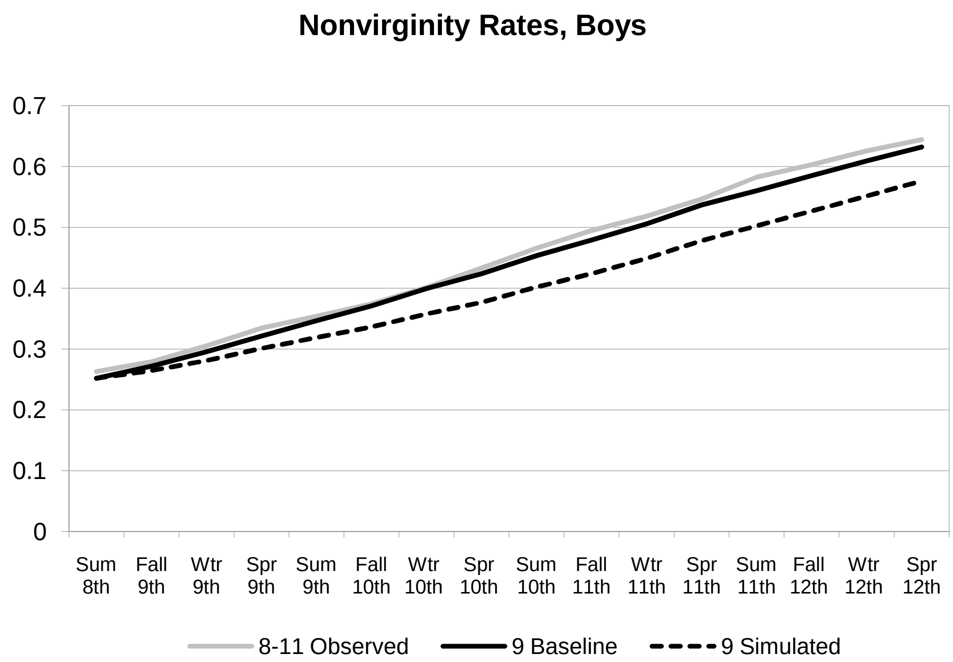
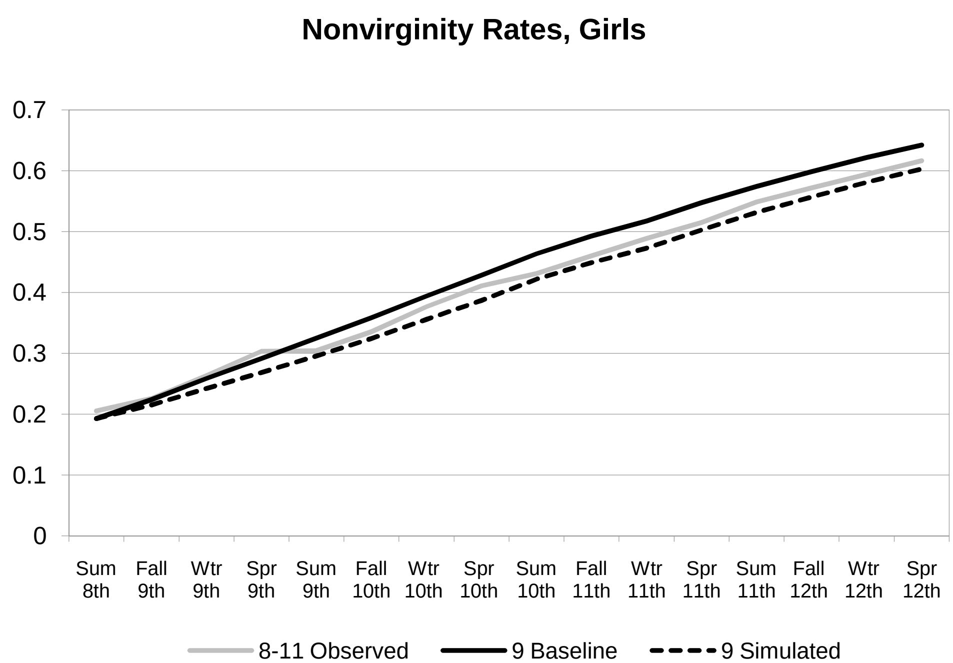


Figure 6b.



NOTES: "8-11 Observed" is 8th-11th grade cohorts, combined; "9 Baseline" is the prediction for the 9th grade cohort from estimated model; "9 Simulated" is the prediction from modified model.

Figure 7: "Low" Type Individuals Never Search (virginity pledge)

Figure 7a.

