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

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Abstract

We estimate the role of benefits and peer effects in technology adoption using data from randomized distribution of menstrual cups in Nepal. Using individual randomization, we estimate causal effects of peer exposure on adoption; using differences in potential returns we estimate effects of benefits. We find both peers and value influence adoption. Using the fact that we observe both trial and usage of the product, we examine the mechanisms driving peer effects. We find that peers matters because individuals learn how to use the technology from their friends, but that they do not affect individual desire to use the cup.

1 Introduction

Why do some individuals or firms adopt new technologies faster or at higher rates than others? This question is of importance to economists in a variety of fields (industrial organization, labor, development, marketing, etc), and has both positive and normative implications. On the positive side, knowing determinants of adoption can help predict adoption patterns (for example, which firms are likely to be first movers, and therefore leap ahead when new technology is introduced); on the normative side, this may help us understand how to encourage adoption of beneficial technologies (for example, fertilizer or vaccinations in the developing world) or understand how to optimally market new goods. Economic analysis of this question naturally starts with evaluating how variation in technology costs and benefits influence differences in adoption (Oster and Quigley, 1977; Oster, 1982; Caselli and Coleman, 2001; David, 1990; Luque, 2002; Duflo et al, 2005). Griliches (1957, 1960,

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1962) produced some of the earliest work on this, arguing that the timing of hybrid corn adoption across US states was a function of differences in hybrid productivity.

Economists and sociologists have also explored the role of social interactions, networks or peer effects in driving adoption (Ryan and Gross, 1943; Saloner and Shepard, 1995; Skinner and Staiger, 2005). In response to Griliches (1957), a number of sociologists argued that social factors were likely to be more important than productivity differences in driving hybrid corn adoption (Brandner and Straus, 1959; Havens and Rogers, 1961). Estimating the role of peers or social interactions in driving adoption (or in determining behavior in general) is made difficult by the problem of correlated unobservables between peers and, especially, between friends (Manski, 1993). As a result, economists and others have focused on a variety of econometric techniques to disentangle peer effects from correlated unobservables (Foster and Rosenzweig 1995; Conley and Udry 2008; Munshi 2003; Figlio 2003; Bandiera and Rasul 2006) including, more recently, explicit randomization (Sacerdote 2000; Kremer and Levy 2006; Mobius, Rao and Rosenblat 2007; Duflo and Saez 2003; Godlonton and Thornton 2008; Miguel and Kremer, 2004; Duflo, Kremer, and Robinson 2006; Miguel and Kremer 2007).

The results on peer effects are some what mixed. Much of the literature (e.g. Foster and Rosenzweig, 1995; Conley and Udry, 2008) finds peer exposure has a positive impact on technology adoption, while recent (randomized) work has found either negative peer effects (Miguel and Kremer, 2007) or no effects (Duflo, Kremer, and Robinson, 2006). One way to make progress on reconciling these results is to examine what mechanisms drive peer effects. There are at least three possible drivers of positive peer effects: individuals benefit from behaving 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. We can see immediately that some of these – for example, learning from friends about how to use a technology – are likely to operate only in cases where the technology is hard to use, which could be useful in explaining differences across products in the existing literature. However, even with randomization it typically has not been possible to identify which of these factors are most important in driving peer effects (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 product value and peer influence in adoption of a new technology;

[1] 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.

(2) evaluate the relative magnitude of these influences in this particular case and (3) provide some initial evidence on what mechanisms drive the peer effects. A menstrual cup is a small, silicone, 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 usage over this time.[2]

We argue that although the menstrual cup may not be *per se* as important as some other technologies (fertilizer, vaccines, contraceptives), this setting has a number of advantages for understanding patterns of technology adoption. First, the individual randomization will allow us to estimate causal peer effects. Second, we have clear and observable (if not necessarily exogenous) variation in the value of the product, which will alow us to estimate the role of "productivity" in driving adoption. Further, having value and peer measures together allows us to compare the relative magnitudes. Third, we have data on cup adoption over time, which will allow us to observe whether these effects change as the product becomes more familiar. Finally, we observe individual reports on both trial and usage of the cup, which we argue will allow us to make progress on identifying the mechanisms behind the peer effects. Overall, we argue that these features of the study allow us to draw fairly sharp conclusions which contribute significantly to our understanding of adoption patterns, and are informative about other technologies which may be more difficult to study directly.

We first use our data to estimate the importance of cup value (benefits and costs) and peers in individual adoption decisions. In this first part of the paper we parallel the existing literature in focusing on whether individuals report *using* the product. Beginning with cup value, we find some evidence that cost and benefit factors drive usage. Girls who have a greater need for mobility – those who work for pay – are more likely to adopt. Further, those for whom their existing technology is more costly – those who report spending more time each month cleaning menstrual cloths – are more likely to adopt. Other measures of benefits to adoption – how far girls have to travel to school, and whether they ever use menstrual pads – do not seem to matter on their own. Jointly these effects are strongly significant, and reasonably large: girls who work for pay are about 20 percentage points more likely to adopt, and every ten minutes of washing cloths increases usage by 3 percentage points.

We then estimate the role of peers in driving adoption. At the baseline survey, girls were

[2]This study also evalauted the impact of menstrual cups on school enrollment; those results are reported in Oster and Thornton, 2009.

asked to list their closest friends, allowing us to identify friendships. Since access to the cups was randomized at the individual level, number of friends in the treatment group is random (conditional on number of total friends), which allows us to estimate causal effects of friend cup ownership on behavior. Further, we are able to identify variations across friendship types – differentiating between strong friendships (where each individual lists the other as a friend) and weak friendships (where the link is only one sided). We find evidence that peers are important in driving adoption. These effects are also large; one additional friend with the cup increases usage by about 18 percentage points three months into the study. Strong friendships are more important than weak friendships in driving adoption.

Turning to variation in adoption over the sample period, we find the effects of cup value are fairly consistent over time. However, the peer effects are much stronger at early months in the study. By six months after distribution, the effect of friends on usage is not significant.

These estimates suggest both cup value and peer effects matter, but the coefficient magnitudes do not address the relevant policy question: would overall usage be maximized by targeting distribution based on cup value, peer networks, or neither? To explore this, we use our estimates to evaluate product usage under three hypothetical scenarios. First, random distribution. Second, value-based distribution (distributing the product to girls with the highest predicted value). Third, peer-based distribution (distribute the product based on peer networks to maximize the number of treatment friends). Our results suggest that both peer-based and value-based distribution dominate random distribution overall. In early months, peer-based and value-based distribution are similarly effective; in later months, and overall, value-based distribution dominates.

Having established a role for both cup value and peer influences in driving adoption, we then attempt to identify the mechanisms through which the peer effects, in particular, operate. As noted above, there are at least three possible mechanisms driving positive peer effects: individuals want to act like their friends, individuals learn about the benefits of the technology from their friends, and individuals learn from their friends about how to use a new technology. Most of the literature has not attempted to separate these explanations.[3] An exception is Miguel and Kremer (2007), who estimate peer effects on adoption of de-worming drugs, and explicitly distinguish between these three avenues of peer effects. 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

[3]The few cases, primiraily 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)

learning about how to use the technology as drivers of peer effects, since both of those would produce positive peer effects. In our case, of course, we find *positive* peer effects, and hence cannot rule out any of these possibilities out of hand.

We will focus in our analysis on separating peer effects on *wanting to use* from peer effects on *success at usage*. We argue that peer effects on usage success point to learning how to use the technology from peers, whereas effects on wanting to use point to either an imitation or learn-about-value mechanism. We are not able to separate out the latter two explanations.

In our data, in each month, we observe individual reports on cup trial and cup usage: did the girl try the cup, and was she able to use it? There is a clear parallel between cup trial and wanting to use, and between cup usage conditional on trial and success at usage. However, it is important to note that what we observe in our data *does not* directly map into wanting to use and success at usage. For example, the decision to try the cup will be affected both by how much someone wants to use it *and* by how likely it is they think they will be successful. In Section 4 we present a model of the adoption process, involving two stages – a decision about wanting to use, and a deterministic success at usage – and show the assumptions (both in the theory and in the estimation) necessary to translate what we observe in the data into estimates of peer effects on wanting to use and success at usage.

Our results – based on the assumptions in the model – provide strong support for the claim that friends are helpful in learning how to use the cup. In early months in the sample, having one additional treatment friend increases the probability of successful usage by 25 percentage points. This effect dissipates over time, perhaps reflecting the concave value of information (i.e. after six months even girls with fewer treatment friends have a large number of friend exposures). In contrast, we find no evidence that peer exposure impacts desire to use the technology – there are some overall effects of peers on cup trial, but they appear to be due to peer influence on expected success.

Notably, our estimates in this section also suggest that, when we focus on trial alone (i.e. ignore the difference in success rates across individuals), we find much stronger evidence that benefits and costs matter. This suggests that benefits and costs actually have an even larger effect on wanting to use the product, and their effect on overall usage is muted by varying probabilities of success, although (as noted) it is more difficult to interpret these benefit and cost measures causally.

