Determinants of Technology Adoption: Peer Effects in Menstrual Cup Take-Up

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Abstract

We estimate the role of peer effects in technology adoption using data from a randomized distribution of menstrual cups in Nepal. Using individual randomization, we estimate causal effects of peer exposure on adoption. We find strong evidence of peer effects: two months after distribution, one additional friend with access to the menstrual cup increases usage by 18.6 percentage points. Using the fact that we observe both trial and usage of the product over time, we examine the mechanisms that drive peer effects. We show evidence that peers impact learning how to use the technology, but find less evidence that peers impact an individual desire to use the menstrual cup.

1 Introduction

Understanding the influence of an individual's peers – friends, acquaintances, neighbors, classmates – on behavior has been of interest to economists in a wide variety of fields, including education (e.g. Sacerdote 2000; Hoxby 2000; Zimmerman 2002; Angrist and Lang 2002; Figlio 2003), labor (e.g. Kling, Liebman and Katz 2007; Munshi 2003), development (e.g. Foster and Rosenzweig 1995; Miguel and Kremer 2004) and industrial organization (e.g., Mas and Moretti 2009; Mobius, Niehaus and Rosenblat 2005). Of particular interest has been the role of peers in technology adoption, either by firms or individuals. Within the field of development, peer effects may have normative

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implications: new technologies frequently have the potential to dramatically improve quality of life, but adoption is often sub-optimally slow (see, among others, Foster and Rosenzweig 1995; Conley and Udry *forthcoming*; Duflo, Kremer, and Robinson 2008; Miguel and Kremer 2004; Munshi 2003; Bandiera and Rasul 2006; Foster and Rosenzweig 2010.).

Estimating the role of peers or social interactions in driving technology adoption is made difficult by the problem of correlated unobservables (Manski, 1993). When the econometrician observes two friends both adopting a new technology, it is difficult to separate whether they learn from each other or if fast-adopter individuals simply have fast-adopter friends. Economists have focused on a variety of econometric techniques to disentangle peer effects from correlated unobservables (Foster and Rosenzweig 1995; Conley and Udry *forthcoming*; Munshi 2003; Figlio 2003; Bandiera and Rasul 2006) including, more recently, explicit randomization (Sacerdote 2000; Kremer and Levy 2008; Mobius, Rao and Rosenblat 2007; Duflo and Saez 2003; Godlonton and Thornton *forthcoming*; Miguel and Kremer 2004; Duflo, Kremer, and Robinson 2008; Miguel and Kremer 2007).

The results on peer effects in technology adoption are somewhat mixed. Much of the literature (e.g. Foster and Rosenzweig 1995; Conley and Udry *forthcoming*) finds peer exposure has a positive impact on technology adoption. However, recent, randomized, work has found either negative peer effects (Miguel and Kremer 2007) or no effects (Duflo, Kremer, and Robinson 2008). One possible way to reconcile these results is to examine what mechanisms drive the effects. There are at least three possible mechanisms: individuals prefer to behave like their friends, individuals learn about the benefits of the technology from their friends, and individuals learn about how to use a new technology from their friends. The third mechanism, in particular, is likely to operate primarily in cases where the technology is difficult to use, which could be useful in explaining differences across technologies in the existing literature. However, existing work has typically not been able to separate these mechanisms (Duflo and Saez 2003; Munshi and Myaux, 2006).[1]

In this paper we use data from a randomized evaluation of menstrual cup distribution in Nepal to: (1) estimate the role of peer influence in adoption of a new technology and (2) provide initial evidence on what mechanisms drive the peer effects we observe. A menstrual cup is a small, silicone,

[1]The few cases, primarily in sociology and demography, in which efforts have been made to distinguish between these mechanisms tend to be plagued by the same type of identification problems inherent in all non-experimental estimates of peer effects (Kohler, Behrman and Watkins 2001). A partial exception is Miguel and Kremer (2007) who find negative peer effects, which effectively rules out two of the three explanations above (wanting to behave like friends and learning from friends); this is discussed in more detail below.

bell-shaped device which is used internally during menstruation; it is completely unfamiliar to our subjects at the start of the study and is unavailable for purchase in Nepal. We enrolled a sample of 198 adolescent girls and their mothers in four schools in Chitwan, Nepal and randomized (at the individual level) allocation of menstrual cups to half of the sample. Subjects were followed for approximately eighteen months and detailed data was collected on cup adoption over this time. Crucially for our analysis of mechanisms, we collected data in each month on whether the girl tried the cup and whether she used it successfully.

In general, adoption of the menstrual cup is quite high, with roughly 60% of girls using the cup by the end of the study. This may be surprising, given that the technology was new (unavailable prior to the study), and the fact that the observed benefits of the cup are fairly limited. As we find elsewhere (Oster and Thornton, 2011) school attendance is not increased by having access to the cup, and the primary observed impact is a decrease of about 20 minutes per day in laundry time during menstruation. However, reports from the girls in the sample indicate there were significant gains in mobility and comfort from using the cup rather than the traditional cloths, suggesting they valued the product highly even if this valuation is difficult to see in observed behaviors.

We begin by using our data to estimate the influence of peers on individual usage of the menstrual cup. The variation we use to estimate the effect of peers on individual use is generated by the randomization: at the baseline survey, girls were asked to list their closest friends who were also part of the study, allowing us to identify friendships. Access to the cup was randomized at the individual level. As a result, although the number of total friends is endogenous, the share of friends who are in the treatment group is random. This methodology is similar to the methodology used by Miguel and Kremer (2007) to estimate peer effects in adoption of deworming drugs; in both cases, the analysis focuses on the treatment group, but the existence of the control group is what generates the random variation.[2]

We find evidence of large positive peer effects. Two months into the study, one additional treatment friend increases cup usage by 18.6 percentage points. This effect dissipates over time: by six months after cup distribution, the effect of friend ownership on usage is no longer significant. This suggests the primary effect of peers is to increase speed of adoption.

After establishing that there are positive peer effects driving adoption, we examine the

[2]It is also the case that in both of these studies the product was available to all individuals for free and the variation in adoption comes from either desire to adopt or ability to use. One difference is that in our setting the product is completely unfamiliar to individuals, which may not be true of the deworming drugs.

mechanisms through which this occurs. As noted above, there are at least three possible mechanisms through which peers could affect adoption: imitation, learning about cup value and learning how to use. We collapse these three mechanisms into two broader categories: peers influencing individual's *wanting to use* (reflecting either imitation or learning about product value) and peers influencing individual's *success at usage* (reflecting learning how to use).

Without additional assumptions, our study data does not allow us to separate these effects empirically. However, after introducing additional structure we use our trial and usage data to evaluate mechanisms. We present a simple two-stage model of the adoption process in which friends can affect both whether their peers want to use the cup and also whether they will be successful at using it. Intuitively, we draw a parallel between attempting to use and *wanting to use,* and successful use conditional on attempting and *success at usage.* We use the structure of the model to make this link explicit. Because this analysis relies in part on some structural assumptions we interpret these results with more caution.

Our results suggest that friends significantly affect *success at usage*. In early months, having one additional treatment friend-month of exposure to the cup increases the probability of successful usage by 3 percentage points (on a baseline probability of around 58%). In contrast, we find less evidence that peer exposure impacts *wanting to use* the new technology. Although girls with more treatment friends are more likely to try the technology, this appears to be due to the fact that they are more likely to be successful at using it, which makes trial more appealing.

The technology in this paper shares features with many other technologies which may be of more intrinsic interest but may be more difficult to study (e.g. fertilizer or vaccines). In particular, the findings here may have strong applicability to the important case of contraceptive technologies, which have many similar features (used primarily by young women, relatively private, related to reproduction). Our results suggest that peer influences might be quite important in encouraging contraceptive take-up.

Further, although the basic design used here is similar to what is used elsewhere (i.e. Miguel and Kremer 2007) our particular experiment has several unique and important features. Because menstruation occurs frequently we are able to observe the evolution of peer effects and learn about the effect of peers on the speed of adoption. In addition, the fact that we observe both trial and usage of the menstrual cup allow us to make progress on understanding some of the mechanisms behind why peers matter.

Our findings suggest that with an easy to use product there may be only limited scope for peer-based targeting, because the primary impact of peers on adoption may not be relevant. In contrast, with a difficult to use product, peer-based targeting could have large effects on the speed of adoption. Consistent with this, positive peer effects are more often found in cases where the product is difficult to use (i.e., adoption of high yield varieties of seeds), and not in cases where the product is easy to use (i.e. adoption of deworming drugs).

The rest of the paper is organized as follows. Section 2 describes the setting, the experimental design, the menstrual cup, and the data that we will be using. Section 3 presents our estimates of the role of peer exposure in driving adoption. Section 4 analyzes the mechanisms that drive these effects. Section 5 concludes.

2 Experimental Design, Survey and Data

The data and results in this paper come from a randomized evaluation of menstrual cups in Chitwan, a district in Southwestern Nepal. Women and girls in this area, as in much of the rest of Nepal, traditionally use cloths during menstruation to soak menstrual blood. These cloths can be unsanitary if not washed carefully, and are reported to be inconvenient and uncomfortable. Sanitary pads are typically familiar to people, but not widely available or used, and the use of tampons is extremely rare. In the evaluation, menstrual cups were distributed randomly to half of the participants, as an alternative to cloths, and usage was observed over time.