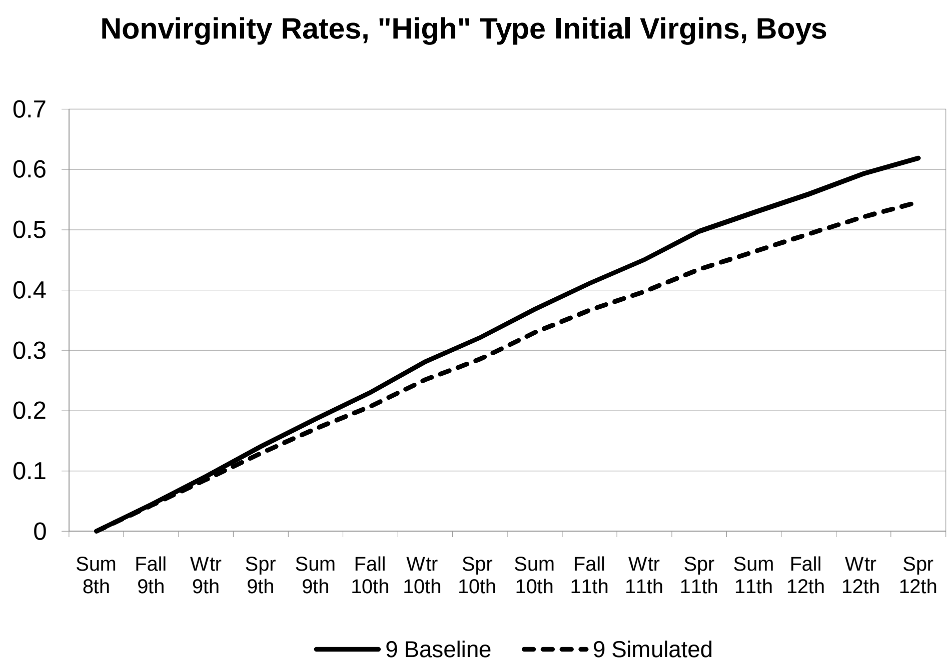
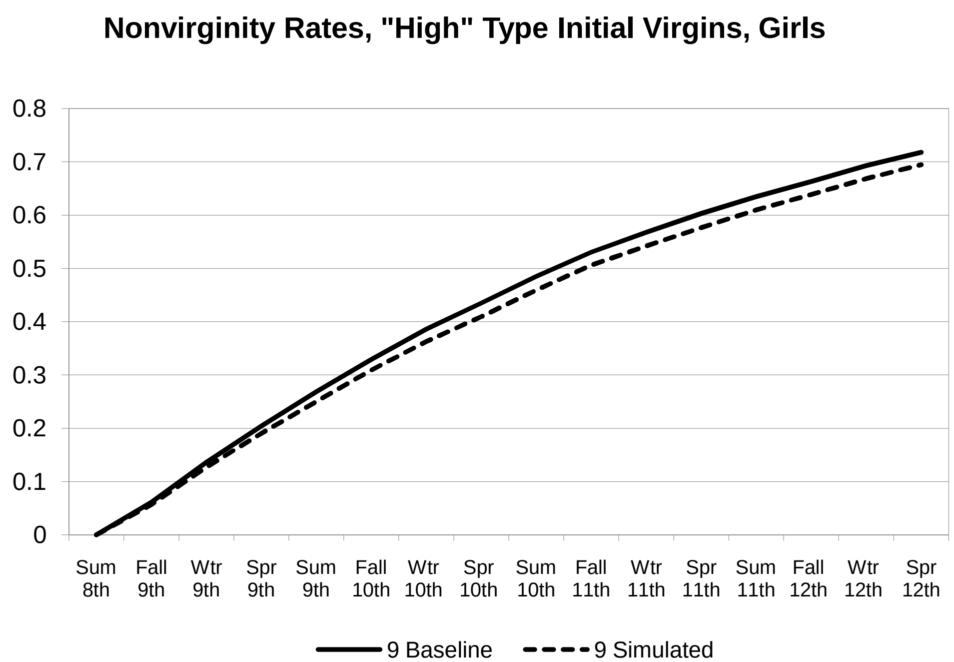


Figure 7b.



NOTES: Graphs show rates among individuals in the 9th grade cohort who enter high school as virgins, and are simulated to be "high" type. "Baseline" and "Simulated" as in previous graphs.

Table 1: Descriptive Statistics: Sample Shares with Given Characteristics

Variable	**Unweighted Share**	**Weighted Share**
Individual and family characteristics		
Hispanic	0.179	0.121
Black	0.217	0.163
Younger child	0.500	0.488
Only child	0.190	0.199
Parent with 16+ years of education	0.278	0.270
Family income > $50K	0.239	0.252
Mother married	0.601	0.625
Foreign-born parent	0.156	0.105
Menarche before age 12 (girls)	0.263	0.248
School characteristics		
Urban school district	0.287	0.257
Ninth grade in separate location	0.151	0.065

Table 2: Correlation between Individual Virginity Status and Nonvirginity Rates of Each Gender-Grade Group at the Same School

Individual	**Comparison Group**							
	Boys				**Girls**			
Gender and grade	Grade 9	Grade 10	Grade 11	Grade 12	Grade 9	Grade 10	Grade 11	Grade 12
Boys								
9	**0.266**	0.229	0.236	0.169	**0.243**	**0.286**	0.190	0.085
10	0.161	**0.216**	0.204	0.116	**0.144**	**0.224**	**0.154**	0.110
11	0.190	0.189	**0.198**	0.149	0.157	**0.188**	**0.151**	**0.119**
12	0.127	0.107	0.144	**0.154**	0.123	0.144	**0.142**	**0.190**
Girls								
9	**0.212**	**0.207**	**0.208**	0.165	**0.194**	0.173	0.156	0.137
10	0.216	**0.214**	**0.200**	**0.144**	0.114	**0.193**	0.199	0.156
11	0.154	0.155	**0.157**	**0.155**	0.094	0.210	**0.220**	0.176
12	0.052	0.116	0.113	**0.191**	0.105	0.150	0.176	**0.168**

Notes: The individual is excluded from the nonvirginity rate for his/her own group.
Peer and supply groups shown in bold.

