Who calls the shots? Financial incentives and provider influence in the adoption of a new health technology*

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Abstract

The choice to adopt an effective healthcare product is often a joint decision between the patient and their medical professional. Many governments and payers use patient subsidies and provider incentives to increase the adoption of new health technologies. Using data from a randomized field experiment in Kenya, we estimate a structural model of patient demand and provider advice for a new contraceptive method. We then use the model to study the welfare effects to the patient from the introduction of demand and supply side incentives to adopt the new technology. This approach allows the study of channels that promote diffusion, including the roles of provider advice, financial incentives and altruism, as well as patient preferences. Taken together, the results suggest that changes in provider advice due to their altruism and financial incentives are key to increasing adoption of the new technology and making incentive programs effective, regardless of whether the incentive targets the patient or the provider. In fact, changes in provider advice account for roughly 95% of the welfare benefits of a policy that reduces the price to the patient. To be effective, incentive policies need to account for the central role that the provider takes in medical decision-making.

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A major issue in technological change in healthcare is the slow diffusion and adoption of highly effective healthcare products, particularly in low- and middle-income countries (LMICs) (Dupas, 2014b; Wulifan et al., 2015; Darroch et al., 2017)[1]. As such, increasing the adoption of these effective health innovations in LMICs continues to be a critical policy concern (Ye et al., 2022; United Nations General Assembly, 2015). Essential to developing cost-effective diffusion strategies is understanding that a patient's decision to adopt new health technologies does not occur in isolation; it is influenced by the information structure of healthcare markets, where skilled agents (medical providers) play a critical role in guiding patients (Arrow, 1963). Despite this, the relative influence of patient demand versus provider agency remains unclear, particularly when studying policies that target patient out-of-pocket costs or provider financial incentives[2].

In healthcare, the decision to adopt a product is a joint problem between the medical professional and the patient (Arrow, 1963; Chandra et al., 2011). Patients rely on the information and advice given by healthcare providers to make informed choices, especially when it comes to new health technologies. A new health product can be considered both an experience good, which patients can only evaluate after use, and a credence good, whose value remains difficult to assess even post-consumption (Dranove, 2011). Medical providers act as expert intermediaries by informing or signaling to patients the value of the medical product through their counseling. Arrow (1963) points out that physicians have a social expectation to act as altruistic agents for the consumer, prioritizing the patient's welfare in their counseling decisions. However, it is not uncommon for providers to also sell the products they recommend to patients or to have financial incentives to promote or prescribe certain treatments (Currie et al., 2014; Iizuka, 2012; Das et al., 2016; Compton et al., 2015; Grennan et al., 2025; Ellis and McGuire, 1986; Casalino et al., 2024; Byambadalai et al., 2023).

Two common strategies in the policymaker's toolkit for influencing the uptake of medical products are price reductions, which target the patients' out-of-pocket costs, and supply-side interventions, which modify providers' incentives. An extensive body of literature in development economics has examined the impact of price reductions (subsidies) on patient demand, with a primary focus on the consumer (patient) as the main decision-making agent (Dupas, 2014a; Berry et al., 2020; Dupas, 2014b; Kremer and Miguel, 2007; Cohen and Dupas, 2010). However, limited evidence exists on whether medical experts influence the patient's response to such policies—or the lack thereof (Dickstein et al., 2024). At the same time, there has been growing interest in performance payments and other supply-side interventions targeting provider incentives, with evidence suggesting these interventions also influence patient demand (Meessen et al., 2011; de Walque et al., 2015; Ahmed et al., 2023; Kremer and Glennerster, 2011). However, the effect on patient welfare of policies that target

[1]There is a set of recent health technologies with a proven record of improving the quality of life for millions of people, exemplifying the potential gains from the diffusion of effective innovations. For example, insecticide-treated bed nets averted almost half a billion cases of malaria between the years 2000 and 2015 (Bhatt et al., 2015) and the introduction of antiretroviral therapies has resulted in 66% of global HIV-positive patients achieving viral suppression (UNAIDS, 2021).

[2]Policy tools that target these margins are not limited to health technology adoption in LMICs. One prominent example of analogous tools is the design of health insurance plans with the aim of preventing moral hazard.

provider incentives can be ambiguous, as providers may distort patient choices (Grennan et al., 2025). Since patients often do not make medical decisions independently, it is essential to understand how financial incentives and prices affect both patient and provider behavior when studying the demand for new health technologies and designing effective policies to promote adoption. This raises a central policy question: to increase the adoption of an effective health technology, should incentives target the patient's out-of-pocket costs or the provider's financial incentives?

In this work, we quantify the influence of provider agency on the adoption of a new contraceptive technology, focusing on the trade-off between policies that target the patient's prices or the provider's incentives. Family planning (FP) is a setting where both provider agency (through the advice they give) and patient preferences over alternatives are likely to be important in determining the treatment choice. We study how the mechanisms of provider advice, financial incentives, altruism, and patient out-of-pocket costs shape the demand curve for the new contraceptive. Understanding how these mechanisms interact with technology adoption allows us to estimate the implications for patient welfare under different policy designs. To answer these questions, we implement a randomized controlled trial (RCT) in a network of private pharmacies in Kenya, comparing the performance of policies targeting patient and provider incentives, and estimate a structural model to study key welfare-relevant mechanisms. In contrast with most previous work, a structural RCT allows us to separately identify the role of the provider as an agent from direct patient responses to these policies.

The market for contraceptives is a setting where studying the role of provider agency on patient choices is important. In contrast to some medical markets where the product choice is often made by the provider on behalf of a patient, patient agency and their personal preferences are particularly relevant when choosing a contraceptive product - often with policies in place to empower the patient's choice. In fact, all family planning options being considered by the patient in this context are available over-the-counter. Nevertheless, patients rely on the information that providers share about family planning to choose the product that best fits their needs. Therefore, this setting is particularly suited to study how patient choices are influenced by expert recommendations and how these dynamics interact with the adoption of a new technology. The structural RCT allows to take lessons from this setting into other contexts by identifying the key mechanisms behind the results.

The RCT tests policies that aim to encourage the adoption of a new subcutaneous injectable contraceptive (referred to as SI for the rest of the paper). Medium-term injectable contraceptives are the most common modern method used in Sub-Saharan Africa (Boadu, 2022). The new type of injectable contraceptive (SI) has several advantages relative to the incumbent intramuscular injectable technology (IMI). SI is safer and more comfortable for the patient, associated with fewer side effects, and has the same efficacy and duration as IMI (Polis et al., 2014; Sherpa et al., 2021; Burke et al., 2014).

In contrast to settings where medical doctors are the first point of contact for patients seeking medical advice, pharmacists in Kenya and other LMICs play a crucial role in patient counseling (Wafula et al., 2022; Burton et al., 2011). In Kenya, patient counseling is an integral part of

the professional training of a licensed pharmacist. However, Kenyan pharmacists are likely to have financial incentives tied to the product advice they give to patients. This is because most pharmacies in Kenya are small independent businesses where the provider often owns the pharmacy (Wafula et al., 2022; Ward et al., 2014; Sabde et al., 2011). This is the case in our study sample, where $\sim 70\%$ of owners are patient-facing providers and all supervise the operations of the pharmacy.

Randomization was done at the pharmacy level, where sites were assigned to one of four groups: a *control group* (C), a *consumer price reduction arm* (T1) where SI prices were lowered to the patient by roughly 60% while holding provider incentives constant, a *pharmacy cost-reduction arm* (T2) where a comparable marginal cost-reduction of SI was given to the pharmacies, and a *pharmacy incentive arm* (T3) where a larger marginal cost-reduction was given to the pharmacies. Pharmacies in the *provider arms* (T2 and T3) could price SI freely, while the price for SI in the consumer arm (T1) was exogenous. Since marginal cost reductions can have an effect on both prices and financial incentives, having two differently sized shocks allows us to separately identify the role of each channel.