2.1 Participants and Survey Timeline

Four schools in and around Bharatpur City in Chitwan District, Nepal were chosen in November of 2006 to participate in the study; of these, two were urban schools and two were peri-urban. Based on the school roster of girls who were enrolled at the start of the school year, 60 seventh-grade and eighth-grade girls from each school were invited, with their mothers, to participate in the study (this represented most of the 7th and 8th graders). Participation was contingent on attendance at the first study meeting. The girls were told that they would receive a gift (pens and stickers) at the meeting, and their mothers received 100 Nepali Rupees (about US$1.45). If a mother was not available, girls were told they could bring an older female relative or guardian to the meeting. Column 1 of Panel A of Table 1 shows the total number of girl participants in each school; 11% to 20% of the invited students in each school were not able to attend the meeting and therefore did not participate in the study. Columns 2 and 3 in Panel A show the composition of the older female participants: 79% of girls participated with their mothers, and 21% with a female relative/guardian.[3]

At the initial study meeting, after informed consent was obtained, a baseline survey was administered to the girls and their mothers. This survey included basic demographic information, as well as questions about school performance and menstruation. At the end of this initial meeting, girls were given identification numbers and a public lottery was held in which twenty-five identification numbers were drawn out of a bag. Girls whose numbers were drawn were assigned to the treatment group with their mother or guardian (we did not separately randomize mothers). Those in the treatment group were asked to remain at the meeting and each was given a menstrual cup. A nurse gave detailed instructions to those in the treatment group on the use of the menstrual cup.[4] Control girls were informed before they left that they would receive the cup at the end of the study.

After the initial meeting, girls were followed for approximately fifteen months (through January 2008). During this time, there was an in-school nurse visit approximately once per month, at which time the treatment girls were asked about their experiences with the menstrual cup. The number of girls interviewed at each visit varied; although there was close to complete coverage in the first few months, on average 81% of treatment girls were available at each visit in later months. There is no systematic attrition across groups.

In February 2008 a second meeting was held in each school. At this meeting, a follow-up survey, similar to the baseline survey, was administered. The control girls and their mothers were given the menstrual cup. Ninety-two percent of the girls in the study attended the follow-up meeting. Of the 15 girls not able to attend the meeting all but one were interviewed by enumerators at a later date (these included 7 treatment and 7 control girls).

2.2 Sanitary Technology

The sanitary technology we use is a menstrual cup, specifically the Mooncup brand cup, shown in Figure 1 (similar cups are sold under the names Keeper and DivaCup).[5] This product is a small, silicone, bell-shaped cup which is inserted in the vagina to collect menstrual blood. For most women

[3]In one case, in school 4, a girl was permitted to particpate without her mother, with a note.

[4]One of the mother-daughter pairs randomized to the treatment group decided not to accept the menstrual cup. We keep this girl in the sample, which means we estimate an intent-to-treat effect. This girl and her mother were each interviewed at the follow-up survey.

[5]For more information, see http://www.mooncup.co.uk/.

the cup has to be emptied approximately every twelve hours during menstruation. Between uses, the cup is washed with soap and water and stored in a cloth bag. With proper care, the cup is reusable for up to a decade.[6]

In the area of Nepal where our experiment takes place, the primary protection women use during their period is menstrual cloths (tampons are not available and pads are expensive and often difficult to obtain). These cloths are placed inside a woman's underwear to soak up menstrual blood. The cloths are washed and reused. The menstrual cup may be a significant improvement over this cloth technology for several reasons. First, if correctly inserted, women should not notice the presence of the menstrual cup and it should not affect mobility. Anecdotal evidence from Nepali women to whom we gave the cup as a pilot suggested that increased mobility was a major advantage – women said that they were able to bicycle and that they even forgot they were having their period. Second, cleaning the menstrual cup for reuse is significantly easier than cleaning the menstrual cloths. The cup is washed with soap and water, which takes only a minute or two; the cloths must be boiled and laundered, typically by hand. Data from our baseline survey indicates this takes an average of 30 minutes per month; time diary reports from the girls indicated they spent about 23 extra minutes per day during their menstruation. All of these factors – increased mobility, ease of use, and no need to wash cloths – were mentioned by girls at the follow-up survey as advantages of the cup.[7]

We argue that the menstrual cup is well suited for studying determinants of technology adoption. First, the technology is not available for purchase in Nepal, meaning we do not have to contend with the concern that some girls initially know more about the technology than others do. Second, although the cup is comfortable to use for most women, it often takes time for people to learn how to insert and remove it comfortably. The cup must be flattened and folded in half in order to insert it into the vagina and it takes some practice to position it correctly to prevent leakage. Given that insertable reproductive devices are rare in Nepal, and that our main respondents were young adolescent girls who were just becoming familiar with their reproductive health, using this

[6]There is no risk of Toxic Shock Syndrome, and generally no risk of complications from the cup. This menstrual cup has been FDA approved in the United States. Like any internal vaginal device (e.g. tampons), the menstrual cup can cause rupture of the hymen. Girls in our setting were carefully told about this during the initial meeting, but this issue is not as significant in Nepal as it would be in a place like Saudi Arabia. It is possible some girls did not use for this reason, but seems unlikely this is a major factor limiting adoption (no girls mentioned this as an issue).

[7]In a second paper using the data from this study (Oster and Thornton, 2011) we evaluate whether these mobility benefits translate into increases in school enrollment; we find they do not and, further, argue that menstruation plays only a small role in school absence. That paper relates to a small literature within economics on menstruation and work/school absence: Ichino and Moretti (2009) find evidence of cyclicality in the absences of female Italian bank workers, which they attribute to menstruation, although these conclusions have been questioned by Rockoff and Herrmann (2009).

technology was likely to take some practice. This suggests that there is scope for understanding the learning component of technology adoption.

2.3 Data

This paper uses three primary elements of the data from the menstrual cup experiment: demographic and cup value data, data on cup adoption and data on friendships.

Demographics and Cup Value: From the baseline survey we make use of a number of control variables on demographics which are summarized in Panel B of Table 1. The average age is 14, and girls are evenly divided between the 7th and 8th grades, by construction. Fifty-two percent of the girls are of Hindu ethnicity and forty-two percent are Tibetan or Tharu; the remaining category is Newari. Eighty-seven percent of girls had their period at the baseline survey. Mothers have an average of about 2.7 years of education and fathers have an average of 5.6 years.

In addition, we include several controls for the value of the cup, to address the fact that girls may differ in how effective they find the cup relative to the alternative.[8] These include whether the girls works for pay (related to the need for mobility) and reported time it takes to wash menstrual cloths (as a measure of how costly the alternative technology is). We use a measure of cloth washing time collected during the baseline survey; the figure is lower than what we see in the time diary, but the correlation between measures is high. These variables are summarized in Panel B of Table 1.

Data on Cup Adoption: After the menstrual cups were distributed at the baseline survey a nurse followed up with roughly monthly visits to the school, at which time data was collected about cup usage. During the nurse visit, each girl in the treatment group was asked if she had used the menstrual cup during her period that month. Although verbal responses differ across girls, typical responses include quotes such as “I use it and feel it is easy,” “I couldn’t insert so I haven’t used it” or “I am afraid to try it.” From these responses we coded whether the girls attempted to use the menstrual cup and whether they were successful. For example, the first quote here would be coded as a successful usage attempt, the second quote would be coded as an unsuccessful usage attempt and the third would be coded as not attempting to use.[9]

To give a sense of the basic patterns of adoption, Figure 2 shows the share of girls attempting

[8] The concept that individual differences in productivity could map into differences in technology adoption references, of course, a large literature on the role of individual productivity differences in driving adoption rates (e.g. Griliches 1957; Oster and Quigley 1977; Oster 1982; Caselli and Coleman 2001; David 1990; Luque 2002; Duflo et al 2005).

[9] Data on trial and usage was collected in an open-ended format since we thought it would elicit more accurate responses from the girls. The nurse focused on getting this information consistently from each girl she spoke with.

to use, the share who successfully used and the share who attempted but failed to use in each month over the course of the study. The numbers above each data point report the sample size in that month. Although the nurse affiliated with our study made an effort to talk with each individual in each month, some girls were not in school during the visits (no girls refused to talk to the nurse conditional on being in school). On average, we observe 81% of girls in each month; we demonstrate there is no differential rate of attendance by number of treatment friends in the next section. For the most part, absences were isolated events and did not represent sample dropout. Among the 68 girls for whom we miss any months of data, 42 are missing in only one or two months and only 8 are sample dropouts.

Successful usage of the menstrual cup increased dramatically in the first six months, from 10% in January 2007 to 60% in June 2007. After this, usage was fairly constant, with little movement from June 2007 to January 2008. The pattern for trying to use is similar, although the line is flatter. The share of girls attempting to use increased from only 60% to 80% over the first months of the study and declined some in the period after that. This decline reflects the fact that there is a decrease in girls who continue to attempt without success. One thing that is important to note is that once a girl used the cup once, continued usage was extremely high. After one month of successful usage, girls used the cup in 91% of subsequent periods. Given this extremely high continued usage rate, we will often refer to girls "adopting" the cup at the first successful usage.

A central issue is whether girls' reported cup usage accurately reflect their actual usage. Although we have no direct observations of cup use, we have evidence of high levels of cup usage using other features of the data. First, in the follow-up data, girls were asked about their use of the cups as well as the use of pads or cloths. Comparing the answers to questions on menstrual sanitary product use between girls in the treatment group and control, in the baseline and at the follow-up surveys, we find that treatment girls were 35 percentage points less likely to report using any cloths than the control and they reported using on average 1.09 fewer cloths per period. There were no significant differences in the reported use of pads between the treatment and control girls. While this still relies on self-reported data, it provides some evidence of the level of substitution between sanitary products.

A second piece of evidence on adoption comes from time-diary data collected from the girls. For the first 10 months of the project, we collected monthly time diaries from each girl. Girls reported their activities for the first 6 days of each month. Using these time diaries, we observe that girls in the control group spend approximately 22 minutes more doing laundry on days when they are menstruating. In contrast, treatment girls who are menstruating spend only an extra 2 minutes on laundry relative to non-period days. This difference between treatment and control on period days is significant (see Online Appendix Table 1). This internal consistency supports the validity of our adoption data.