Returning to the issue of policy, our results suggest that with a product that is easy to use, there is only limited argument for peer-based targeting. In contrast, with a product which is difficult to use, peer-based targeting may dominate random distribution *and* value-based targeting, especially in a situation in which there is relatively limited heterogeneity across individuals in product value. To the extent that peer effects have more often been found in cases where the product is difficult to use (for example, high yield seeds), and not in cases where the product is easy to use (i.e. de-worming drugs), these results may shed some light on why that occurs in the data.[4]

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 baseline estimates of the role of cup value and peer exposure in driving adoption, including comparing the relative magnitudes. Section 4 then presents a simple framework for thinking about the adoption decision, and provides our evidence on mechanisms. Section 6 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 South-western 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, but most importantly, 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 rags, and take-up was observed over time.

2.1 Participants and Survey Timeline

Four schools in and around Bharatpur City in Chitwan District, Nepal were chosen to participate in the study; of these, two were urban schools and two were peri-urban. The study began in November, 2006. Based on a school roster listing 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 $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

[4]Our results also show that peer effects dissapate over time; to the extent that some existing work has focused on looking for peer effects at the end of a study – a long time after distribution – this could explain why they are not observed.

school; between 7 and 12 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.

At the initial study meeting, a baseline survey was administered to the girls and their mothers. This survey included basic demographic information, as well as questions about school performance, menstruation and self-esteem. At the end of this initial meeting, the randomization was carried out. Girls had been given identification numbers, and the randomization was done with a public lottery, drawing twenty-five numbers out of a bag. Girls whose numbers were drawn were assigned to the treatment group with their mother or guardian (we did not randomize girls and their mothers separately). The treatment girls and their guardians were asked to remain at the meeting and each were given a menstrual cup. A nurse gave detailed instructions to those in the treatment group on the use of the menstrual cup.[5]

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. Due to attrition, the number of girls interviewed at each visit varied; although there was close to complete coverage in the first few months, typically approximately 80 of the 101 treatment girls were available at each visit in later months.

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. In addition, the control girls and their female guardians were given the menstrual cup. One hundred and eighty-three 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 name Keeper and Diva Cup).[6] This product is a small, silicone, bell-shaped cup which is inserted in the vagina to collect menstrual blood. For most women the cup will have to be emptied approximately every twelve hours during menstruation. Between

[5] One of the mother-daughter pairs randomized to the treatment group decided not to accept the menstrual cup. We analyze the intention to treat effect, and keep this girl in our sample for analysis. This girl and her mother were each interviewed at the follow-up survey.

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

uses, the cup is washed with soap and water and stored in a cloth bag. With proper care, the cup is re-usable for up to a decade. 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. The MoonCup comes in two sizes: a smaller size for girls and women before childbirth, and a larger size for women who have given birth, or who are over 30.

In the area of Nepal where our experiment takes place, the primary protection women use during their period is menstrual cloths. These cloths are placed inside a woman's underwear to soak up menstrual blood. The cloths are washed and re-used. The menstrual cup may be a significant improvement over this cloth technology for several reasons. First, if correctly inserted, women should not noticed the presence of the menstrual cup and it will not impair mobility; the same cannot be said for the cloths. Indeed, anecdotal evidence from Nepali women to whom we gave the cup as a pilot suggested that increased mobility was a major advantage – women said they were able to bicycle, and that they even forgot they were having their period. Second, cleaning the menstrual cup for re-use is significantly easier than cleaning the menstrual cloths. The cup should be washed with soap and water, which takes only a minute or two; the cloths must be boiled and laundered, typically by hand, which takes a (reported) average of 30 minutes per month. All of these factors – increased mobility, ease of use, and no need to wash rags – were mentioned by girls at the follow-up survey as advantages of the cup. Finally, it is possible that additional privacy is another advantage of the cup – in principle, use of the cup can be hidden, which is not possible when menstrual cloths must be hung up outside to dry. Whether or not this is an advantage depends, in part, on whether girls and women would prefer to hide their period.

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 know more about the technology initially than others do. Second, the advantages of the cup – increased mobility, for example, or decreased time processing cloths – will vary across individuals, allowing us to estimate the effects of benefits and costs on usage. Finally, although the MoonCup is comfortable to use for most women, it often takes time for people to learn how to insert and remove it comfortably; indeed, when girls in our sample were asked about disadvantages of the cup, the most common response (reported by 30% of the girls in the sample) was "difficult to insert". 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 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 four primary elements of the data from the menstrual cup experiment: data on demographics, data on cup adoption, data on cup costs and benefits, data on friendships and basic demographics.

Demographics: From the baseline survey we make use of a number of control variables on demographics (age, grade, etc), 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, as was designed by the stratified randomization. Forty-seven percent of the girls are of Hindu ethnicity (while other ethnic groups consist of Tibetan-Burmese, Tharu, or Newari). Eight-seven percent of girls have had their period at the baseline survey. Education rates among parents are low, but not zero: mothers have an average of about 2.7 years of education, fathers an average of 5.6 years.

Information on Cup Adoption: As mentioned in Section 2.1, 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 the 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 tried the menstrual cup and whether they used it. For example, the first quote here would be coded as both trying and using (by definition we assume that in order to use one must try), the second quote would be coded as trying but not using and the third would be coded as not trying or using.

To give a sense of the basic patterns of adoption, Figure 2 shows trial and usage of the menstrual cup 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. Usage of the menstrual cup increases dramatically in the first six months, from 10% in January to 60% in June. After this, usage is fairly constant, with little movement from June, 2007 to January, 2008. The pattern for trial of the cup is similar, although the line is flatter. Trial increase only from 60% to 80% over the first months of the study; trial rates decline some in the period after that, likely reflecting a decrease in girls who continue to try without using.

Given our reliance on the adoption data, a central issue is whether the girls reported cup usage accurately reflect their actual cup usage. Although we are unable to determine this entirely, we have evidence of high levels of cup usage using other features of the data. 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 including their time spent on cooking, domestic and agriculture work, and schooling, for example. Using these time diaries, we observe significant differences in time use on days girls are menstruating. We observe that girls in the control group spend approximately 22 minutes more doing laundry on days when they are menstruating. This is presumably due to the extra time needed to wash their menstrual rags. In contrast, treatment girls who are menstruating spend 20 minutes less time doing laundry than control girls who are menstruating. Further, the high levels of usage are confirmed in the follow-up survey. While both the time diary and the follow-up survey are also self-reports, they point to a level of internal consistency which we think is supportive of the validity of our adoption data.

Cup Costs and Benefits: As noted in the discussion of the menstrual cups above, two clear advantages of the menstrual cup, relative to the existing technology of menstrual cloths, are increased mobility and decreased time washing rags. This suggests that any activities which affect the need for mobility across girls could affect the benefit of the menstrual cup, and on the converse side, variations in time it takes to wash menstrual cloths might affect the relative cost of the menstrual cups. We identify several variables which measure relative benefits and costs: whether the girl works for pay or not and how long it takes her to get to school (both related to the need for mobility), reported time it takes to wash cloths each month at the baseline survey, and whether the girl had ever used pads at the baseline (since pads are more convenient than cloths). These variables are summarized in Panel C of Table 1. Roughly 45% of the girls in the sample ever work for pay; they travel an average of 15 minutes to school, and spend 30 minutes per month washing menstrual cloths. Twenty-two percent of the sample had ever used sanitary pads.[7]

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 use data on friendships collected in the baseline survey. In this survey, before the randomization took place, each of the girls

[7] We use "ever use pads" rather than "use pads regularly" since, consistnet with our claim of limited sanitary pad usage, only 2% of the girls in the sample report using pads regularly.

was asked to list their three closest friends who were also at the meeting. On average, girls listed 2.6 close friends with 68 percent listing 3 friends and 25 percent listing 2 friends (Table 1, Panel C). This information allows us calculate friendships, and number of friends. Our primary measure of friendships is total friends, which includes everyone whom the individual lists as a friend and anyone who lists them as a friend. On average, each girl had 3.8 total friends with a maximum of 7 friends. In addition, we consider two subsets of total friends: strong friendships (bilateral links only) and weak friendships (unilateral links only). It would also be possible, in principle, to separate weak friends into two groups by direction of listing. We have done this, but find no differences across the weak friend types. We therefore focus on the weak versus strong distinction only.

In our survey we asked only about the three 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 permissable friends) and 75% answered four 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 individuals friends.

3 Effects of Benefits, Costs, Peers on Technology Adoption

This section presents our baseline estimates of the determinants of adoption of the menstrual cup. In this section, we are concerned with simply estimating the patterns in the data. In particular, we hope to derive baseline, overall, estimates of the impact of cup value and peers on cup adoption. The first subsection below presents our empirical strategy, with a focus on how we estimate causal effects of peers, and the second subsection presents our results. The third subsection briefly discusses the relative magnitude of the cup value and peer influences.