For the analysis, we introduce a structural model of patient demand and provider advice along with reduced form evidence from the RCT to study the channels that lead to the adoption of the new technology. Taken together, the results suggest that the provider's counseling role is key in increasing adoption of the new technology, regardless of whether the intervention targets the patient's prices or the provider's incentives. Even in this setting with low income levels and over-the-counter products, prices alone cannot account for the effects on adoption of the new technology that are observed. The counseling of providers responds to both subsidy types, and the patient's demand for the new technology responds very strongly to the counseling of the provider. These dynamics lead to large effects on the patient's welfare regardless of the subsidy type and point to the importance of information channels.

Moreover, we find that overlooking the provider's role in the patient's decision-making can cause traditional exclusion restrictions to fail when estimating the demand curve for a health product, even if reasonable price instruments are available (such as the exogenous variation in cost-shifters generated by T2 and T3). This typically results in underestimating the demand elasticity for the new technology and could understate the potential impact of direct price reductions for the patient.

The reduced form evidence indicates large effects from the consumer and provider arms on patient demand and provider counseling. First, there are substantial adoption effects in all treated groups, with no significant differences between provider and consumer subsidies. On average, the share of family planning (FP) transactions that include an SI sale increases by 21 percentage points at treated sites, compared to just 2% in the control group. These adoption effects are not driven by increased availability of SI in the study sites. Product availability accounts for at most 3 percentage points of the estimated effect on adoption. Thus, most of the adoption effect from subsidies is concentrated at the intensive margin.

The interventions also led to a substitution away from other family planning options and alternative sources of care, such as competing pharmacies and public sector clinics. It is important to

consider these substitution effects since they help account for the patient's choice set and outside options when estimating the welfare effects of incentivizing the new technology. A census of competing pharmacies and public clinics reveals that patient cost reduction subsidies do draw patients away from alternative sources of care. Transaction data suggests that patients substitute away from short-term methods available within the study site when adopting SI.

Provider financial incentives and patient prices vary meaningfully across arms, despite similar effects on adoption. Hence, price changes alone do not explain adoption effects. The analysis shows that pharmacies in the provider arms absorb most of the incentives through higher markups, passing a third or less of the marginal cost reduction to consumers. On average, patients in the pharmacy subsidy arms pay twice as much as those in the consumer price reduction arm.

Providers change their counseling and advice in response to both types of policies, explaining the adoption effects in the absence of price reductions. Using data from a mystery shopper activity and provider surveys, we find that providers in all arms are more likely to recommend the new technology, and pharmacists in the provider subsidy arms (T2 and T3) are much more likely to share information about SI, with increases up to 0.82 standard deviations over the control group level. Providers in treated arms discuss alternative options with the patient at similar rates to the control group, suggesting that overall patients in treated arms are making more informed choices.

The structural model of patient demand and provider advice allows us to disentangle the role of the distinct channels being explored in the reduced form results. We find that provider behavior has a leading role in shaping the demand for the new technology since patients strongly respond to providers' recommendations. In fact, in this setting patients are perfectly inelastic to changes in the price of the new technology conditional on the provider's advice. Providers, on the other hand, respond to both changes in the patient's out-of-pocket costs and their financial incentives to recommend the new technology. Conditional on the provider's financial incentives, patients have a mean demand elasticity of -1.13, suggesting that the provider's response to a change in the patient's out-of-pocket costs generates the downward slope of the demand curve in this setting. Therefore, the patient-provider interaction shapes the patient's demand curve for this new technology.

Irrespective of whether the subsidy targets patient prices or provider incentives, the provider's advice response is the mechanism behind the effects on adoption. Providers internalize the patient's expenditure due to their altruism, so they are more likely to recommend the new technology when patient cost-reduction subsidies are in place, thus increasing adoption. However, providers also maximize their own financial incentives, so positive shocks to the pharmacy incentives motivate them to recommend more the new technology, raising the consumers' willingness to pay for SI.

These results suggest that neglecting the role of provider agency in the patient's choice can lead to incorrect policy and welfare conclusions, as well as violations of commonly assumed exclusion restrictions in the literature. The financial incentives of the provider are often positively correlated with the price paid by the patient. With higher financial incentives, providers are more likely to share information about the new technology, influencing the patient's demand. This means that studying the patient's choice in isolation, even when using reasonable instruments for prices such as

supply-side cost shifters (which are known to be exogenous in T2 and T3), could lead to the incorrect conclusion that the patient's demand curve is flat or upward-sloping with respect to price, which downplays the effectiveness of price reduction policies. By controlling for the financial incentives of the provider, our model recovers a downward sloping demand curve with a mean elasticity that is consistent with estimates from other experimental and quasi-experimental studies.

Finally, the parameter estimates of the model along with data from the mystery shopper activity allow for the study of policy counterfactuals and the analysis of subsidies' impact on patient welfare. We find substantial welfare effects from introducing the new technology into the patient's choice set along with the subsidies. However, if providers did not have an active counseling role, most of the welfare gains resulting from the subsidies would not be attained relative to the control group. In fact, roughly 95% of the welfare effect of a price reduction to the patient is the direct result of changes in the provider's counseling. Therefore, information channels during counseling are crucial for the success of these subsidy interventions. Without these information channels, price changes for the new technology do not affect the patient's demand.

Related Literature. This paper makes several contributions to the existing literature. First, the existing literature on health product subsidies (price reductions) as a policy tool to increase adoption in LMICs has largely focused on patient (user) demand in isolation and patient learning from their personal experiences or peer effects (Dupas, 2014b; Kremer and Miguel, 2007; Dupas, 2014a; Berry et al., 2020). Therefore, this paper contributes to this literature by considering the role of expert intermediaries and how they respond to the presence of patient price reduction policies. It also contributes to a wider literature on technology adoption and subsidies in developing settings (Bensch and Peters, 2020; Meredith et al., 2013; Tarozzi et al., 2014; Molyneaux and Gertler, 2000), but with a stronger emphasis on the supply-side effects of these policies.

This paper also contributes to the literature on provider agency and the impact of financial and altruistic incentives on treatment decisions (Das et al., 2016; Currie et al., 2014; Kolstad, 2013; Iizuka, 2012; Dickstein, 2017; Hackmann et al., 2024; Grennan et al., 2025). However, instead of focusing on the provider's decision on behalf of the patient, this paper examines a setting where the patient is the primary decision-maker, while considering the provider's advice, which may be influenced by financial incentives, similar to Xiang (2021). A key contribution of this paper to the provider agency literature is that it identifies the structural model using high-quality data on provider advice and counseling practices from our field activities, along with experimental variation in prices and incentives from the RCT. This approach allows us to avoid relying on strong parametric assumptions about patient-provider choice dynamics.

This study speaks to a core issue in healthcare economics: understanding the demand for health products and services in the presence of expert intermediaries (Arrow, 1963; Chandra et al., 2011). The influence of providers on patients' demand curves and price sensitivity is not only relevant for the adoption of new health technologies but also for broader economic considerations. For instance, the literature on optimal insurance design has traditionally focused on policies that target the patient's

individual incentives, such as increasing cost-sharing, to mitigate moral hazard (Zeckhauser, 1970; Manning et al., 1987). However, it has been found that provider advice and incentives significantly contribute to unnecessary medical spending (Saini et al., 2017; Clemens and Gottlieb, 2014; Gruber and Owings, 1996). Thus, interventions targeting provider incentives could be effective in reducing costs without excluding low-income patients from essential care (Dickstein, 2017; Dickstein et al., 2024). The model and findings of this paper highlight the need to consider the roles of both patients and providers when designing policies aimed at influencing the demand for health products.

Finally, this study also contributes to the literature on the pass-through of subsidies and promotions by retailers when the cost-reduction policy is implemented upstream (Busse et al., 2006; Besanko et al., 2005; Walters, 1989). A key difference in the Kenyan pharmacies setting relative to the existing literature is the presence of provider agency, leading to increases in adoption despite the lack of subsidy passthrough.