Data on Friendships: The object of interest when we consider effects of peers on technology adoption will be the number of friends who also received the cup. We generate this measure using data on friendships collected in the baseline survey. Before the randomization took place, each of the girls was asked to list their 3 closest friends who were also at the initial meeting.[10] Our primary measure of friendships is total friends, which includes everyone who the individual lists as a friend and anyone who lists them as a friend. On average, girls listed 2.6 close friends with 68% listing 3 friends and 25% listing 2 friends; when we add in people who list the girl a as a friend, the average girl has 3.8 total friends, with a maximum of 7 (Table 1, Panel B). Consistent with the randomization, we see that an average of 50% of a girl's friends are in the treatment group (Table 1, Panel B). In addition to the total number of friends, we also consider the strength of friendships, distinguishing between strong friendships (bi-directional links) and weak friendships (uni-directional links).[11]

3 Peer Effects on Technology Adoption

This section presents our baseline estimates of the effect of peers on adoption of the menstrual cup.

3.1 Empirical Strategy

Identifying causal effects of peers is challenging. The main concern, as outlined by Manski (1993) relates to the issue of correlated unobservables: friends often have similar characteristics, meaning if we observe friends acting similarly, it is difficult to separate whether they act similarly because they are influencing each other or because they were *ex ante* similar. Consider first the case without

[10] In our survey we asked only about the 3 closest friends; we did not allow respondents to list all of their possible friends. In practice, this truncation likely does not miss very many friends: in the follow-up survey, we asked how many girls the respondent considered to be her close friend (without truncating the total permissible friends) and 75% answered 4 or fewer, with a median number of 3. In addition, given the randomization, we are able to obtain an unbiased estimate of the impact of additional treatment friends even if we do not observe all of an individual's friends.

[11] It would also be possible, in principle, to separate weak friends into two groups by the direction of who lists whom. In the analysis, when we make this distinction in the direction of listing, we find no differences and therefore focus on the weak versus strong friendship type distinction only.

randomization in which researchers have access to cross-sectional data including girls for whom they observe menstrual product ownership/usage and friendships. It would certainly be possible to run a regression to estimate the effect of friend ownership on product use in this setting. However, it would not be correct to interpret these estimated coefficients causally: if individual characteristics are correlated with friend characteristics, it is likely that individuals who own the cup also have friends who own the cup *not* because they are affected by their friends, but because they are similar to them. In our case, we use the explicit randomization to identify causal peer effects. We outline this strategy in detail below.

Identifying Causal Peer Effects

As discussed in Section 2, at the baseline survey we asked girls in our sample to list their friends. These friends are endogenously chosen by the girls themselves and not randomly allocated. We randomly allocate ownership of the menstrual cup across girls. Because randomization of the cup is at the individual level, not only is individual ownership random, but which, and how many, of the individual's friends get the cup is also random. Consider a simple example of a girl in the treatment group with two total friends. She faces a 50% chance that each of her friends will also be in the treatment group. This means there is a randomly generated 25% chance she has no treatment friends, 50% chance of one treatment friend and 25% chance of two treatment friends. Our analysis compares cup usage across girls who have the same number of total friends, but – by chance – have a different number of treatment friends. This randomization allows us estimate the causal effect of the number of treatment friends (who own the cup) on cup adoption. The analyses are run among only girls in the treatment group; however, the existence of the control individuals (i.e. the randomization) is crucial to the identification, because it drives the exogenous variation in number of treatment friends. As noted in the introduction, this methodology is similar to that used in Miguel and Kremer (2007).

In our simplest analysis we compare cup usage rates across individuals who all have the same number of *total* friends. Within each of these groups, the number of friends who were assigned to the treatment group – and thus have access to the cup – is determined randomly. Our regression analyses then estimate the impact of number of treatment friends controlling for total number of friends. Our primary results condition on a linear control for total number of friends. We also show (in the Online Appendix) results which control for dummy variables for total number of friends and results which estimate the impact of the share of friends in the treatment group. In all cases, we rely on the fact that number of treatment friends is randomly allocated conditional on total number of friends which, by extension, means the share of treatment friends is exogenous even unconditionally.

Estimating Equation

We begin by estimating the relationship between cup usage and treatment friends at three different points in time (February 2007; August 2007 and January 2008), which gives a sense of how the coefficients vary over time. In each case, the variable for usage is equal to one if the individual reported successfully using the cup in that month and zero otherwise. We estimate a Probit model, specified in Equation (1) below.

$$Pr(Used_i = 1) = \Phi(\gamma + \delta_1(\text{Treatment Friends}_i) + \mathbf{\Pi X}_i + \mu_i) \tag{1}$$

$\mathbf{X_i}$ is a vector of controls (e.g., controls for total friends, age, grade, test scores, school fixed effects, parental education, family income and measures of cup value), and "Treatment Friends$_i$" is our measure of treatment friends (either number of treatment friends or share). We report marginal effects from the Probit model. Specifically, we report the average of the marginal effects: for each variable we estimate the marginal effect on usage for every individual and we take the average of those effects and that is the reported coefficient. In practice, this is done by running a probit model and using the "margeff" command in Stata (note that this is distinct from what is done by the Stata "dprobit" command, which reports the marginal effect for the *average* individual). Although these estimates are typically similar, in our setting the effects from "dprobit" are the same in terms of significance but in most cases much larger in magnitude. This appears to be due to the inclusion of school fixed effects. Since we have two schools with very high levels of usage and two schools with very low levels of usage, once we include school fixed effects in the regression we do have an "average" individual. The estimate of the marginal effect for the average individual is therefore arbitrary (alternative specification results are available upon request).[12]

In addition to looking at the effects on usage at these three points in time we undertake three

[12]We assume independence across girls, so do not cluster the standard errors. One concern is that there may be correlation among girls in similar overall peer groups. In practice, the schools are small enough such that in most cases all girls are linked in a single large peer group, so if we were to cluster it would be more or less at the school level. This seems extreme. However, we have run models with this type of clustering and, if anything, the standard errors are smaller (results available from the authors).

additional analyses. First, we estimate a probit model measuring whether an individual ever uses the cup during the entire time period. Second, we estimate a simple linear model to estimate the effect of friends on the first month of successful usage, conditional on ever using. Finally, we estimate a hazard model for date of adoption; in that case, the unit of observation is an individual-month.

One important note is that we estimate the effect of friend *ownership* on cup adoption, rather than friend usage. Because of the structure of the randomization, ownership is what is determined randomly; friend usage may be correlated with individual usage for all of the same reasons that correlated unobservables are a problem without randomization. If ownership only mattered through usage, we could instrument for usage with ownership. However, this assumes away other possible ownership impacts (for example, girls could want to use less when friends own the cup, if exposure makes people suspicious of the cup).

Balancing on Observables

The central assumption in our empirical strategy is that, conditional on the total number of friends, the number of treatment friends is randomly assigned. To test the validity of this randomization, we compare baseline characteristics among girls with different numbers of treatment friends, conditional on their total number of friends.[13] We regress each baseline characteristic of interest on indicators for number of treatment friends and number of total friends. Coefficients on the number of treatment friends from these regressions are shown in Table 2. In most cases, these coefficients are small and statistically insignificant, suggesting the randomization was successful, at least in terms of observables. One exception is the variable indicating whether a girl had ever worked for pay. Girls in our sample who have more treatment friends are significantly more likely to work at baseline; this likely reflects our small sample size and appears to have occurred by chance. We include this control in all regressions which addresses this difference.[14]

[13] A separate issue is whether the treatment and control groups are balanced which is not the central issue for this analysis. However, a test for balancing in these groups (replicated from Oster and Thornton, 2011) is presented in Online Appendix Table 2. These balancing tests are discussed in more detail in Oster and Thornton (2011).

[14] The length of time working, conditional on working at all, *is* balanced across number of treatment friends, suggesting this lack of balance is not likely to be systematic. Moreover, there are no significant differences in working between treatment and control girls, or differences in the likelihood that mothers were working for pay, suggesting there was no targeting on girls who work (and who have more treatment friends).

3.2 Results: Peer Effects on Technology Adoption

We begin by showing our central results of the effects of the number of treatment friends in graphical form. As noted in Table 1, the total number of friends that an individual has (including friends the individual lists and friends who list the individual) ranges from 1 to 7. The majority of individuals (60%) have either 3 or 4 total friends. Focusing on these two groups, Figure 3A shows the usage probability during the first three months of the sample, grouped by number of total friends. Within each group, the number of treatment friends is experimentally generated by the randomization and we can interpret differences in usage as a causal effect.

Figure 3A shows strong evidence of peer effects. Within either group, we see cup usage increasing in the number of treatment friends. For example, among the group with 4 total friends, there is no usage in the first three months for those with zero treatment friends, and then usage increases as the number of treatment friends increases, to as high as 100% for the (very small) sample of individuals who have 4 treatment friends. Although the sample sizes are small here, the regression coefficients reported (from simple regressions of usage on number of treatment friends) indicate that the impact of number of treatment friends on usage is large and highly significant.

Figure 3B shows an identical graph, but focuses on usage in the *last* three months of the study, rather than the first three. In this case, we see that the peer effects have diminished – usage rates among those with no friends in the treatment group are similar to usage for individuals with many friends. The regression results do indicate some evidence of continued peer effects on individuals with 4 total friends, but no evidence of peer effects in the 3 total friend group.

In Table 3 we provide statistical evidence on peer effects. In this case, we include all individuals and control for number of total friends. Panel A includes only the control for total number of friends and school fixed effects (since our randomization was within school). Panel B reports results including additional controls. The first three columns estimate the impact of treatment friends on adoption at three specific months: February 2007 (2 months after distribution), August 2007 and January 2008 (the last month before the follow-up survey). Consistent with Figure 3A, we find strong evidence of peer effects in February 2007: one additional treatment friend increases the chance of adoption by 18.1 percentage points (or 18.6 percentage points when we look at Panel B). This effects dissipates in the later months, consistent with Figure 3B: by the end of the study, those with more treatment friends are not using at higher rates than those with fewer treatment friends. Figure 4 explores the timing of these effects in more detail (based on the regression with full controls) and shows the effect of peer exposure is large and significant in early months (through March 2007) and positive but not significant in the later months.