3.1 Empirical Strategy

We estimate the relationship between cup usage, cup value and peers using the regression specification below, which assumes a linear relationship between the variables of interest and usage.

$$Used_i = \gamma + \delta_1(\text{Friend Exposure}_i) + \delta_2(Benefits_i) + \delta_2(Costs_i) + \mathbf{\Pi X_i} + \mu_i \tag{1}$$

where $\mathbf{X_i}$ is a vector of controls (e.g., age, grade, test scores, school fixed effects, parental education, family income), and friend exposure is the number of friends in the treatment group. The unit of observation is the individual, and we note that these regression are estimated only for treatment individuals. We begin by estimating this regression at three different points in time (March, 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 using the cup in that month and zero otherwise. In addition, we will show analyses where we stack the observations and include all months in a single regression, with an observation being an individual-month. The variables remain the same, but in this case we will also control for a time trend and cluster standard errors by individual.

There are identification issues in estimating the influence of benefits and costs on adoption, and in estimating peer effects. The latter identification issue is much more obviously problematic, and we therefore address that first. The basic issue, as outlined by Manski (1993) is the reflection problem: 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. Here we use explicit randomization to identify the peer effects.

Consider first the case without randomization; for example, if our data was from a cross section of girls for whom we observed product ownership/usage and friendships. It would certainly be possible to estimate Equation (1) in this setting, where the measure of friend exposure is friend ownership or usage of the cup. However, it is not possible to interpret these coefficients causally: if individual characteristics are correlated with friend characteristics, it is possible that individuals who own the cup also have friends who own the cup *not* because they learn from their friends, but because they are similar to them.

In contrast, in our evaluation we randomly allocate ownership of the menstrual cup. The randomization is at the individual level, so not only is individual ownership random, but the number of friends who own the cup is also random (conditional on total number of friends).[8] This means that we can estimate the causal impact of friend ownership (number of treatment friends) on individual usage. It is important to note here, however, that we *cannot* estimate the impact of friend

[8]Our measure of friend exposure is number of treatment friends. This is random only conditional on total number of friends; we will therefore condition on total number of friends when we do this analysis. To see why conditioning on total number of friends address this issue, denote $Y \in \{0,1\}$ the individual binary outcome (uses or not) and D as the number of friends in the treatment group. The object we hope to estimate is $\Lambda = Pr(Y = 1|D = \Phi) - Pr(Y = 1|D = \Phi - 1)$ that is, the difference in the potential outcome (using the technology) when the individual has one fewer friend. We do not observe the same person with both Φ and $\Phi - 1$ friends, and what we estimate empirically is $\hat{\Lambda} = Pr(Y_{\Phi} = 1|D = \Phi) - Pr(Y_{\Phi-1} = 1|D = \Phi - 1)$ Assume that each individual has a constant number of total friends H (empirically, this is achieved by controlling for total number of friends). Whether each of these friends is in the treatment group is random. As a result, conditional on H, the number of treatment friends is random. This means that $Pr(Y_{\Phi} = 1|D = \Phi) = Pr(Y_{\Phi-1} = 1|D = \Phi) = Pr(Y|D = \Phi)$ and similarly for $Pr(Y_{\Phi-1})$. As a result, $\Lambda = \hat{\Lambda}$ and the estimation generates unbiased estimates of the treatment effect of friends on adoption.

usage on individual usage; we can only measure the effects of friend ownership. Friend usage, conditional on ownership, is likely to be determined by the same unobservables as individual usage, so this coefficient would not have a causal interpretation. The effect of having more treatment friends includes many elements: the effects of friends on knowledge about how to use the product, any stigma associated with the product, the effect of your friends having seen the product, etc.

There are also concerns with identifying causal effects of benefits or costs of the cup. Our measures of these variables – distance to school, working, time spent washing menstrual cloths – may be correlated with other individual demographics like income or parental education. Although we control for the most obvious of these (parental education and income), there may be some that are omitted. Unfortunately, we do not have exogenous variation in these measures which lessens our ability to make causal statements about the effect of cup benefits and costs. However, there are two encouraging notes. First, at least one of these variables – time washing cloths – is influenced largely by the length and flow volume of the period, which is arguably exogenous. Second, empirically we do not see much correlation between standard demographics and adoption behavior, suggesting the omitted variable bias may be small. It is also worth noting that, from the standpoint of using these variables for prediction or forecasting, the possibility of omitted variable bias is less important.

Balancing on Observables: Before we present the main results, it is useful to briefly address whether our data is balanced on observables, which is an indication of a valid randomization procedure and is important for comparing individuals with more or fewer treatment friends. The treatment and control group were generally balanced on observable characteristics (Panel A of Table 2). There was no difference in number of friends, previous use of menstrual pads, or whether a girl's father had knowledge of when the girl got her period. There is a ten percentage point difference in the likelihood of having started her period. All results below are robust to excluding any girl who did not have her period at baseline.[9]

Although comparison of treatment and control are important as a general validation, the analysis below uses variation in number of treatment friends. Given this, perhaps the more relevant issue is whether the data is balanced across groups with different numbers of treatment friends. Of course, number of treatment friends is only random *conditional on* total number of friends, so we can ask whether number of treatments friends is correlated with these variables in a regression in which

[9] This imbalance may prompt concern that the cup was strategically given to girls who were already menstruating. Extensive discussions with the survey team suggest this was not likely to be the case. In addition, there is no evidence that the cup was more likely to be given to mothers who were still menstruating (89.7% menstruating in treatment group; 86.9% in comparison, p=.54), alleviating this concern somewhat.

we condition on total friends. Coefficients on number of treatment friends from these regressions are shown in Panel B of Table 2. These coefficients suggest the randomization was successful, at least relative to observables. In nearly all cases there is no significant relationship between the demographic variables and number of treatment friends. Of the twelve tests, only one (minutes to school) is significant at the 10% level, consistent with what we would expect based on chance.

3.2 Estimating Determinants of Adoption

Table 3 presents our baseline results on adoption, estimating the relationship between cup usage in different periods and our independent variable measures of costs, benefits and peer exposure.[10] Columns 1-3 estimate the relationship for three months of the study – the beginning (March, 2007), midway through (August, 2007) and at the end (January, 2008). We see some evidence that benefits matter: girls who work for pay and those who report spending more time washing menstrual cloths are more likely to use the cup, although these effects are not strongly significant. At the bottom of the table we present *p*-values for the test that these are jointly significant in the correct direction; we find that this is only the case in the final month in the sample.[11]

In Columns 4 and 5 of Table 3 we show our analyses of the stacked data, where an observation is an individual-month; this may allow for greater precision. Column 4 analyzes the overall effect of these variables on adoption and finds stronger evidence that benefits and costs matter. In particular, girls who work for pay are 20 percentage points more likely to use the cup, and each additional ten minutes of washing rags increases cup usage by 3 percentage points. The joint test of all of the coefficients together is strongly significant. In Column 5 we interact these measures with time. We do not find any significant variation in the effect of working over time, although the coefficient on time washing rags is larger in later months. Again, jointly the effects of cup value are highly significant in this stacked regression.

Turning to peer effects, we again report on the regressions in Table 3. We find consistently strong evidence that peers matter for adoption. Increased peer exposure to the cup increases usage, much more so in early months. In March, three months after distribution, one additional treatment friend increases usage by around 12 percentage points (Column 1). Effects in the middle and later

[10]This table reports marginal effects from probit regressions. Rather than the marginal effect evaluated at the average, which is what the "dprobit" command does in Stata, however, we report the average of the marginal effects. Because levels of adoption vary so widely by school there is really no "average" person in the data, when we include school fixed effects, and marginal effects from the "dprobit" command are implausibly large, and very different from the OLS estimates.

[11]The coeffcient on time to school is actaully incorrectly signed relative to our theory; we therefore constrain the test to test whether this coefficient is positive.

months are smaller and not significant. Columns 4 and 5 are consistent with this pattern: the overall effect of treatment friends is large and significant in Column 4, and when we include the interaction with time in Column 5 we find a large positive main effect, and a negative and significant interaction. Figure 3 explores the timing of these effects in more detail and graphs coefficients on interactions between month dummies and number of treatment friends for each month after cup distribution. Consistent with Table 3, the effects of peer exposure is large and significant in early months (through March) and positive but not significant in the later months.

In general, we see very little effect of the demographic controls on adoption. The one strong pattern is that there are a large variations across schools in adoption, with highest adoption in school 1 and lowest in schools 3 and 4.[12] One demographic control we might have expected to have an effect is exam grade. The literature on technology adoption frequently cites levels of human capital as predictive of early adoption (Oster and Quigley, 1977; Caselli and Coleman, 2001). In this case, although we do not have variation in years of schooling we do have variation in exam scores, which is an alternative measure of human capital. Although the coefficients on this variable are positive, they are not consistently significant.

As we have noted, it is possible in our data to separate out different friendship types and to explore which are more important in driving adoption. The regressions in Table 4 replicate Table 3, but report effects by friendship type. Controls for our measures of benefits and costs, and for demographics, are included but not shown (full regressions are available from the authors). As discussed, we use two measures of friends: strong friends (both girls list each other) and weak friends (the friend lists the respondent, but not vice versa or the respondent lists the friend, but not vice versa). We find that strong friendships are more important than weak friendships. This is particularly true later in the sample. The effect of weak friendships falls off very quickly, but the effect of strong friendships persists.