Table 3: 2SLS Estimates of Effect of Social Interactions, Boys

	All Instruments Excluded				School-by-Grade Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Grade 9	**Grade 10**	**Grade 11**	**Grade 12**	**Grade 9**	**Grade 10**	**Grade 11**	**Grade 12**
PANEL A: Reference group is same-gender peers								
Group share	0.376**	0.564**	0.608**	0.517**	0.168	1.330**	0.744*	0.281
nonvirgin	(0.083)	(0.084)	(0.087)	(0.142)	(0.377)	(0.401)	(0.292)	(0.471)
Overid. test	8.87	13.26	19.80	3.41	6.38	5.43	6.33	2.41
p-value	0.26	0.07	0.01	0.85	0.50	0.61	0.50	0.93
PANEL B: Reference group is combined peer and supply groups								
Group share	0.519**	0.836**	0.812**	0.484**	0.962+	2.651**	1.801*	1.965*
nonvirgin	(0.093)	(0.095)	(0.129)	(0.120)	(0.518)	(0.579)	(0.825)	(0.999)
Overid. test	8.61	15.80	12.40	2.89	4.07	3.41	11.50	5.24
p-value	0.38	0.05	0.13	0.94	0.85	0.91	0.18	0.73

Robust standard errors in parentheses. Standard errors are clustered at the level of reference groups, in non-FE models.
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 4: 2SLS Estimates of Effect of Social Interactions, Girls

	All Instruments Excluded				School-by-Grade Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Grade 9	**Grade 10**	**Grade 11**	**Grade 12**	**Grade 9**	**Grade 10**	**Grade 11**	**Grade 12**
PANEL A: Reference group is same-gender peers								
Group share	0.609**	0.690**	0.602**	0.660**	0.656	1.046+	0.956**	0.720*
nonvirgin	(0.092)	(0.086)	(0.085)	(0.100)	(0.505)	(0.543)	(0.371)	(0.320)
Overid. test	2.94	7.20	13.64	7.78	3.78	5.05	8.24	1.93
p-value	0.94	0.52	0.09	0.46	0.88	0.75	0.41	0.98
PANEL B: Reference group is combined peer and supply groups								
Group share	0.629**	0.820**	0.697**	0.751**	-0.404	0.135	1.455	1.431*
nonvirgin	(0.112)	(0.111)	(0.105)	(0.114)	(0.729)	(0.847)	(0.938)	(0.631)
Overid. test	8.44	11.93	14.59	7.84	7.73	7.95	10.55	3.82
p-value	0.39	0.15	0.07	0.45	0.46	0.44	0.23	0.87

Robust standard errors in parentheses. Standard errors are clustered at the level of reference groups, in non-FE models.
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 5: Alternative Fixed Effects 2SLS Specifications, Boys

	Baseline FE Estimates				Limited Set of Variables				Limited Var. and Lagged Group Outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(5)	(6)	(7)	(8)
	Grade 9	**Grade 10**	**Grade 11**	**Grade 12**	**Grade 9**	**Grade 10**	**Grade 11**	**Grade 12**	**Grade 9**	**Grade 10**	**Grade 11**	**Grade 12**
PANEL A: Reference group is same-gender peers												
Group share	0.168	1.330**	0.744*	0.281	-0.053	1.528**	0.751	0.779	-0.081	1.305**	0.896	1.004
nonvirgin	(0.377)	(0.401)	(0.292)	(0.471)	(0.447)	(0.484)	(0.502)	(0.743)	(0.448)	(0.463)	(0.578)	(0.993)
Overid. test	6.38	5.43	6.33	2.41	4.92	3.05	2.07	0.84	4.91	5.40	1.79	0.81
p-value	0.50	0.61	0.50	0.93	0.18	0.38	0.56	0.84	0.18	0.14	0.62	0.85
F-stat. on instr.	14.19	19.18	41.68	16.49	20.18	24.78	29.59	14.52	27.42	26.30	20.76	6.98
PANEL B: Reference group is combined peer and supply groups												
Group share	0.962+	2.651**	1.801*	1.965*	1.004	3.038**	6.222*	3.621+	1.393+	2.890**	3.228+	2.193
nonvirgin	(0.518)	(0.579)	(0.825)	(0.999)	(0.743)	(0.791)	(2.810)	(1.908)	(0.835)	(0.783)	(1.664)	(1.815)
Overid. test	4.07	3.41	11.50	5.24	1.84	1.15	0.17	0.48	0.75	2.46	2.36	3.29
p-value	0.85	0.91	0.18	0.73	0.61	0.76	0.98	0.92	0.86	0.48	0.50	0.35
F-stat. on instr.	40.06	91.51	68.08	18.55	49.32	68.50	8.32	12.33	55.85	103.93	14.34	9.11