Columns 4-6 of Panel A of Table 3 show additional estimates of the effects of peers on adoption. In Column 4 we find that having more treatment friends has a weak impact on the chance of ever using successfully (and no impact when we include controls). Columns 5 and 6 reinforce our finding that friends affect timing of adoption. The dependent variable in Column 5 is the first month that the girl used the cup, if she ever used it. The evidence in this regression shows that each additional treatment friend decreases time to adoption by 0.7 months.[15] Column 6 shows this effect is also present when using a hazard model.

The estimates in Panels A and B of Table 3 are very similar. Consistent with our balanced randomization, including demographic controls does not have a large impact. It also suggests that it is unlikely other unobservables would change our results (as in Altonji, Elder and Taber 2000). We also see some evidence that indicators of the potential benefit of adopting the cup mattered in overall use. Girls who work for pay and girls who take longer to wash their menstrual cloths at the baseline survey adopted at higher rates. Time spent washing cloths, in particular, had long-lasting effects. Variation in this variable is likely due to how heavy a girl's period is.[16] We find large variation across schools in adoption, with highest adoption in schools 1 and 2 (96% of girls ever using in school 1 and 84% in school 2) and lowest in schools 3 and 4 (44% and 40%, respectively), but because of the small sample size of the number of schools, it is not possible to attribute the lower or higher rates of adoption in the schools to one particular factor.[17]

The Online Appendix Table 3 shows similar analyses with varying functional forms (first controlling for dummies for number of total friends rather than a linear control and, second, estimating the impact of share of friends with the cup). The results with dummies are virtually identical and the evidence on shares shows the same pattern (although the exact numbers are

[15] Recall that once an individuals use the cup once, 91% of them continue using it, so early usage leads to earlier continual adoption in nearly all cases.

[16] Particularly notable is the relationship, or lack thereof, between adoption and human capital. The literature on technology adoption frequently cites levels of human capital as predictive of early adoption (Oster and Quigley 1977; Caselli and Coleman 2001). While in our sample we do not have variation in years of schooling we do have variation in baseline exam scores, an alternative measure of human capital. Although the coefficients on this variable are positive, they are not consistently significant. Similarly, parents' education and income seem to have little effect on adoption, suggesting that socioeconomic status does not play a role.

[17] Maternal education is slightly lower at the high-adoption schools, and working is also slightly higher. However, there is no trend in test scores, and there are no differences in the number of treatment friends or share of friends in the treatment group. Further, these schools are all in the same area, so they would not differ in cultural norms. Ultimately, without more schools it is impossible to attribute these differences to one particular factor.

obviously different).[18]

Taken together, the evidence in Table 3 and Figures 3 and 4 suggest strong evidence of peer effects. These seem to operate through encouraging earlier adoption of the cup: those with more friends start using faster, although by the end of the study usage rates are fairly similar.[19]

Effects by Friendship Type: Recall that we classify friendships into two categories: strong friends (both girls list each other) and weak friends (only one individual lists the other). The regressions in Table 4 replicate Panel B of Table 3, but report effects by friendship type. Other controls (those reported in Panel B of Table 3) are included but not shown. We find that strong friendships are more important than weak friendships in cup use. This is particularly true later in the study. The effect of weak friendships falls off very quickly, but the effect of strong friendships persists.

4 Peer Effect Mechanisms: Wanting to Use or Success at Usage

The results in the previous section suggest that friend cup ownership matters for adoption. However, thus far we have not made progress on the more fundamental question of *why or how* friends matter for cup adoption. In this section we address this question. It is important to note that although the results in this section use the randomization, they also rely to a much greater extent on a more structural model of behavior. For these reasons, the conclusions in this section should be taken with greater caution than the basic peer effects estimates presented above.

4.1 Outline and Graphical Evidence

Peer exposure may matter because peers affect whether an individual wants to use the technology. This could occur either because of imitation (individuals want to act like their friends) or because peers affect individual perceptions about technology value (Miguel and Kremer 2007; Kohler, Behrman and Watkins 2001). Peers could also matter if people learn how to use the technology from their friends (Duflo and Saez 2003; Munshi and Myaux 2006; Miguel and Kremer 2007). The existing literature has generally been unable to separate these mechanisms. An exception is Miguel and

[18] Online Appendix Figure 1 provides another visual representation of the data in which we run regressions using all months in the sample and estimate the impact of dummy variables for "treatment-friend-months." This figure shows the same pattern: initial friend-months of exposure have the largest impacts.

[19] It is important to be clear on the interpretation of the declining peer effect over time. As time passes, even girls with few or no close treatment friends learn to use the cup. They could, for example, learn from the study nurse, or through friends of friends; our sample is too small to estimate these indirect impacts of peers. The fact that we see fewer peer effects later in the study does not mean peers do not matter, but suggests that as information diffuses broadly, everyone has enough "peers" to learn.

Kremer (2007), who estimate peer effects on adoption of deworming drugs and explicitly distinguish between these avenues. They find *negative* peer effects – individuals with more peers in early adopter schools are less likely to adopt – which effectively rules out either imitation or learning about how to use the technology as drivers, since both of those would produce positive effects. In our case, since we find *positive* peer effects, we cannot rule out any of these possibilities.

To address the mechanisms, in this section we present a model and a set of results which rely on the fact that we observe separate measures of successful and failed usage attempts. We assume there are two stages in determining the adoption of a new technology: first, individuals decide whether or not they would like to use the technology; second, they may or may not be successful at using the technology. We posit that technology value affects whether an individual *wants to use* (first stage) and knowledge about how to use affects *success in using* (second stage). Intuitively, this implies that observing peer impacts on cup trial would indicate that peer exposure impacts the value of the technology, and observing peer effects on cup usage *conditional on trial* would indicate that peer exposure impacts how quickly girls learn how to use the new technology.

Figures 5A and 5B present the simplest graphical analysis of this issue. These figures echo Figure 3A in structure but focus on peer effects on usage conditional on trial (Figure 5A) and peer effects on trial (Figure 5B). We focus on the first three months due to the fact that peer effects occur only early in the sample; thus we do not show analogs to Figure 3B (these are available from the authors). Focusing first on Figure 5A, we see strong evidence that peers impact successful usage conditional on attempting to use the cup. This figure looks very similar to Figure 3A, and the regression estimates of the effects of additional treatment friends on successful usage are highly significant. We observe a point estimates of 0.128 (s.e. 0.062) among those with 3 total friends and 0.193 (s.e. 0.056) among those with 4 total friends. This points towards an impact of peers on learning how to use the cup. In Figure 5B, we also see some evidence that peers impact attempting to use the cup, although these results are weaker and less significant (point estimates of 0.079 (s.e. 0.053) among those with 3 friends and 0.121 (s.e. 0.051) among those with 4 friends). Taken at face value, these graphs suggest that peers may matter for both successful usage and wanting to use, although they seem to be more important for successful usage.

Although these graphs are suggestive, there are two central issues to be addressed which relate to the interplay between the two outcomes of interest. First, we are only able to observe successful usage among girls who actually attempt to use. This means our estimates of peer impacts on learning to use are valid only for a select sample of girls. If the peer effects on usage success were to be different for the sample of girls who do not try, this affects the generalizablity of our results. This is unlikely to be a significant issue, for several reasons. Most obviously, this is not a problem if wanting to use the cup is unrelated to the impact of peers on successful use. This does not seem like an unreasonable assumption. Second, even if the OLS estimates are not valid for the entire sample, they are valid for the group that is relevant, namely those who actually want to use the product. Put differently, although these estimates may not directly reflect the relevant parameter in the model, they do reflect the parameters which we would observe in the world. As we will see below, our ultimate conclusions about the impact of peers on ability to use the cup echo very strongly the evidence in Figure 5A.

A second, and much more important issue is that the decision to try to use is very likely to be affected by expectations of success: if a girl knows she will not be successful, she is unlikely to try. Given this, if there are peer impacts on usage success, this may mechanically translate into peer impacts on attempting to use. Below, we develop a simple model of this decision which makes these issues clear and we suggest an estimation strategy to address these concerns.

4.2 Two Stage Process of Technology Adoption

As above, assume there are two stages in determining the adoption of a new technology. We denote the overall probability of usage as p_u, the probability that an individual wants to use as p_w and the probability of success at using as p_s. These are all functions of friendships and of observables. In particular, denote f_i as the number of treatment friend exposures to the cup (i.e. total months of exposure), and x_i as a vector of controls, which includes demographics, total numbers of friends and months since distribution. In addition, denote v_i as the value of the cup. Overall probability of usage can be written as:

$$p_u(f_i, x_i, v_i) = p_w(f_i, x_i, v_i)p_s(f_i, x_i, v_i) \tag{2}$$

Thus far, we have established a positive relationship between friend exposure and overall use of the cup: $\frac{dp_u}{df_i} > 0$. This is consistent with either $\frac{dp_w}{df_i} > 0$ or $\frac{dp_s}{df_i} > 0$, or both. In this framework, we propose that $\frac{dp_s}{df_i} > 0$ indicates that friends matter because they help individuals learn about how to use the cup and that $\frac{dp_w}{df_i} > 0$ indicates that friends matter because they affect cup value (either through imitation or through learning about value of the cup). In our data we observe whether or not someone attempts to use, and whether she is successful conditional on attempting. These decisions map into p_w and p_s in the theoretical framework, in ways detailed below.

Attempt to Use: We assume that attempting usage of the the cup has a cost, which we denote $\epsilon_i \sim H(.)$ and which is paid regardless of whether or not the attempt is successful. There is no additional cost of using after the attempt.[20] An individual will attempt to use the cup if the benefits exceed the cost. Denote the benefit of the cup for individual i as B_i. These benefits are experienced only if the girl is able to successfully use the cup; in contrast, the costs are paid at the time of the attempt. This means that the girl will be more likely to try if she feels she is more likely to be successful, since her benefits are effectively adjusted by her probability of success. Denoting the expected probability of success as $E[p_s(f_i, x_i, v_i)]$ a girl will attempt to use the cup if the following holds:

$$B_i E[p_s(f_i, x_i, v_i)] > \epsilon_i \tag{3}$$

We can rescale the benefits and costs to be in terms of probabilities, so the benefits are reflected in $p_w(f_i, x_i, v_i)$. Denote the rescaled cost as $\hat{\epsilon}_i$. We can then rewrite Equation (3) in terms of the scaled probabilities below.

$$p_w(f_i, x_i, v_i) E[p_s(f_i, x_i, v_i)] > \hat{\epsilon}_i \tag{4}$$

Success at Usage: In the data we observe whether or not a girl is successful at using the cup conditional on having attempted. Formally, we observe $p_s(f_i, x_i, v_i)$ conditional on Equation (4) holding.