The results here point most strongly to a role for peer exposure in driving menstrual cup adoption. The effect of peers appears to be very large, especially early on and from strong ties. Moving from zero friend with the cup to three friends with the cup increases early usage by somewhere between 30 and 60 percentage points in early months. We also find evidence for a role of private returns to adoption (benefits and costs) in driving take-up. Working for pay and spending more time washing menstrual cloths are both predictive of adoption. These effects are also quite

[12] 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 factor.

large: girls who work are 20 percentage points more likely to adopt early on, and increasing washing time by 30 minutes per month increases the chance of adoption by 9 percentage points. However, comparing the magnitudes of the effects in this way is not obviously informative about which set of influences is “more important”; the next subsection briefly addresses this issue.

3.3 Evaluating Magnitudes: Relative Value of Distributions Schemes

There are, of course, a variety of ways we might consider evaluating the relative magnitudes of the effects of value of a technology versus the effect of friendships on adoption. One possibility is, as we do above, to simply compare the coefficients magnitudes from Table 3. However, we argue this does not address the clearest normative question: what distribution scheme would maximize adoption?

In this subsection, we use the estimates from Table 3 to address this question directly. We consider three distribution schemes: random distribution, value-targeted distribution (use our measures of value to predict usage, then distribute to the top half of the girls in terms of predicted usage) and peer-targeted distribution (distribute the cup to individuals based on their peer networks, with the goal of maximizing the average number of friends with the cup).

In each of the three cases we envision allocating the cup to half of the girls in the treatment sample and predict their usage based on the coefficients we estimate in Table 3. Figure 4 graphs predicted usage under each distribution scheme, over time. Both types of targeted distribution dominate the random distribution scheme. Even by the end of the period, predicted usage rates are 25 percentage points higher with value-based targeting, and 10 percentage points higher with peer-based targeting. In the very early periods, both value and peer-based targeting give similar gains; however, in the longer run, value-based targeting dominates. By the end of the period, usage under the value-based targeting scheme is roughly 15 percentage points higher than with peer-based targeting.

Overall, consistent with the argument that both peers and cup value matter for adoption, we see both of these distribution schemes dominate random distribution. However, value-based targeting ultimately dominates. This is, perhaps, surprising given that the coefficient on friendships are typically larger than the coefficients on cup costs and benefits. There are two factors which contribute to this result. First, by the end of the sample the effect of peers are not significant, whereas the effect of benefits continues to matter. Second, the gain in number of peers with the cup is not enormous, relative to the random case, even when we target to maximize treatment friends. Even though the effect of friends is large, the difference in number of friends in the various conditions is not.

This methodology – considering different distribution schemes – could be applied to a variety of technologies. However, the specific conclusion – that value-based targeting dominates – is specific to the case of menstrual cups. Although this could be valuable for someone interested in maximizing menstrual cup usage, we noted at the start of this paper that menstrual cups are not a technology that policy-makers typically focus on. In order to make progress on whether these conclusions are applicable to other types of technologies, we cannot stop at simply estimating the effects of peers and benefits on overall adoption: we need to understand better why these factors matter. To the extent that we can identify, for example, that peers matter through learning how to use rather than through imitation, that would suggest that peer-based distribution would be most useful for hard-to-use technologies. With this as partial motivation, and the more general motivation that understanding why peers matter is of interest, we turn to mechanisms.

4 What Mechanisms Drive These Effects?

The results above show that peer exposure and private cup value affects adoption. Why does this occur? In this section we attempt to separate the some of the mechanisms by which peer effects, in particular, could affect adoption. Peer exposure to the technology may matter because peers affect the value of a technology, or because people learn about how to use the technology from their friends (Duflo and Saez 2003; Munshi and Myaux, 2005; Miguel and Kremer, 2007). Within the category of peers affecting technology value, this could occur either because of imitation (individuals want to act like their peers) or because peers affect individual perceptions about technology value (Miguel and Kremer, 2007; Kohler, Behrman and Watkins, 2001). Separating out these mechanisms in the case of peer effects is especially relevant in our case, where we find *positive* peer effects and therefore cannot rule out any of these possibilities without further exploration.

Our data has an unusual features which may allow us to make progress on separating out these effects: we observe both trial and usage of the product. We argue that, under the assumptions of the simple model outlined below, this will allow us to separate the effect of friends on technology value from the effect of friends on knowledge about how to use the product. However, our data is not sufficient to fully separate all three mechanisms described above: we will be unable to draw conclusions about whether friends affect cup value through imitation (people want to act like their friends, so friends with the cup increase value) versus friends affecting cup value through learning about value from friends (the Miguel and Kremer (2007) mechanism). Despite this, we argue that even separating peer effects on knowledge about how to use from peer effects on value represents significant progress.

One thing to note immediately – based only on the results in Section 3 – is that the fact that the effect of peers varies over time is more consistent with one of the learning stories (learning about how to use or learning about value) than with the imitation story. If peers matter because people want to imitate their friends, these effects should persist over time. The fact that the effects do not persist suggests that imitation is, probably, a small part of the story. As we will see, this intuition is consistent with what we find in the fuller analysis.

4.1 Mechanisms: Theoretical Framework and Estimation

We assume there are two stages in determining usage of a new technology. First, individuals decide whether or not they would like to adopt; second, they may or may not be successful at adopting. We posit that technology value affects the first stage (whether or not an individual wants to adopt) and knowledge about how to use affects the second stage (whether adoption is successful).

Denote the overall probability of cup usage as p_u, the probability that an individuals *wants* to use the cup as p_w and the probability that they are successful at using the cup as p_s and note that $p_u = (p_w)(p_s)$. We are interested in how friends affect adoption. Denote the number of treatment friends (i.e. friends with the cup) as f. Thus far, we have established that $\frac{dp_u}{df} > 0$; this is consistent with either $\frac{dp_w}{df} > 0$ or $\frac{dp_s}{df} > 0$, or both. We will argue that $\frac{dp_s}{df} > 0$ indicates that friends matter because they help people learn about how to use the cup; $\frac{dp_w}{df} > 0$ indicates that friends matter because they affect cup value (either through imitation or through learning about value).

Peer Effects on Usage Success

Working backward, we begin by analyzing the second stage of the adoption process: success at use. We assume that the success at usage is a function of knowledge about how to use the cup and that this knowledge can be gained from friend exposures to the cup f; we denote success at using $p_s(f)$.[13] Importantly, we are assuming that this probability of success is deterministic – given the knowledge an individual has, there is some fixed probability of success. Put differently, we assume that success is not determined by individual effort, and there is no *decision* made by individuals in this second stage. This is the crucial assumption in the model. It is also important in

[13] It is also likely over time – either through the nurse visits, mothers, other non-friend peers, etc – girls will gain knowledge about the cup even without friend exposures. We abstract away from this in the model, but allow for it empirically by controlling for a time trend where appropriate.

interpreting our data. Specifically, we interpret the reports we see in the data as reflecting a two stage process of "trial" and "usage".

Without this assumption we cannot separate these mechanisms. However, it is not the only possible assumption. For example, one could think of this as 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, what we observe in the data 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 our assumption is reasonable, but it's obviously important to keep in mind, given the role it plays in our estimation of these mechanisms.

Turning to the data, we directly observe usage success – usage conditional on trial – but only for individuals who try the cup. This introduces a potential selection problem. We discuss below the possibility that girls with higher cup value will be more likely to try the cup. If this is true, *and* if the impact of peer exposure on success is different for girls with high cup value than those with low cup value, then estimates based on the selected set of girls who try the cup will be misleading.

We therefore provide two sets of estimates. First, we estimate $\frac{dp_s}{df}$ based on a simple OLS regression of cup usage on friendship, restricting to girls who try the cup. These estimates will be reasonable only if the selection bias is small or non-existent. Second, we estimate the same regression using a Heckman selection model. This selection model requires us to identify some variable(s) which influence trial but do not influence the ability to use; similar to the exclusion restriction in an IV strategy, this selection model is only as good as the selection variable. In our case we have an obvious candidate: variations in menstrual frequency. As is often true with adolescents, some girls in our sample do not get their period in some months. This includes girls who had not begun menstruation at the start of the study, but also includes some girls who simply missed their periods in particular months. Since there is no ability to try the cup when a girl does not have her period, but there is no reason to think this is otherwise correlated with ability to use, this provides an appropriate selection criteria.[14] In the end, this estimation allows us to identify whether friends matter for learning how to use the cup. We will also estimate how these coefficients vary over time.

