

Increasing the Take-up of Public Health Services: Evidence from a Field Experiment at Scale in Uruguay

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Abstract

In this paper we test whether the promotion of digital government tools and the provision of behaviorally-informed messages increases take-up of medical visits for cervical cancer screening. Using a multi-arm field experiment at scale in Uruguay, and administrative records from national health services, we find that the intervention more than doubled medical appointments and attendance rates over a 12-week period. Most of the effects are driven by women encouraged to use digital government tools on top of behaviorally oriented messages. These women attended the screening appointments about 3 times more than the control group, while those motivated only with messages attended 1.5 times more. Our results highlight the potential of investing in digital government tools to decrease transactions costs and improve the take-up of public services.

1. Introduction

Increasing the take-up of public services is a challenge across policy areas. Some competing barriers to the adoption of these services are related to information, behavioral constraints, and transaction costs (Finkelstein and Notowidigdo, 2019; Haushofer, John and Orkin, 2019). An extensive body of literature has studied the experimental provision of information (Haaland, Roth, and Wohlfart, 2020) and there is increasing evidence assessing strategies to address behavioral bottlenecks (Datta and Mullainathan 2014), but there is much less evidence studying transaction costs.¹ Most of the studies in this area relate to assistance interventions helping with the application to benefits (Deshpande and Li 2019, Dinarski 2018 et al., Finkelstein and Notowidigdo, 2019). A similar but much less studied set of related policies are those aiming at investing in state

¹ There is, however, an extensive descriptive literature coming from the public administration field. See for example, Herd and Moynihan (2018) on the administrative burdens faced by citizens when trying access to public services.

capacity to reduce bureaucracy and lower transaction costs.² Advances in technology and the digitization of administrative procedures have the potential to improve the delivery of public services (Roseth et al 2018, OECD 2019).

In this paper we test whether the promotion of digital government tools and the provision of behaviorally-informed messages increases take-up of an important public health prevention service for women: cervical cancer screening. Cervical cancer is one of most common causes of women's mortality worldwide (WHO, 2020a) and one of the most treatable forms of cancer given early detection and management (WHO, 2020b). Nevertheless, many women fail to take the standard screening tests such as the Papanicolaou Test (PAP smear) even when offered cost-free by the health provider. This is a critical issue particularly in developing countries, where absence of preventive health behaviors can lead to increased mortality rates (Dupas, 2011).

We partnered with the Ministry of Health and the national e-Government Agency (AGESIC) in Uruguay to invest in digital government capacities in two steps. The first step was to consolidate information that was digitized but disperse, coming from a register of health users, an electronic clinical history of patients, and the medical appointments system. In second place, we worked with our partners to design and implement an application to schedule PAP smear appointments online. The application, compatible with smart phones and with desktop computers, allowed users to make appointments choosing from a set of available dates and times at their local clinic.

We then conducted a field experiment at scale in Montevideo, the capital city, encouraging women to schedule and attend cervical cancer screening appointments. We randomized about the complete female population of public health users (47,600 women) to four treatment arms and one pure control group.

We randomized women to receive SMS messages with either an encouragement to schedule appointments at their local clinic as they would usually do (i.e., status quo regarding scheduling process), or to schedule online using the link to the application (i.e. lowering their transaction costs in appointment scheduling). We paired each of the encouragement messages with either benefit- or risk-framed information about the PAP smear, thus generating four treatment groups.

² A very recent set of studies in India and Pakistan are related to this topic. See Muralidharan, Niehaus and Sukhtankar, (2016, 2020); Bossuroy, Delavallade and Pons (2019); Muralidharan, Niehaus, Sukhtankar and Weaver (2020); and Callen, Gulzar, Hasanain, Khan and Rezaee (2020).

We included differently framed messages based on evidence that people might be more responsive to knowing what they might lose by not doing something as opposed to being told how much it benefits them. Women in the pure control group received no messages or additional information.

We tested effects on two main behavioral outcomes and a host of secondary measures. Our main outcome indicators are whether women made and attended appointments over a 12-week period. We computed intention-to-treat (ITT) estimates and two sets of local average treatment effects (LATEs), taking into account both the successful delivery and receipt of the SMS messages. We describe our ITT results next, which as customary, are conservative compared to our LATE estimates.

Using administrative records from the national health authorities, we find that women randomized to the treatment groups doubled their screening appointments rates vis-à-vis the control group (3.3 percentage points -pp.- over a control mean of 2.7%). The effects were much larger for women randomized to the lower transaction cost component (5.2 pp.) compared to those with the status quo component (1.3 pp.). Whether messages were benefit- or risk framed did not make meaningful differences within these components.

These effects on appointment scheduling are informative about participant's intentions to follow the advice embedded in our treatment arms. Because it is well documented that intentions often differ from actions (see, e.g., Beshears, Milkman and Schwartzstein, 2016), we used further administrative records to complement the previous intention outcome and estimate effects on the action of women, i.e., whether they attended their appointments. Our findings show that the intervention doubles attendance rates too, with an effect of 2.3 pp. over a control mean of 1.9%. The pattern of effects by treatment arms replicates as well: the effects for women targeted with the transaction cost reduction were 3.2 pp., compared with 1.4 pp. for those in the status quo group, with no differences by the framing of the messages.

These results suggest that the components of our intervention helped women to overcome some obstacles to take the PAP smear. To explore in depth which of those barriers were lowered we needed additional data on secondary outcomes, which the administrative records lack. Thus, we supplemented the administrative data with an endline survey of a subsample of about 2,500 participating women, evenly distributed across the four treatment arms and the control group.

We collected data on a set of plausible mechanisms through which treatment effects might operate. These include women's knowledge about the PAP smear and its costs, their beliefs about the importance of testing, and risks of not taking the test, and preferences for public services, among others.

The survey results show that women were already highly informed about the PAP smear and its importance. Therefore, we hypothesize that part of our treatment effects worked through the salience of the encouragements. Rather than providing women new information, our messages appear to have brought the PAP smear to their minds. Our findings also indicate that the higher impacts are indeed working through the reduction of transactions costs, particularly for those who received the link to make appointments online. Treated women report to find it easier to make appointments, and less likely to say they would make appointments in person at health centers.

Our study complements the literature aimed at increasing preventive-health services with behavioral insights (Kremer, Rao and Schilbach, 2019), that has delivered mixed results.

Our effects are sizable compared to the successfully implemented behaviorally informed interventions in other countries for similar health behaviors. For example, Milkman et al (2012) find a 1 pp increase over a control mean of 6.2% in the fraction of people making and sticking to appointments to be screened for colon cancer in the US. Huf et al (2020) found that SMS reminders improved cervical screening participation in the UK in 4 pp, over a much higher control mean of 34%. Milkman et al (2011) found an increase of 1.5 to 4 pp from using implementation intention prompts on influenza vaccination rates in the US. Busso, Cristia, and Humpage (2015) found that personal reminders increased demand for vaccination by 2.2 pp. (over a control mean of 6%) in Guatemala.

At the same time, other recent similar interventions have found no effects. Goldzahl et al (2018) tested four behavioral interventions in France with a large scale RCT and found no effects on mammography use. Bronchetti, Huffman, and Magenheimer (2015) report that lower-cost nudges did not affect overall vaccine take-up for a sample of undergraduate students in Philadelphia. Carrera et al (2018) found no effects of a planning intervention for a sample of a private gym in a large Midwestern city in the U.S.

Our study contributes to the literature in two important ways. First, it contributes with evidence of an experiment at scale. This is important in general because it helps with concerns related to the inability to detect effects in small-scale interventions as some of the ones described above. Even if effects are detected, those might not replicate when scaling, in part because of characteristics inherent to the original sample and also because of the challenges associated to implementing the same program at a larger organizational scale (Muralidharan and Niehaus, 2017). On top of this, we provide novel evidence for a region of the developing world (South America) in which there is practically no evidence of experiments at scale. The country in our particular setup – Uruguay – is relatively small in terms of population (3.5 million), but the 47,600 participants in our experiment are close to the population of women who are users of the public health provider in Montevideo.³ Randomizing at this scale lets us address the concern that small-scale pilot would not replicate in this region of the world. What makes our study more informative to this respect is that we surveyed a subsample of participating women and therefore we have an estimate of the differential effects versus the full sample. We find larger estimates on our subsample, consistent with respondents being more connected to cell phones and internet, engaged with their health, among other characteristics. If we had implemented the intervention on this subsample only, we could have mistakenly expected to have higher effects once scaling.

Second, this study contributes to the literature on the use of new technologies in the public sector. Digital technology has reduced the cost of storage, computation, and transmission of data (Goldfarb and Tucker, 2019) and governments are developing the capacity to use it for policy. There is much less causal evidence on the importance of reducing transaction costs to improve public service uptake.⁴ Our results complement a recent wave of studies assessing different ways to use of technology to improve state capacity in developing countries (Muralidharan et al., 2016, Bossuroy, Delavallade and Pons, 2019; Callen et al 2020, Muralidharan, et al 2020a, 2020b).

Our findings suggest that investment in state capacity and promoting digital government tools is important and likely to generate the most meaningful impacts on public service delivery. The literature has documented that purely based behavioral interventions have delivered mixed results, which highlights the potential of investing in digital government tools beyond interventions that provide information, reminders or planning interventions. The prospect of investing in digital

³ The population of Montevideo, the capital city, represents approximately 40% of the country's population.

⁴ There is also literature document case studies and qualitative evidence on the e-government and the delivery of public services. See for example Ayachi et al (2016), Sirendi and Taveter (2016), Bertot et al (2016) or Linders et al (2018).

state capacity might be even more important in developing countries, where low service delivery uptake is often associated with weak institutional capacity.

The remainder of this paper is organized as follows. Section 2 provides a brief description of the setting in which the intervention took place. In section 3 and 4 we describe our experimental design and the data, respectively. Section 5 outlines the empirical strategy and section 6 discusses our results. We present our main conclusions in Section 7.

2. Background

Uruguay is a small country in South America with about 3.5 million inhabitants, of whom approximately 1.4 million live in Montevideo. With an PPP-adjusted GDP per capita of US\$22,500 (World Bank, 2019) Uruguay ranks among the most developed Latin American countries, yet still lags well behind the OECD average (US\$46,500) or the U.S. (US\$65,300). Therefore, the country faces the development challenges of a middle-income country.

The health system in Uruguay (National Integrated Health System, SNIS) provides health coverage for the entire population (WHO, 2015) through a National Health Insurance (SNS) financed by a National Health Fund (FONASA).⁵ People can enroll either with the private or public health care providers.⁶ The public healthcare system is operated by the Administration of State Health Services, known as ASSE (Administración de los Servicios de Salud del Estado). The users of ASSE belong to the lower quintiles of household income; about 84% of them belong to the bottom two quintiles (Ministerio de Salud de Uruguay, 2018).

One area of challenges in the health services is related to cervical cancer testing. This type of cancer is the fourth leading cause of cancer-related deaths in the world (Ferley et al 2013) and the fifth leading cause among women in Uruguay (Barrios et al 2017). The WHO (World Health Organization, 2013) states that cervical cancer is one of the most successfully treatable forms of cancer, if detected early and managed effectively.

⁵ FONASA brings together all the social security funds destined to finance health services.

⁶ About a 56% is enrolled with private health care providers and 34% with the public sector provider. Another 6.5% is enrolled with military, police and other 3% with special private insurance providers (Ministerio de Salud de Uruguay, 2018).

Uruguay has made the PAP smear cost-free at ASSE's clinic centers, and women are legally allowed to take one day off from their jobs (paid) to take the test. We surveyed a sample of ASSE's female users and found that essentially all respondents report to be familiar with the PAP smear (98% does) and most (73%) know that they could take it cost-free at the ASSE clinics. They are also aware they can take a day off from their jobs to take the test (92% reports to know); and 80% report to believe that they should take the PAP smear regularly.

Yet in Montevideo, 60% of women aged 30 to 70 affiliated to the public healthcare system have not taken the cervical cancer screening in the past three years; and nationally, another about 61% of the women who die from cervical cancer in Uruguay are affiliates to the public health provider (Registro Nacional de Cáncer, 2016).

In our survey, information and transaction costs related to appointment scheduling are referred as the most common barriers for service uptake. Among those who never took the PAP smear, 80% reported to face these obstacles. When asked if they know how to schedule an appointment, 23% indicated that they do not know how to do it, while 57% reported to believe that they needed to go to the clinic centers in person to do so.