Robust standard errors in parentheses.
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 6: Alternative Fixed Effects 2SLS Specifications, Girls

	Baseline FE Estimates				Limited Set of Variables				Limited Var. and Lagged Group Outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(5)	(6)	(7)	(8)
	Grade 9	**Grade 10**	**Grade 11**	**Grade 12**	**Grade 9**	**Grade 10**	**Grade 11**	**Grade 12**	**Grade 9**	**Grade 10**	**Grade 11**	**Grade 12**
PANEL A: Reference group is same-gender peers												
Group share	0.656	1.046+	0.956**	0.720*	0.283	0.322	1.244+	0.597	0.092	0.294	1.710+	0.540
nonvirgin	(0.505)	(0.543)	(0.371)	(0.320)	(0.673)	(0.727)	(0.669)	(0.365)	(0.573)	(0.501)	(0.875)	(0.379)
Overid. test	3.78	5.05	8.24	1.93	1.64	2.44	0.78	0.66	1.72	2.29	0.16	1.40
p-value	0.88	0.75	0.41	0.98	0.65	0.49	0.85	0.88	0.63	0.51	0.98	0.70
F-stat. on instr.	5.34	14.10	20.17	24.07	8.69	12.73	19.88	49.76	16.10	23.84	8.97	43.45
PANEL B: Reference group is combined peer and supply groups												
Group share	-0.404	0.135	1.455	1.431*	-1.088	1.011	3.008*	1.018	-0.754	0.434	1.602	1.149
nonvirgin	(0.729)	(0.847)	(0.938)	(0.631)	(1.393)	(1.355)	(1.522)	(0.801)	(1.040)	(1.074)	(0.994)	(1.294)
Overid. test	7.73	7.95	10.55	3.82	4.38	3.66	0.96	1.91	4.52	4.28	2.37	2.76
p-value	0.46	0.44	0.23	0.87	0.22	0.30	0.81	0.59	0.21	0.23	0.50	0.43
F-stat. on instr.	35.76	26.49	14.04	18.27	18.36	19.61	11.00	26.17	38.27	28.07	21.49	11.37

Robust standard errors in parentheses.
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 7: Structural Parameter Estimates

Parameter	Boys	Girls
Age		
α	0.082	0.166
	(0.063)	(0.044)
Peer preference interaction		
γ	0.182	0.200
	(0.070)	(0.057)
Arrival rate		
λ_0 : 9th grade	-2.612	-2.369
	(0.317)	(0.245)
λ_0 : 10th grade	-2.873	-2.420
	(0.308)	(0.245)
λ_0 : 11th grade	-2.921	-2.442
	(0.333)	(0.240)
λ_0 : 12th grade	-2.865	-2.395
	(0.345)	(0.247)
λ_{11} : same grade	0.556	0.210
	(0.398)	(0.279)
λ_{12} : below / above	0.260	0.022
(boys / girls)	(0.254)	(0.157)
λ_{13} : above / 2 above	0.254	0.197
(boys / girls)	(0.183)	(0.154)

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Table 7. (continued)

Parameter	**Boys**	**Girls**
(continued)		
Type values		
ω^{L}	-0.270	-0.287
	(0.089)	(0.053)
ω^{H}	-0.107	-0.089
	(0.066)	(0.056)
Terminal values		
$v(\omega^{L})$	-1.608	-0.156
	(0.806)	(0.443)
$v(\omega^{H})$	-0.142	0.722
	(0.880)	(0.938)
Type probabilities (π^{H})		
Constant term	0.625	-0.369
	(0.857)	(0.531)
Y_0 : 9th grade	0.596	1.765
own gender	(2.438)	(1.635)
Y_0 : 9th grade	-0.291	2.633
opposite gender	(2.247)	(1.543)
Black	3.023	0.369
	(2.219)	(0.499)
Younger child	0.741	-0.209
	(0.603)	(0.379)
Only child	1.970	2.908
	(1.494)	(1.249)
Parent educ.	-2.237	-2.386
	(1.432)	(1.125)

Table 8: Probability of Search among Virgins, by Type, and Marginal Effects of Lagged Peer Nonvirginity Rates

Grade	**Boys**					**Girls**			
	Probability of Search			**Marginal Peer Effect**		**Probability of Search**			**Marginal Peer Effect**
	Low type	High type	Weighted average			Low type	High type	Weighted average	
9th	0.133	0.466	0.316	0.324		0.196	0.651	0.388	0.341
10th	0.236	0.572	0.415	0.304		0.338	0.787	0.511	0.329
11th	0.366	0.647	0.508	0.222		0.459	0.863	0.601	0.220
12th	0.511	0.675	0.593	0.123		0.506	0.886	0.629	0.119

Notes: Weighted averages combine the search probability for each type weighted by probability that an individual is of each type. Marginal peer effects show the weighted averages of the marginal effects for each type.