Because of these interdependencies – that we observe wanting to use only adjusted by probability of success, and success only conditional on Equation (3) holding – actually estimating $\frac{dp_s}{df_i}$ and $\frac{dp_w}{df_i}$ is empirically challenging. In the next sections, we outline how we use the data to identify these peer effects.

In moving from the theory to the data, we make one important and central assumption: once an individual decides to try the cup, there is no effort margin on trying, and success is simply determined by factors fixed at that point (in particular, friend exposure and demographics). Formally, this amounts to assuming that $\frac{dp_s}{dv_i} = 0$. That is, we assume that the probability that an

[20] We argue this is a reasonable assumption, since most of the difficult and uncomfortable aspects of using the cup involve trying to insert it. In this setting, the cup was free. In the case of other technologies or other settings there may be opportunity costs of adoption, or other costs that might be important in the decision to try to adopt.

individual is able to successfully use the cup does not depend on cup value (either actual or perceived). Probability of success is a function only of the knowledge about how to use the cup (derived from friends) and, possibly, individual demographic characteristics. Given this assumption, moving forward we will refer to p_s as a function only of f_i and x_i: $p_s(f_i, x_i)$. A related assumption is that the cost of trying, $\hat{\epsilon}_i$ is not a function of peers.

This is a crucial assumption because it is necessary for us to interpret the reports from participants about cup trial and usage as reflecting the elements of the model. Without this assumption, our two-stage process effectively collapses into a single decision about wanting to use, in which success at usage simply reflects how much the person wants to use, and how hard they are willing to try. In that case, "trial" and "usage" would simply reflect different intensities of desired usage and it would not make sense to think about a two-stage model. Ultimately, we feel that this assumption is reasonable, but it is important to keep in mind, given the role that it plays in our estimation of these mechanisms. If this assumption is not valid, we effectively lose our ability to interpret cup "trial" and "usage" as separate events, and our analysis of the data could not be informative about mechanisms.

4.3 Peer Effects on Successful Usage

Estimation Strategy

We work backward and begin by first analyzing the second stage of the adoption process: successful usage. We observe $p_s(f_i, x_i)$ directly in the data: it is successful usage conditional on attempting to use (shown in Figure 5A). However, we observe this only for individuals who attempt to use at all. We do not observe the probability of success among those who do not choose to try. This introduces a potential selection problem which was discussed briefly above. More specifically, girls who want to use more, or who have lower costs of attempting to use, will be more likely to try the cup. If peer effects on successful usage are different for these girls than for those who do not want to try, then simple OLS estimates will be valid only for this selected sample of girls.

We first estimate $\frac{dp_s}{df_i}$ with an OLS regression of cup usage on friend exposure, restricting the sample to girls who have tried the cup. These estimates are valid for the relevant sample of girls who try to use the cup. Further, these estimates will be valid for the whole sample if the selection issues are small. In addition, as a robustness strategy to address the selection issue directly, we estimate the same regression using a Heckman selection model.

Running this selection model requires us to identify some variable which influences trial but does not influence knowledge of how to use.[21] In our case we use month-on-month variations in whether a girl has her period since girls typically do not try to use the cup if they do not have their period. This variation is driven primarily by the fact that menstrual cycles are not regular during early years of menstruation (for a discussion of menstrual cycle length among adolescents, see American Academy of Pediatrics, 2006). In our data, 15 treatment girls miss their period at least once during the study and 11 of these miss in just one month. We believe that missed periods at this age (more accurately, long cycle lengths) are unlikely to be otherwise correlated with ability to use the cup. Not having one's period is a very good predictor of not trying the cup, but some girls do report trying to use in months they do not have their period, perhaps for practice. It seems at least plausible that these girls are the ones who are most interested in using the cup. For both of these reasons, this provides an appropriate selection criteria.

Results

Figure 5A showed a portion of our OLS results visually, and suggested that without any selection adjustment the impact of peers on usage success was large and statistically significant. Table 5 estimates these impacts statistically. We use individual-month observations and estimate the effect of number of treatment-friend-months of exposure. Columns 1-3 present the OLS estimates and Columns 4-6 present corresponding Heckman Selection estimates.[22] Both the OLS and Heckman models give extremely similar results. This suggests that the selection issues raised above are not very salient in practice. Overall, having more exposure to treatment friends is strongly correlated with successful usage of the cup. This is especially true during early months (Columns 2 and 5), although the effect remains significant in later months (Columns 3 and 6).

The evidence in Table 5 suggest that peer exposure to this technology affects the ability to use the cup successfully. This suggests that peers matter for adoption because people learn from others about how to use. The estimates are largest in early months after distribution, which is consistent

[21] Note that the selection model is only as good as the selection variable. An example of a common use of the Heckman selection framework is in estimating the returns to schooling for women. Many women are out of the labor force, so estimating returns to schooling only for women who are in the labor force will yield estimates which are only valid for that selected sample. A common selection instrument in this case is the presence of young children: women who have young children are less likely to be in the labor force but (by assumption) do not have a different wages other than for this reason. As in this case, we are looking for a selection variable which influences the desire to try the cup, or the ability to try, but does not influence ability to use.

[22] The first stage regressions for the Heckman Selection model are shown in Online Appendix Table 4. In the whole sample period (Column 4), the excluded selection variable of not having a period that month has a z-statistic of 5.28 and a marginal effect of -0.72.

with our overall finding that peer effects are larger early on.

We next move to the first stage of the adoption process, when individuals decide whether they want to use the cup.

4.4 Peer Effects on Trial (Wanting to Use)

Estimation Strategy

When making the decision to try the cup, the expected probability of success of trial is an important factor (Equation 4). As noted in Section 4.1, we cannot simply estimate the effect of friends on usage attempts and interpret them as an effect of wanting to use. This is especially true since we find in Section 4.3 that friends matter for successful usage. Given this, observing that friends matter for attempting to use might well reflect only their effect on expected usage success, not effects on wanting to use. In contrast to the selection concerns discussed above, this is likely to be a significant concern since we know from the evidence above that friends do impact success at usage.

In order to identify the causal effects of peers on wanting to use the cup ($\frac{dp_w}{df_i}$), we would ideally like some exogenous variation that affects the expected probability of success, $E[p_s(f_i, x_i)]$. Unfortunately, in this case, we have no obvious candidate for this in our data limiting our ability to identify $\frac{dp_w}{df_i}$. However, we argue that we can use the structure of the model to estimate this parameter.

Recall Equation (2): $p_u(f_i, x_i, v_i) = p_w(f_i, x_i, v_i)p_s(f_i, x_i)$. Differentiating this equation with respect to f_i yields the following expression: $\frac{dp_u}{df_i} = p_w(f_i, x_i, v_i)\frac{dp_s}{df_i} + p_s(f_i, x_i)\frac{dp_w}{df_i}$. Rearranging to give an expression for our quantity of interest, $\frac{dp_w}{df_i}$, yields:

$$\frac{dp_w}{df_i} = \frac{\frac{dp_u}{df_i} - p_w(f_i, x_i, v_i)\frac{dp_s}{df_i}}{p_s(f_i, x_i)} \tag{5}$$

Several of these values have been estimated thus far in the analysis. We estimated $\frac{dp_u}{df_i}$, the effect of friend exposure on overall adoption, in Table 3. In Section 4.3 (Table 5) we estimated $\frac{dp_s}{df_i}$, the effect of friend exposure on the probability of a successful trial. The object $p_w(f_i, x_i, v_i)$ is the probability that an individual wants to use the cup overall; based on Equation (4) we note that this is the probability of attempting to use conditional on expecting to be successful for sure. We do not observe this directly in the data, since we only observe attempts at usage as determined by Equation (4). However, by the end of the study, most girls who try are successful; we can infer from this that expected success ($E[p_s(f_i, x_i)]$) should be close to 100%. Using this later part of the sample, we predict the probability of attempting to use for each girl in the sample, and define this as her p_w. Put simply, this is the probability of wanting to use when $E[p_s(f_i, x_i)] \approxeq 1$. In the Online Appendix we will also provide estimates where we assume everyone wants to use ($p_w = 1$).

The object $p_s(f_i, x_i)$ is the probability of success, on average, for all individuals, including those who do not attempt to use. We can estimate this based on the results in Section 4.3 above. Specifically, we run the regressions from Table 5 and use them to predict p_s for each individual. Given these four parameter estimates, we can calculate $\frac{dp_w}{df_i}$ for each individual and take the average across individuals; we generate bootstrapped standard errors.[23] It is important to note that, even more than the analysis in Section 4.3, these results require significant assumptions about these parameters, and a heavy reliance on the structure of the model. They should be taken with more caution.

Results

We begin by estimating OLS regressions of the impact of friendships on cup trial, which echo Figure 5B. Consistent with the discussion above, finding an effect of friends on trial in these naive regressions could reflect friends impacting wanting to use (p_w) or could reflect friends impacting success at usage (p_s) and individual trial responding to their probability of usage success.

Columns 1-3 of of Table 6 estimates these OLS regressions (regressions are estimated on observations stacked at the individual-month level, as in Table 5). The coefficient on number of treatment friend exposures in Column 1 is positive although not statistically significant. In early months, however, there is a relatively strong positive relationship between treatment friend exposures and attempts to use (Column 2), which is also what we observed in Figure 5B.