The Government of Uruguay is explicitly committed to the digitalization of public services (United Nations, 2018). Accordingly, the national e-Government Agency (AGESIC) has taken important steps towards the digitization of public services and internal administrative processes in the country (Roseth et al., 2018).⁷

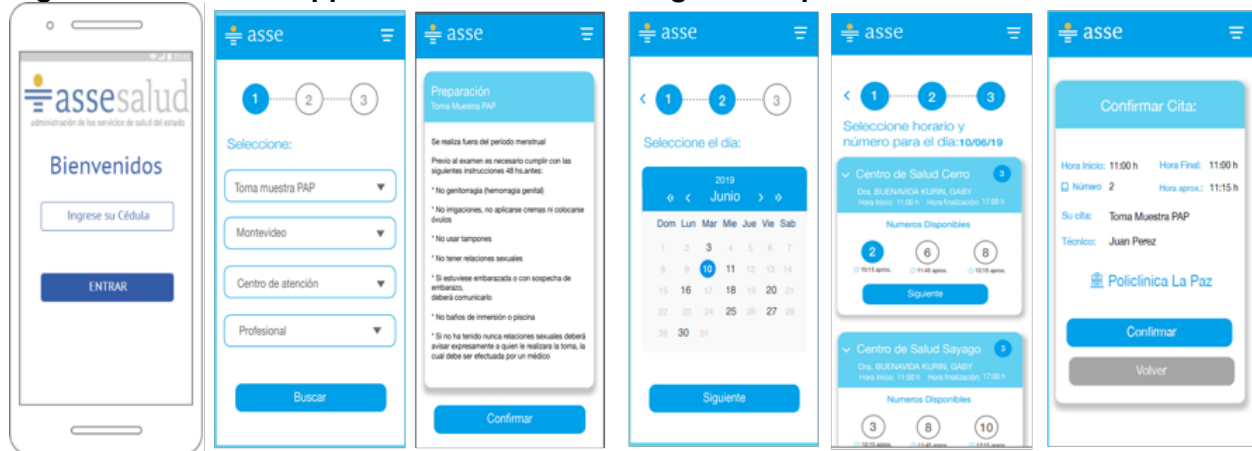
We partnered with ASSE and AGESIC to design and implement an online tool to schedule PAP smear appointments with ASSE clinics.⁸ We developed an application for users to make their own appointments using their national identification number. The application consolidated information coming from different sources: the digitized register of health users in Uruguay, the electronic clinical history of patients, and the medical appointments system (Sistema de Gestión de Consultas). The application also included a system to remind users of their appointments. The

⁷ Uruguay is well-established as the regional leader in digital government and is recognized as a leading country on the world stage. In the 2018 United Nations ranking of e-government development, Uruguay placed #34 in the world, and #1 in Latin America. It is also institutionally strong in comparison to its regional peers: it ranks first in LAC in the Democracy Index (EIU, 2018), the Corruption Perceptions Index (Transparency International, 2017) and the Rule of Law Index (World Justice Project, 2018).

⁸ We designed this tool specifically for this project. Given the promising results we document in this paper, ASSE intends to broaden the use of the tool for all types of appointments, for all its members.

application is compatible with smart phones, desktop computers, and different operating systems. Figure 1 illustrates the online tool interface when using a smartphone.

Figure 1. The online appointment interface using a smartphone



In this context, we implemented a field experiment at scale targeting the obstacles faced by women to conduct the PAP smear. We promoted cervical cancer screening using the online tool paired with a benefit-framed or loss-framed messages, as we describe in detail in the next section. We leveraged on three key factors to implement our intervention. First, the significant government experience in providing digital public services and their commitment to implement the online tool. Second, ASSE's good reputation among its enrollees. In our survey, about 90% of respondents report that ASSE provides medium to high quality services and another 90% reports to have medium to high confidence in the institution. Third, Uruguayan citizens report to have access and be frequent users of internet. A recent AGESIC survey shows that 86% of adults use internet daily, and 9 out of 10 connect using a cell phone (AGESIC, 2019). This backdrop – commitment to provide e-government services, good reputation, and high rates of internet usage – provided an ideal setting for our intervention based on text messages and internet links, which we describe next.

3. Experimental Design

In this section we describe our experimental design. First, we present the conditions for eligibility and randomization procedures. Then, we describe the intervention, the implementation timeline implementation, and finally, we detail our outcome measures.

Intervention. The intervention was designed to increase the scheduling and take-up of cervical cancer screening, a particularly important preventive health behavior. We implemented the intervention in four treatment arms and one pure control group. Women in the control group continued with the health center's standard procedures regarding appointment scheduling, and they did not receive messages or additional information.

Women in the treatment arms were randomized to receive encouragement messages to schedule appointments (online or not) paired with information about the PAP smear (benefit or risk framed). Table 1 classifies the four treatment arms accordingly.⁹

Treatment arms 1 and 2 (first row of Table 1) were encouraged to make appointments online through informational messages that included a link to use the online scheduling tool. We designed this component as an effort to decrease transaction costs in appointment scheduling. Women that made appointments through the online channel were also sent one reminder message 48 hours prior to their appointment. Those in treatment arms 3 and 4 received messages recommending recipients to schedule their appointments at their respective health center as usual. We label this component as the Status Quo regarding appointment scheduling.

In addition, we framed the information included in the messages as benefits or risks, to test whether different ways of providing content constrained behavior. Messages for women in column 1 of Table 2 (treatment arms 1 and 3) emphasized the benefit and importance of taking the PAP smear. Messages for women in column 2 (treatment arms 2 and 4), were framed to highlight the importance of the PAP smear considering the risks associated to cervical cancer.

All messages were personalized with the first name of the recipient and signed by the ASSE, the Ministry of Health and the municipal government (*Intendencia Municipal de Montevideo*). We list the respective messages by treatment arm below:

- Treatment Arm 1: *Hi [Name]! The PAP can prevent cervical cancer. It is important to get screened, here is a link to schedule an appointment*

⁹ Note that this is not a factorial (or cross-cutting) design as defined in Duflo, Glennerster and Kremer (2007) and discussed in Muralidharan, Romero and Wüthrich (2020). In a cross-cutting design, the interaction of two interventions A and B, would result in four groups: no interventions (*pure control*); A only; B only; and A and B together. In our case, each of the four treatment arms and the pure control group are individually defined ex-ante and not the result of interacting two interventions. See Table A in the Appendix for a comparison of these different designs.

- Treatment Arm 2: *Hi [Name]! Every three days a woman dies of cervical cancer. Not taking the PAP could cost you your life, here is a link to schedule an appointment*
- Treatment Arm 3: *Hi [Name]. The PAP smear can prevent cervical cancer. It is important to get screened, schedule your test at your health center.*
- Treatment Arm 4: *Hi [Name]. Every three days a woman dies of cervical cancer. Not taking the PAP could cost you your life, schedule your test at your health center.*

Eligibility and Randomization. We focus on women aged between 30 to 70 because the prevalence of cervical cancer starts to peak up at 30 and declines after 70 (Bottaro et al., 2010).¹⁰ We designed our intervention to take place in Montevideo for two reasons. First, internet connectivity was a condition for our intervention to work and Montevideo has the country's highest internet penetration rates (Rivoir & Landinelli, 2017). Second, in Montevideo, the public health care provider had the capacity to provide the extra PAP smears that could be demanded because of our intervention. We further restricted eligibility to women enrolled in ASSE subsidized by the National Health Fund, to make sure we would meet the potential demand for additional PAP tests.

ASSE prepared a dataset with the eligible women and shared it with us to conduct the randomization in May of 2019. By then, ASSE had approximately 1.4 million members in the country, 35% of whom were enrollees of the National Health Fund. Half of them (250,000) were women, and approximately 76,000 resided in Montevideo. From those 76,000 women, 58,800 were aged between 30 and 70, with at least one registered cell phone number¹¹ and thus, eligible for our study. This list of 58,800 women shared by ASSE included information on birth date, and date of the last PAP smear if it was made within 5 years. In accordance with Uruguayan data protection legislation, we were not provided with the phone numbers or any personal identifiable information. All our analysis was done with anonymous identifiers generated by ASSE.

As documented in our preregistered analysis plan¹², we estimated we would need a sample of 5,000 women per treatment arm to achieve a minimal detectable effect size of 1 percentage point

¹⁰ In addition, professional organizations (American Cancer Society, 2019; Saslow et al., 2012; Smith et al., 2016) recommend more frequent cervical cancer screening after age 30 and some also suggest that routine exams should be discontinued for older women (above 65), but academic articles have argued against a stopping age (see, e.g., White, Shoemaker & Benard, 2017).

¹¹ For the implementation of the text message treatments, we used the phone numbers gathered by ASSE. Numbers stay up to date because the information is checked every time women attend a health care facility.

¹² We registered our experiment in the American Economic Association Registry for Randomized Controlled Trials—#AEARCTR-0004716.

on take-up rates between arms, at the 0.05 level of statistical significance and with an 80 percent of power. We ended up randomizing 5,700 per each of our four treatment arms, totaling 22,800 women to treatment, and 24,800 women to a pure control group, as we show in Table 2, column 1.¹³ We randomized the remaining eligible women (11,200) to a contingency sample, to be drawn upon in the event of a high rate of failed text message deliveries, which was not necessary to use.

We expected our intervention to be less successful with more time passed since women took the last PAP. According to the WHO guidelines (World Health Organization, 2013), the cervical cancer screening interval (frequency) should not be less than 5 years. Using the information provided by ASSE we classified those who took the PAP less than 5 years ago as ‘On time’ and those who took the exam 5 years ago or more as ‘Overdue’.

Following the recommended common practice (see e.g., Duflo et al 2007; Athey and Imbens, 2016) we stratified our randomization using the available covariates in our administrative data, which were the time passed since last PAP (5 years or more) and age (for which we used four brackets of 10 years each). This procedure ensures a more precise inference as compared to randomization without stratification.¹⁴ In Table 2, columns 2 and 3 decompose column 1 by the time since the last PAP smear. From the 58.5K eligible women, 30.3 K had taken the PAP smear within the last 5 years (the ‘on-time’ group) and 28.5K had not (the ‘overdue’ group). Column 2 counts women in the former group and column 3 does the same for the latter.

Implementation and Timeline. An external firm was hired to send the text-messages to the different treatment arms, recording which type of message where sent to whom, how many, and on which date. Messages were sent each Tuesday¹⁵ starting on November 18, 2019 and until February 11, 2020 on a rolling basis. Messages to women in the “on time” group were sent during November and December and then to the “overdue” group during January and February. Each

¹³ At the time of the randomization we discussed with ASSE the possibility of having an additional treatment arm with 1,000 observations, which would have resulted in having 23,800 women in all treatment groups and 23,800 in the control group. Women in that treatment arm would have been offered the possibility to conduct an HPV test at home, but we could not implement this version due to logistic restrictions and operational cost. We decided to place the 1,000 women in the control group, which is why we ended up having 22,800 in treatment arms and 24,800 in the control group.

¹⁴ As Duflo et al (2007) explains, stratifying is more efficient than controlling for these variables ex-post because it ensures an equal proportion of treated and untreated units within each strata, minimizing the variance of our estimates.

¹⁵ Most of the messages were sent on Tuesday afternoons, the exception being two times in December (Mondays 23th and 30th). Because of the high volume of SMSs to be sent, the operative system sent messages in batches without recording a specific time of delivery for each individual message. However, we know that messages were sent between 1pm and 7pm during the respective delivery day.

woman could receive at most four messages over four weeks. If during that period the recipient scheduled an appointment, then she stopped receiving the messages.¹⁶

Main Outcome Measures. Our two main pre-specified outcomes measure intentions and actions. We measure whether women scheduled appointments for a PAP smear, and whether they attended that appointment. We collected these two variables from ASSE's administrative records from their medical appointments system, measured between November 18, 2019 and March 3, 2020.¹⁷

Scheduling an appointment informs us about women's intentions to follow the advice embedded in our treatment arms. If recipients already know that taking the PAP smear is important and they are fully aware of the benefits of taking and risks of not taking the exam, then we should see no differences on this outcome between our treatment arms 3-4 and the control group. If in addition, the transaction costs associated to making an appointment are sufficiently low, then we would not expect to find no effects when comparing treatment arms 1 and 2 to the control group.

Because intentions do not always translate into actions, we complement the previous outcome with whether women attended their appointments. Finding effects associated to this outcome would tell us that some of the constraints on behavior were eased by our intervention. Results for the different treatment arms would tell which of the components of our intervention helped women to overcome the obstacles to take the PAP smear.