Table 9: Average Arrival Rates, and Marginal Effects of Search Behavior among the Opposite Gender

Grade	**Boys**					**Girls**			
		Marginal Supply Effects					**Marginal Supply Effects**		
	Arrival Rate	Same grade	Grade below	Grade above		**Arrival Rate**	Same grade	One grade above	Two grades above
9^{th}	0.103	0.051	NA	0.024		0.108	0.020	0.002	0.019
10^{th}	0.101	0.050	0.024	0.023		0.106	0.020	0.002	0.019
11^{th}	0.106	0.052	0.025	0.024		0.094	0.018	0.002	NA
12^{th}	0.099	0.050	0.023	NA		0.097	0.018	NA	NA

Table 10: Type Distribution

	Boys	Girls
Probability of high type among virgins at the beginning of ninth grade	0.55	0.43
Partial effects of:		
Black race	0.42	0.06
Being a younger child	0.12	-0.03
Being an only child	0.30	0.47
Parent with 16+ years educ.	-0.41	-0.36

Table 11: Approximation of Equilibrium Beliefs (quarterly growth in nonvirginity rates)

	Boys			**Girls**	
	Observed	Simulated		Observed	Simulated
Grade intercepts:					
9th grade	0.014	0.019		0.022	0.024
	(0.003)	(0.003)		(0.004)	(0.004)
10th grade	0.013	0.022		0.023	0.022
	(0.004)	(0.004)		(0.005)	(0.004)
11th grade	0.014	0.028		0.018	0.017
	(0.005)	(0.005)		(0.005)	(0.005)
12th grade	0.015	0.023		0.024	0.017
	(0.005)	(0.005)		(0.004)	(0.005)
Peer group nonvirginity rate:					
Linear term	1.048	1.019		1.047	1.050
	(0.014)	(0.015)		(0.015)	(0.016)
Squared term	-0.089	-0.050		-0.088	-0.086
	(0.014)	(0.015)		(0.016)	(0.015)
Supply groups nonvirginity rates					
Group 1	0.020	0.008		0.012	0.014
(same grade)	(0.006)	(0.006)		(0.007)	(0.007)
Group 2†	0.008	0.007		0.007	0.006
	(0.006)	(0.006)		(0.005)	(0.005)
Group 3†	0.001	-0.001		0.001	-0.002
	(0.004)	(0.004)		(0.006)	(0.005)
R-sq.*	0.965	- - -		0.960	- - -
N	2079	2079		2084	2084
SUR test statistic (obs. vs. sim.)			13.69		
P-value (χ^2, 18 d.f.)			0.75		

Standard errors in parentheses.

* R-squared calculated from separate regressions by gender, with constant term and no 9th grade dummy.

† Group 2 is grade below for boys and grade above for girls. Group 3 is grade above for boys and two above for girls.

Table A-1: 2SLS Estimates for Being Sexually Experienced by Grade, using Same-Gender Peer Group, Boys

	All Instruments Excluded				School-Grade Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Grade 9	**Grade 10**	**Grade 11**	**Grade 12**	**Grade 9**	**Grade 10**	**Grade 11**	**Grade 12**
Nonvirginity rate among reference group								
Peer group	0.376**	0.564**	0.608**	0.517**	0.168	1.330**	0.744*	0.281
	(0.083)	(0.084)	(0.087)	(0.142)	(0.377)	(0.401)	(0.292)	(0.471)
Individual characteristics								
Hispanic	0.153**	0.179**	0.112**	0.061	0.171**	0.200**	0.143**	0.074
	(0.040)	(0.040)	(0.038)	(0.038)	(0.048)	(0.048)	(0.044)	(0.046)
Black	0.240**	0.202**	0.164**	0.105**	0.252**	0.213**	0.188**	0.127**
	(0.040)	(0.035)	(0.035)	(0.036)	(0.043)	(0.043)	(0.040)	(0.040)
Younger child	0.064*	0.056*	0.033	-0.003	0.062*	0.047	0.026	-0.003
	(0.026)	(0.025)	(0.029)	(0.031)	(0.027)	(0.029)	(0.029)	(0.029)
Only child	0.146**	0.093**	0.067*	0.099**	0.148**	0.087*	0.064+	0.090**
	(0.032)	(0.029)	(0.034)	(0.037)	(0.035)	(0.036)	(0.036)	(0.035)
Mother married	-0.111**	-0.076**	-0.062*	0.020	-0.120**	-0.092**	-0.074*	0.022
	(0.031)	(0.026)	(0.030)	(0.029)	(0.030)	(0.031)	(0.029)	(0.028)
Foreign-born	-0.101*	-0.133**	-0.076*	-0.053	-0.072	-0.109*	-0.040	-0.049
parent	(0.044)	(0.033)	(0.031)	(0.038)	(0.045)	(0.043)	(0.041)	(0.048)
Upper income	-0.020	-0.027	-0.003	-0.001	-0.016	-0.035	-0.005	0.000
	(0.028)	(0.031)	(0.031)	(0.033)	(0.031)	(0.034)	(0.033)	(0.033)
Parental education	-0.122**	-0.100**	-0.092**	-0.077*	-0.106**	-0.105**	-0.081**	-0.080*
(4 years college)	(0.025)	(0.028)	(0.030)	(0.034)	(0.027)	(0.030)	(0.031)	(0.031)
Overidentification test	8.87	13.26	19.80	3.41	6.38	5.43	6.33	2.41
p-value	0.26	0.07	0.01	0.85	0.50	0.61	0.50	0.93
F-stat., first-stage instr.	35.33	24.13	18.15	6.68	14.19	19.18	41.68	16.49
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Observations	2241	2713	2873	2908	2241	2713	2873	2908