1 Conceptual framework

This section explores the consumer decision-making process in the context of healthcare provider advice. We begin with a two-product model to analyze the welfare implications for the patient resulting from the provider's counseling. We then present the complete framework within the family planning setting.

1.1 Adoption of a new technology, provider advice, and patient welfare

The existing literature has examined the welfare implications for consumers when they make product choices with imperfect information (Handel and Schwartzstein, 2018). Importantly, the welfare implications for patients receiving advice from providers are not immediately clear, given the potential for distortions in patient choice (Grennan et al., 2025; Bronnenberg et al., 2015).

Assume that a patient i has two products available: an old technology o priced at p_o and a new technology n priced at p_n. The patient is familiar with the old technology, so its value, $v_{o,i}$, is known. However, the patient is unfamiliar with the new technology and does not know its true value, $v_{n,i}$. Instead, the patient has a prior belief of the new technology's value, $\hat{v}_{n,i}$.

The patient seeks counseling from a medical provider d before making a purchase decision. The provider can decide how to counsel the patient on the new technology. Specifically, the provider can choose whether to recommend the new technology, or not, denoted by $\theta \in \{0, 1\}$. If the provider recommends the new technology to the patient ($\theta = 1$), the patient updates their perceived value of the new technology to $\bar{v}_{n,i}$. If the provider does not recommend the new technology ($\theta = 0$), the patient's perceived value for the new technology stays unchanged after interacting with the provider, that is $\bar{v}_{n,i} = \hat{v}_{n,i}$[3]. A counseled patient purchases the new technology if they believe that it offers enough value relative to its price, that is, if $\bar{v}_{n,i} - v_{o,i} > p_n - p_o$.

[3]There are alternative ways of micro-founding how advice influences the perceived value of a product relative to other alternatives. For example, the patient could negatively update their prior if the provider does not recommend the new technology. When studying patient choices empirically, we care about the effect of advice θ on $\bar{v}_{n,i} - v_{o,i}$, so several alternative approaches are observationally equivalent when all patients interact with a provider.

Welfare effects of the provider counseling — To illustrate that the welfare effect of advice is ambiguous, consider two extreme scenarios. First, suppose that the provider's advice ($\theta = 1$) perfectly updates the patient's understanding of the new technology's value, meaning $\bar{v}_{n,i} = v_{n,i}$. In this case, the provider's recommendation is **welfare-increasing** for patients who purchase the new technology only after receiving the provider's recommendation. Formally, if $\hat{v}_{n,i} - v_{o,i} < p_n - p_o$ and $v_{n,i} - v_{o,i} > p_n - p_o$, then the patient's welfare increases due to the provider's counseling; otherwise, it remains unchanged.

In contrast, assume that the patient's prior belief was correct, and that the provider's recommendation distorts the patient's perception of the new technology's value, in other words, assume that the provider is over-recommending the product. For example, let $\bar{v}_{n,i} > v_{n,i} = \hat{v}_{n,i}$. In this scenario, the provider's advice is **welfare-decreasing** for patients who change their purchase decision due to the provider's recommendation. Formally, if $v_{n,i} - v_{o,i} < p_n - p_o$ and $\bar{v}_{n,i} - v_{o,i} > p_n - p_o$, then the patient's welfare decreases due to the provider's counseling; otherwise it remains unchanged.

The truth is likely context-specific, falling between these two extremes. With sufficient information about the patient-provider interaction, however, one can assess whether the provider's counseling is more likely to update or distort the patient's valuation of the new technology.

1.2 Patient's demand for a new family planning technology

Here, we present an empirical framework that extends the two-product model to a setting with provider incentives and multiple family planning alternatives for the patient. In addition to the old (IMI) and new (SI) technologies, patients can choose across other family planning options k such as oral contraceptives, emergency contraceptives, condoms, and an outside option[4]. Let patient i's perceived utility for alternative k (given by $\bar{v}_{i,k,d}$)[5] be a function of product characteristics, as well as an "expert advice" component $\theta_{d,i,k} \in \{0, 1\}$, which results from the patient's interaction with the provider d:

$$\bar{v}_{i,k,d} = \underbrace{\alpha p_k + \beta x_k + \epsilon_{i,k}}_{\substack{\text{Characteristics observed} \\ \text{by the patient}}} + \underbrace{\delta \theta_{d,i,k}}_{\text{Provider's advice}} \tag{1}$$

In equation 1, p_k is the price of alternative k which is observed by the patient, and x_k are observable product characteristics to the patient and researcher. When a patient interacts with a provider, they observe whether the provider recommends the product or not $\theta_{d,i,k} \in \{0, 1\}$. In this case, δ is the weight that the patient puts on the provider recommendation. The provider's recommendation is being modeled as an additional product attribute, which can be interpreted as the impact on product k's perceived utility from the provider endorsing or recommending that product. In other words, the provider's recommendation updates the patient's perceived value of a product depending on δ, analogous to the two-product model presented above[6]. Parameters α and

[4] All alternatives available in the study sites are over-the-counter and do not require a prescription.

[5] Note that the following equation relates to the patient's perceived value, which does not directly indicate the welfare implications for the patient; welfare is discussed at a later stage.

[6] As discussed in section 5, allowing for θ to enter additively (as a product characteristic) will allow us to estimate

β are coefficients for the patient's preferences over other product characteristics observed by the researcher *conditional* on the recommendation of the provider. Let $\epsilon_{i,k}$ be a random component to the patient's preferences, unobserved by the researcher. This random component can include the patient's prior knowledge about the product, unobserved product characteristics to the researcher, and a random taste shock, so instruments will be needed to causally interpret estimates for α and δ (Berry and Haile, 2021).

1.3 Provider's advice model

Since the main aim of this exercise is to study the introduction of SI, let the provider recommendation component $\theta_{d,i,k}$ be only active for the new technology ($k = SI$)[7]. Therefore, the provider problem becomes a binary choice on whether to recommend or not the new technology to the patient $\theta_{d,i,SI} \in \{0, 1\}$. Medical providers likely care about patient welfare and potentially about their own (i.e. the pharmacy's) financial incentives. Let the functional form of the provider d's advice be given by:

$$\theta_{d,i,k} = 1\{ \underbrace{W(p_{SI}) + e_{i,d}}_{\substack{\text{Internalized patient's} \\ \text{welfare (altruism)}}} + \underbrace{\lambda f(p, c)}_{\text{Financial incentives}} \geq 0\} 1\{k = SI\} \tag{2}$$

In equation 2, $W(p_{SI}) + e_{i,d}$ is the part of the patient's welfare that the provider internalizes (due to the provider's altruism[8]), where $W(p_{SI})$ is the mean value to the patient (from the provider's perspective) of choosing product SI at price p_{SI}. The term $e_{i,d}$ represents a provider-patient shock to this mean value. Note that $W(p_{SI}) + e_{i,d}$ does not necessarily need to be defined by $\bar{v}_{i,k,d}$ (value from the patient's perspective), and in general we would expect the provider's internalized welfare to differ from the patient's perspective since the provider is a medical expert. At the same time, the provider's recommendation choice depends on the potential financial incentives of recommending SI, given by $f(p, c)$, where p is the vector of prices and c is the vector of marginal costs for all family planning products available in a site. The parameter $\lambda \geq 0$ is the weight that providers put on financial incentives relative to the patient's expected welfare. Given the potential endogeneity of the $e_{i,d}$ shock (due to unobserved provider and patient characteristics), instruments are required to recover λ.

Note that since $\theta_{d,i,k}$ is binary, $f(p, c)$ has a natural functional form as the expected change in profits from recommending the new technology:

the effect of advice on patient choices with exogenous variation from the RCT. Section 6 discusses how to estimate welfare effects under this framework.

[7] Another motivation for this assumption is that we observe proxies for this component when $k = SI$, so we can use data and exogenous variation from the RCT to inform the estimates of the relevant information parameters in the model.