Secondary Outcomes. While appointment scheduling and take-up are our primary outcomes of interest, we also study secondary outcomes to explore mechanisms through which treatment effects might operate. We supplemented our administrative data with an endline survey applied¹⁸ to a subsample of approximately 2,500 women, all of whom took the exam more than five years ago. We surveyed women in this group because we expected our intervention to have lower effects on them, and therefore we believed we should collect additional data to get a deeper understanding of the obstacles to screening they face. In addition, we wanted to be powered to

¹⁶ The online system also sent automatic reminders 48 hours prior to all women who scheduled appointments.

¹⁷ We have specific information on whether each woman scheduled, attended, cancelled, or did not show up for her appointment.

¹⁸ The surveys were carried by phone by a specialized external firm. We provided ASSE with random subsamples of each treatment arm and the control group, which they merged with phone numbers and then shared those with the firm. They implemented the survey in two rounds, one carried out in February and the other completed in April 2020.

detect differences across treatment arms, and therefore we sampled surveyed women to be equally distributed across treatment arms and the control group.

We measure participants' knowledge about the PAP smear, their beliefs about the importance of testing, and costs and obstacles they face for appointments and take-up. Finding effects on these secondary outcomes vis-à-vis the control group, or between treatment arms, would be suggestive of whether lack of information and transactions costs constrained behavior absent the intervention. We also asked interviewers to classify the respondents' patience and attitude during the survey, in the spirit of DellaVigna and Paserman (2005) and Cadena and Keys (2015).

Finally, we also collected additional information to complement the limited covariates available from administrative sources. We surveyed women on demographics such as household composition, income, education levels and internet usage.

4. Data

Our study uses administrative records from national health services, supplemented with survey data and the national registry of PAP smears appointments. The data employed in this study is described below.

Table 3 shows descriptive statistics for the full sample of women under study. They are 47,600 women affiliated to the public healthcare system, aged 49 years old on average, in a range age of 30 to 70. The World Health Organization (WHO) suggests that women older than 30 should take the Pap smear every five years. In our sample, 60% of women had not taken the exam in the last three years. Consistent with our stratified randomization (see section 3), half did not take it in the last five years. For those women, their last PAP appointment was on average 1.8 years ago. As detailed in the previous section, a total of 24,800 (52%) women belong to the control group and 22,800 (48%) to our treatment group. Within this group, each treatment arm has 5,700 observations (12% each).

We describe our survey sample in Table 4. We first describe the 2,462 women using the same variables from Table 3. Surveyed women are 51 years old on average, consistent with being a subsample of the 'Overdue' group (i.e., none has taken the PAP smear in the last 5 years). By

design, women are equally distributed across the control group, and four treatment arms (20% each).

The next variables in Table 4 describe further demographics collected in the survey. Overall, our survey sample is similar in characteristics to those in the second quintile of national income according to official household surveys. School attendance in Uruguay has been compulsory until nine years of education are completed (lower secondary education) since 1973 (OECD, 2016). Given their age, our respondents were educated under that regime and have consistently about 9 years of schooling on average. Their households are composed, on average, by 3.2 persons, compared to a national average of 2.8 and a mean of 3.2 for those in the 2nd income quintile (World Bank, 2018). Finally, 38% of the respondents live in a household with at least one child (younger than 14 years old).

Their monthly household income is about \$18,400 Uruguayan Pesos (about \$420 U.S. dollars), which situates our sample in about the second quintile of the national income (mean \$18,900 Uruguayan Pesos). About 40% indicate to be married or have a partner, 29% report to be single, 22% divorced and 9% are widows. Only 43% report to be employed, while the remaining 57% reports to be either housewife (30%), retired (17%) or unemployed (9%). From those working, about 48% contribute to the state-owned Uruguayan social security institute (BPS, *Banco de Prevision Social*).

We use the information in Table 4 to show that our control and treatment groups are similar on a host of observable characteristics. We first conduct tests for joint orthogonality, regressing each treatment arm dummy on the set of covariates from Table 4, as we show in Table 5. For each estimation in columns, we include a row with the p-values of the F-test for joint significance of all balance variables, all of which are 0.578 or higher.

We also conducted individual tests of balance, across control and treatment arms in Table 6, Panels 1 and 2. Each column shows the results of a separate regression of each variable on indicators for treatment arms and a constant. Columns 1 and 2 in Panel 1 show results for the full sample, using as dependent variables age and whether women took the PAP smear within the last 3 years, respectively. Column 3 onwards do the same for the survey sample, for each variable in Table 4. Each regression also includes a formal test of equality of the treatment arm coefficients.

The results show no differences between the treatment and control group that are statistically significant at the 1 percent level, with magnitudes that are small compared to the control mean. Two differences are significant, which is about what we would expect by chance. We compare differences in 17 variables in Table 5, so we expected 1.7 of them to be significant at the 10 percent level due to chance. Women in the treatment arm 3 are more likely to be unemployed ($p=0.05$) and those in arm 2 are more likely to be widows ($p=0.10$). As we show later, conditioning on these covariates does not change our coefficients of interest and serve mainly to improve precision of our estimates, as is customary in well implemented RCTs.

5. Empirical Strategy

This section outlines our empirical strategy to compute intention-to-treat and local average treatment effects.

Intention-to-treat (ITT) Effects. Our main estimating equations are

$$(1) \quad Y = \pi_1 + \mathbf{X}'\gamma_1 + \delta \sum_{j=1}^4 Arm_j + \varepsilon_1$$

$$(2) \quad Y = \pi_2 + \mathbf{X}'\gamma_2 + \sum_{j=1}^4 Arm_j \cdot \alpha_1 (j \leq 2) \cdot \alpha_2 (j > 2) + \varepsilon_2$$

$$(3) \quad Y = \pi_3 + \mathbf{X}'\gamma_3 + \sum_{j=1}^4 \beta_j Arm_j + \varepsilon_3$$

where Y is an outcome variable, Arm_j is an indicator for random assignment to the treatment arm j , $\mathbf{X}$ is a vector of predetermined control variables, $(j \leq 2)$ and $(j > 2)$ are indicator variables, and ε_1 , ε_2 and ε_3 are idiosyncratic error terms.

These equations allow us to test different parameters of interest. Estimating the parameter δ in equation 1 provides us the overall intention-to-treat effect of our intervention. The overall effect is relevant because it tells us whether women randomized to receive our messages had a different behavior compared to a scenario with no intervention. Informed women, with sufficiently low transaction costs associated to appointments, should see no change in their behavior. Otherwise, we expect this parameter to be higher than zero.

We are also particularly interested in the effects of promoting the online appointment system, conditional on the information component in our messages. The estimates of parameters α_1 and

α_2 in equation 2 represent the effects of being randomized to the group that received information plus a link to make appointments, and those who received information and the status-quo encouragement, respectively, vis-à-vis the control group, respectively. We also implement a formal test of equality of the treatment coefficients α_1 and α_2 . We expect α_1 to be higher, as it estimates the effect of reducing transaction costs on top of providing information.

In equation 3 we augment the equation 1 by including separate indicators for each treatment arm to separately identify their effects. Each β_j gives us the average difference on the outcome Y for women randomized to the treatment arm j compared to those randomized to the control group. We also examine differences due to providing different types of information (benefits or risks) in our messages, conditional on receiving the link ($H_0: \beta_1 = \beta_2$) and unconditionally ($H_0: \beta_3 = \beta_4$).

We estimate equations (1) to (3) for both the full sample and the survey sample. Following Bruhn and McKenzie (2009), we control for our randomization method in all our estimations. For the full sample, the vector X includes stratum dummies based on age and time since the last pap. For our survey sample, X includes additional covariates, such as household size, children at home, household income, and marital and occupational status. Given the randomized nature of our treatment assignment, in our setup the inclusion of covariates does not change the estimated coefficients and rather serves to increase precision of our estimates. We report Eicker-Huber-White standard errors for all our estimates.¹⁹

Local Average Treatment Effects (LATEs). The estimation of equations (1)-(3) provides us with intention-to-treat effects. We complement these parameters with the estimation of two set of policy relevant LATEs, taking into account the successful delivery and receipt of the messages.

The messaging system produces the information of whether messages are successfully sent to each of the phone numbers randomized to treatment. These data are available for the full sample. We instrument the successful delivery of messages using random assignment to estimate a first set of LATEs.

We estimate a second set of LATEs for our survey sample. According to the messaging system, the delivery of our messages was successful for all women in this sample. This does not guarantee, however, that messages were opened by recipients. They could save the message the read it later (and forget to do so), delete it before reading, etc. Thus, we went further and

¹⁹ As noted in Section 3, we randomized our intervention at the individual level. If we had randomized a cluster of individuals (like health centers) to treatment instead, then we would need to cluster at that unit level (e.g., the health center level). That is not the case in the present design (see Abadie, Athey, Imbens, & Wooldridge, 2017).

asked survey respondents to acknowledge the receipt of our messages. We instrument the reporting of receiving each type of message using the random assignment.

We conservatively interpret our LATE estimates as upper-bound effects of our intervention because they are going to scale-up our ITT estimates by construction. We for both set of LATEs we use two-stage least squares to estimate:

$$(4) \quad Y = \eta_1 + \mathbf{X}'\theta_1 + \delta_K \sum_{j=1}^4 RM_j + u_1$$

$$(5) \quad Y = \eta_2 + \mathbf{X}'\theta_2 + \sum_{j=1}^4 RM_j \cdot \alpha_{K1}(j \leq 2) \cdot \alpha_{K2}(j > 2) + u_2$$

$$(6) \quad Y = \eta_3 + \mathbf{X}'\theta_3 + \sum_{j=1}^4 \beta_{Kj} RM_j + u_3$$

Where RM_j is defined as whether the message for treatment arm j was sent (i.e., the phone number was not rejected by messaging system), or whether survey respondents report to have received the type j of message and the rest of variables are defined as described above. The parameters of interest are the estimates of δ_K , α_{K1} , α_{K2} and β_{Kj} , where $K=D,R$ for delivery and receipt of messages, respectively. For each equation 4 to 6, we report the corresponding Cragg-Donald (CD, 1993) weak instrument test statistics, which jointly tests the rank of the instruments. With one instrument (as in equation 4), the Cragg-Donald statistic is equivalent to the F-statistic. The CD values are well beyond critical values (see Stock and Yogo, 2005) rejecting that our instruments are weak. In the Appendix, we include the complete first-stage results, confirming that the randomization is strongly correlated with successfully sending (or receiving) each type of message.

6. Results

This section presents our results. Women in the treatment groups significantly increased their probability of both scheduling and attending the appointments vis-à-vis the control group. Our most conservative estimates show the magnitude of the overall effects to be sizable, more than doubling the control groups rates.

One of our key findings is that most of the overall effect is driven by the lower transaction cost component, on top of information and independent of the framing of messages. For women encouraged to make appointments online, the attendance and scheduling rates are about 3.0

times larger than the control group. For those encouraged to schedule appointments as usual, rates are 1.5 times larger than the control group.

This section is organized as follows. First, we document treatment effects on our main outcomes for the full sample of participating women. Then, we study women in our survey sample. For them, we also estimate effects on secondary outcomes, exploring their role as mechanisms driving effects.

6.1. Full Sample

Average Effects. Tables 7 and 8 shows the intention-to-treat (ITT) and LATE estimates for the full sample of 47,600 women randomized to the control group or treatment arms. Both tables present the estimates from equations (1), (2) and (3) on our two main outcomes of interest: scheduling and attending the PAP smear appointments. The difference between effects on these two outcomes is an estimation of declaring intentions versus acting.

The estimates in columns 1 and 4 of Table 7 show the overall ITT effect ($\hat{\delta}$) on each outcome. On average, women in the treatment groups were 3.3 percentage points (pp) more likely to schedule appointments (over a control mean of 2.7 percent) and 2.3 pp more likely to attend (over a control mean of 1.9 percent). These ITT effects represent 122 percent and 121 percent increases over the control group, respectively.

Columns 2 and 5 in Table 7 display the estimates of equation (2), showing that effects are larger for women randomized to receive the lower transaction cost component ($\hat{\alpha}_1$) compared to the status quo encouragement ($\hat{\alpha}_2$), both conditional receiving information. Women in the latter group were 1.3 pp and 1.4 pp more likely than the control group to scheduled appointments and attend the medical visit. When the lower transaction cost is added, the coefficients jump to 5.2 pp and 3.2 pp respectively. The table shows that the differences between these treatment groups are statistically significant (p-value<0.01).