Models without fixed effects also include dummies for urban school districts and districts where the ninth grade is separated from the rest of high school.

Robust standard errors in parentheses.

+ significant at 10%; * significant at 5%; ** significant at 1%

Table A-2: 2SLS Estimates for Being Sexually Experienced by Grade, using Same-Gender Peer Group, Girls

	All Instruments Excluded				School-Grade Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Grade 9	**Grade 10**	**Grade 11**	**Grade 12**	**Grade 9**	**Grade 10**	**Grade 11**	**Grade 12**
Nonvirginity rate among reference group								
Peer group	0.609**	0.690**	0.602**	0.660**	0.656	1.046+	0.956**	0.720*
	(0.092)	(0.086)	(0.085)	(0.100)	(0.505)	(0.543)	(0.371)	(0.320)
Individual characteristics								
Early menarche	0.065*	0.089**	0.082**	0.097**	0.065*	0.085**	0.078**	0.094**
	(0.028)	(0.024)	(0.024)	(0.026)	(0.027)	(0.030)	(0.029)	(0.026)
Hispanic	0.068*	0.012	-0.023	-0.059	0.097*	0.049	-0.003	-0.034
	(0.033)	(0.040)	(0.040)	(0.039)	(0.046)	(0.047)	(0.045)	(0.041)
Black	0.069*	0.051	0.043	0.023	0.082+	0.050	0.094*	0.064+
	(0.028)	(0.034)	(0.029)	(0.025)	(0.045)	(0.040)	(0.039)	(0.037)
Younger child	-0.031	-0.011	0.004	0.041	-0.023	-0.012	-0.001	0.037
	(0.029)	(0.027)	(0.029)	(0.032)	(0.027)	(0.030)	(0.030)	(0.027)
Only child	0.055	0.083*	0.084*	0.115**	0.052	0.073+	0.081*	0.099**
	(0.039)	(0.036)	(0.034)	(0.032)	(0.036)	(0.038)	(0.037)	(0.031)
Mother married	-0.050+	-0.039	-0.056*	-0.063**	-0.052+	-0.043	-0.052+	-0.060*
	(0.028)	(0.026)	(0.026)	(0.024)	(0.029)	(0.030)	(0.029)	(0.026)
Foreign-born	-0.082+	-0.038	-0.093*	-0.085*	-0.070	-0.029	-0.082+	-0.085*
parent	(0.043)	(0.043)	(0.043)	(0.035)	(0.045)	(0.051)	(0.049)	(0.041)
Upper income	-0.013	0.010	-0.003	0.011	-0.009	0.008	-0.016	0.010
	(0.025)	(0.029)	(0.030)	(0.039)	(0.030)	(0.033)	(0.034)	(0.032)
Parental education	-0.100**	-0.094**	-0.125**	-0.121**	-0.097**	-0.100**	-0.124**	-0.122**
(4 years college)	(0.025)	(0.026)	(0.034)	(0.029)	(0.026)	(0.031)	(0.033)	(0.031)
Overidentification test	2.94	7.20	13.64	7.78	3.78	5.05	8.24	1.93
p-value	0.94	0.52	0.09	0.46	0.88	0.75	0.41	0.98
F-stat., first-stage instr.	14.54	10.44	13.49	8.55	5.34	14.10	20.17	24.07
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Observations	2381	2849	2963	3141	2381	2849	2963	3141

Models without fixed effects also include dummies for urban school districts and districts where the ninth grade is separated from the rest of high school.
Robust standard errors in parentheses.
+ significant at 10%; * significant at 5%; ** significant at 1%

Table A-3: 2SLS Estimates for Being Sexually Experienced by Grade, using Peer and Supply Groups, Boys