Columns 4-6 of Table 6 show results from our structural estimation of $\frac{dp_w}{df_i}$.[24] The estimated effects of treatment friend exposure in this case are smaller in magnitude, and never significant. The fact that the difference between the naive estimates and the structural estimates is largest in early months may correspond to evidence in Table 5, where we find that friends matter most for <u>success at usage</u> during early months of the study. As a robustness check, Online Appendix Table 5 shows similar estimates, but with the assumption that $p_w = 1$. These coefficients are even smaller

[23] We could also have taken the average p_w and average p_s and used these to calculate the average $\frac{dp_w}{df_i}$; this gives the same solution as calculating for each individual and averaging.

[24] We do not report coefficients on controls here, since the estimates are generated based on running several regressions and calculating a non-linear combination of coefficients; standard errors are bootstrapped. In this sense there are no "controls" to report, even though they are included in the regressions that generate this estimate.

and similarly insignificant. Note that these estimates are fairly noisy and, while we come close, we cannot reject that the coefficient in Column 1 of Panel B of 6 is as large as that in Column1 of Table 5. This gives yet another note of caution to these results.

Willingness to Pay

In addition to the structural approach of estimating how peers affect wanting to use the cup, we take advantage of a question in the follow-up survey asking each girl: "Would you be willing to pay X for the menstrual cup?", with X ranging from 500 to 2500 Nepali Rupees (US$7 and US$33, respectively). We code girls as willing to pay 500Rs if they say yes when $X = 500$Rs; willing to pay 1000Rs if they say yes when $X = 1000$Rs, and so on up to 2500Rs. The average of this variable is 1380Rs, which is about US$18. Note that these values are quite high and very likely higher than we would see if these questions were not hypothetical. Nevertheless, we feel that this variable indicates to some extent how much an individual may value the cup. We focus on girls who have ever used the cup, since we expect them to have $E[p_s(f_i, x_i)] \approxeq 1$ and estimate whether those with more friends have greater willingness to pay.

Column 7 of Table 6 presents the results. The coefficient is relatively small relative to the variable mean. One additional treatment friend increases willingness to pay by an insignificant 188Rs, or about 12% of the mean. This suggests that once we hold constant the ability to use the cup, friends do not affect cup value and, by extension, do not affect wanting to use, consistent with the previous results.[25]

In summary, the evidence presented in this section most strongly supports the claim that friends matter in girls ability to use the cup, rather than wanting to use the cup. We can see this in simple graphs (Figure 5A), as well as in regressions. Although selection concerns could drive our results, we argue they are unlikely to do so in theory, and they do not in practice. In addition, in many ways the only relevant group to estimate these parameters on are those girls who are willing to try. Given this, the simple graphs and OLS regressions exactly capture the parameters of interest. In contrast, we find less evidence that peers matter for wanting to use. Although naive regressions suggest some impact early on, these analyses suffer from the fact that girls who know they will be successful are more likely to try. Once we attempt to adjust for this, we find little or no impact of

[25] An interesting related question is whether treatment friends impact willingness to pay among control girls. We might expect this to be the case despite the evidence in Column 7, since control girls with more treatment friends may have a better sense of how to use the cup, and be more optimistic about their own usage. In practice, a regression of the form in Column 7 limited to control girls shows similar coefficients (147 versus 188) and the estimate is not significant (available from the author).

peers on friend cup trial.

5 Conclusion

This paper analyzes peer effects in the adoption of a new technology using data from a randomized evaluation of menstrual cup provision in Nepal. Although menstrual cups may be a relatively minor technology, we argue that the data and setting have a number of advantages for this analysis. First, the menstrual cup is completely new and unfamiliar, and it is somewhat difficult to use and requires learning, features shared with other important technologies (contraceptives in particular). Second, because we randomize at the individual level, we have exogenous variation in peer exposure, which allows us to causally estimate peer effects on adoption. Third, our data contain rich information on both trial and usage of the cup allowing us to make progress on separating out mechanisms by which peers affect adoption.

We find strong evidence that peer exposure to the cup drives adoption. Girls with more treatment friends adopt the cup more quickly. Our analysis of mechanisms suggests that peers are most important for individuals to learning about how to use the product, rather than influencing individuals wanting to use the product.

The results here may have policy implications which go beyond the particular case of the menstrual cup. In many cases policymakers face choices about how best to distribute technologies in order to maximize adoption. The results here indicate that the appropriate targeting is likely to depend on specific characteristics of the product – in particular, how much variation there is in the likelihood of success – which could be a function of underlying abilities or in the difficulty of learning the technology.

We also believe the findings in this paper may also guide methodology. First, peer effects are more important in early months after product distribution, suggesting there is value in observing adoption over time. Had we observed cup usage only at the follow-up survey we would have missed these effects. This may also reflect the fact that all individuals in the sample eventually learn how to use the product. Second, the discussion of mechanisms here suggests that more data on patterns of adoption – in particular, collecting more information about the way that individuals are deciding whether or not to adopt – may be valuable in understanding the mechanisms through which these effects operate.

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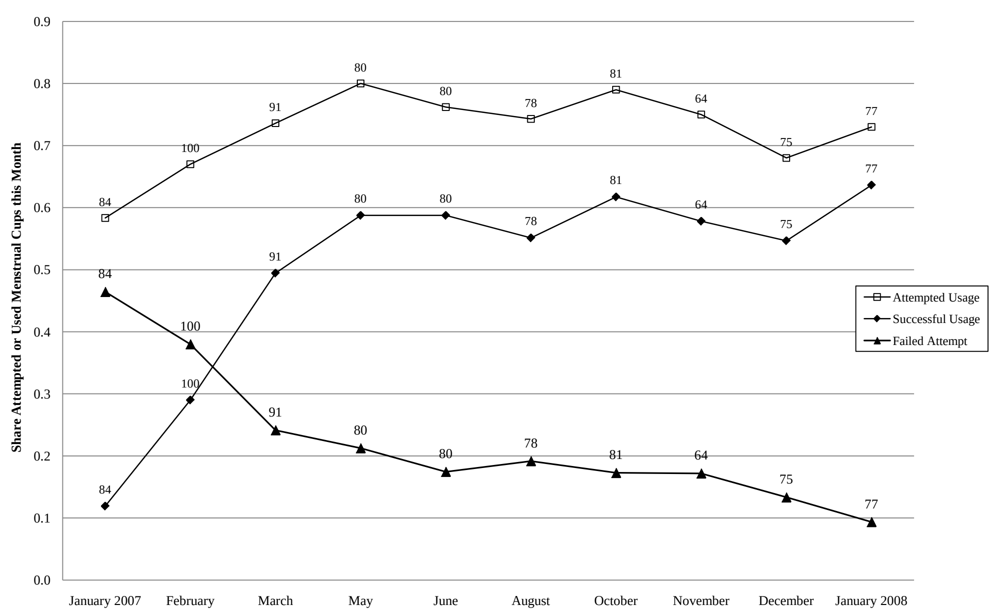
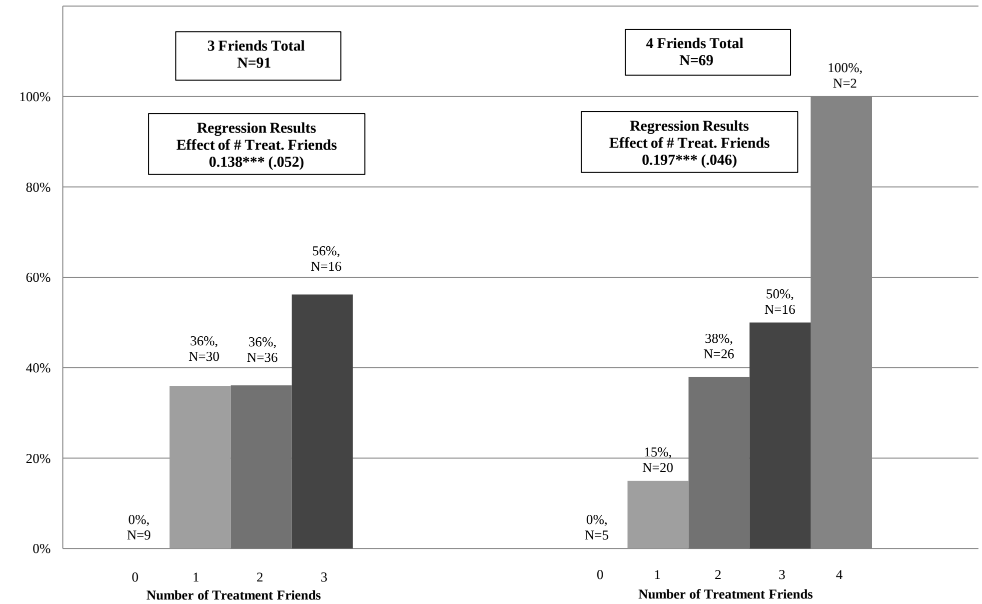
Figure 1: MoonCup Photo

Figure 2:
Menstrual Cup Attempted Usage, Successful Usage and Failed Attempts over Time



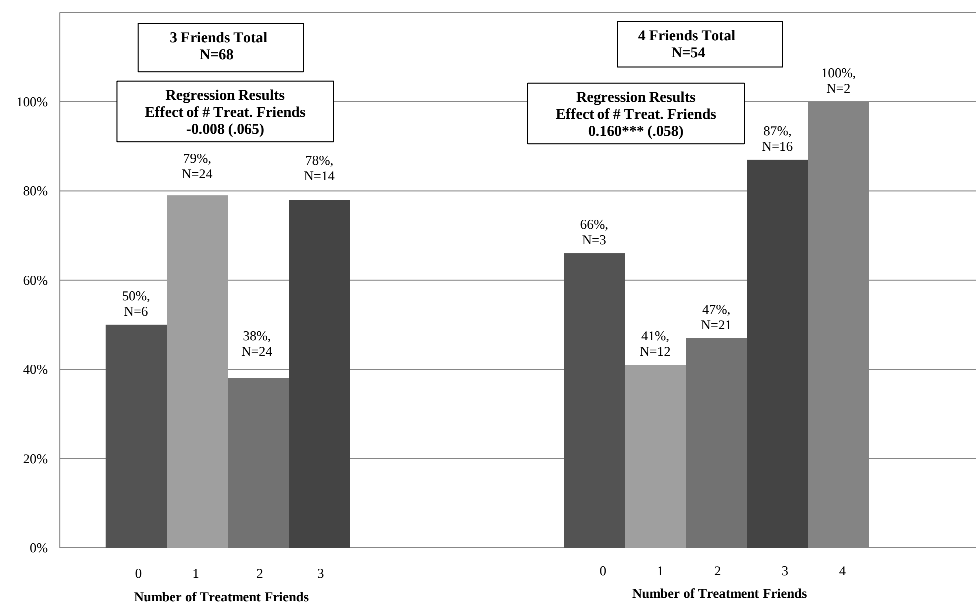
Notes: This figure shows evolution of usage of the menstrual cup, over time. Cups were distributed in November or December of 2006. The labels indicate the number of individuals observed in each month. There are a total of 101 treatment individuals.