Our design allows us to further decompose effects using the framing of the information sent to women. We report the estimates of equation (3) in columns 3 and 6. The estimates show that when encouraging women to use the online tool, framing the messages as benefits has a higher effect on scheduling than when messages are risk-framed (5.9 pp vs 4.6 pp, p-value=0.01). This differential effect vanishes when we estimate effects on attending the appointments (3.3 pp vs

3.1 pp, $p\text{-value}=0.61$). Benefits-focused messages appear to pique interest but, at the end of the day, are no better than risk messages for getting women to act and attend their appointments.

Our precisely estimated LATEs, reported in Table 8, are about 11% larger than the ITT estimates. The reason is that the first-stage coefficient is about 0.9 and therefore $LATE=ITT/0.9=1.11$ ITT. This result indicates that the effects of our intervention would have been 11 percent higher had the messaging system delivered all messages successfully. We thus think of our ITT effects as providing a lower bound of the effect of our intervention.

Heterogeneity by Time since last PAP Smear and Age Group. We also documented whether treatment effects vary by the time passed since the last PAP smear and age group. The main takeaway is that effects are larger for women in the ‘on-time’ group compared to those in the ‘overdue’ group. In other words, women who took the exam at some point in the last five years appear to be more receptive to our intervention than those who did not take the PAP smear. In addition, our estimated effects are smaller for the oldest women in the ‘overdue’ group.

Effects by on-time vs overdue groups. Table 9 provides the results of estimating equations (1) to (3) on our two main outcomes, separately for the ‘on time’ and ‘overdue’ groups and computes its difference. Columns 1 and 2 show the coefficients from separate regressions on appointment scheduling and columns 4 and 5 do the same for attendance rates. Columns 3 and 6 present the coefficients from fully interacted regressions, indicating the difference between coefficients for the different groups.

A first result is that the relative importance of treatment effects within each group is similar to the pattern for the full sample. However, we also find differences across these groups. The results in the first row indicate that overall effects on both appointments and attendance rates are approximately 1 pp higher for the ‘on-time’ group. This difference is completely driven by the lower transaction cost component, as shown in the second row.

Effects are differential when lower transaction costs are part of the treatment; women with ‘on-time’ status present effects that are 2.6 pp and 1.5 pp higher on appointment scheduling and attendance rates, respectively. For women who are targeted with information and status quo encouragement, the effects remain the same (independent of the framing of the information sent).

Effects appear to be higher for scheduling appointments when combined with benefits information (vs with risks information), but that difference vanishes for attendance rates. Overall, this finding suggests that women more naturally inclined to schedule a PAP smear close to the recommended frequency are also more inclined to take advantage of making appointments online.

Effects by age group within the on-time and overdue groups. Table 10 shows our ITT estimates by age within the on-time (panel 1) and overdue (panel 2) groups. Columns 1 to 4 show the coefficients from separate regressions on appointment scheduling for four age groups: 30-39, 40-49, 50-59 and 60-70. Columns 6 to 9 do the same using attendance rates as the outcome. Column 5 and 10 show the difference between the younger and older groups for both outcomes, from fully interacted regressions.

The magnitude of the coefficients decreases for both scheduling and attendance for the oldest women in the overdue group. When comparing the effects against the respective control group, the effects represent an increase in scheduling ranging from 154 percent to 285 percent, and an increase in attendance ranging from 150 percent to 300 percent. The relative magnitude of the effects increases with age. Effects for women in the 60-70 'overdue' age group are the largest.

6.2. Survey Sample

We now document results for our survey sample. As described before, all women in this sample belong to the 'overdue' group, i.e., they did not take the PAP smear within the last five years. Given a limited budget and their lower rate of PAP take-up, we decided that it was policy relevant to learn more from this group.

Average Effects. Table 11 shows the ITT estimates for our survey sample. The ITT effects are higher than those for all women in the 'overdue' group. In particular, the overall effects ($\hat{\delta}$) on appointment scheduling and attendance are 6.3 and 4.7 percentage points, compared to 2.8 and 1.9 pp for the full overdue group (shown in Table 9), respectively. The data suggests that the control groups of both the survey and overdue groups are similar, because display the same mean for appointments scheduling (1.6 percent) and attendance (1 percent). As before, effects are significantly larger (about twice) on both outcomes for women encouraged to use the online system compared to those encouraged to make appointments at their clinics.

Table 12 shows our second set of LATE estimates, which adjust for compliance rates as measured by respondents recalling receiving our messages. The overall LATE estimates are 10.8 and 8.0 percentage points on appointments and take-up rates. For both sets of ITT and LATE estimates the pattern of treatment effects for surveyed women is similar to results for the full sample. Effects are again larger for women targeted with information plus the lower transaction cost component, followed by women targeted with information and the status quo encouragement. As for the full sample, the framing of the information sent does not have a differential effect on our main outcomes for women in the survey sample.

Exploring Mechanisms

We included a host of questions to explore mechanisms in the endline survey, related to the transaction costs of scheduling appointments, knowledge about the PAP smear and perceptions about public services. Our results suggest that our intervention translated into changes in behavior by making the PAP smear more salient to women and mostly, easing their way to schedule appointments.

Transaction Costs. One component of our intervention targeted transaction costs, easing the process of scheduling appointments. In Table 13 we show estimates on secondary outcomes related to perceptions about appointment scheduling. We asked respondents how they would schedule their appointments and used their answers as dependent variables in columns 1 to 5. In columns 6 and 7, we estimate effects on the respondents' perception on how easy scheduling appointments is.

Those in the treatment groups are more likely to report that they would schedule appointments via Internet (3.7 pp over less than 1 percent in the control group). Consistent with our design, these effects are two times as high for women who were encouraged to use the online system (5.0pp.) compared to those who did not (2.3pp.). This last group did not receive a link to make an appointment but were encouraged to make an appointment at their local clinic. We hypothesize that the message motivated some of them to go online and discover the online tool, which ASSE made available for everyone to sign into.²⁰

²⁰ Another piece of evidence that supports this hypothesis is that no women without the link made appointments through the web system, among those randomized to treatment in the first round (when the online system was not available for everyone).

Another consistent result is that women in the treatment groups are less likely to say they would make an appointment in person. In a similar pattern, those who receive the link to make appointments are 6.3 pp less likely to say they would make appointments in person, which is about a 10 percent decrease compared to the control mean of 73 percent. This result suggests that the online system could help to decongest health services, keeping off people who would otherwise visit the clinic centers to schedule appointments.

The effects for other ways of making appointments, such as phone calls and not knowing how to make appointments are of small magnitude and measured with less precision. With that caveat in mind, the sign of the coefficients is consistent with our intervention, as women randomized to treatment report to be less likely to make appointments by phone call, and less likely to not know how to schedule.

In columns 6 and 7, we show that treated women report that it is easier to schedule appointments compared to those in the control group. The coefficient in column 6, of 0.099, is equivalent to 0.9 standard deviations, as the mean rating in the control group is of 4.11 with a standard deviation of 1.09). Similar to the results for the other secondary outcomes, the magnitude of this effect appears to be higher for those who received the link versus those who did not (0.12 versus 0.077) though we lack statistical power to differentiate both coefficients at conventional levels.

In column 7 we also show that a higher fraction of women reports that is very easy (6.9 pp over 47 percent) to make appointments. These effects tend to be higher for women who received the link to make appointments online (8 pp.) versus those who did not (5.8 pp increase).

Overall, these results suggest that the larger impacts are working through reduction of transactions costs, making easier to schedule appointments which translates into actual behavior later.

Information. The information component of our intervention emphasized the importance of taking the PAP smear to prevent cervical cancer and was also explicit about the mortality risk of not taking the test. In Table 14 we present estimate effects of our intervention on knowledge and perceptions about the PAP smear.

Columns (1) to (4) show estimates effects on the perception of how important the PAP is and whether it saves lives. The results indicate that independent of treatment status, women perceive the PAP smear to be very important and that most of them believe that taking the test can save

lives. All coefficients are non-significant at conventional levels, and their magnitude is very small relative to the control mean. For example, women in the control group rate the importance of the PAP with 4.7 on a 1.0 to 5.0 scale, and 78 percent report the PAP to be very important (value 5.0 on the 1.0-5.0 scale). Similarly, when asked to rate whether the PAP could save lives, women in the control group report a mean of 4.5 in the 1.0-5.0 scale; and 73 percent report to believe that the PAP smear would definitely save lives (value 5 on the 1.0 to 5.0 scale).

In the next columns (5) to (8) we include estimates on additional variables related to PAP knowledge. As for the previous variables, the results show zero effects. Essentially women in the control group report to know the PAP (98 percent), 73 percent indicate they know that the PAP is free, most are aware they can take off one day of work to take the test (92 percent); and 79 percent reports to believe that they should take the PAP smear every year.

These results suggest that the information component in our messages did not provide additional knowledge to women. This finding implies that information does not play a main role behind our treatment effects. We hypothesize that rather than providing new information, our messages brought the PAP exam to their minds, encouraging women to take the test.

Perceptions about Public Services. We also explore whether our intervention had effects beyond the content of the messages (i.e., beyond information and transactions costs). The hypothesis is that by contacting users, our intervention could have improved women's perception about health public services and the government, which in turn could mediate some of our main treatment effects.

Our results, in Table 15, show small and non-significant effects on women's perception about public services' quality or safety, nor on the confidence users have on ASSE services or whether they believe that the government cares about them.

Women rated the quality of ASSE services with a 3.9 out of 5, and almost 70 percent indicated that the quality was high or very high. In addition, we show that women reported to have high or very high confidence in ASSE (65 percent). Results in columns 1 to 4 show that there are non-detectable differences by treatment status on these secondary outcomes. We also asked women to rate how safe they perceive the electronic public services. They rate safety with a 3 in the 1-5 scale and 54 percent believe that those services are safe or very safe to use. Columns 5 and 6 show that the estimates on these outcomes are indistinguishable from zero at conventional

significance levels. We finally asked more generally whether the government cares about them. They rated the government care a bit lower (3 in a 1-5 scale), with 40% reporting to believe the government really cares (the high or very high categories), with no distinguishable variation by treatment status. These estimates suggest the treatment effects on our main outcomes are not driven by enhanced perceptions about ASSE or the government.

Overall, the results from exploring mechanisms suggest that the reduction of transactions costs related to appointments is the major driver behind our treatment effects on women's behavior.

Heterogeneity

We finally study heterogeneous treatment effects by women's characteristics that are invariant to our intervention. Table 16 present results by age, education, income, and household size and composition (proxied by whether children live at home), while Table 17 includes estimates by frequency of Internet use, use of cell phone to connect and commuting time from home to the local clinic center.

Panels in Tables 16 and 17 show ITT estimates from separate regressions by subgroup on PAP appointments (columns 1 and 2) and attendance rates (columns 4 and 5). We divide women in sub-groups using the corresponding sample median. For example, women are in the older group if their age is equal or higher than the sample median and in the younger group if not. All the individual coefficients reported in these columns are statistically significant. In columns 3 and 6, we report the difference between these subgroup effects, computed from fully interacted regressions.

The main takeaway is that we find heterogeneous effects on scheduling appointments, but these shrink and are not statistically distinguishable from zero when examining appointment attendance rates.

ITT effects on scheduling appointments tend to be higher for younger women, for those who are more educated or have higher income levels, and for women living in more numerous households or with children. Effects are also higher for women who reported using internet with higher frequency, those who use their cell phone to connect, and for women living closer to the health center.

7. Conclusions

The low take-up of social benefits via public service is a puzzling empirical regularity (Blanco and Vargas 2013, Muralidharan et al 2020), and increasing the take-up could benefit billions of people (World Bank, 2003). This issue becomes critical in particular regarding health in developing countries, because absence of preventive health behaviors can lead to increased mortality rates (Dupas, 2011).

In this paper we address this problem combining an investment in digital state capacity with behavioral nudges, aiming to increase the demand for an important preventive health care services: cervical cancer screening. We partnered with the Government in Uruguay to design and implement an online appointment system. We then conducted a field experiment at scale with 47,600 participating women, randomized to a pure control group and four treatment arms. Our intervention encouraged women to either schedule via the online system or to make appointments as usual, with either benefits- or risk-framed informative messages.

Our main empirical results show that women in the four treatment arms make and attend appointments at a substantially higher rate (between 2-3 times) than their counterparts in the pure control group. Our results by treatment arms show that the effects are driven by both the salience of our intervention and by the reduction in transaction costs generated by the online system.

These findings complement recent studies assessing the use of technology to improve state capacity in developing countries (Muralidharan et al., 2016, Callen et al 2020, Muralidharan, et al 2020a, 2020b), and the literature pointing to the importance of salience effects in many policy contexts (family health behaviors, Fadlon and Nielsen, 2019; energy consumption, Allcott and Taubinsky, 2015; and taxation, Farhi and Gabaix, 2020; to name a few).