Peer Effects on Wanting to Use

We next move to the first stage of the decision process, when individuals decide whether or not they want to use the cup. We model wanting to use the cup as a function of peers who have the

[14] Only about 4% of the individual-months in the data are girls who do not have their period that month. However, the first stage of the selection model is very strong, with a t-statistic of roughly 6 on the "No Period" measure.

cup (f) and private cup benefits (b). We denote the probability that the individual want to use as $p_w(f, b)$. In this stage, we assume the individuals *do* make a decision, trading off the desire to use against the costs of usage, which we denote $\epsilon_i \sim H(.)$. Individuals will want to use the cup if $p_w(f, b) > \epsilon_i$. We are primarily interested in the parameter $\frac{dp_w}{df}$; we will also provide estimates of $\frac{dp_w}{db}$, although based on the assumptions of the model these should be qualitatively similar to $\frac{dp_u}{db}$ (which is captured by the results in Section 3).

Turning to the data, we would ideally observe whether or not an individual wants to use the cup; however, what we observe in the data is cup trial. These are not the same. In particular, denote the girl's expected probability of successful use as $E[p_s(f)]$ (which is defined for everyone, regardless of whether or not they try the cup). Assuming that the cost ϵ_i is experienced even if the girl is not successful at using, she will want to *try* if the equation below holds.

$$E[p_s(f)]p_w(f, b) > \epsilon_i \tag{2}$$

This introduces the estimation challenge: observing that trial varies with friendship, given this setup, is consistent either with an effect of friends on wanting to use *or* an effect of friends on expected usage success. In order to estimate the effects of peers on wanting to use alone ($\frac{dp_w}{df}$), we would ideally like to use some exogenous shifter of $E[p_s(f)]$. Unfortunately, there is no obvious candidate for this type of variable. This will limit, to some extent, our ability to identify $\frac{dp_w}{df}$. However, we argue there are several ways that we can use the assumptions of the model, and the features of the data, to estimate this parameter.

Our first strategy takes advantage of the structure of the model. In particular, we recall that $p_u = p_w p_s$. We differentiate this equation with respect to f, which gives the following expression $\frac{dp_u}{df} = p_w \frac{dp_s}{df} + p_s \frac{dp_w}{df}$. Rearranging to give an expression for our quantity of interest, $\frac{dp_w}{df}$, yields

$$\frac{dp_w}{df} = \frac{\frac{dp_u}{df} - p_w \frac{dp_s}{df}}{p_s} \tag{3}$$

This suggest that, if we can observe values for the elements on the right hand side of this equation, we can provide an estimate for $\frac{dp_w}{df}$.

Note first that we observe $\frac{dp_u}{df}$ based on the analysis in the Section 3 (Table 3). In addition, we argue above that we can estimate the effect of friends on success: $\frac{dp_s}{df}$. The objects p_w and p_s are the overall probability of wanting to use and success at usage. First, p_w is the probability that people want to use assuming they expect to be successful. We do not observe this directly in the data, but note that by the end of the period (when expected success is close to 100%), we consistently find about 75% of individuals trying the cup; given this, we assume that $p_w = 0.75$. Second, p_s is the probability of success for all individuals, including those who do not use. We estimate this from the second stage analysis described above: we run the regressions to estimate $\frac{dp_s}{df}$, and predict p_s from these same regressions. We use these values together to calculate $\frac{dp_w}{df}$, and generate bootstrapped standard errors. Using this structural approach we can explore how the effects of friends on wanting to use vary over time.

We also pursue two non-structural approaches to estimate $\frac{dp_w}{df}$. First, we limit the estimation to situations in which $E[p_s(f)] \simeq 1$; that is, we look for time periods or situations in which success seems very likely. In particular, we note that success is much higher in later months of the study (this can be seen in Figure 2), and explore whether the effect of friends is different in these months. Second, we take advantage of a question in the follow-up survey asking about individual "willingness to pay" for the cup. We define willingness to pay based on a series of questions in which girls were asked "would you be willing to pay X for the menstrual cup?" We code them 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 $18. This is actually quite a lot of money and the usual caveats about willingness to pay questions apply here. Nevertheless, we feel that this variable indicates to some extent how much individuals value the cup. We again focus on girls who have used the cup, for whom we expect $E[p_s(f)] = 1$ and estimate whether those with more friends have greater willingness to pay. Neither of these approaches will allow us to estimate variation over time in the friendship effect.

Benefit Effects on Wanting to Use

Focusing briefly on the effect of cup benefits on wanting to use, we note that in this model we only allow benefit to affect adoption through wanting to use. Under this assumption, regressing either cup trial or cup usage on benefits should give a similar estimate of the effect of benefits on wanting to use; the latter estimation is already done in Table 3. However, given the model above, it *is* possible for these coefficients to differ if the difference between expected probability of success and actual probability of success varies with benefit levels. For example, if people with high cup benefits are systematically over-confident about their success, then we should estimate larger impacts of cup benefits on trial than on usage.

4.2 Results: Mechanisms

Peer Effects on Usage Success

We begin by estimating the impact of friendships on success at using the cup. We estimate two models: an OLS regression of usage conditional on trial, and a Heckman selection model. Figure 5 shows the coefficient on number of treatment friends, over time, from the two types of models. We note first that, for most of the time period, usage success is significantly higher for individuals with more treatment friends. In early months after distribution this is as high as 25 percentage points per treatment friend. There appears to be some downward trend in these coefficients over time – the effects are the largest at early months in the sample, although the variation over time is noisy. Comparing the estimates for the OLS to the Heckman estimates we see very little difference in the coefficient magnitudes, suggesting limited selection bias in this specification.

In addition to exploring variation over time visually, Table 5 estimates the effect of treatment friends on success at using. To generate these regressions we stack the individual-month observations and include all months in the regression (as in Columns 4 and 5 of Table 3). Our independent variable of interest is number of treatment friends. Columns 1 and 3 estimate the baseline effects of treatment friend months on usage success, in the OLS and Heckman framework. We find, consistent with Figure 5, positive impacts. The estimates suggest that one additional treatment friend increases the probability of usage success by around 10 percentage points. Columns 2 and 4 include interactions with month. Again consistent with Figure 5, we see the effect of friends on success is very large in early months and decreases over time.

The evidence in Figure 5 and Table 5 suggest that peer exposure to this technology affects adoption, at least in part, through effects on knowledge about how to use the cup, which results in usage success. The estimates suggest that these effects are largest in early months after distribution. This is consistent with some concavity in the $p_s(f)$: one additional friend exposure is more valuable when the initial level of exposure is lower.

Peer Effects on Wanting to Use

We turn now to estimate how friendship affects wanting to use the cup, the first stage of the decision. We begin by showing the first – naive – estimates of the impact of friendships on cup trial. As we discuss above, seeing an impact of friendships on cup trial overall is consistent either with friendship effects on wanting to use, or with anticipated friendship effects on success; since we know from Table 5 that friends do affect success, this is particularly important. Columns 1 and 2 of Table 6 estimate these naive regressions (with regressions stacked at the individual-month level, as in Table 5). We see positive and statistically significant effects of treatment friends on cup trial, although the effects are smaller than what we see in Table 5. Column 2 indicates there is no significant variation in these coefficients over time.

In Columns 3 and 4 of Table 6 we show our first methodology for estimating $\frac{dp_w}{df}$, in this case using the structure of the model.[15] In contrast to Columns 1 and 2, we see no evidence that friendships affect wanting to use. The coefficient in Column 3 is about half the size of the coefficient in Column 1, and not significant. Column 4, again, points to no variation over time.

Figure 6 graphs the coefficients on number of treatment friends, by month, for the naive estimates and the structural estimates. This graph gives some sense of what is driving the difference in coefficients between Columns 1 and 3 of Table 6. In particular, in the naive estimates we see a fairly large coefficient on treatment friends in February, one of the early months in the sample. We do not see this once we attempt to account for the influence of friendships on success. It is, perhaps, not surprising that we see the largest difference in coefficients in February, when the effect of friends on usage success (in Figure 5) is largest.

Columns 5 and 6 of Table 6 present the results of our other two tests. In Column 5 we limit the sample to later months (after May) when the probability of success is closer to one. The coefficient is smaller than the comparable coefficient on Column 1, and is not significant; in fact, it is quite close in size and significance to the structural estimates in Column 3. Finally, in Column 6 we estimate the effect of friends on willingness to pay for the cup, limiting to girls who have used the cup at least once; the assumption is that they know they could be successful at using it, and we want to explore how their reported cup value correlates with friends. The coefficient is relatively small relative to the variable mean. One additional treatment friend increases willingness to pay by an insignificant 174Rs, or about \$2 on a mean of \$18.

Overall, the results here point toward the conclusion that friendships do not influence whether girls want to use the menstrual cup. Although in the baseline – naive – estimate there does seem to be some effect on trial, that seems to be spurious, and more likely due to the fact that people with more friends expect to be successful at using. It is important to note, however, that the most we can conclude here is that friendships do not matter *overall* in this stage of the decision. We noted above that at this stage there are two possible mechanisms: friendships mattering through desire for imitation, and friendships mattering because friends help you learn about the benefits of the cup. It is possible that friends are a positive influence through imitation, but a negative influence through learning about benefits, and these balance out overall to zero. We think this is unlikely,

[15] Note that we do not report coeffiencts 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.

since we have little evidence that friends would have a negative influence through learning. For example, among the individuals who use the cup, 100% of them, at the follow-up survey, report that they would recommend it to someone of their age (overall, including the girls who did not use, 95% said they would recommend the cup). Nevertheless, we cannot draw strong conclusions about separating these two mechanisms; we can say only that together their effect appears to be zero.