	All Instruments Excluded				School-Grade Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Grade 9	**Grade 10**	**Grade 11**	**Grade 12**	**Grade 9**	**Grade 10**	**Grade 11**	**Grade 12**
Nonvirginity rate among reference group								
Peer and supply	0.519**	0.836**	0.812**	0.484**	0.962+	2.651**	1.801*	1.965*
groups combined	(0.093)	(0.095)	(0.129)	(0.120)	(0.518)	(0.579)	(0.825)	(0.999)
Individual characteristics								
Hispanic	0.166**	0.203**	0.152**	0.077*	0.176**	0.197**	0.138**	0.088+
	(0.035)	(0.041)	(0.035)	(0.039)	(0.049)	(0.045)	(0.044)	(0.047)
Black	0.231**	0.196**	0.184**	0.114**	0.260**	0.203**	0.184**	0.128**
	(0.040)	(0.034)	(0.037)	(0.038)	(0.043)	(0.041)	(0.039)	(0.040)
Younger child	0.063*	0.057*	0.042	-0.002	0.064*	0.047+	0.032	-0.000
	(0.027)	(0.025)	(0.026)	(0.030)	(0.027)	(0.028)	(0.028)	(0.029)
Only child	0.146**	0.092**	0.069*	0.100**	0.153**	0.085*	0.070*	0.087*
	(0.030)	(0.028)	(0.032)	(0.033)	(0.035)	(0.035)	(0.035)	(0.036)
Mother married	-0.111**	-0.075*	-0.065*	0.016	-0.120**	-0.075*	-0.075**	0.025
	(0.035)	(0.030)	(0.032)	(0.028)	(0.030)	(0.030)	(0.029)	(0.028)
Foreign-born	-0.090*	-0.113**	-0.051	-0.037	-0.067	-0.107**	-0.056	-0.043
parent	(0.042)	(0.033)	(0.035)	(0.041)	(0.045)	(0.040)	(0.043)	(0.048)
Upper income	-0.016	-0.022	0.006	0.001	-0.020	-0.044	-0.000	-0.003
	(0.028)	(0.026)	(0.032)	(0.033)	(0.031)	(0.033)	(0.033)	(0.034)
Parental education	-0.114**	-0.085**	-0.080**	-0.075**	-0.103**	-0.106**	-0.084**	-0.081*
(4 years college)	(0.022)	(0.030)	(0.028)	(0.028)	(0.027)	(0.029)	(0.031)	(0.032)
Overidentification test	8.61	15.80	12.40	2.89	4.07	3.41	11.50	5.24
p-value	0.38	0.05	0.13	0.94	0.85	0.91	0.18	0.73
F-stat., first-stage instr.	20.91	28.39	20.06	10.72	40.06	91.51	68.08	18.55
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Observations	2241	2713	2873	2908	2241	2713	2873	2908

Models without fixed effects also include dummies for urban school districts and districts where the ninth grade is separated from the rest of high school.
Robust standard errors in parentheses.
+ significant at 10%; * significant at 5%; ** significant at 1%

Table A-4: 2SLS Estimates for Being Sexually Experienced by Grade, using Peer and Supply Groups, Girls

	All Instruments Excluded				School-Grade Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Grade 9	**Grade 10**	**Grade 11**	**Grade 12**	**Grade 9**	**Grade 10**	**Grade 11**	**Grade 12**
Nonvirginity rate among reference group								
Peer and supply	0.629**	0.820**	0.697**	0.751**	-0.404	0.135	1.455	1.431*
groups combined	(0.112)	(0.111)	(0.105)	(0.114)	(0.729)	(0.847)	(0.938)	(0.631)
Individual characteristics								
Early menarche	0.064*	0.083**	0.082**	0.096**	0.067*	0.078**	0.084**	0.094**
	(0.025)	(0.023)	(0.022)	(0.025)	(0.026)	(0.028)	(0.028)	(0.026)
Hispanic	0.061+	-0.023	-0.052	-0.076*	0.095*	0.046	-0.010	-0.035
	(0.033)	(0.037)	(0.040)	(0.034)	(0.045)	(0.044)	(0.043)	(0.042)
Black	0.058*	0.025	0.020	0.007	0.076+	0.054	0.096*	0.064+
	(0.028)	(0.036)	(0.031)	(0.029)	(0.044)	(0.038)	(0.038)	(0.038)
Younger child	-0.032	-0.007	0.003	0.039	-0.019	-0.002	-0.000	0.038
	(0.028)	(0.025)	(0.029)	(0.027)	(0.027)	(0.027)	(0.029)	(0.027)
Only child	0.050	0.091*	0.089**	0.112**	0.050	0.082*	0.085*	0.101**
	(0.037)	(0.037)	(0.033)	(0.027)	(0.035)	(0.035)	(0.036)	(0.031)
Mother married	-0.046+	-0.036	-0.055*	-0.067**	-0.049+	-0.043	-0.050+	-0.060*
	(0.026)	(0.028)	(0.027)	(0.020)	(0.029)	(0.029)	(0.028)	(0.026)
Foreign-born	-0.077+	-0.035	-0.113**	-0.094**	-0.067	-0.019	-0.081	-0.092*
parent	(0.039)	(0.040)	(0.042)	(0.032)	(0.042)	(0.047)	(0.049)	(0.042)
Upper income	-0.005	0.015	0.000	0.012	-0.008	0.005	-0.021	0.006
	(0.027)	(0.031)	(0.033)	(0.036)	(0.029)	(0.031)	(0.033)	(0.032)
Parental education	-0.099**	-0.099**	-0.125**	-0.117**	-0.098**	-0.092**	-0.118**	-0.122**
(4 years college)	(0.025)	(0.023)	(0.036)	(0.033)	(0.026)	(0.030)	(0.033)	(0.032)
Overidentification test	8.44	11.93	14.59	7.84	7.73	7.95	10.55	3.82
p-value	0.39	0.15	0.07	0.45	0.46	0.44	0.23	0.87
F-stat., first-stage instr.	34.12	24.95	10.18	10.1	35.76	26.49	14.04	18.27
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Observations	2381	2849	2963	3141	2381	2849	2963	3141