[8] For the purposes of this paper, altruism relates to what the provider believes might benefit the patient's welfare.

$$
\begin{aligned}
f(p,c) &= \mathbb{E}[\pi|\theta=1] - \mathbb{E}[\pi|\theta=0] \\
&= \mathbb{E}[\Sigma_k m_k 1(k)|\theta=1] - \mathbb{E}[\Sigma_k m_k 1(k)|\theta=0] \\
&= \Sigma_k m_k P[k|\theta=1] - \Sigma_k m_k P[k|\theta=0] \\
&= \Sigma_k m_k (P[k|\theta=1] - P[k|\theta=0])
\end{aligned} \tag{3}
$$

In equation 3, π is the transaction-level profit for the pharmacy from the encounter between provider d and patient i. In particular, these profits are a sum of markups m_k for the different family planning products available in a site interacted with indicators for whether the patient chooses that product[9]. Due to the linearity of expectation operators, this is simplified as the sum of markups times the change in probabilities of patient choice for product k due to the provider's advice. The vector of markups, in this setting, is defined as $m = p - c$.

1.4 Framework implications

The framework implies that both patient subsidies and provider incentives can have an effect on both patient demand and provider behavior. Shifts to either the financial incentives to the provider or the out-of-pocket costs of the patient can influence the provider's behavior when counseling the patient, and in turn, the patient's valuation of the alternatives can be influenced by the provider's advice.

To see why this is the case, note that parameters δ, λ, and α are all relevant to understand the slope of the demand curve in this framework. If $\delta \neq 0$, the provider's advice to the patient will have an impact on the patient's willingness to pay for the new technology. If the decision to recommend the new technology to the patient is orthogonal to the price vector or $\delta = 0$, then α can be interpreted as the classical price parameter in demand estimation. However, if the decision to recommend the new technology to the patient is a function of the price vector and $\delta \neq 0$, then $\frac{\partial}{\partial p_{SI}} \bar{v}_{i,SI,d} = \alpha + \delta \frac{\partial \theta_{d,SI}}{\partial p_{SI}} \neq \alpha$. There can be two reasons why θ is not orthogonal to the price vector in the framework presented above. First, if $\lambda \neq 0$, then the provider's advice is a function of the financial incentives to the pharmacy $f(p,c)$, which in turn is a function of the price vector. In this case, the provider is not a perfect agent for the patient and responds to shifts in the financial incentives of the pharmacy. Second, the provider might internalize the patient's expenditure as part of the patient's welfare, that is, providers might recommend products that offer a better value to the patient for their money.

As a consequence, focusing on the patient's choice behavior in isolation can potentially result in misleading conclusions. If, for instance, providers are very responsive to changes in their financial incentives and patients are responsive to provider advice, the correlation between $f(p,c)$ and p_{SI} could lead to estimates of an upward-sloping demand curve with respect to changes in prices without appropriate controls for the provider's financial incentives (even with exogenous marginal cost shifters as instruments). This would in turn lead to incorrect conclusions about whether price re-

[9] This definition could be extended to include dynamic effects on profits from repeat customers if patient identifiers were available in the data. However, the results imply that the spot incentives considered here are first order.

duction policies are effective. Figure 1 shows how a positive correlation between prices and financial incentives could lead to misguided conclusions about the patient's responsiveness to price changes.

Note that the welfare implications of the provider's counseling role for the patient remain unclear. As described in the two-product model, this depends on whether the provider's advice accurately updates or distorts the patient's perception of the new technology's value. Both possibilities have merit. For example, Currie et al. (2014) finds that provider incentives during counseling are the main driver of antibiotic overuse in China, while Wagner et al. (2024) concludes that financial incentives from providers do not explain inappropriate child diarrhea treatments in India; instead, strong patient ex-ante preferences are to blame. In the US, physician prescribing and counseling patterns have been shown to have both positive and negative welfare effects on patients (Compton et al., 2015; Grennan et al., 2025). In section 6, we estimate the welfare implications for the patient within this framework by analyzing evidence from field activities. This evidence helps determine whether provider advice informs or distorts patients' valuations of SI.

2 Family planning and injectable contraceptives in Kenya

Contraceptives in private pharmacies in Kenya — Private pharmacies in Kenya are an important source of family planning care despite the availability of free contraceptives in public facilities (Escamilla et al., 2018). Private pharmacies are particularly popular among underserved populations, such as young and unmarried women, who face barriers to accessing public facilities, including longer travel times and social stigma (Escamilla et al., 2018; USAID, 2018). In fact, over 30% of women (and 48% of unmarried women) in Kenya choose private pharmacies as their main source of family planning care (KNBS, 2015). To reach populations underserved by the public health system, local governments and non-profits collaborate with private pharmacies to subsidize certain health products. Simultaneously, manufacturers often introduce upstream subsidies (e.g., the Accord for a Healthier World program).

Injectable contraceptives — Reversible injectable contraceptives, with doses taken every 3 months, are the most popular modern contraceptive method in Kenya, accounting for over 42% of modern method use (UN-DESA, 2019). There are multiple reasons for their popularity in this setting. Following a treatment course can be easier and more convenient than methods that rely on daily doses (e.g. contraceptive pills). Longer-term methods like injectables have a lower probability of failing since the chances of missing a dose are greatly diminished given their lower frequency (Polis et al., 2016). In addition, injectables offer a discreet alternative to short-term methods, which is particularly relevant for women who wish to avoid pregnancy without their partner or cohabitants finding out.

However, there is evidence of barriers to access to injectables and other appropriate methods in private pharmacies. In our control group, only 10% of patients purchase injectables, far below the national average (most users in the country access injectables through the public sector). On the other hand, roughly 50% of pharmacy patients rely on emergency contraceptives, and existing literature suggests this is often due to inappropriate use. It is common for younger women in

Kenya to use emergency contraceptives improperly as their primary method of birth control, taking multiple doses per year (Keesbury et al., 2011; Chin-Quee et al., 2014); injectables can serve as a more effective, safer, and discreet alternative for these women.

Price and supply-side barriers could both contribute to the gap in access between pharmacies and public clinics. For example, one pharmacist in our context noted that a challenge with discouraging patients from inappropriately using emergency contraception is that it is affordable and familiar to the patient, as well as the most profitable option for the pharmacy. Other providers noted the effort of delivering and explaining injectables during busy times as a significant barrier to counseling patients on this option.

The new type of subcutaneous injectable contraceptive (SI) offers several advantages over the incumbent intramuscular injectable (IMI) and is potentially a better fit for a pharmacy context[10]. The key difference between SI and IMI is the delivery method, since the underlying active ingredient is the same. IMI is an intramuscular injectable, meaning that the medication is delivered into the muscle. SI, on the other hand, is delivered subcutaneously, so it requires a much smaller syringe, making it a less invasive injection. Moreover, SI comes in a pre-filled, non-reusable syringe, eliminating the risk of administering an incorrect dosage or transmitting pathogens due to providers inappropriately reusing a syringe. Finally, the administered dose is 1/3 lower for SI relative to IMI, while having the same efficacy (Sherpa et al., 2021). Studies have found that patients and providers who have experience with both products prefer SI on average, leading to longer-term adoption (Sherpa et al., 2021; Polis et al., 2014; Burke et al., 2014). Patients also report slightly fewer side effects from SI use (Polis et al., 2014; Burke et al., 2014).

Medical providers in pharmacies — In Kenya, pharmacists play an active role in counseling patients. Pharmacists need to be registered with the Pharmacy and Poisons Board and have a university degree from a 4'year pharmacy program which includes patient counseling and clinical training[11]. Medical providers in private pharmacies offer a range of services, including family planning counseling, injections, malaria testing and treatment, and HIV tests.

3 Experimental design and study sample

The data and main exogenous variation for analysis comes from a cluster randomized control trial where pharmacies were randomly assigned to either a subsidy or to the control group. This section explains the experimental sample, treatment arms, randomization procedure, and the data sources collected for analysis. For a summary of the experimental design, see table 1.