Figure 3A:
Peer Effects in First 3 Months



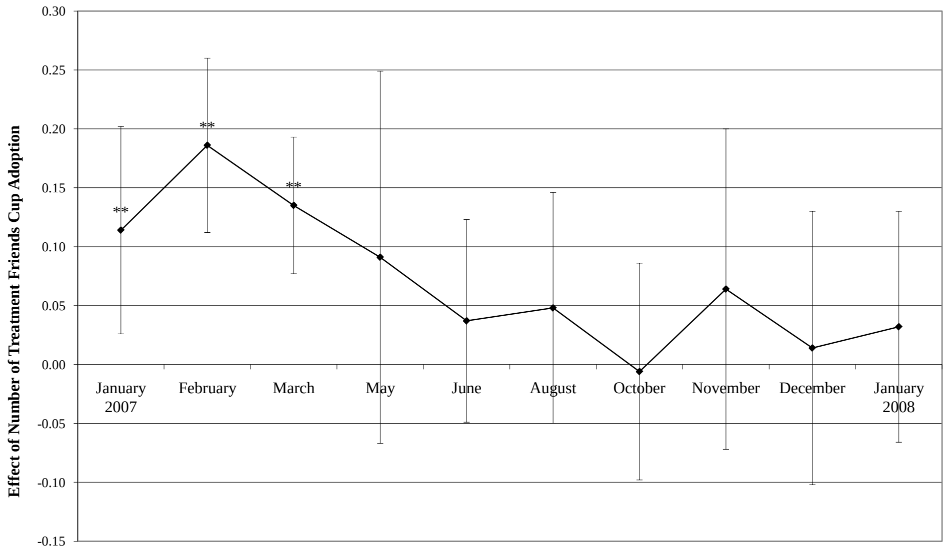
Notes: This figure shows usage by number of treatment friends, grouped by number of *total* friends. This figure reports the average of usage in January, February and March of 2007, the first three months of the study. Regression coefficients are marginal effects from a probit regression of usage on number of treatment friends within the sample with constant total number of friends.

Figure 3B:
Peer Effects in Last 3 Months



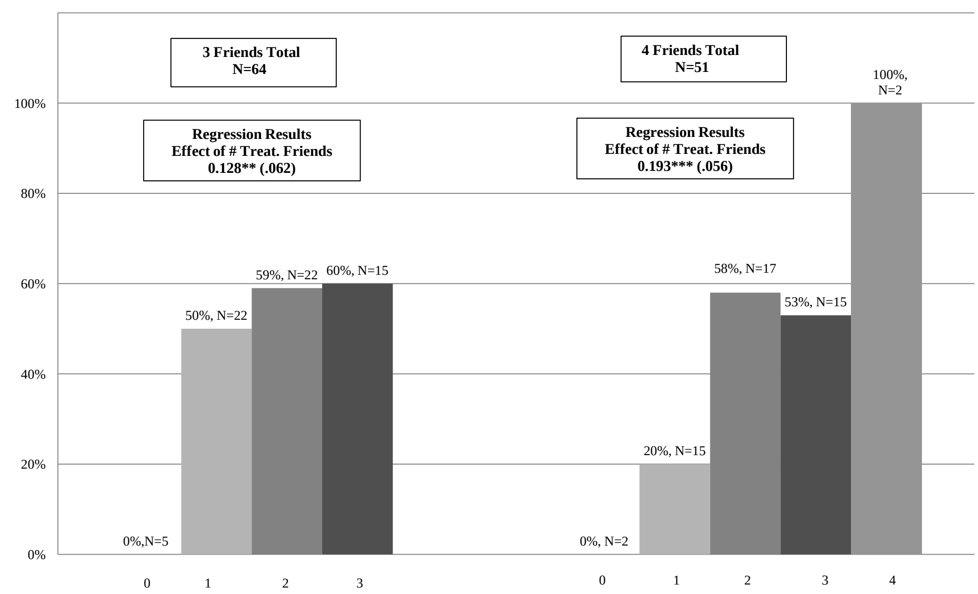
Notes: This figure shows usage by number of treatment friends, grouped by number of *total* friends. This figure reports the average of usage in November and December of 2007 and January 2008 (at the end of the study). Regression coefficients are marginal effects from a probit regression of usage on number of treatment friends within the sample with constant total number of friends.

Figure 4:
Estimated Effect of Treatment Friends on Menstrual Cup Usage, by Month



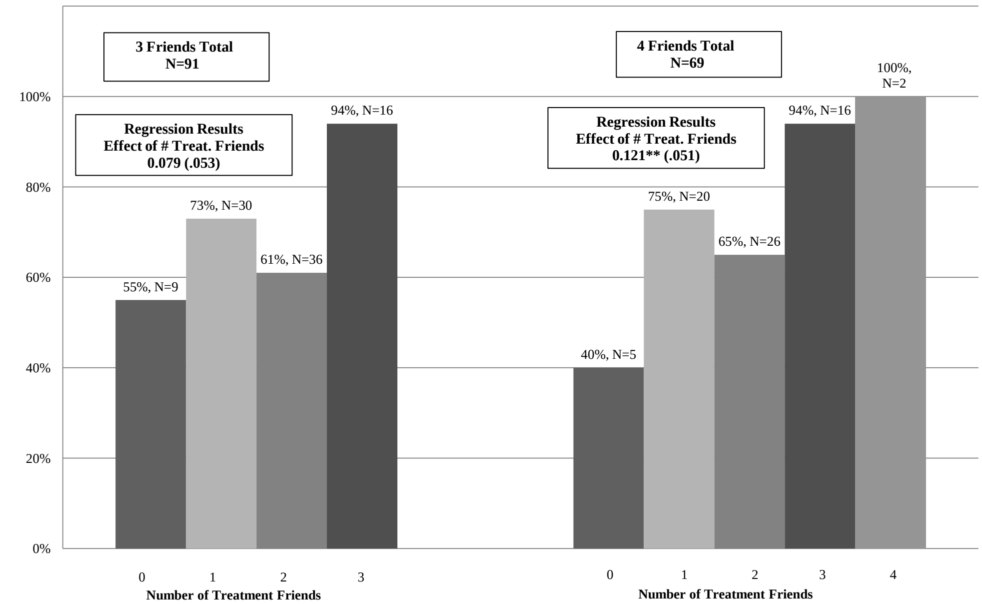
Notes: This figure shows coefficients on number of treatment friends from regressions run in each month. In all cases the dependent variable is menstrual cup usage in that month. 95% confidence intervals are shown. ** significant at 5% level; * significant at 10% level

Figure 5A:
Peer Effects on Successful Usage, First 3 Months



Notes: This figure shows usage by number of treatment friends, grouped by number of *total* friends, conditional on trying to use the cup. This figure reports the average of usage in January, February and March os 2007, the first three months of the study. Regression coefficients are marginal effects from a probit regression of usage on number of treatment friends within the sample with either three total friends or four total friends.

Figure 5B:
Peer Effects on Cup Trial, First 3 Months



Notes: This figure shows cup trial by number of treatment friends, grouped by number of *total* friends. This figure reports the average of cup trial in January, February and March of 2007, the first three months of the study. Regression coefficients are marginal effects from a probit regression of usage on number of treatment friends within the sample with either three or four total friends.

Table 1: Summary Statistics

Panel A: Number of Participants

	Girls	*Mothers*	*Female Relative*
School 1	54	41	13
School 2	48	35	13
School 3	48	41	7
School 4	48	40	7

Panel B: Summary Statistics

	Mean	*Standard Deviation*	*# of Observations*
Age	14.2	1.23	197
7th Grade (0/1)	0.53	0.50	198
Test Score Last Year	-0.08	1.18	198
Father Hindu	0.52	0.50	198
Father Tharu or Tibetan	0.42	0.49	198
Income Category	2.55	1.55	190
Mother's Yrs. Educ.	2.69	3.90	190
Father's Yrs. Educ.	5.61	4.70	190
Menses at baseline (0/1)	0.87	0.33	197
Work for Pay	0.22	0.41	198
Days/Week Worked (if >0)	2.51	1.93	43
Time to Wash Cloths	30.9	32.2	197
Number of friends	3.78	1.35	198
Share of Friends Treatment	0.51	0.27	196

Notes: This table shows summary statistics. All girls were in either 7th or 8th grade. Age at menses is reported only for girls who have their menses at baseline. Total number of friends includes all friends the individual lists, plus any people who list her as a friend. The omitted ethnicity category is Newari. Income categories range from 1-6, and correspond to yearly incomes of: Less than 25,000 Rs, 25k-50k, 50k-75k, 75k-100k, 100k-150k, 150k+.