Finally, our results have direct and relevant policy implications. In a context with rapid advances of technology, governments are developing the capacity to store and use abundant data. Investing in digital government tools and complementing them with interventions that improve “last-mile” delivery might generate the most meaningful impacts on the take-up of social benefits.

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APPENDIX

Table A. A cross-cutting Experimental Design

		Intervention A (information)	
		No	Yes
Intervention B (encouragement)	No	Control	Arm 1
	Yes	Arm 2	Arm 3

Note: In a cross-cutting design, the interaction of two interventions A and B, would result in four groups: no interventions (*pure control*); A only; B only; and A and B together. In our case, each of the four treatment arms and the pure control group are individually defined ex-ante and not the result of interacting two interventions, as we show in Table 1 in the text.

Table 1: Treatment Arms, by Component

Appointment Encouraged to be made:	Information on:	
	Benefits	Risks
Online (Lower Transaction Cost Component)	Arm 1	Arm 2
At Health Center (Status Quo Component)	Arm 3	Arm 4

Notes: [Table 1](#) shows the content of the behaviorally informed messages in our treatment arms. We sent information on benefits taking and risk of taking the PAP smear (in columns), and encouraged women to make appointments using our online system or as usual at their local health center (in rows).

Table 2: Number of Eligible Women by Randomization Status

Status	(1)	Time Since Last PAP smear	
	All	(2) On-Time (< 5 years)	(3) Overdue (≥ 5 years)
Treatment	22,800	11,400	11,400
Arm 1	5,700	2,850	2,850
Arm 2	5,700	2,850	2,850
Arm 3	5,700	2,850	2,850
Arm 4	5,700	2,850	2,850
Control	24,800	12,400	12,400
All Participating Women	47,600	23,800	23,800
Refreshment	11,200	6,500	4,700
All Eligible Women	58,800	30,300	28,500

Notes: [Table 2](#) shows the number of eligible women randomized to treatment (and each treatment arm), control, and a refreshment sample.

Table 3: Descriptive Statistics, Full Sample

Variable	(1) Observations	(2) Mean	(3) Std. Dev.	(4) Min	(5) Max
Age	47,600	48.56	11.34	30.41	69.90
No PAP taken in last 3 years	47,600	0.60	0.49	0.00	1.00
No PAP taken in last 5 years	47,600	0.50	0.50	0.00	1.00
Years since last PAP appointment	23,800	1.79	1.33	0.01	5.00
Control Group	47,600	0.52	0.50	0.00	1.00
Treatment:					
Benef. Info. + Lower Transaction Cost	47,600	0.12	0.32	0.00	1.00
Risks Info. + Lower Transaction Cost	47,600	0.12	0.32	0.00	1.00
Benef. Info. + Status Quo	47,600	0.12	0.32	0.00	1.00
Risks Info. + Status Quo	47,600	0.12	0.32	0.00	1.00

Notes: [Table 3](#) shows descriptive statistics using administrative information for the full sample of women participating in our experiment. By design, the variable 'Years since last PAP' is available for the half of the sample, i.e., women who had taken the PAP smear within the last 5 years.

Table 4: Descriptive Statistics, Survey Sample

Variable	(1) Observations	(2) Mean	(3) Std. Dev.	(4) Min	(5) Max
Administrative Information					
Age	2,462	51.14	11.49	30.42	69.89
No PAP taken in last 5 years	2,462	1.00	0.00	1.00	1.00
Control Group	2,462	0.20	0.40	0.00	1.00
Treatment:					
Benef. Info. + Lower Transaction Cost	2,462	0.20	0.40	0.00	1.00
Risks Info. + Lower Transaction Cost	2,462	0.20	0.40	0.00	1.00
Benef. Info. + Status Quo	2,462	0.20	0.40	0.00	1.00
Risks Info. + Status Quo	2,462	0.20	0.40	0.00	1.00
Survey Demographics					
Years of Schooling	2,462	8.69	3.62	3.00	17.00
Husband/partner Schooling	980	8.37	3.43	3.00	17.00
Household Size	2,462	3.24	1.80	1.00	17.00
At least one child (age 14 or less)	2,462	0.38	0.49	0.00	1.00
Household Income	2,462	18.4	11.7	5	55
Marital Status:					
Married/Partner	2,462	0.40	0.49	0.00	1.00
Single	2,462	0.29	0.46	0.00	1.00
Divorced	2,462	0.22	0.42	0.00	1.00
Widow	2,462	0.09	0.28	0.00	1.00
Occupation:					
Employed	2,462	0.43	0.50	0.00	1.00
Housewife	2,462	0.30	0.46	0.00	1.00
Retired	2,462	0.17	0.38	0.00	1.00
Unemployed	2,462	0.09	0.28	0.00	1.00
Contributing to BPS	996	0.48	0.50	0.00	1.00

Notes: Table 4 shows descriptive statistics for the 2,462 women surveyed at endline, using administrative and survey information. No women in this sample took the PAP smear within the 5 last years. The husband/partner schooling is available for those who report to be married or have a partner, which is about 40% of the sample (n=980). The variable 'at least one child' reports the fraction of women living in a household with at least one child aged 14 or younger. The household income is reported in a monthly basis, and is expressed in thousands of Uruguayan Pesos (URU\$). The mean of 18,400 URU\$ equals to 433 US\$, approximately. The dichotomous variables under 'Marital Status' and 'Occupation' add to 100%, respectively. The last variable 'Contributing to BPS' refers to the fraction of women who report to contribute to the state-owned Uruguayan social security institute BPS (*Banco de Prevision Social*).

Table 5: Balance, Joint Test

	(1)	(2)	(3)	(4)
	Arm 1	Arm 2	Arm 3	Arm 4
Age	-0.000 (0.001)	-0.001 (0.001)	0.000 (0.001)	0.000 (0.001)
Years of Schooling	-0.000 (0.003)	0.001 (0.003)	-0.001 (0.002)	-0.001 (0.002)
Household Size	-0.002 (0.005)	-0.003 (0.006)	0.002 (0.006)	-0.002 (0.006)
At least one child (age 14 or less)	0.013 (0.021)	0.003 (0.022)	0.000 (0.022)	-0.005 (0.022)
Household Income	-0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)
Single	-0.009 (0.174)	-0.022 (0.179)	0.015 (0.181)	-0.004 (0.181)
Married/Partner	-0.016 (0.174)	-0.008 (0.178)	-0.019 (0.181)	-0.003 (0.181)
Divorced	-0.027 (0.174)	0.026 (0.179)	0.005 (0.181)	-0.018 (0.181)
Partner	0.046 (0.029)	0.002 (0.028)	0.018 (0.027)	-0.011 (0.028)
Widow	-0.016 (0.176)	0.074 (0.181)	0.001 (0.182)	-0.022 (0.182)
Employed	-0.031 (0.072)	0.026 (0.069)	-0.066 (0.078)	-0.108 (0.081)
Housewife	-0.007 (0.073)	0.017 (0.071)	-0.061 (0.080)	-0.112 (0.082)
Retired	0.004 (0.075)	0.006 (0.072)	-0.067 (0.081)	-0.136 (0.084)
Unemployed	-0.060 (0.076)	0.051 (0.074)	-0.127 (0.081)	-0.048 (0.086)
Constant	0.269 (0.200)	0.208 (0.201)	0.250 (0.205)	0.304 (0.206)
F-Test	0.669	0.578	0.787	0.782
Mean Dep. Variable	0.120	0.120	0.120	0.120
Observations	2,462	2,462	2,462	2,462
Sample	Survey	Survey	Survey	Survey

Notes: Table 5 shows the results of four separate regressions (in columns). Each column shows the estimation of a regression of the treatment arm dummy on the set of covariates from Table 4. For each estimation in columns, we include a row with the p-values of the F-test for joint significance of all balance variables, all of which are 0.578 or higher. Robust standard errors are in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level respectively.

Table 6: Balance, Individual Tests**Panel 1**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Age	No PAP Last 3 Years	Age	Schooling	Husband Schooling	HH Size	HH Children	HH Income(b)
$\hat{\beta}_1$: Benef. Info. + Lower Transaction Cost	-0.097 (0.167)	-0.001 (0.007)	-0.588 (0.737)	-0.206 (0.235)	-0.187 (0.342)	-0.011 (0.111)	0.028 (0.031)	-0.871 (0.727)
$\hat{\beta}_2$: Risks Info. + Lower Transaction Cost	0.069 (0.167)	-0.004 (0.007)	-0.449 (0.720)	0.042 (0.239)	-0.527 (0.358)	-0.079 (0.116)	0.010 (0.031)	0.217 (0.772)
$\hat{\beta}_3$: Benef. Info. + Status Quo	-0.113 (0.167)	0.004 (0.007)	-0.248 (0.731)	-0.092 (0.233)	0.194 (0.354)	-0.015 (0.113)	0.014 (0.031)	0.042 (0.743)
$\hat{\beta}_4$: Risks Info. + Status Quo	0.041 (0.167)	0.004 (0.007)	-0.477 (0.720)	-0.053 (0.238)	-0.553 (0.342)	-0.049 (0.114)	0.002 (0.031)	0.060 (0.773)
Control Mean	48.576	0.603	51.494	8.752	8.589	3.275	0.373	18.534
Observations	47,600	47,600	2,462	2,462	980	2,462	2,462	2,462
Test: $\hat{\beta}_1 = \hat{\beta}_2 = \hat{\beta}_3 = \hat{\beta}_4$ (p-value)	0.765	0.789	0.975	0.749	0.110	0.930	0.868	0.400
Sample	Full	Full	Survey	Survey	Survey	Survey	Survey	Survey

Panel 2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Married	Single	Divorced	Widow	Employed	Housewife	Unemployed	Retired	Contributing to BPS
$\hat{\beta}_1$: Benef. Info. + Lower Transaction Cost	-0.001 (0.031)	-0.002 (0.029)	-0.017 (0.026)	0.020 (0.017)	-0.035 (0.031)	0.040 (0.029)	-0.018 (0.017)	0.001 (0.025)	-0.009 (0.050)
$\hat{\beta}_2$: Risks Info. + Lower Transaction Cost	-0.036 (0.031)	-0.030 (0.028)	0.022 (0.027)	0.044** (0.018)	-0.003 (0.032)	-0.001 (0.029)	0.008 (0.018)	-0.013 (0.024)	0.021 (0.049)
$\hat{\beta}_3$: Benef. Info. + Status Quo	-0.040 (0.031)	0.014 (0.029)	0.006 (0.027)	0.020 (0.017)	-0.003 (0.032)	0.022 (0.029)	-0.028* (0.017)	-0.007 (0.024)	0.066 (0.049)
$\hat{\beta}_4$: Risks Info. + Status Quo	-0.015 (0.031)	0.011 (0.029)	-0.006 (0.026)	0.010 (0.017)	-0.014 (0.032)	0.006 (0.029)	0.021 (0.019)	-0.032 (0.024)	0.028 (0.049)
Control Mean	0.414	0.295	0.221	0.068	0.444	0.283	0.090	0.181	0.457
Observations	2,462	2,462	2,462	2,462	2,462	2,462	2,462	2,462	996
Test: $\hat{\beta}_1 = \hat{\beta}_2 = \hat{\beta}_3 = \hat{\beta}_4$ (p-value)	0.564	0.412	0.514	0.345	0.702	0.500	0.021	0.561	0.535
Sample	Survey	Survey	Survey	Survey	Survey	Survey	Survey	Survey	Survey

Notes: Table 6 shows balance across the control and treatment arms. The columns show separate regressions of the covariates in Table 4 as dependent variables on treatment arm indicators and a constant. Robust standard errors are in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level respectively.