3.1 Study sample and sample selection

The experimental sample of sites consists of 137 pharmacies located across 21 counties in rural and urban Kenya. Figure A.1 shows the distribution of the study sites across the country - many

[10] SI is branded as *Sayana Press*, and IMI is branded as *Depo-Provera*. Both are manufactured by the same company.

[11] Pharmacist requirements are available at the Kenyan Pharmacy and Poisons Board website: https://web.pharmacyboardkenya.org/registration-and-enrollment, accessed Feb. 2023.

are concentrated in western Kenya, but there is also a sizable number near Nairobi and Mombasa. Pharmacies in the sample are predominantly located in rural and peri-urban areas, with 35% of sites being classified as urban. On average 13% of monthly pharmacy sales in the study sites included sexual and reproductive health products.

All pharmacies in the study sample have at least one staff member qualified to provide family planning counseling to patients. For additional details on the study sample and provider characteristics, see appendix A.1.

This study was implemented in pharmacies that are users of an inventory management system by Maisha Meds. Maisha Meds is a social enterprise based in Kenya that serves as a pharmaceutical benefits manager for the independent pharmacies in the study. Maisha Meds provides the study sites with an inventory management, restocking, and business support platform, along with access to a point of sales (POS) system. This allows the analysis to utilize standardized administrative data across the study sites. Moreover, Maisha Meds integrated the experimental subsidy structures into the POS system.

All pharmacies in the Maisha Meds network that were located in the 21 study counties were screened for eligibility. The inclusion criteria was the following: a minimum distance of 0.5KM between study sites, up-to-date business licenses, and past family planning sales records in the Maisha Meds POS system. From the 190 sites that were eligible to participate and could be reached, 137 consented and were onboarded into the distinct study arms.[12]

3.2 Randomization

Randomization was done at the site level[13] with stratification on urbanicity, past availability of SI, and family planning sales volumes. Sites were randomized in 5 waves between July and November 2022. On average, there are 5 months of administrative data after treatment per site with a minimum of 3 months. The smallest wave of randomization consisted of 23 sites, and randomization waves stopped once a minimum arm size of 33 sites for all arms was achieved. All arms had a positive probability of assignment in each wave, and wave indicators were included as controls during analysis.

3.3 Treatments

The study has 4 arms: a control group (n= 33) and 3 treatment arms, with 137 sites participating and a minimum of 33 sites per arm[14]. The treatment arms consist of the following: consumer price reduction (n=35), pharmacy cost reduction (n=33), and pharmacy incentive (n=36).

[12] A balance table is included in appendix A.1, where joint tests of orthogonality reject imbalance across arms.

[13] Less than 2% of randomized sites shared owners. In these cases, randomization was done at the owner level so that all sites with the same ownership had the same treatment assignment.

[14] Arms have unequal sizes since at each randomization wave all arms were possible assignments even if the minimum of 33 sites had been achieved for some arms.

3.3.1 Description of study arms

Control group (C): Sites assigned to the control group do not receive any incentives or subsidies for SI through this study. SI was not supplied by Maisha Meds as part of the subsidy program, but it was available through alternative distributors in the study area. Prices are set by pharmacies in the POS system.

Consumer price reduction arm (T1): Sites in the consumer price reduction arm receive SI stock through the Maisha Meds program. Prices to the consumer are fixed at a subsidized rate of 50KES in the POS system (roughly a 60% price reduction). The pharmacy keeps the 50KES paid by the patient for SI. The 50KES price is benchmarked against the mean markup in the pre-study data and similar non-study sites in order to keep provider incentives constant on average[15].

Pharmacy cost-reduction arm (T2): Sites in the pharmacy cost-reduction arm receive SI stock through the Maisha Meds program. Prices to the consumer for SI are set by the pharmacy during onboarding and can be updated at any time by the site. The pharmacy keeps the price charged to the patient.

Pharmacy incentive (T3): This arm is identical to the pharmacy cost-reduction, except for the inclusion of a pharmacy incentive (per sale transfer to the pharmacy) of 50KES.

The treatment structure by arm is summarized in table 1. In addition, all arms had access to emergency contraceptive (EC), HIV testing, and malaria product subsidies through the Maisha Meds program (including the control group). Furthermore, posters displaying the prices of these products were supplied to all study sites, as well as a fact sheet with information about SI to providers (see A.2), including the control arm. Any site in the RCT could own their own stock of SI from other suppliers, which they could sell at their chosen prices.

3.3.2 Interpretation of treatments

In the RCT, there are two broad categories of incentives: consumer price reductions and provider/pharmacy incentives. The consumer price reduction arm (T1) reduces patient prices while keeping provider incentives constant, so following the conceptual framework we expect it to influence demand mainly through price (either directly through α or indirectly through the provider's altruism). The pharmacy cost-reduction arm (T2) and pharmacy incentive arm (T3), on the other hand, are (differently sized) reductions in the marginal cost of administering SI, which can affect both patient prices (if subsidies are passed through) and provider financial incentives. Having two separate marginal cost shocks (T2 and T3) therefore allows us to separately identify the role of prices and financial incentives on demand in the structural model.[16]

[15] During the study period, the 50KES benchmark continued to match the control group's mean markup, as well as the non-experimental sample of Maisha Meds network sites.

[16] While all arms can affect the price paid by the consumer $p(T)$ (by design in T1, and endogenously in T2 and T3), the $t = 50KES$ pharmacy incentive in T3 shifts the relationship between prices and markups by 50KES: for $T \in \{T1, T2\}$ we have $price = markup$, whereas in T3 $price = p(T3) < p(T3)+50 = markup$. The treatment assignments therefore generate independent variation in prices and provider financial incentives, allowing us to separately identify their roles in provider behavior and patient demand.

3.4 Data sources

1. Administrative data: Transaction-level data includes product characteristics, prices to the patient, cost of the product to the facility, and quantities sold. The Point of Sales (POS) system data includes almost 27,000 family planning patient encounters across all study arms. The first two weeks of data were dropped after the onboarding date of each site to account for an adjustment period to the subsidy system. Data was collected between August 2022 and March 2023.
2. Mystery shoppers: Trained enumerators posed as patients following one of two standardized profiles to collect information on the characteristics of the counseling interaction with a provider[17]. There were 228 visits across 114 facilities (2 per site), collecting information on the quality of family planning counseling and the information shared with patients, among other site and provider characteristics. Providers were not explicitly informed of the activity, and enumerators were unaware of the study design and treatment assignments. Data was collected between December 2022 and February 2023. Appendix A.2 describes the patient profiles, enumerator training, and sample in more detail.
3. Pharmacy endline survey: Near the end of the study, pharmacy owners and, when possible, one additional client-facing provider completed a survey on site characteristics, self-reported practices, and provider views, beliefs, and characteristics. A total of 202 surveys were completed across 124 sites[18] in February 2023. Enumerators were unaware of the study design and treatment assignments.
4. Pharmacy and clinic census: To measure patients' outside options, trained enumerators surveyed the nearest family planning providers (private and public clinics, hospitals, and pharmacies) within a 10-minute driving radius of each study site. For each study site, the nearest 4 such sites were surveyed when consent was granted. Of 789 unique sites identified, 455 were surveyed[19], yielding data on FP product availability, quantities sold, prices, and basic site characteristics. This activity occurred in February 2023, near the end of the study period.

4 Results

We estimate all reduced form treatment effects using the double/debiased machine learning approach of Chernozhukov et al. (2018); appendix A.3 provides additional details about this approach.

[17] The final mystery shopper activity sample includes 82% of our study facilities. The activity excluded facilities in coastal Kenya due to budget constraints, and a small number of sites were unable to be visited due to seasonal closures or renovations. Take-up effects are not significantly different for this sub-sample in table A.6.

[18] A subset of sites did not consent to participate in the survey.