Benefit Effects on Wanting to Use

Again, we turn briefly to the effects of cup benefits on wanting to use. The coefficients in Column 1 of Table 6 also provide the basis for this discussion. As we noted above, with appropriate expectations we would expect these coefficients to be similar to the estimates on overall usage in Column 4 of Table 3. In practice, we see much stronger results in this case: all four measures of benefits and costs significantly affect cup trial, and in the expected direction. Based on the brief discussion above, this is consistent with over-optimism about success among girls with high benefits of usage. Of course, more would need to be done – likely with different data – to prove that this is the mechanism behind the variation in coefficients.

Summary

There are at least two important conclusions from these results on mechanisms. First, and most importantly, from a positive standpoint our analysis of peer effects supports the theory that peers matter in adoption because individuals learn about how to use the technology from them. In contrast, we argue that peers *do not* matter through affecting individual wanting to use the new technology, although our estimation has more limitations in this case.

Second, the combination of the evidence of the effects of benefits and the evidence of the effects of friendships fleshes out the comparison of magnitudes in Section 3 and Figure 4. In that case, we provided an analysis of which of these two avenues matters most, considering our specific product. Based on our analysis of mechanisms, we argue that value-based targeting is likely to dominate even more strongly for technologies that are easy to use. Because friends seem to matter primarily for learning about how to use the product, without any variation in success probability, friendship should not matter at all; further, the analysis of benefit effects on trial suggest that benefits are even more predictive if we ignore the success margin. Given these two points, value-based targeting will heavily dominate if a product is easy to use. In contrast, for a product with limited heterogeneity in wanting to use, but a lot of variation in probability of success, targeting on peer networks becomes more attractive. This is particularly true in cases where the goal is to target fast adoption, since friends affect speed of adoption more than ultimate adoption.

This suggests that, to the extent one wants to use these results to make statements about other types of technologies, it is important to think about where these technologies lie on the heterogeneity-in-value versus heterogeneity-in-success space. For a product like de-worming drugs, where there is likely to be almost no heterogeneity in success, we would not expect to see peers affect adoption, and targeting based on value is likely to be more successful. In contrast, for a complicated technology – say, a computer – we would expect to see more effect of peers on adoption, and peer-based targeting could be good, at least for short-term adoption.

5 Conclusion

This paper analyzes the determinants of adoption of a new technology using data from a randomized evaluation of menstrual cup provision in Nepal, focusing on the role of peer effects and technology value in driving adoption. Despite the fact that the menstrual cup may not be *per se* the most important technology, we argue that the data and setting have a number of advantages for this analysis. First, the menstrual cup is a completely new and unfamiliar technology and it is somewhat difficult to use, meaning that it shares features with a number of other important technologies (e.g. fertilizer or contraceptives). Second, because we randomize at the individual level, we have exogenous variation in peer exposure, which allows us to estimate causal peer effects. Third, our data have sufficiently rich information on adoption – in particular, we observe both trial of the cup and usage of the cup – that we are able to make progress on separating out the mechanisms by which peers, in particular, affect adoption.

We find strong evidence that both peer exposure and cup value drive adoption. Girls with more treatment friends adopt much more quickly. The same is true of girls who we expect to get greater benefits from the cup – for example, those who work for pay and those who report spending more time washing their menstrual cloths. Our analysis of mechanisms suggests that peers are important for learning about how to use the product; however, they do not seem to play an important role in driving individuals' *wanting to use* the product.

The results here may have policy implications which go beyond the particular case of the menstrual cup. As we note above, this technology shares features – difficulty of use, unfamiliarity – with a variety of other important technologies. In many of these cases policy-makers face a choice about how to distribute the technologies to maximize use. Assuming that not everyone will want to use the a product, or be successful at using it, what is the right way to distributed a limited number of products? The results here shed some light on this issue, indicating 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.

In addition to these implications for policy, we believe the findings in this paper may also guide methodology. First, peer effects are more important in early months after product distribution. This likely reflects the concave nature of the value of information – some more information is very helpful, moving from having a lot of information to even more is less helpful. This suggests 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. 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 very valuable in understanding the mechanisms through which these effects operate.

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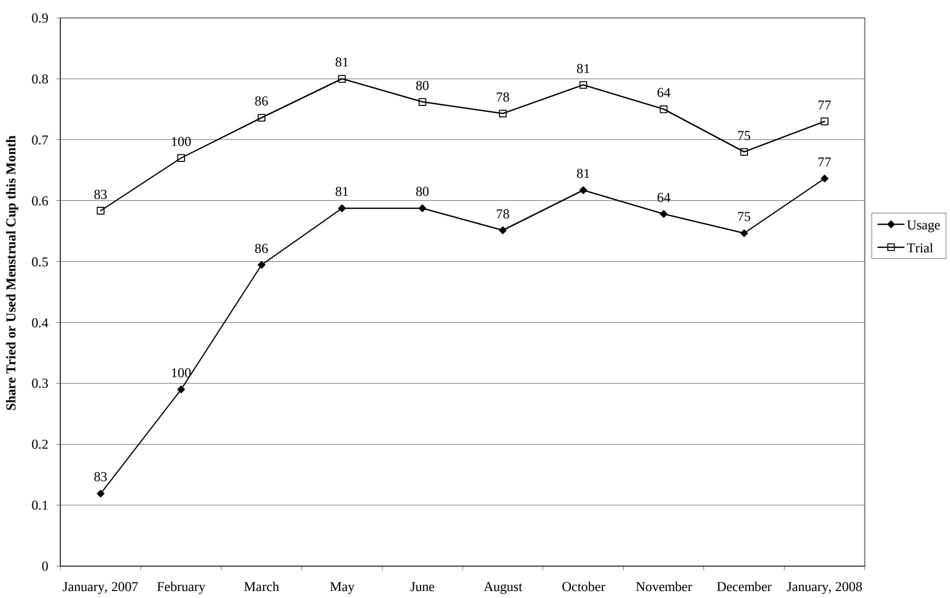
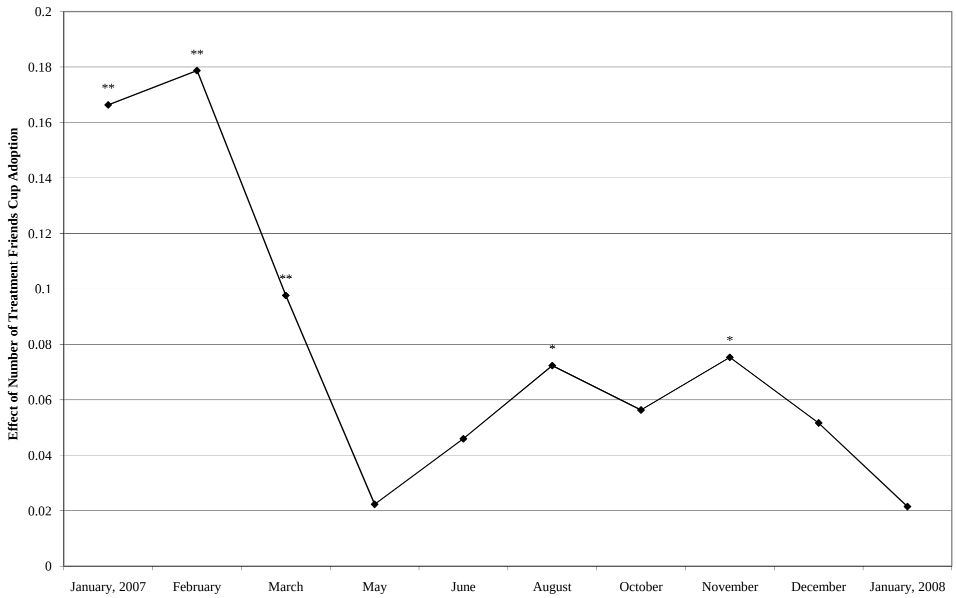
Figure 1: MoonCup Photo