Table 7: ITT Estimates for the Full Sample

	Scheduling			Attendance		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\delta}$: Treatment	0.033*** (0.002)			0.023*** (0.002)		
$\widehat{\alpha}_1$: Info. + Lower Trans. Cost		0.052*** (0.003)			0.032*** (0.002)	
$\widehat{\alpha}_2$: Info. + Status Quo		0.013*** (0.002)			0.014*** (0.002)	
$\widehat{\beta}_1$: Benef. Info. + Lower Trans. Cost			0.059*** (0.004)			0.033*** (0.003)
$\widehat{\beta}_2$: Risks Info. + Lower Trans. Cost			0.046*** (0.004)			0.031*** (0.003)
$\widehat{\beta}_3$: Benef. Info. + Status Quo			0.014*** (0.003)			0.015*** (0.003)
$\widehat{\beta}_4$: Risks Info. + Status Quo			0.013*** (0.003)			0.013*** (0.002)
$H_0 : \widehat{\alpha}_1 = \widehat{\alpha}_2$		0.000			0.000	
$H_0 : \widehat{\beta}_1 = \widehat{\beta}_2$			0.009			0.615
$H_0 : \widehat{\beta}_3 = \widehat{\beta}_4$			0.902			0.538
Observations	47,600	47,600	47,600	47,600	47,600	47,600
Control Group Mean	0.027	0.027	0.027	0.019	0.019	0.019
Sample	Full	Full	Full	Full	Full	Full
Strata	Yes	Yes	Yes	Yes	Yes	Yes

Notes: [Table 7](#) shows the intention-to-treat results from estimating equations (1), (2) and (3) for the full sample of women participating in our study. In columns 1 to 3, the dependent variable is an indicator for whether women made a PAP appointment. In columns 4 to 6, the dependent variable is an indicator for whether women attended the PAP appointment. In columns 1 and 4, we include a single treatment indicator equal to one if women were randomized to any treatment arm. In columns 2 and 4, we include a separate indicator for whether women were randomized to received information plus online encouragement, and those who received information and status-quo encouragement, respectively. In columns 3 and 6 we included a separate indicator for each of the four treatment arms. The lower panel displays the p-values of F-tests for the differences between treatment parameters. All regressions control for our randomization method, by including stratum dummies based on age and time since the last pap. Robust standard errors are in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level respectively.

Table 8: LATE Estimates for the Full Sample

	Scheduling			Attendance		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\delta}_D$: Treatment	0.037*** (0.002)			0.026*** (0.002)		
$\widehat{\alpha}_{D1}$: Info. + Lower Trans. Cost		0.059*** (0.003)			0.036*** (0.002)	
$\widehat{\alpha}_{D2}$: Info. + Status Quo		0.015*** (0.002)			0.016*** (0.002)	
$\widehat{\beta}_{D1}$: Benef. Info. + Lower Trans. Cost			0.066*** (0.004)			0.037*** (0.003)
$\widehat{\beta}_{D2}$: Risks Info. + Lower Trans. Cost			0.051*** (0.004)			0.035*** (0.003)
$\widehat{\beta}_{D3}$: Benef. Info. + Status Quo			0.015*** (0.003)			0.017*** (0.003)
$\widehat{\beta}_{D4}$: Risks Info. + Status Quo			0.015*** (0.003)			0.015*** (0.003)
$H_0 : \widehat{\alpha}_{D1} = \widehat{\alpha}_{D2}$		0.000			0.000	
$H_0 : \widehat{\beta}_{D1} = \widehat{\beta}_{D2}$			0.010			0.632
$H_0 : \widehat{\beta}_{D3} = \widehat{\beta}_{D4}$			0.892			0.529
Observations	47,600	47,600	47,600	47,600	47,600	47,600
Control Group Mean	0.027	0.027	0.027	0.019	0.019	0.019
Sample	Full	Full	Full	Full	Full	Full
Strata	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage Cragg-Donald Statistic	212,044	106,009	52,987	212,044	106,009	52,987

Notes: Table 8 shows LATE results, from estimating equations (4), (5) and (6) for the full sample of women participating in our study. We instrumented the successful delivery of messages with random assignment. About 90% of all messages within each treatment arm was successfully delivered. No messages were delivered to women in the control group. In columns 1 to 3 the dependent variable is an indicator for whether women made a PAP appointment. In columns 1 and 4, we include a single treatment indicator equal to one if women were randomized to any treatment arm. In columns 2 and 4, we include a separate indicator for whether women were randomized to received information plus online encouragement, and those who received information and status-quo encouragement, respectively. In columns 3 and 6 we included a separate indicator for each of the four treatment arms. The lower panel displays the p-values of F-tests for the differences between treatment parameters. All regressions control for our randomization method, by including stratum dummies based on age and time since the last pap. The bottom row reports the Cragg-Donald (1993) weak instrument test statistics, which jointly tests the rank of the instruments. With one instrument, the Cragg-Donald statistic is equivalent to the F-statistic. The values are well beyond critical values (see Stock and Yogo, 2005) so we reject that our instruments are weak. Robust standard errors are in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level respectively.

Table 9: ITT Estimates for the On-time and Overdue groups, Full Sample

Coefficient	Scheduling			Attendance		
	(1) On-Time	(2) Overdue	(3) Difference (1)-(2)	(4) On-Time	(5) Overdue	(6) Difference (4)-(5)
$\hat{\delta}$: Treatment	0.038*** (0.003)	0.028*** (0.002)	0.010*** (0.004)	0.027*** (0.003)	0.019*** (0.002)	0.008** (0.003)
$\hat{\alpha}_1$: Info. + Lower Transaction Cost	0.065*** (0.004)	0.039*** (0.003)	0.026*** (0.005)	0.039*** (0.004)	0.025*** (0.003)	0.015*** (0.004)
$\hat{\alpha}_2$: Info. + Status Quo	0.011*** (0.003)	0.016*** (0.003)	-0.005 (0.004)	0.015*** (0.003)	0.014*** (0.002)	0.002 (0.004)
$\hat{\beta}_1$: Benef. Info. + Lower Transaction Cost	0.077*** (0.006)	0.041*** (0.004)	0.036*** (0.008)	0.040*** (0.005)	0.026*** (0.004)	0.013** (0.006)
$\hat{\beta}_2$: Risks Info. + Lower Transaction Cost	0.054*** (0.006)	0.038*** (0.004)	0.016** (0.007)	0.039*** (0.005)	0.023*** (0.003)	0.016*** (0.006)
$\hat{\beta}_3$: Benef. Info. + Status Quo	0.011** (0.004)	0.016*** (0.003)	-0.005 (0.006)	0.016*** (0.004)	0.015*** (0.003)	0.001 (0.005)
$\hat{\beta}_4$: Risks Info. + Status Quo	0.011** (0.004)	0.016*** (0.003)	-0.005 (0.006)	0.014*** (0.004)	0.012*** (0.003)	0.002 (0.005)
$H_0 : \hat{\alpha}_1 = \hat{\alpha}_2$:	0.000	0.000		0.000	0.000	
$H_0 : \hat{\beta}_1 = \hat{\beta}_2$:	0.004	0.643		0.926	0.472	
$H_0 : \hat{\beta}_3 = \hat{\beta}_4$:	0.975	0.879		0.758	0.545	
Observations	23,800	23,800		23,800	23,800	
Control Group Mean	0.038	0.016		0.027	0.010	

Notes: Table 9 shows the intention-to-treat results, from estimating equations (1), (2) and (3) for women in the on-time group (columns 1 and 4) and the overdue group (columns 2 and 5), respectively. Columns 3 and 6 display the coefficients from fully interacted regressions, indicating the difference between coefficients by subgroups. Outcomes are the same as described in Table 7. The lower panel displays the p-values of F-tests for the differences between treatment parameters. All regressions control for age stratum dummies. Robust standard errors are in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level respectively.

Table 10: ITT Estimates by Age and On-time and Overdue groups, Full Sample**Panel 1: On-Time Group**

Coefficient	Scheduling					Attendance				
	(1) Age [30,40)	(2) Age [40,50)	(3) Age [50,60)	(4) Age [60,70]	(5) Dif. 1-4	(6) Age [30,40)	(7) Age [40,50)	(8) Age [50,60)	(9) Age [60,70]	(10) Dif. 6-10
$\hat{\delta}$: Treatment	0.032*** (0.006)	0.039*** (0.006)	0.041*** (0.006)	0.043*** (0.006)	-0.010 (0.009)	0.020*** (0.005)	0.030*** (0.005)	0.030*** (0.005)	0.032*** (0.006)	-0.011 (0.007)
$\hat{\alpha}_1$: Info. + Lower Trans. Cost	0.060*** (0.008)	0.069*** (0.008)	0.065*** (0.009)	0.068*** (0.010)	-0.008 (0.013)	0.031*** (0.007)	0.044*** (0.007)	0.041*** (0.007)	0.045*** (0.008)	-0.014 (0.011)
$\hat{\alpha}_2$: Info. + Status Quo	0.005*** (0.006)	0.008*** (0.006)	0.018*** (0.007)	0.018*** (0.007)	-0.014 (0.009)	0.010*** (0.006)	0.017*** (0.006)	0.018*** (0.006)	0.019*** (0.007)	-0.009 (0.009)
$\hat{\beta}_1$: Benef. Info. + Lower Trans. Cost	0.071*** (0.011)	0.082*** (0.012)	0.078*** (0.013)	0.078*** (0.014)	-0.007 (0.015)	0.022*** (0.008)	0.047*** (0.010)	0.047*** (0.010)	0.050*** (0.012)	-0.028** (0.013)
$\hat{\beta}_2$: Risks Info. + Lower Trans. Cost	0.049*** (0.011)	0.057*** (0.011)	0.052*** (0.011)	0.058*** (0.013)	-0.009 (0.015)	0.040*** (0.009)	0.040*** (0.009)	0.036*** (0.010)	0.040*** (0.011)	0.000 (0.013)
$\hat{\beta}_3$: Benef. Info. + Status Quo	-0.001*** (0.008)	0.008*** (0.008)	0.020*** (0.009)	0.026*** (0.010)	-0.027* (0.015)	0.005*** (0.007)	0.017*** (0.008)	0.024*** (0.009)	0.025*** (0.010)	-0.020 (0.013)
$\hat{\beta}_4$: Risks Info. + Status Quo	0.010*** (0.009)	0.008*** (0.008)	0.015*** (0.009)	0.011*** (0.008)	-0.001 (0.014)	0.015*** (0.008)	0.016*** (0.008)	0.013*** (0.008)	0.013*** (0.008)	0.002 (0.012)
Test: $\hat{\alpha}_1 = \hat{\alpha}_2$: p-Value	0.000	0.000	0.000	0.000		0.006	0.001	0.010	0.008	
Test: $\hat{\beta}_1 = \hat{\beta}_2$: p-Value	0.129	0.110	0.117	0.290		0.122	0.567	0.420	0.514	
Test: $\hat{\beta}_3 = \hat{\beta}_4$: p-Value	0.292	0.963	0.639	0.238		0.290	0.938	0.304	0.299	
Observations	7,378	7,055	5,556	3,811		7,378	7,055	5,556	3,811	
Control Group Mean	0.049	0.042	0.032	0.019		0.035	0.029	0.025	0.015	

Panel 2: Overdue Group

Coefficient	Scheduling					Attendance				
	(1) Age [30,40)	(2) Age [40,50)	(3) Age [50,60)	(4) Age [60,70]	(5) Dif. 1-4	(6) Age [30,40)	(7) Age [40,50)	(8) Age [50,60)	(9) Age [60,70]	(10) Dif. 6-10
$\hat{\delta}$: Treatment	0.034*** (0.005)	0.031*** (0.005)	0.026*** (0.005)	0.020*** (0.003)	0.013** (0.006)	0.023*** (0.004)	0.018*** (0.004)	0.020*** (0.004)	0.015*** (0.003)	0.009* (0.005)
$\hat{\alpha}_1$: Info. + Lower Trans. Cost	0.044*** (0.007)	0.048*** (0.007)	0.041*** (0.007)	0.026*** (0.005)	0.018** (0.008)	0.027*** (0.005)	0.027*** (0.006)	0.028*** (0.006)	0.018*** (0.004)	0.009 (0.007)
$\hat{\alpha}_2$: Info. + Status Quo	0.024*** (0.006)	0.014*** (0.005)	0.011*** (0.005)	0.014*** (0.004)	0.009 (0.007)	0.020*** (0.005)	0.010*** (0.004)	0.013*** (0.005)	0.011*** (0.003)	0.009 (0.006)
$\hat{\beta}_1$: Benef. Info. + Lower Trans. Cost	0.028*** (0.008)	0.060*** (0.011)	0.043*** (0.009)	0.034*** (0.007)	-0.007 (0.010)	0.016*** (0.006)	0.035*** (0.008)	0.029*** (0.008)	0.026*** (0.006)	-0.010 (0.008)
$\hat{\beta}_2$: Risks Info. + Lower Trans. Cost	0.060*** (0.010)	0.037*** (0.009)	0.038*** (0.009)	0.017*** (0.006)	0.043*** (0.010)	0.037*** (0.008)	0.018*** (0.007)	0.026*** (0.008)	0.010*** (0.005)	0.027*** (0.008)
$\hat{\beta}_3$: Benef. Info. + Status Quo	0.029*** (0.008)	0.018*** (0.008)	0.013*** (0.007)	0.005*** (0.004)	0.024** (0.010)	0.026*** (0.007)	0.015*** (0.007)	0.014*** (0.006)	0.003*** (0.003)	0.023*** (0.008)
$\hat{\beta}_4$: Risks Info. + Status Quo	0.018*** (0.008)	0.009*** (0.007)	0.010*** (0.007)	0.024*** (0.007)	-0.006 (0.010)	0.013*** (0.006)	0.005*** (0.005)	0.011*** (0.006)	0.019*** (0.006)	-0.006 (0.008)
Test: $\hat{\alpha}_1 = \hat{\alpha}_2$: p-Value	0.016	0.000	0.000	0.056		0.328	0.011	0.027	0.186	
Test: $\hat{\beta}_1 = \hat{\beta}_2$: p-Value	0.012	0.084	0.716	0.058		0.034	0.096	0.773	0.037	
Test: $\hat{\beta}_3 = \hat{\beta}_4$: p-Value	0.321	0.358	0.736	0.012		0.150	0.204	0.721	0.013	
Observations	6,279	5,768	5,520	6,233		6,279	5,768	5,520	6,233	
Control Group Mean	0.022	0.018	0.016	0.007		0.013	0.012	0.011	0.005	

Notes: Table 10 shows the intention-to-treat results, from estimating equations (1), (2) and (3) by age groups for women in the on-time group (panel 1) and the overdue group (panel 2), respectively. In each panel, columns 1 to 4 show the coefficients from separate regressions on appointments scheduling for four age groups: 30-39, 40-49, 50-59 and 60-70. Columns 6 to 9 do the same using attendance rates as the outcome. Column 5 and 10 show the difference between the youngest and oldest groups for both outcomes, from fully interacted regressions. Robust standard errors are in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level respectively.