[19] We keep 452 observations since 3 survey sites were identified as experimental sites based on location and business name

4.1 Adoption and diffusion of SI

Pharmacy sales of SI: The three subsidy structures lead to large and similar increases in the probability that a patient encounter results in an SI sale (column 1 of table 2)[20]. Each arm raises the share of family planning transactions that include SI by at least 18 percentage points, and we cannot reject that the effects are equal across arms ($p > 0.50$; see appendix table A.2 for arm-specific estimates, pooled results, and additional tests). Note that despite the fact that the total incentive amount in T3 is higher than in T1 and T2, its effect on adoption is not significantly larger than the other arms, suggesting diminishing returns. Pooling the treated arms, the increase is 21 percentage points over a control-group share of 2%, a roughly 1,050% increase.

Substitution patterns with incumbent alternatives: Substitution patterns across product categories are similar in all treatment arms. Columns 2 and 3 of table 2 present analysis analogous to column 1, but the outcome variables are now the share of transactions in a site that include a given product category for non-SI FP options. All family planning products available in the transaction data of the study sites can be categorized as: injectables (including SI and IMI), condoms (male or female), emergency contraceptives (EC), and oral contraceptives (OC). Therefore, injectable contraceptives are the only medium to long-term method available in our study sites, while short term methods are composed by non-injectables: condoms, EC, and OC. Overall, the analysis finds evidence of large substitution effects away from short term methods across all treated arms.

Ex-ante, one would expect strong substitution away from IMI given that it is the only other injectable available in the market, is produced by the same manufacturer and has the same active molecule, and is the only other medium to long-term method in our study sites. Moreover, SI dominates IMI across multiple product characteristics. However, in column 2 we only observe a small and non-significant reduction in the share of transactions that include an IMI sale in treated sites. The reduction is only marginally significant at the 10% level for the pharmacy incentive arm (4 percentage points), but not significant for the pharmacy cost-reduction and consumer price reduction arms (1 percentage point in both cases). Appendix table A.3 presents additional pooled results across arms and statistical tests. Pooled together, there is no significant reduction in IMI sales in treated sites (3 percentage points). It is worth noting that the control group's average is only 8%, so the analysis might not be powered to estimate significant effects for this outcome. The estimated effects are all negative across arms, and represent 13%-50% reductions relative to the control group's average, so in economic terms they are not small effects. Nevertheless, it seems like increased adoption of SI is being driven by patients who were not previous users of injectables.

For short-term methods (EC, OC, and condoms), there are strong substitution effects in treated pharmacies (column 3). There is a reduction of 16 to 19 percentage points in treated arms relative to the control group in the share of transactions that include a short-term method. Columns 3-5 of the appendix table A.3 show the effects on specific short term methods and additional statistical tests. There are no significant differences across arms. The results suggest that substitution is strongest away from oral contraceptives, bringing shares of injectables and OC closer to national

[20] Conditional on a sale being made.

patterns (KNBS, 2022). There is also significant substitution away from emergency contraceptives, specifically for the pharmacy incentive arm, consistent with some women switching from EC misuse toward injectables as a more effective and discreet option (section 2). Finally, there is no significant effect on condom sales in the treated sites, although the coefficients are negative. This is not surprising since condoms can be complementary products given that they prevent STIs, are often purchased by male patients, and can be used in combination with hormonal contraceptive options like SI.

Patient selection across sites: We use the pharmacy and clinic census to test whether the adoption effects reflect patient selection across sites rather than changes in product choice. Because patients have many nearby alternatives (each study site has on average 14 competing pharmacies or clinics offering FP within 2km), higher SI purchases at treated sites could in principle reflect patients drawn from surrounding markets. Linking each surveyed census site to the treatment status of its nearest RCT site (columns 4-6 of table 2), we estimate competitive effects on FP volumes using double-selection lasso Poisson regressions (Belloni et al., 2016).

Competitive effects appear only in the consumer price reduction arm. The provider arms show no significant effect on surrounding-site volumes (coefficients within one standard error of zero), whereas sites near consumer price reduction pharmacies sell about 41% fewer long-term methods (column 4; IRR$-1 = -0.41$, SE $= 0.20$), an effect concentrated in injectables (column 5). The higher adoption of SI in the provider arms therefore appears to be driven by changes in patients' product choice rather than patient selection, while in the consumer arm it is partially driven by patient sorting across sites.

Decomposition into extensive and intensive margin effects: The higher adoption of SI in treated arms could reflect increased availability (an extensive margin) or changes in patient choice conditional on availability (an intensive margin). Availability alone does not appear to drive the effects: about 47% of control sites already stock SI, yet only 2% of their transactions include an SI sale (table A.15, column 1). Treatment effects on availability are nonetheless large, as essentially all treated sites stock SI[21].

Intensive margin effects appear to drive the higher adoption of SI. Conditional on availability, the pooled treatment effect is 18 percentage points (columns 2-3 of table A.15; see also table A.5), only 3 percentage points below the pooled adoption effect. Because availability is endogenous rather than randomized, these estimates are a lower bound; a Heckman model that controls for selection into stocking SI (column 4) confirms intensive-margin effects of 0.21-0.26, consistent with the main adoption estimates in table 2[22].

[21] Having SI in stock does not imply recorded SI sales: only 15% (80%) of control (treated) sites registered any SI sales during the study period.

[22] In the first stage, a Probit models whether a site stocks SI as a function of whether it stocked SI prior to the RCT, a ward wealth index, the ward's population, the number of surrounding competitors, and urbanicity indicators. The first-stage p-value is 0.05.

4.2 Mechanisms: Prices, markups, and counseling

Price passthrough: effects on prices and markups. Prices and provider financial incentives vary meaningfully across arms depending on whether the incentive targets the patient or the provider (column 1 of table 3, which summarizes the price and information mechanisms; appendix table A.12 reports the full set of price specifications and tests). In the consumer price reduction arm (T1), the price of SI falls by 74KES relative to the control-group mean of 129KES (essentially equal to the 75KES subsidy design benchmark), so patients received essentially 100% of the subsidy as intended[23]. Because the average cost of stocking SI is 75KES, the benchmarked 50KES markup roughly matches the control-group mean markup, holding per-sale provider incentives constant in T1. In the provider arms, by contrast, pass-through is limited: prices fall by only about 34% of the subsidy in the pharmacy cost-reduction arm (26KES, T2) and 18% in the pharmacy incentive arm (22KES, T3), pooling to a 23KES reduction. We reject with high significance that the provider and consumer arms have equal pass-through, so patients in the provider arms pay roughly twice as much for SI as in T1, while providers there earn higher markups.

The fact that we do not find differences in adoption across arms in table 2, despite there being a significant difference in patient prices between the provider and consumer arms, suggests that the effects on take-up are not purely mediated by the retail price of the technology being subsidized. In fact, in the pharmacy incentive arm where the treatment effect on adoption is largest, SI is sold at the highest average price across treated arms. Therefore, a different channel is likely responsible for the increase in the patient's willingness to pay for the new technology in the provider arms.

Information channels: effects on counseling and advice. The field activities suggest that provider advice and counseling respond to all treatment arms, with the response concentrated where providers' financial incentives are largest. Providers in treated pharmacies report being more likely to recommend SI, and the mystery shopper data let us assess whether these recommendations lead patients toward more informed decisions. Overall, providers in treated arms share more information about SI without reducing what they share about alternative methods, so patients appear to make more informed choices.

The information-channel columns of table 3 (columns 2-6) present these results. Providers in all treated arms are substantially more likely to recommend SI over the old injectable to interested patients (29 to 44 percentage points, column 2), with no significant differences across arms. The SI-specific information shared during mystery shopper visits rises most where financial incentives are largest: 0.74 to 0.82 SD in the provider arms (T2, T3) versus a smaller, insignificant 0.34 SD in the consumer arm (column 4). Consistent with this, providers in the higher-incentive arms are more likely to report recommending SI for medical reasons, whereas in T1 recommendations lean on SI's lower price (column 3). This added attention to SI does not crowd out other counseling: there are no significant effects on general FP information or information about alternative methods (columns 5-6), and only 1 of 228 mystery shopper visits reported that they felt pressured to purchase SI

[23]Some treated sites owned their own stock of SI outside of the subsidy program, which they could sell at their chosen prices; prices for SI are therefore site-level averages. See table A.12 for details.