Figure 2:
Menstrual Cup Trial and Usage Over Time



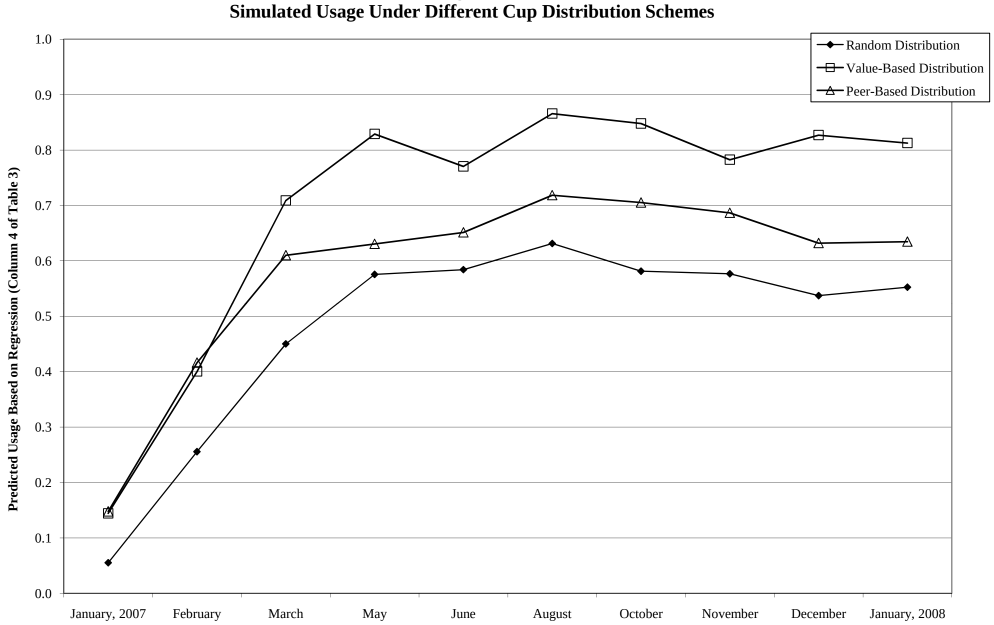
Notes: This figure shows evolution of usage of the menstrual cup, over time. Cups were distributed in November or December of 2006. The labels indicate the number of individuals observed in each month. There are a total of 101 treatment individuals.

Figure 3
Estimated Effect of Treatment Friends on Menstrual Cup Usage, by Month



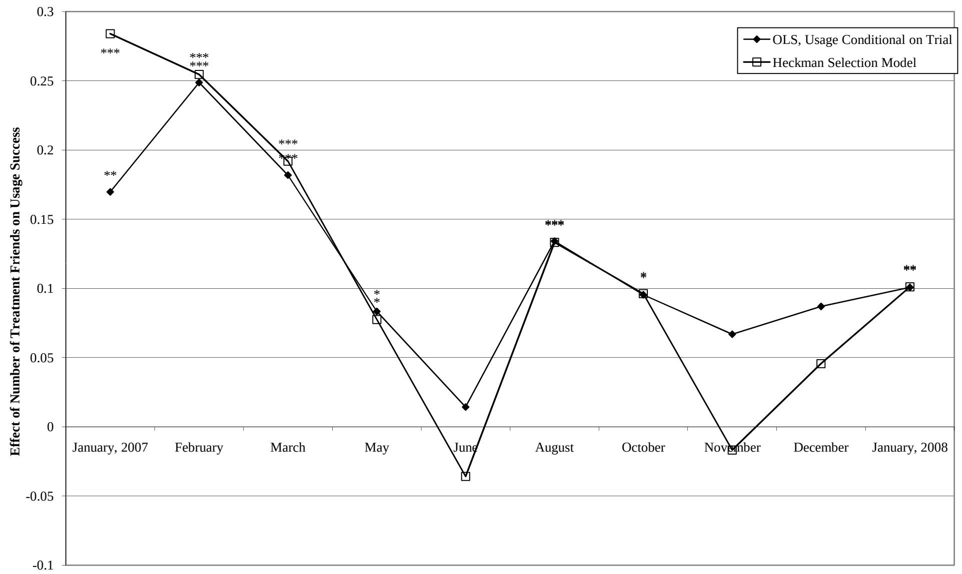
Notes: This figure shows coefficients on number of treatment friends interacted with month dummies from a regression where the dependent variable is menstrual cup usage. ** significant at 5% level; * significant at 10% level

Figure 4
Simulated Usage Under Different Cup Distribution Schemes



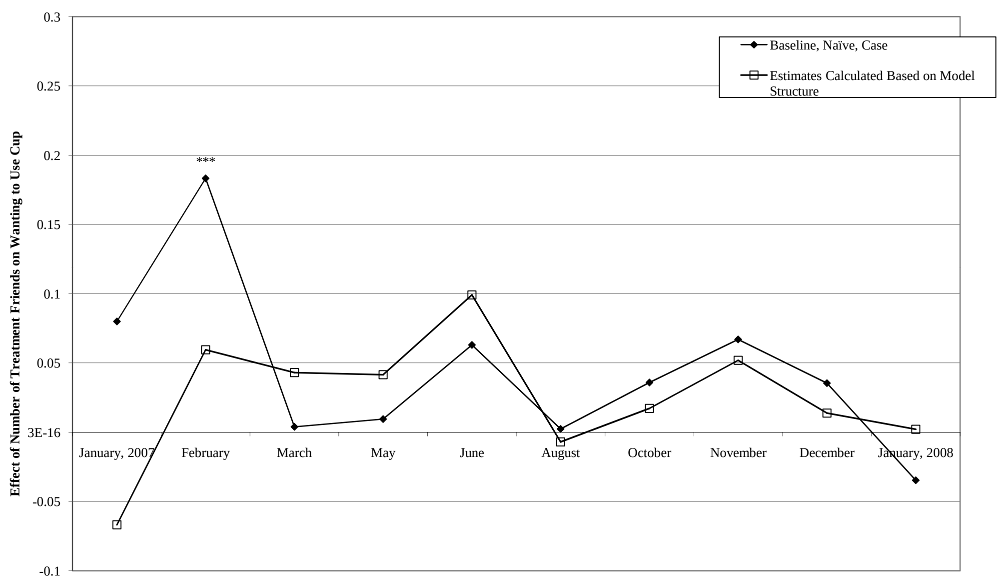
Notes: This figure shows the predicted usage under three different distribution schemes, based on our estimates in Section 4. Value-based distribution means giving the cup to people with highest predicted cup value; peer-based distribution means distributing by peer networks to maximize average number of friends with the cup among girls who also have the cup

Figure 5
Estimated Effect of Treatment Friends on Success at Using Menstrual Cup, by Month



Notes: This figure shows coefficients on number of treatment friends from a regression estimating usage success (usage conditional on trial, either adjusted or not adjusted for selection). Regressions are run separately for each month. *** significant at 1% level;** significant at 5% level; * significant at 10% level

Figure 6
Estimated Effect of Treatment Friends on Wanting to Use Cup, by Month



Notes: This figure shows first marginal effect estimates from a probit regression of cup trial on number of treatment friends (the OLS baseline results); the other series shows the estimates of the effect of treatment friends calculated based on the structure of the model in Section 5. *** significant at 1% level.

Table 1. *Summary Statistics*

Panel A: Number of Participants			
	Girls	*Mothers*	*Female Relative*
School 1	54	41	13
School 2	48	33	13
School 3	48	42	6
School 4	48	35	8
Panel B: Summary Statistics on Demographics			
	Mean	*Standard Deviation*	*# of Observations*
Age	14.2	1.23	197
7th Grade (0/1)	.53	.50	198
Test Score Last Year	-.08	1.18	198
Father Hindu Ethnicity	.51	.50	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)	.87	.33	197
Panel C: Summary Statistics on Analysis Variables			
	Mean	*Standard Deviation*	*# of Observations*
Work for Pay	.45	.50	198
Minutes to School	14.6	9.0	197
Time to Wash Cloths	30.9	32.2	197
Ever used sanitary pads (0/1)	.22	.41	197
Number of friends	3.78	1.35	198
Share of Friends Treatment	.51	.27	196

Notes: This table shows simple summary statistics on sample sizes and basic demographics. All girls were in either 7th or 8th grade. Age at menses and use of sanitary pads are 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. Income categories range from 1-6, and correspond to yearly incomes of: Less than 25,000 Rs, 25k-50k, 50k-75k, 75k-100k, 100-150k, 150k+.

Table 2. ***Balancing Tests***

Panel A: Balancing on Treatment and Control		
	Treat (n=101)	*Control (n=96)*
Work for Pay	.43	.47
Minutes to School	14.0	15.3
Time to Wash Cloths	29.7	32.2
Ever used sanitary pads (0/1)	.20	.24
Number of friends	3.82	3.74
Share of Friends Treatment	.52	.50
Age	14.21	14.23
7th Grade (0/1)	.50	.55
Test Score Last Year	-.17	.00
Father Hindu	.50	.53
Income Category	2.49	2.62
Mother's Yrs. Educ.	2.48	2.91
Father's Yrs. Educ.	6.02	5.17
Menses at baseline (0/1)	.92*	.82

Panel B: Balancing on # Treatment Friends	
	Coeff. on # of Treat. Friends (Std. Error)
Work for Pay	.007 (.038)
Minutes to School	-1.32* (.690)
Time to Wash Cloths	3.37 (2.47)
Ever used sanitary pads (0/1)	-.006 (.031)
Age	.090 (.094)
7th Grade (0/1)	.006 (.038)
Test Score Last Year	-.097 (.090)
Father Hindu	.053 (.038)
Income Category	-.132 (.121)
Mother's Yrs. Educ.	-.199 (.306)
Father's Yrs. Educ.	-.179 (.369)
Menses at baseline (0/1)	-.027 (.025)

Standard errors in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%

Notes: This table shows balancing tests for the demographics and friend variables by treatment and control and by number of treatment friends. Total number of friends includes all friends the individual lists, plus any people who list her as a friend. Income categories range from 1-6, and correspond to yearly incomes of: Less than 25,000 Rs, 25k-50k, 50k-75k, 75k-100k, 100-150k, 150k+.