Models without fixed effects also include dummies for urban school districts and districts where the ninth grade is separated from the rest of high school.
Robust standard errors in parentheses.
+ significant at 10%; * significant at 5%; ** significant at 1%

Table A-5: Fixed Effects 2SLS with Separate Instruments by Gender

	Boys				Girls			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Grade 9	**Grade 10**	**Grade 11**	**Grade 12**	**Grade 9**	**Grade 10**	**Grade 11**	**Grade 12**
Reference group is combined peer and supply groups								
Group share	0.944*	2.797**	1.116	1.092+	0.147	0.719	1.101+	0.824+
nonvirgin	(0.412)	(0.554)	(0.739)	(0.569)	(0.672)	(0.612)	(0.579)	(0.462)
Overid. test	9.59	6.10	21.45	6.11	13.42	11.50	20.21	10.21
p-value	0.89	0.99	0.16	0.99	0.64	0.78	0.21	0.86
F-stat. on instr.	70.44	78.58	50.22	34.83	23.85	35.01	27.82	24.99

Table A-6: Falsification Exercise: Social Effect on Height, Boys

	All Instruments Excluded					School-by-Grade Fixed Effects				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Grade 9	**Grade 10**	**Grade 11**	**Grade 12**	**All grades**	**Grade 9**	**Grade 10**	**Grade 11**	**Grade 12**	**All grades**
PANEL A: Reference group is same-gender peers										
Group mean	0.703**	0.446*	0.503**	0.677**	0.570**	0.769*	0.265	0.568	0.901*	0.649**
height	(0.183)	(0.177)	(0.143)	(0.152)	(0.115)	(0.376)	(0.490)	(0.447)	(0.350)	(0.244)
Overid. test	7.29	8.17	8.44	12.44	20.34	3.01	2.56	3.05	3.38	11.70
p-value	0.40	0.32	0.30	0.09	0.93	0.88	0.92	0.88	0.85	1.00
PANEL B: Reference group is combined peer and supply groups										
Group mean	0.763**	0.702**	0.774**	0.866**	0.778**	0.770	1.371*	0.215	1.341*	1.02**
height	(0.280)	(0.267)	(0.210)	(0.185)	(0.146)	(0.651)	(0.642)	(1.156)	(0.639)	(0.389)
Overid. test	14.52	11.49	5.61	8.52	26.04	2.61	3.88	3.52	6.99	20.68
p-value	0.07	0.18	0.69	0.38	0.86	0.96	0.87	0.90	0.54	0.97

Dependent variable is height in inches, and group mean height is also in inches.
Robust standard errors in parentheses. Standard errors are clustered within reference groups, except for FE models.
+ significant at 10%; * significant at 5%; ** significant at 1%;

Table A-7: Falsification Exercise: Social Effect on Height, Girls

	All Instruments Excluded					School-by-Grade Fixed Effects				
	(1) **Grade 9**	(2) **Grade 10**	(3) **Grade 11**	(4) **Grade 12**	(4) **All grades**	(9) **Grade 9**	(10) **Grade 10**	(11) **Grade 11**	(12) **Grade 12**	(12) **All grades**
PANEL A: Reference group is same-gender peers										
Group mean	0.303+	0.481**	0.558**	0.624**	0.453	-0.130	0.251	0.523*	0.443	0.103
height	(0.164)	(0.165)	(0.188)	(0.151)	(0.145)	(0.223)	(0.392)	(0.256)	(0.562)	(0.182)
Overid. test	14.13	12.95	17.45	9.34	32.52	8.61	6.90	7.91	4.64	27.77
p-value	0.08	0.11	0.03	0.31	0.59	0.38	0.55	0.44	0.80	0.80
PANEL B: Reference group is combined peer and supply groups										
Group mean	0.374+	0.351+	0.511**	0.503**	0.432	-0.381	0.100	-0.001	0.200	-0.065
height	(0.215)	(0.187)	(0.132)	(0.181)	(0.11)	(0.625)	(0.744)	(0.586)	(0.417)	(0.332)
Overid. test	9.91	10.34	6.86	11.69	32.50	8.61	6.14	8.82	4.62	28.98
p-value	0.27	0.24	0.55	0.17	0.59	0.38	0.63	0.36	0.80	0.75

Dependent variable is height in inches, and group mean height is also in inches.
Robust standard errors in parentheses. Standard errors are clustered within reference groups, except for FE models.
+ significant at 10%; * significant at 5%; ** significant at 1%;