(in T1). Finally, provider knowledge improves similarly across arms: they are more comfortable administering injectables and more aware that SI has fewer side effects than IMI, with no effect on knowing when SI is unsuitable (appendix table A.13). Thus the weaker information-sharing in the consumer arm does not reflect less provider knowledge.

5 A model for patient demand and provider's advice

This section presents the estimation strategy and results for a patient demand and provider advice model following the conceptual framework in section 1. Estimation relies on the exogenous variation generated by the RCT along with detailed data on marginal costs and proxies for advice

5.1 Estimation of parameters in the provider advice model

Model components in the data. — The primary measure of whether providers recommend the new technology comes from the provider survey, where providers reported which product they recommend to patients interested in injectables and why. We set $\theta = 1$ if half or more of the providers interviewed in a site recommend SI (column 2 of table 3)[24]. Because this measure, like the others, is observed at the site rather than the patient level, equation 2 can only be estimated after excluding the patient index i.

This site-level assumption can be interpreted as patients encountering one of two provider counseling types with respect to the new technology (i.e. SI-amenable providers vs non-SI amenable providers)[25]. Note that this does not necessarily imply that providers recommend SI to every patient when $\theta = 1$, but rather that these are providers that are likely open to counseling the patient on this option if they deem it appropriate. This observable measure of θ (as well as those in the robustness checks) lets us test the role of counseling on patient demand directly, rather than relying on structural assumptions to identify the information-channel parameters.

The primary measure of $f(p, c)$ was constructed using the administrative data on prices and marginal costs of stocking each family planning product. The formula for $f(p, c)$ is given by equation 3. The shifts in probability $(P(k|\theta = 1) - P(k|\theta = 0))$ were calculated with a linear model of the shares of transactions in a site that include each product category on θ using data from all sites with SI availability[26]. Therefore, shifts in probability from the recommendation decision are held constant across sites and act as a scaling parameter for the product-category markups[27].

[24] Provider model estimates are robust to alternative definitions of θ, including using a combination of variables such as provider knowledge about SI and indicators for various self-reported reasons for recommendation (medical, low price, etc...). Mystery shoppers could not accept injectable contraceptives during their visits to the sites for safety and ethical reasons, so there is no comparable measure for whether providers recommend SI to these trained enumerators. Furthermore, the mystery shopper activity excluded sites in Coastal Kenya due to implementation costs. Table A.18 shows how model components correlate with measures from the mystery shopper activity.

[25] This is consistent with evidence that provider fixed effects strongly predict treatment choices (Iizuka, 2012; Datta and Dave, 2017; Kiang et al., 2020).

[26] See table A.7 for the estimates of the shifts in probabilities. Results are robust to various definitions of θ.

[27] It is possible that the proposed $f(p, c)$ measure does not include other unobserved marginal costs associated with providing SI to the patient. In the conceptual framework, this potentially unobserved differential cost — which can be thought of as a measurement error with non-zero mean — would enter as a term that cannot be separately identified from the constant term in the estimating equation, but $f(p, c)$ still allows for the identification of model

Estimation strategy. — We exploit exogenous variation from the RCT to estimate the provider model parameters. To do so, we assume that the provider's altruism is given by $W(p_{SI}) = \kappa p_{SI} + C$, where C is a constant[28] and p_{SI} is the price for the new technology. By explicitly modeling whether providers internalize patient's expenditures, valid instruments for $f(p, c)$ and p_{SI} allow us to recover λ and κ [29]. Parameter κ summarizes how providers respond to changes in the patient's out-of-pocket costs due to their altruism towards the patient[30].

The model is estimated through maximum likelihood using data from sites that stock the new technology. In particular, the error term e_d is assumed to follow a normal distribution leading to a standard IV probit model (Rivers and Vuong, 1988):

$$\theta_{d,SI} = 1\{C + \kappa p_{SI,d} + \lambda f(p_d, c_d) + \boldsymbol{w_d}\gamma + e_d \geq 0\} \tag{4}$$

$$\begin{pmatrix} p_{SI,d} \\ f(p_d, c_d) \end{pmatrix} = \boldsymbol{w_d}\Pi_1 + \boldsymbol{z_d}\Pi_2 + \boldsymbol{v_d} \tag{5}$$

where $\boldsymbol{w_d}$ is a vector of site controls and $\boldsymbol{z_d}$ are instruments for $p_{SI,d}$ and $f(p, c)$. The vector of error terms is assumed to be joint-normal, i.e. $(e_d, \boldsymbol{v_d}) \sim N(\boldsymbol{0}, \boldsymbol{\Sigma_v})$, with $Var(e_d)$ normalized to 1 and the other terms of the covariance matrix are estimated[31]. Instruments $\boldsymbol{z_d}$ are indicators for the three treatment arms in the RCT, which capture exogenous variation on both the price and the markup of SI. In the main specification, control variables $\boldsymbol{w_d}$ include an indicator for prior availability of SI and whether the site is located in Kisumu county[32].

5.2 Estimation of parameters in the patient's demand model

Model components in the data. — As in the provider model, patient-level measures of $\theta_{d,i,k}$ are not observed. We therefore estimate a version of equation 1 that replaces $\theta_{d,i,k}$ with the fitted recommendation probability from the provider model, $\hat{\theta}_{d,k}$, equal to $\hat{\theta}_{d,SI}$ (the average structural function of the predicted probabilities from equation 4) when $k = SI$ and zero otherwise[33].

We use administrative data from the study sites to generate a standardized measure of price p_k for the various family planning options k in a site. For all methods we transform prices so that they

parameters since this error is likely uncorrelated with the RCT variation.

[28] This could be extended to include patient characteristics observed by the researcher if patient-level recommendation data was observed.

[29] Assuming constant term C is not restrictive since this term represents mean value at the origin.

[30] See footnote 10 for definition of altruism in this setting.

[31] The Stata command *ivprobit* implements this estimator. Moreover, estimation is robust to alternatively using control functions for $f(p, c)$ and p_{SI} and fitting a standard probit model.

[32] Results are robust to either including all stratification variables as controls and excluding all control variables. Nevertheless, including these two control variables strikes a balance between increasing power in our estimations and allowing for bootstrap inference.

[33] An alternative approach is to plug-in directly the site-level information measure $\theta_{d,SI}$ rather than the fitted probabilities. Parameter estimates are not sensitive to either choice, but measure $\hat{\theta}_{d,k}$ offers some advantages. For instance, it being continuous relaxes the assumptions needed to use a control function to deal with the endogeneity in the model, and simplifies the computation of counterfactuals that impact the recommendation probabilities. Moreover, it allows for the derivation of a simple closed-form decomposition of the demand curve, which is discussed in section 5.4

are normalized by the number of doses sold in a package. Doses are defined following the World Health Organization "Defined Daily Dose" (DDD) units for each Anatomical Therapeutic Chemical (ATC) classification (WHO, 2024).

The estimation equation includes two observable product characteristics x_k. The first is an indicator for whether product k is a long-term method (SI or IMI), which is equivalent to an indicator for whether the product is an injectable contraceptive in the data. The second characteristic is the common use failure rate of the family planning method from the World Health Organization's provider global handbook (WHO, 2022)[34].

We define an outside option with value normalized to zero ($\bar{v}_{i,0,d} = 0$) as the number of long-term contraceptive methods sold at a representative surrounding site (the average of the 4 closest surveyed census sites)[35]. The outside option thus summarizes alternative sources of care for long-term methods, motivated by the reduced form competitive effects on long-term method sales in surrounding markets (table 2)[36].