Table 11: ITT Estimates for the Survey Sample

	Scheduling			Attendance		
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\delta}$: Treatment	0.064*** (0.008)			0.047*** (0.007)		
$\hat{\alpha}_1$: Info. + Lower Trans. Cost		0.087*** (0.011)			0.059*** (0.009)	
$\hat{\alpha}_2$: Info. + Status Quo		0.040*** (0.009)			0.035*** (0.008)	
$\hat{\beta}_1$: Benef. Info. + Lower Trans. Cost			0.089*** (0.015)			0.059*** (0.013)
$\hat{\beta}_2$: Risks Info. + Lower Trans. Cost			0.085*** (0.015)			0.059*** (0.012)
$\hat{\beta}_3$: Benef. Info. + Status Quo			0.043*** (0.012)			0.039*** (0.011)
$\hat{\beta}_4$: Risks Info. + Status Quo			0.037*** (0.012)			0.030*** (0.010)
$H_0 : \hat{\alpha}_1 = \hat{\alpha}_2$		0.000			0.021	
$H_0 : \hat{\beta}_1 = \hat{\beta}_2$			0.827			0.992
$H_0 : \hat{\beta}_3 = \hat{\beta}_4$			0.659			0.521
Observations	2,462	2,462	2,462	2,462	2,462	2,462
Control Group Mean	0.016	0.016	0.016	0.010	0.010	0.010
Sample	Survey	Survey	Survey	Survey	Survey	Survey
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table 11 shows the intention-to-treat results, from estimating equations (1), (2) and (3) for our survey sample. In columns 1 to 3, the dependent variable is an indicator for whether women made a PAP appointment. In columns 4 to 6, the dependent variable is an indicator for whether women attended the PAP appointment. In columns 1 and 4, we include a single treatment indicator equal to one if women were randomized to any treatment arm. In columns 2 and 4, we include a separate indicator for whether women were randomized to received information plus online encouragement, and those who received information and status-quo encouragement, respectively. In columns 3 and 6 we included a separate indicator for each of the four treatment arms. The lower panel displays the p-values of F-tests for the differences between treatment parameters. All regressions control for age and the set of demographics displayed in Table 4. Robust standard errors are in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level respectively.

Table 12: LATE Estimates for the Survey Sample

	Scheduling			Attendance		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\delta}_R$: Treatment	0.108*** (0.014)			0.080*** (0.012)		
$\widehat{\alpha}_{R1}$: Info. + Lower Trans. Cost		0.146*** (0.019)			0.099*** (0.016)	
$\widehat{\alpha}_{R2}$: Info. + Status Quo		0.070*** (0.016)			0.060*** (0.013)	
$\widehat{\beta}_{R1}$: Benef. Info. + Lower Trans. Cost			0.134*** (0.023)			0.088*** (0.019)
$\widehat{\beta}_{R2}$: Risks Info. + Lower Trans. Cost			0.155*** (0.026)			0.107*** (0.022)
$\widehat{\beta}_{R3}$: Benef. Info. + Status Quo			0.068*** (0.019)			0.061*** (0.016)
$\widehat{\beta}_{R4}$: Risks Info. + Status Quo			0.066*** (0.021)			0.054*** (0.018)
$H_0 : \widehat{\alpha}_{R1} = \widehat{\alpha}_{R2}$		0.000			0.023	
$H_0 : \widehat{\beta}_{R1} = \widehat{\beta}_{R2}$			0.522			0.494
$H_0 : \widehat{\beta}_{R3} = \widehat{\beta}_{R4}$			0.940			0.769
Observations	2,462	2,462	2,462	2,462	2,462	2,462
Control Group Mean	0.027	0.027	0.027	0.019	0.019	0.019
Sample	Full	Full	Full	Full	Full	Full
Strata	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage Cragg-Donald Statistic	721	361	188	721	361	188

Notes: Table 12 shows LATE results, from estimating equations (4), (5) and (6) for our survey sample. We instrumented the receipt of messages (as reported in the survey) with random assignment. On average about 60% of women in the treatment arms and a 1.6% of those in the control group report to have received messages. In columns 1 to 3 the dependent variable is an indicator for whether women made a PAP appointment. In columns 1 and 4, we include a single treatment indicator equal to one if women were randomized to any treatment arm. In columns 2 and 4, we include a separate indicator for whether women were randomized to received information plus online encouragement, and those who received information and status-quo encouragement, respectively. In columns 3 and 6 we included a separate indicator for each of the four treatment arms. The lower panel displays the p-values of F-tests for the differences between treatment parameters. All regressions control for age and the set of demographics displayed in Table 4. The bottom row reports the Cragg-Donald (1993) weak instrument test statistics, which jointly tests the rank of the instruments. With one instrument, the Cragg-Donald statistic is equivalent to the F-statistic. The values are well beyond critical values (see Stock and Yogo, 2005) so we reject that our instruments are weak. Robust standard errors are in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level respectively.

Table 13: ITT Effects on Perceptions about Appointment Scheduling

	How would you schedule an appointment?:					How easy is scheduling?:	
	(1) Via Internet	(2) In Person	(3) By Phone	(4) Other Way	(5) Do not know	(6) On a 1-5 Scale	(7) Very Easy (Value 5)
$\widehat{\delta}$: Treatment	0.037*** (0.006)	-0.041* (0.022)	-0.014 (0.016)	0.007 (0.008)	-0.009 (0.015)	0.099* (0.055)	0.069*** (0.025)
$\widehat{\alpha}_1$: Info. + Lower Trans. Cost	0.050*** (0.008)	-0.063** (0.025)	-0.007 (0.018)	0.012 (0.009)	-0.014 (0.017)	0.120** (0.059)	0.080*** (0.027)
$\widehat{\alpha}_2$: Info. + Status Quo	0.023*** (0.007)	-0.019 (0.024)	-0.021 (0.018)	0.002 (0.009)	-0.004 (0.017)	0.077 (0.060)	0.058** (0.027)
$\widehat{\beta}_1$: Benef. Info. + Lower Trans. Cost	0.053*** (0.011)	-0.075*** (0.029)	-0.005 (0.021)	0.010 (0.011)	-0.010 (0.019)	0.139** (0.068)	0.085*** (0.032)
$\widehat{\beta}_2$: Risks Info. + Lower Trans. Cost	0.047*** (0.011)	-0.051* (0.029)	-0.008 (0.021)	0.014 (0.011)	-0.018 (0.019)	0.102 (0.069)	0.074** (0.032)
$\widehat{\beta}_3$: Benef. Info. + Status Quo	0.026*** (0.009)	-0.045 (0.029)	-0.015 (0.020)	0.006 (0.010)	0.011 (0.020)	0.147** (0.068)	0.080** (0.032)
$\widehat{\beta}_4$: Risks Info. + Status Quo	0.021** (0.009)	0.008 (0.028)	-0.027 (0.020)	-0.001 (0.010)	-0.018 (0.019)	0.006 (0.071)	0.036 (0.032)
$H_0 : \widehat{\alpha}_1 = \widehat{\alpha}_2$	0.004	0.033	0.318	0.208	0.434	0.366	0.343
$H_0 : \widehat{\beta}_1 = \widehat{\beta}_2$	0.695	0.405	0.892	0.756	0.634	0.577	0.743
$H_0 : \widehat{\beta}_3 = \widehat{\beta}_4$	0.622	0.066	0.543	0.493	0.149	0.044	0.172
Observations	2,462	2,462	2,462	2,462	2,462	2,462	2,462
Control Group Mean	0.01	0.73	0.13	0.02	0.11	4.11	0.47
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: [Table 13](#) shows intention-to-treat estimates on perceptions about appointment scheduling, for our survey sample. The panels in the table show estimates of equations (1), (2) and (3). In columns 1 to 5, the dependent variables are indicators to how women report they would make an appointment. In columns 6 and 7, the dependent variable is their perception of how easy is to schedule appointments (on a 1-5 scale), and an indicator for whether women think it is very easy to do so (value 5 on the 1-5 scale). The lower panel displays the p-values of F-tests for the differences between treatment parameters. All regressions control for age and the set of demographics displayed in [Table 4](#). Robust standard errors are in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level respectively.

Table 14: ITT Effects on PAP Smear Knowledge

	PAP Importance:		PAP Saves Lives:		(5)	(6)	(7)	(8)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	On a	Very	On a	Definitely	Knows	PAP	Skip	PAP
	1-5	High	1-5	Yes	the	is	Work	Every
	Scale	(Value 5)	Scale	(Value 5)	PAP	Free	Day	Year
$\hat{\delta}$: Treatment	-0.018 (0.032)	-0.009 (0.021)	0.055 (0.045)	0.029 (0.022)	-0.004 (0.007)	0.023 (0.022)	0.004 (0.014)	-0.009 (0.021)
$\hat{\alpha}_1$: Info. + Lower Trans. Cost	-0.035 (0.036)	-0.020 (0.023)	0.054 (0.050)	0.034 (0.024)	-0.008 (0.008)	0.009 (0.024)	0.009 (0.015)	-0.011 (0.023)
$\hat{\alpha}_2$: Info. + Status Quo	-0.001 (0.035)	0.002 (0.023)	0.056 (0.050)	0.024 (0.024)	0.000 (0.008)	0.038 (0.024)	-0.001 (0.015)	-0.007 (0.023)
$\hat{\beta}_1$: Benef. Info. + Lower Trans. Cost	-0.028 (0.041)	-0.020 (0.027)	0.026 (0.058)	0.024 (0.028)	-0.011 (0.010)	-0.003 (0.028)	-0.006 (0.018)	-0.006 (0.026)
$\hat{\beta}_2$: Risks Info. + Lower Trans. Cost	-0.043 (0.043)	-0.020 (0.026)	0.081 (0.057)	0.044 (0.027)	-0.004 (0.009)	0.020 (0.028)	0.025 (0.016)	-0.016 (0.026)
$\hat{\beta}_3$: Benef. Info. + Status Quo	-0.022 (0.043)	-0.002 (0.026)	0.036 (0.059)	0.028 (0.028)	-0.001 (0.009)	0.022 (0.028)	-0.012 (0.018)	-0.006 (0.026)
$\hat{\beta}_4$: Risks Info. + Status Quo	0.019 (0.039)	0.006 (0.026)	0.076 (0.055)	0.021 (0.028)	0.001 (0.009)	0.054 (0.027)	0.010 (0.017)	-0.008 (0.026)
$H_0 : \hat{\alpha}_1 = \hat{\alpha}_2$	0.261	0.241	0.952	0.618	0.241	0.133	0.377	0.842
$H_0 : \hat{\beta}_1 = \hat{\beta}_2$	0.729	0.990	0.333	0.444	0.541	0.411	0.059	0.709
$H_0 : \hat{\beta}_3 = \hat{\beta}_4$	0.330	0.767	0.478	0.809	0.820	0.230	0.205	0.925
Observations	2,462	2,462	2,462	2,462	2,462	2,462	2,462	2,462
Control Group Mean	4.73	0.78	4.51	0.73	0.98	0.73	0.92	0.79

Notes: Table 14 shows intention-to-treat estimates on PAP smear knowledge, for our survey sample. The panels in the table show estimates of equations (1), (2) and (3). In columns 1 and 2 the dependent variable is women's perception about the PAP smear importance (on a 1-5 scale), and an indicator for whether women think it is very important (value 5 on the 1-5 scale). In columns 3 and 4 the dependent variable is their perception on whether the PAP smear can save lives (on a 1-5 scale), and an indicator for whether women think it definitely does (value 5 on the 1-5 scale). The columns 5 to 8 include estimates on additional variables related to PAP knowledge: whether women report to know the PAP, whether they report to know that the PAP is free at health centers, whether they are aware they can skip one day of work to take the test and whether they believe that they should take the PAP smear every year. The lower panel displays the p-values of F-tests for the differences between treatment parameters. All regressions control for age and the set of demographics displayed in Table 4. Robust standard errors are in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level respectively.