Table 2: Balancing Tests

	Coeff. on # of Treat. Friends (Std. Error)
Age	0.090 (0.091)
7th Grade (0/1)	0.006 (0.038)
Test Score Last Year	-0.097 (0.090)
Father Hindu	0.053 (0.038)
Father Tharu or Tibetan	-0.058(0.037)
Income Category	-0.132 (0.121)
Mother's Yrs. Educ.	-0.199 (0.306)
Father's Yrs. Educ.	-0.179 (0.369)
Menses at baseline (0/1)	-0.027 (0.025)
Work for Pay	0.099 (0.031)***
Days Worked (if >0)	0.058 (0.324)
Time to Wash Cloths	3.37 (2.47)
# Months Observed in Sample	0.301(0.237)

Notes: This table shows balancing tests by number of treatment friends. Total number of friends includes all friends the individual lists, plus any people who list her as a friend. The omitted ethnicity category is Newari. Income categories range from 1-6 (definitions in Table 1 notes). *** significant at 1%.

Table 3: Determinants of Menstrual Cup Usage

Dependent Variable:	*Used Menstrual Cup During:*			*Ever Used*	*First Month*	*Hazard Model*
	Feb. 2007	*Aug. 2007*	*Jan. 2008*	*Mooncup*	*Used (1-10)*	*for Usage*
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: School Fixed Effects and Total Number of Friends Control Only						
#Treat Friends	0.1805***	0.0817*	0.0741	0.0782*	−0.6026**	1.207***
	(0.036)	(0.048)	(0.047)	(0.039)	(0.244)	(0.063)
#Friends	−0.0815**	−0.0614	−0.0057	−0.052*	−0.0450	0.9435
	(0.035)	(0.035)	(0.036)	(0.03)	(0.204)	(0.041)
Number of Obs	100	78	77	101	657	810
Panel B: With Demographic Controls						
#Treat Friends	0.1864***	0.0481	0.0326	0.0408	−0.6884***	1.221***
	(0.037)	(0.049)	(0.049)	(0.042)	(0.256)	(0.073)
#Friends	−0.0841**	−0.071**	−0.0136	−0.0489*	−0.0135	0.9102**
	(0.031)	(0.033)	(0.032)	(0.028)	(0.208)	(0.044)
Work for Pay	0.3512**	0.4754**	0.472***	0.2063	−1.5146*	2.018***
	(0.154)	(0.103)	(0.071)	(0.188)	(0.894)	(0.455)
Days Worked	−0.0755**	−0.1282**	−0.1519***	−0.0071	0.1431	0.879**
	(0.032)	(0.048)	(0.047)	(0.072)	(0.201)	(0.047)
Time to Wash Cloths	0.0026*	0.0048*	0.0043*	0.0033	−0.0077	1.001
	(0.001)	(0.003)	(0.002)	(0.002)	(0.008)	(0.002)
Age	0.0382	0.0679*	0.0733	0.0598*	−0.2929	1.094*
	(0.034)	(0.04)	(0.044)	(0.032)	(0.193)	(0.057)
Grade	0.1529**	−0.1547	−0.0528	−0.0838	−0.4358	0.856
	(0.063)	(0.099)	(0.086)	(0.077)	(0.446)	(0.094)
Father Tharu or Tibetan	−0.2341**	−0.1352	−0.244**	−0.1315	0.0724	0.788*
	(0.068)	(0.107)	(0.069)	(0.09)	(0.565)	(0.111)
Father Newari	0.1335	0.0018	−0.2375	−0.1802	−0.1599	1.035
	(0.183)	(0.252)	(0.23)	(0.176)	(1.333)	(0.316)
School #2	−0.2967***	−0.2854**	−0.2487**	−0.2523**	2.0892***	0.5057***
	(0.046)	(0.085)	(0.093)	(0.089)	(0.578)	(0.074)
School #3	−0.3645***	−0.4992***	−0.4925***	−0.4373***	2.2847***	0.303***
	(0.055)	(0.104)	(0.111)	(0.114)	(0.749)	(0.061)
School #4	−0.3922***	−0.5723***	−0.6261***	−0.5472***	2.965***	0.214***
	(0.042)	(0.071)	(0.061)	(0.088)	(0.813)	(0.044)
Exam Score	0.0291	0.0598	−0.013	0.0155	−0.1519	1.038
	(0.027)	(0.05)	(0.029)	(0.029)	(0.195)	(0.045)
Mom Educ.	0.0151	0.0311	0.0018	0.0234**	−0.0409	1.057***
	(0.013)	(0.02)	(0.013)	(0.011)	(0.074)	(0.021)
Dad Educ.	−0.0126	−0.0247	−0.0293*	−0.0318**	−0.0206	0.970*
	(0.01)	(0.016)	(0.015)	(0.012)	(0.071)	(0.017)
Family Income	0.0208	0.0458	0.0771**	0.0403	−0.3755**	1.088**
	(0.025)	(0.036)	(0.034)	(0.028)	(0.151)	(0.041)
Number of Obs.	96	74	73	97	65	772
Mean of Dep.Var.	0.29	0.55	0.64	0.66	3.22	

Notes: This table shows the effect of peers on cup usage. The first three columns use one month of data each. The fourth column estimates the effect of treatment friends on ever using the cup; the fifth column estimates peer effects on first month of usage, conditional on ever using. The sixth column shows estimates from a hazard model for usage; the coefficients reported are hazard ratios and the unit of observation is a person-month. Columns 1-4 report marginal effects from a Probit model; Column 5 uses OLS and Column 6 is a Cox Proportional Hazard Model. The mean of the dependent variable (reported at the bottom of the table) applies to both panels. Standard errors are in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table 4: Influence of Friend Type on Menstrual Cup Adoption

Dependent Variable:	*Used Menstrual Cup During:*			*Ever Used*	*First Month*	*Hazard Model*
	Feb. 2007	*Aug. 2007*	*Jan. 2008*	*Mooncup*	*Used (1-10)*	*for Usage*
	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory Variables:						
#Strong Treat. Fr.	0.2655^{***}	0.1497^{*}	0.3099^{**}	0.1481^{*}	-0.8201^{**}	1.288^{***}
	(0.066)	(0.092)	(0.137)	(0.088)	(.4040)	(0.119)
#Weak Treat. Fr.	0.1421^{***}	-0.0004	-0.001	-0.0017	-0.604^{**}	1.190^{**}
	(0.047)	(0.058)	(0.049)	(0.048)	(0.305)	(0.083)
Controls for # Fr.	YES	YES	YES	YES	YES	YES
Number of Obs.	96	71	72	97	65	772
Mean of Dep. Var.	0.29	0.55	0.64	0.66	3.22	

Notes: This table shows the effect of peers on cup usage separated by friend type. The first three columns use one month of data each. The fourth column estimates the effect of treatment friends on ever using the cup; the fifth column estimates peer effects on first month of usage, conditional on ever using. The sixth column shows estimates from a hazard model for usage; the coefficients reported are hazard ratios and the unit of observation is a person-month. Strong friends are bidirectional – both individuals list the other – and weak friends are unidirectional. Regressions include the controls from Table 3, including controls for number of friends. Standard errors are in parentheses; *significant at 10%; **significant at 5%; ***significant at 1%.

Table 5: Peer Effects on Successful Usage

	Dependent Variable: Used Menstrual Cup					
	OLS: Used Condition on Trial			*Heckman Selection*		
				Selection: No Period		
	(1)	(2)	(3)	(4)	(5)	(6)
	Entire Sample	*First 5 Months*	*Later 5 Months*	*Entire Sample*	*First 5 Months*	*Later 5 Months*
Explanatory Variables:						
#Treat. Fr. Months	0.0138^{***}	0.0298^{**}	0.0120^{**}	0.0131^{***}	0.0306^{***}	0.0119^{***}
	(0.005)	(0.011)	(0.004)	(0.004)	(0.011)	(0.004)
#Friend Months	-0.0079^{*}	-0.0142	-0.0075^{*}	-0.0073^{*}	-0.0147^{*}	-0.0072^{*}
	(0.004)	(0.009)	(0.004)	(0.004)	(0.008)	(0.004)
CONTROLS	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Number of Obs.	562	297	265	772	416	356
Mean of Dep.Var.	0.68	0.58	.79	0.49	0.41	0.59

Notes: This table shows the estimates of the effect of peers on success at menstrual cup usage. The first three columns estimate OLS regression of usage conditional on trial; Columns 4-6 estimate Heckman Selection models, where the selection is on whether or not the individual tried, and the selector variable is "no period this month." Controls for demographics are included in all columns (the same controls as in Table 3, minus controls for benefits). Standard errors are in parentheses, clustered by individual; *significant at 10%; **significant at 5%; ***significant at 1%.

Table 6: Peer Effects on Wanting to Use Menstrual Cup

	OLS (Naive Regressions) Dependent Var.: Tried Menstrual Cup			*Structural Estimates*			*Willingness to Pay Dep. Var.: WTP, Rs.*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Entire Sample	*First 5 Months*	*Later 5 Months*	*Entire Sample*	*First 5 Months*	*Later 5 Months*	
Explanatory Variables:							
#Treat. Fr. Months	0.0066	0.0371***	0.0038	0.004	0.0142	0.0015	
	(0.005)	(0.014)	(0.005)	(0.005)	(0.010)	(0.005)	
#Treatment Friends							188.39
							(126.77)
CONTROLS	**YES**	**YES**	**YES**	**N/A**	**N/A**	**N/A**	**YES**
Number of Obs.	772	264	508	772	264	508	67
Mean of Dep .Var	0.72	0.66	0.75	0.72	0.66	0.75	1589

Notes: This table shows estimates of the effect of peers on wanting to use the cup. The first three columns show baseline effects of these variables on trial; the coefficient should not be interpreted as effects on wanting to use. Columns 4-6 provide estimates of friend effects on wanting to use based on structural assumptions in the model (standard errors are bootstrapped). Column 7 estimates effects on reported willingness to pay for the cup at follow-up. Controls for demographics are included in Columns 1-3 and 7 (the same controls as in Table 3). In the case of the structural estimates the controls are incorporated when we estimate the parameters that go into the structural estimation. Standard errors are in parentheses, clustered by individual when appropriate; *significant at 10%; **significant at 5%; ***significant at 1%.