Table 3. ***Determinants of Menstrual Cup Adoption***

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:			*Use Menstrual Cup During:*		
	Mar, 2007	*Aug, 2007*	*Jan, 2008*	*All Months*	*All Months*
Explanatory Variables:					
# Treatment Friends	.1154***	.074	.0014	.0839***	.1596***
	(.031)	(.056)	(.059)	(.032)	(.039)
# Total Friends	−.0525*	−.0843**	.0193	−.0383*	−.0711***
	(.028)	(.037)	(.043)	(.021)	(.027)
Work for Pay	.3079***	.1951	.1931*	.1946***	.0719
	(.109)	(.13)	(.104)	(.075)	(.097)
Minutes to School	−.0106**	−.0062	−.0119**	−.0038	−.0009
	(.005)	(.007)	(.006)	(.003)	(.005)
Ever Use Pads	.0341	.1105	−.1546	−.0569	.0836
	(.096)	(.128)	(.132)	(.075)	(.092)
Time to Wash Rags	.0048***	.0055**	.0061***	.003***	−.0001
	(.002)	(.003)	(.002)	(.001)	(.001)
Months Since Distribution				.0301***	.0258*
				(.004)	(.015)
# Treat Friends × Month					−.0108***
					(.004)
# Friends × Month					.0042
					(.003)
Work × Month					.0119
					(.009)
Mins to School × Month					−.0004
					(.001)
Use Pads × Month					−.0174
					(.012)
Wash Time × Month					.0005**
					(.0001)
Age	.0447	.0363	.0391	.0422	.0449*
	(.03)	(.047)	(.046)	(.026)	(.026)
Grade	−.0562	−.1793**	−.0795	−.0409	−.0527
	(.063)	(.091)	(.09)	(.049)	(.047)
Ethnicity=Tebeto	−.1112	−.1391	−.2349**	−.1416***	−.1423***
	(.103)	(.134)	(.102)	(.052)	(.051)
Ethnicity=Newar	−.178	−.0714	−.2834	−.1218	−.127
	(.165)	(.255)	(.22)	(.163)	(.154)
School 2	−.2071***	−.2288*	−.1588	−.1991***	−.1955***
	(.078)	(.124)	(.127)	(.062)	(.061)
School 3	−.3671***	−.4277**	−.3223*	−.3675***	−.3546***
	(.082)	(.142)	(.173)	(.084)	(.082)
School 4	−.5676***	−.547***	−.5178***	−.4761***	−.4669***
	(.05)	(.119)	(.149)	(.061)	(.061)
Noramalized Exam Score	.0283	.1048*	.0205	.0318*	.0317*
	(.041)	(.057)	(.034)	(.02)	(.019)
Mother's Educ.	−.0006	.0242	−.0095	.0079	.008
	(.014)	(.019)	(.017)	(.009)	(.009)
Father's Educ.	−.0028	−.0192	−.0202	−.0076	−.0088
	(.014)	(.016)	(.016)	(.007)	(.007)
Family Income	.1126***	.0395	.0692*	.0449**	.043**
	(.03)	(.042)	(.039)	(.021)	(.021)
P-value, Joint Sig. of Value Vars.	.06	.22	.06	.002	.010
Number of Obs.	87	74	73	772	772

Standard errors in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%
Notes: This table shows the effect of cup benefits, costs and peer exposure on usage. The first three columns use one month of data each; the fourth and fifth column use all months of data, with standard errors clustered by individual.

Table 4. *Influence of Friend Type on Menstrual Cup Adoption*

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:			*Use Menstrual Cup During:*		
	Mar, 2007	*Aug, 2007*	*Jan, 2008*	*All Months*	*All Months*
Explanatory Variables:					
# Strong Treat. Fr.	.1607***	.1984***	.1931**	.1687***	.1694***
	(.05)	(.076)	(.095)	(.045)	(.061)
Total # Strong Fr.	−.0623	−.1651***	−.0272	−.0727**	−.0965**
	(.045)	(.06)	(.064)	(.032)	(.044)
# Weak Treat. Fr.	.0831*	.0082	−.0139	.0429	.1326***
	(.045)	(.065)	(.053)	(.038)	(.044)
Total # Weak Fr.	−.0397	−.0521	.0068	−.0205	−.0474
	(.032)	(.043)	(.04)	(.025)	(.03)
Months Since Distribution				.0305***	.025*
				(.004)	(.015)
# Strong Treat Fr. × Month					.0008
					(.008)
# Strong Fr. × Month					.0027
					(.005)
# Weak Treat Fr. × Month					−.0122***
					(.005)
# Weak Fr. × Month					.0034
					(.004)
Number of Obs.	87	74	73	772	772
COST/BENEFIT CONTROLS	YES	YES	YES	YES	YES
DEMOGRAPHIC CONTROLS	YES	YES	YES	YES	YES

Standard errors in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%
Notes: This table shows the effect of peer exposure on usage separated out by friend type. The first three columns use data from three time periods; the fourth and fifth column use all months of data, with standard errors clustered by individual. Controls for cup cost/benefits and demographics are included in all columns (the same controls as in Table 3). Strong friends: both list each other; Weak friends: respondent lists, friend does not list her or friend lists respondent, not visa versa. We report the average marginal effect from Probit models.

Table 5. *Peer Effects on Menstrual Cup Usage Success*

	(1)	(2)	(3)	(4)
	Dependent Variable: Used Menstrual Cup			
	OLS: Used Conditional on Trial		*Heckman Selection Model*	
			Selection: No Period This Month	
Explanatory Variables:				
# Treatment Friends	$.1182^{***}$	$.1889^{***}$	$.1092^{***}$	$.1793^{***}$
	(.036)	(.054)	(.029)	(.047)
# Total Friends	$-.0612^{**}$	$-.0815^{**}$	$-.0548^{**}$	$-.0731^{*}$
	(.025)	(.039)	(.024)	(.039)
Months Since Distribution	$.0388^{***}$	$.0457^{**}$	$.0376^{***}$	$.0453^{***}$
	(.005)	(.015)	(.005)	(.015)
# Treat Friends × Month		$-.0086^{**}$		$-.0085^{**}$
		(.004)		(.004)
# Friends × Month		.0027		.0024
		(.004)		(.004)
DEMOGRAPHIC CONTROLS	YES	YES	YES	YES
Number of Obs.	562	562	772	772

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

Table 6. ***Peer, Benefit and Cost Effects on Wanting to Use***

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:			*Tried Menstrual Cup*			*Willingness to Pay*
	Baseline		*Structural Estimates*		*Late Months Only*	
Explanatory Variables:						
# Treatment Friends	$.061^{**}$	$.0895^{**}$	.0332	.0165	.0327	174.8477
	(.028)	(.037)	(.044)	(.039)	(.038)	(132.477)
# Total Friends	−.0243	−.0371			−.0133	−115.2202
	(.018)	(.026)			(.026)	(110.835)
Work for Pay	$.0898^{*}$	−.0389			$.1371^{**}$	−384.6595
	(.053)	(.099)			(.062)	(300.259)
Minutes to School	$.0056^{**}$	.006			$.0055^{*}$	1.0636
	(.002)	(.004)			(.003)	(16.528)
Ever Use Pads	$-.1386^{**}$	−.0782			$-.1396^{*}$	−80.8246
	(.061)	(.094)			(.083)	(327.119)
Time to Wash Rags	$.0032^{***}$	$.0038^{***}$			$.0031^{**}$	2.1546
	(.001)	(.001)			(.002)	(4.361)
Months Since Distribution	.0061	.0058			−.0048	
	(.005)	(.013)			(.0072)	
# Treat Friends × Month		−.0042		.00001		
		(.005)		(.009)		
# Friends × Month		.0018				
		(.004)				
Work × Month		.0167				
		(.011)				
Mins to School × Month		−.0001				
		(.0000)				
Use Pads × Month		−.0068				
		(.01)				
Wash Time × Month		−.0001				
		(.0001)				
P-value, Joint Sig. of Value Vars.	.0005	.001			.017	.75
DEMOGRAPHIC CONTROLS	YES	YES	N/A	N/A	YES	YES
Number of Obs.	772	772	772	772	432	65

Standard errors in parenthesis, clustered by individual. * significant at 10%; ** significant at 5%; *** significant at 1%
Notes: This table shows estimates of the effect of peers, costs and benefits on wanting to use the cup. The first two columns show baseline effects of these variables on trial; the coefficients on peers should not be interpreted as effects on wanting to use. The third column provides estimates of friend effects on wanting to use based on structural assumptions in the model (standard errors are bootstrapped). The fourth column provides these estimate based on the assumption that probability of success in late months is high. The fifth column estimates effects on reported willingness to pay for the cup at follow-up. Controls for demographics are included in all columns (the same controls as in Table 3).