Table 15: ITT Effects on Perceptions about e-Government and ASSE Services

	ASSE Quality:		ASSE Confidence:		eGovt Safety:		Govt Cares:	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	On a	High+	On a	High+	On a	High+	On a	High+
	1-5	(4, 5	1-5	(4, 5	1-5	(4, 5	1-5	(4, 5
	Scale	Value)	Scale	Value)	Scale	Value)	Scale	Value)
$\hat{\delta}$: Treatment	0.052 (0.054)	0.018 (0.023)	0.014 (0.052)	0.001 (0.024)	-0.005 (0.070)	-0.026 (0.025)	0.112 (0.072)	0.034 (0.025)
$\hat{\alpha}_1$: Info. + Lower Trans. Cost	0.071 (0.059)	0.011 (0.025)	0.056 (0.056)	0.020 (0.026)	0.027 (0.077)	-0.017 (0.027)	0.114 (0.079)	0.028 (0.027)
$\hat{\alpha}_2$: Info. + Status Quo	0.034 (0.059)	0.026 (0.025)	-0.028 (0.057)	-0.019 (0.026)	-0.037 (0.077)	-0.035 (0.027)	0.110 (0.079)	0.041 (0.027)
$\hat{\beta}_1$: Benef. Info. + Lower Trans. Cost	0.077 (0.068)	0.019 (0.029)	0.068 (0.064)	0.025 (0.030)	0.117 (0.089)	0.019 (0.031)	0.109 (0.092)	0.030 (0.031)
$\hat{\beta}_2$: Risks Info. + Lower Trans. Cost	0.064 (0.067)	0.003 (0.029)	0.044 (0.065)	0.015 (0.030)	-0.063 (0.088)	-0.052* (0.031)	0.118 (0.090)	0.025 (0.031)
$\hat{\beta}_3$: Benef. Info. + Status Quo	0.053 (0.068)	0.025 (0.029)	0.004 (0.066)	-0.004 (0.030)	-0.048 (0.089)	-0.039 (0.031)	0.121 (0.092)	0.055* (0.031)
$\hat{\beta}_4$: Risks Info. + Status Quo	0.014 (0.069)	0.026 (0.029)	-0.061 (0.067)	-0.034 (0.030)	-0.027 (0.088)	-0.031 (0.031)	0.099 (0.090)	0.027 (0.031)
$H_0 : \hat{\alpha}_1 = \hat{\alpha}_2$	0.443	0.470	0.070	0.066	0.299	0.414	0.956	0.554
$H_0 : \hat{\beta}_1 = \hat{\beta}_2$	0.844	0.571	0.713	0.739	0.038	0.024	0.919	0.871
$H_0 : \hat{\beta}_3 = \hat{\beta}_4$	0.574	0.994	0.343	0.338	0.810	0.819	0.812	0.381
Observations	2,462	2,462	2,462	2,462	2,462	2,462	2,462	2,462
Control Group Mean	3.86	0.69	3.93	0.65	3.05	0.54	2.98	0.40
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: [Table 15](#) shows intention-to-treat estimates on PAP smear knowledge, for our survey sample. The panels in the table show estimates of equations (1), (2) and (3). In columns 1 and 2 the dependent variable is women's perception about the PAP smear importance (on a 1-5 scale), and an indicator for whether women think it is very important (value 5 on the 1-5 scale). In columns 3 and 4 the dependent variable is their perception on whether the PAP smear can save lives (on a 1-5 scale), and an indicator for whether women think it definitely does (value 5 on the 1-5 scale). The columns 5 to 8 include estimates on additional variables related to PAP knowledge: whether women report to know the PAP, whether they report to know that the PAP is free at health centers, whether they are aware they can skip one day of work to take the test and whether they believe that they should take the PAP smear every year. The lower panel displays the p-values of F-tests for the differences between treatment parameters. All regressions control for age and the set of demographics displayed in [Table 4](#). Robust standard errors are in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level respectively.

Table 16: Heterogeneous ITT Estimates

Panel 1: Age						
Coefficient	Appointments			Take-up		
	(1) Younger	(2) Older	(3) Dif. (1)-(2)	(4) Younger	(5) Older	(6) Dif. (4)-(5)
$\hat{\delta}$: Treatment	0.095 (0.013)	0.044 (0.011)	0.051*** (0.017)	0.066 (0.011)	0.035 (0.009)	0.031** (0.014)
$\hat{\alpha}_1$: Information + Lower Transaction Cost	0.098 (0.017)	0.081 (0.015)	0.018 (0.023)	0.058 (0.013)	0.060 (0.013)	-0.002 (0.018)
$\hat{\alpha}_2$: Information Only	0.091 (0.017)	0.006 (0.010)	0.085*** (0.020)	0.073 (0.015)	0.009 (0.009)	0.064*** (0.017)
Panel 2: Education						
Coefficient	Appointments			Take-up		
	(1) Higher	(2) Lower	(3) Dif. (1)-(2)	(4) Higher	(5) Lower	(6) Dif. (4)-(5)
$\hat{\delta}$: Treatment	0.076 (0.009)	0.044 (0.017)	0.031* (0.019)	0.053 (0.008)	0.036 (0.013)	0.017 (0.015)
$\hat{\alpha}_1$: Information + Lower Transaction Cost	0.099 (0.013)	0.068 (0.021)	0.031 (0.024)	0.069 (0.011)	0.043 (0.016)	0.026 (0.019)
$\hat{\alpha}_2$: Information Only	0.052 (0.010)	0.019 (0.018)	0.033 (0.021)	0.038 (0.009)	0.030 (0.015)	0.008 (0.017)
Panel 3: Household Income						
Coefficient	Appointments			Take-up		
	(1) Higher	(2) Lower	(3) Dif. (1)-(2)	(4) Higher	(5) Lower	(6) Dif. (4)-(5)
$\hat{\delta}$: Treatment	0.068 (0.009)	0.051 (0.018)	0.017 (0.021)	0.047 (0.008)	0.047 (0.013)	0.000 (0.015)
$\hat{\alpha}_1$: Information + Lower Transaction Cost	0.100 (0.013)	0.053 (0.022)	0.047* (0.026)	0.064 (0.011)	0.045 (0.016)	0.020 (0.020)
$\hat{\alpha}_2$: Information Only	0.037 (0.010)	0.050 (0.022)	-0.012 (0.024)	0.030 (0.009)	0.049 (0.017)	-0.019 (0.019)
Panel 4: Household Size						
Coefficient	Appointments			Take-up		
	(1) Larger	(2) Smaller	(3) Dif. (1)-(2)	(4) Larger	(5) Smaller	(6) Dif. (4)-(5)
$\hat{\delta}$: Treatment	0.081 (0.010)	0.038 (0.014)	0.043** (0.017)	0.054 (0.008)	0.037 (0.012)	0.017 (0.014)
$\hat{\alpha}_1$: Information + Lower Transaction Cost	0.107 (0.014)	0.058 (0.018)	0.049** (0.023)	0.067 (0.012)	0.046 (0.015)	0.021 (0.019)
$\hat{\alpha}_2$: Information Only	0.054 (0.012)	0.020 (0.015)	0.034* (0.019)	0.040 (0.010)	0.028 (0.013)	0.012 (0.017)
Panel 5: Children at Home						
Coefficient	Appointments			Take-up		
	(1) Yes	(2) No	(3) Dif. (1)-(2)	(4) Yes	(5) No	(6) Dif. (4)-(5)
$\hat{\delta}$: Treatment	0.082 (0.013)	0.053 (0.011)	0.029* (0.017)	0.053 (0.012)	0.044 (0.008)	0.009 (0.014)
$\hat{\alpha}_1$: Information + Lower Transaction Cost	0.096 (0.017)	0.083 (0.015)	0.013 (0.023)	0.057 (0.015)	0.061 (0.012)	-0.004 (0.019)
$\hat{\alpha}_2$: Information Only	0.067 (0.016)	0.024 (0.011)	0.043** (0.019)	0.048 (0.014)	0.027 (0.009)	0.022 (0.017)

Notes: Table 16 show ITT estimates from separate regressions by subgroup on PAP appointments (columns 1 and 2) and take up rates (columns 4 and 5) in Panels 1 to 5. We divide women in subgroups using the corresponding sample median. For example, women are in the older group if their age is equal or higher than the sample median and in the younger group if not. All the coefficients reported in these columns are individually statistically significant. In columns 3 and 6, we report the difference between these subgroup effects, computed from fully interacted regressions. Robust standard errors are in parentheses. For columns 3 and 6, †, **, * indicate statistical significance at the 1, 5 and 10 percent level respectively.

Table 17: Heterogeneous ITT Estimates

Panel 1: Internet Use						
Coefficient	Appointments			Take-up		
	(1) 1	(2) 0	(3) Dif. (1)-(2)	(4) 1	(5) 0	(6) Dif. (4)-(5)
$\hat{\delta}$: Treatment	0.070 (0.009)	0.020 (0.024)	0.051** (0.025)	0.051 (0.007)	0.020 (0.024)	0.031 (0.025)
$\hat{\alpha}_1$: Information + Lower Transaction Cost	0.095 (0.012)	0.038 (0.030)	0.056* (0.032)	0.062 (0.010)	0.038 (0.030)	0.023 (0.031)
$\hat{\alpha}_2$: Information Only	0.046 (0.010)	0.003 (0.024)	0.043* (0.026)	0.040 (0.009)	0.003 (0.024)	0.037 (0.026)
Panel 2: Cell Phone Use						
Coefficient	Appointments			Take-up		
	(1) 1	(2) 0	(3) Dif. (1)-(2)	(4) 1	(5) 0	(6) Dif. (4)-(5)
$\hat{\delta}$: Treatment	0.071 (0.009)	0.025 (0.018)	0.046** (0.020)	0.051 (0.007)	0.025 (0.018)	0.026 (0.019)
$\hat{\alpha}_1$: Information + Lower Transaction Cost	0.095 (0.012)	0.043 (0.024)	0.053* (0.027)	0.062 (0.010)	0.043 (0.024)	0.019 (0.026)
$\hat{\alpha}_2$: Information Only	0.046 (0.010)	0.007 (0.018)	0.039* (0.021)	0.040 (0.009)	0.007 (0.018)	0.033 (0.020)
Panel 3: Distance to Health Center (less 30 min or more)						
Coefficient	Appointments			Take-up		
	(1) Close	(2) Far	(3) Dif. (1)-(2)	(4) Close	(5) Far	(6) Dif. (4)-(5)
$\hat{\delta}$: Treatment	0.070 (0.009)	0.015 (0.033)	0.056 (0.034)	0.049 (0.007)	0.032 (0.026)	0.017 (0.026)
$\hat{\alpha}_1$: Information + Lower Transaction Cost	0.093 (0.012)	0.041 (0.039)	0.053 (0.041)	0.058 (0.010)	0.062 (0.033)	-0.004 (0.034)
$\hat{\alpha}_2$: Information Only	0.047 (0.010)	-0.011 (0.034)	0.057 (0.035)	0.039 (0.009)	0.003 (0.025)	0.037 (0.027)

Notes: Table 17 show ITT estimates from separate regressions by subgroup on PAP appointments (columns 1 and 2) and take up rates (columns 4 and 5) in Panels 1 to 5. We divide women in subgroups using the corresponding sample median. For example, women are in the older group if their age is equal or higher than the sample median and in the younger group if not. All the coefficients reported in these columns are individually statistically significant. In columns 3 and 6, we report the difference between these subgroup effects, computed from fully interacted regressions. Robust standard errors are in parentheses. For columns 3 and 6, ***, ** and * indicate statistical significance at the 1, 5 and 10 percent level respectively.