The data used for the demand and provider advice model estimation is from a subset of the RCT site sample. First, only sites that stock SI are included since the price for SI is only observed in that case. Moreover, only sites for which provider data and census data is available are included in order to have measures for θ and the outside option. Finally, we exclude a site for which there is only 1 product alternative available. This leads to a sample size of 98 sites, representing 24,640 patient-choice cases. A patient-choice case is defined as a patient encounter in the administrative data or a long-term method sale in the surrounding market. For transactions where multiple products categories were purchased, each transaction-category is considered as a separate case in order to keep the dimension of the product-space low[37].

Estimation strategy. — To estimate the patient demand model we assume that the error terms in equation 1 are distributed i.i.d. with a type I extreme-value distribution, and that taste parameters for observable product characteristics β_i are random following a multinomial normal distribution $\beta_i \sim N(\beta, \Sigma_U)$, where the diagonal elements of Σ_U are estimated and the off-diagonal elements are assumed to be zero. This leads to the widely used multinomial Logit model with random coefficients (McFadden and Train, 2000).

The estimation of the patient's demand model parameters is threatened by the potential endogeneity of the error term $\epsilon_{i,k}$ given that it could be correlated with unobserved product and provider attributes, including the error term in the provider model. Therefore, instruments for both p_k and $\theta_{d,SI}$ are required. We follow Petrin and Train (2010) in implementing a control function approach

[34]Results are robust to including fixed effects for each alternative, although the data lacks additional variation to estimate more flexible substitution patterns across options in that case.

[35]Results are robust to defining the representative site in terms of the closest 1, 2, 3, and 4 sites to each study site. See table A.10 for more details on the definition and comparisons with alternative definitions.

[36]There were no competitive effects on short-term methods in surrounding markets and focusing on long-term methods is advantageous since a unit sold represents a single patient encounter.

[37]In the existing literature this discrete choice assumption is standard when working with aggregate sales data. This is a reasonable assumption in this setting since less than 9% of transactions in the data include multiple categories. Results are robust in linear probability models to defining shares in a similar way to section 4.1 where multi-product transactions are allowed.

for discrete choice models. Specifically, we regress the endogenous variables ($\hat{\theta}_{d,SI}$ and p_k) on a vector of instruments in a first stage (equation 6) and include the first stage residuals as controls in the maximum likelihood estimation of the demand model (equation 7)[38]:

$$\begin{aligned} p_{d,k} &= \boldsymbol{x_k} a_1 + \boldsymbol{z_{d,k}} b_1 + \mu_{d,k,1} \\ \hat{\theta}_{d,SI} &= \boldsymbol{z_{d,SI}} b_2 + \mu_{d,SI,2} \end{aligned} \tag{6}$$

$$\bar{v}_{i,k,d} = \alpha p_{d,k} + \beta x_k + \delta \hat{\theta}_{d,k} + \phi_1 \hat{\mu}_{d,k,1} + \phi_2 \hat{\mu}_{d,SI,2} + \epsilon_{i,k} \tag{7}$$

where $\mu_{d,k,1}$ and $\mu_{d,SI,2}$ ($\hat{\mu}_{d,k,1}$ and $\hat{\mu}_{d,SI,2}$) are the error terms (residuals) from the first stage and $\boldsymbol{z_{d,SI}}$ are instruments for $p_{d,k}$ and $\hat{\theta}_{d,SI}$[39].

In addition to the RCT treatment indicators, estimation requires an additional set of instruments since the endogenous variables include observations for products for which there was no experimental variation in prices and marginal costs. Therefore, the preferred estimation includes 2 additional instruments: the marginal cost to the pharmacy of stocking the various family planning options (which is interacted with treatment indicators), and the component of $f(p,c)$ that does not include SI. The motivation for using marginal cost data is straightforward since the "Hausman instrument", which is widely used in the demand estimation literature (Berry and Haile, 2021), proxies for these cost shifters. In this case the cost-shifters are directly observed in the data. The motivation for using the non-SI component of $f(p,c)$, i.e. $\Sigma_{-SI} m_k (P[k|\theta = 1] - P[k|\theta = 0])$, is less clear. This component summarizes the provider's outside option when recommending SI since it is an index of markups for the alternative products that are in stock in a site. The relevance of this instrument for the information parameter follows from the provider model. The exclusion restriction likely holds since it is an index of the marginal costs and prices of ALL family planning products in a site, so it is unlikely to be correlated with unobserved product attributes of SI. Nevertheless, results are robust to instead using the average markups of family planning products in the study site's market from the census survey, as well as transaction-level non-normalized marginal costs for all FP products available in a site.

5.3 Instruments, identification, and the role of θ in the model

Figure 2 plots $f(p,c)$ and p_{SI} to visualize the variation generated by the RCT. The price of SI and $f(p,c)$ enter directly the provider's model equation (Eq. 4), so exogenous variation in p_{SI} and c_{SI} identifies the provider model parameters. However, we require additional motivation for using the price and marginal cost instruments for the information measure θ in the patient's demand model.

The decision of providers to recommend the new technology — θ — is only one dimension of the provider's counseling. Providers can use different counseling practices, spend different amounts of time with the patient, or even pressure the patient to buy a specific product. In the interest of tractability, the model reduces the dimensionality of the provider counseling to the decision of

[38] Maximum likelihood estimation of this model offers the advantage that it explicitly controls for differences in the choice sets across patient encounters.

[39] Note that only the case where $k = SI$ we have that $\theta_{d,k}$ is endogenous, since otherwise it is defined to be 0.

whether to recommend or not the new technology since it has an intuitive interpretation. Tables A.7, A.8, and A.18 in the appendix show that the provider model can be alternatively estimated with other information measures that reduce the dimensionality of multiple counseling characteristics, with similar patterns to the ones observed in the main results.

The main motivation for using variation in provider financial incentives as instrument for θ is that conditional on the price paid (which the model controls for), patient treatment choices should not respond directly to the marginal cost or markup of SI. Since patients do not directly observe the marginal costs and markups of the distinct family planning products, any patient response to changes in the financial incentives of the provider must be driven by changes in the counseling of the provider. This implies that the instruments can be altering the patient's demand for the new technology through multiple dimensions of the provider counseling. In-so-far as we interpret θ as a one-dimensional proxy for the counseling behavior of the provider in regards to the new technology, the instruments allow us to estimate δ and α through the distinct counseling channels that are correlated with the recommendation decision.

5.4 The slope of the demand curve

A price effect on patient choice is not only driven through a direct patient response, but also through changes in the advice of the provider. This is because the price of SI appears directly in the patient's demand equation and indirectly through the provider counseling equation. In particular, the slope of $\bar{v}_{i,k,d}$ with respect to p_k when $k = SI$ can be decomposed into three components:

$$\begin{aligned} \frac{\partial}{\partial p_{SI}} \bar{v}_{i,k,d} &= \alpha + \delta \frac{\partial \hat{\theta}_{d,SI}}{\partial p_{SI}} \\ &= \underbrace{\alpha}_{\substack{\text{Direct patient} \\ \text{effect} \\ (1)}} + \underbrace{\delta\kappa\phi(\boldsymbol{p_d}, \boldsymbol{c_d}, \boldsymbol{w_d})}_{\substack{\text{Provider altruism} \\ (2)}} + \underbrace{\delta\lambda(P[SI|\theta=1] - P[SI|\theta=0])\phi(\boldsymbol{p_d}, \boldsymbol{c_d}, \boldsymbol{w_d})}_{\substack{\text{Provider's incentives} \\ (3)}} \end{aligned} \tag{8}$$

where $\phi(\boldsymbol{p_d}, \boldsymbol{c_d}, \boldsymbol{w_d})$ is the normal density function evaluated at $(\boldsymbol{p_d}, \boldsymbol{c_d}, \boldsymbol{w_d})$.

Component (1) is the direct effect of price on the patient's perceived value of SI. This effect relates to the patient's price elasticity conditional on the provider's advice. In a world where the patient is the sole agent in making a treatment decision and is fully informed about the product characteristics, we would generally expect this coefficient to be negative. On the other hand, if the provider is the main agent in determining the treatment choice this coefficient would be zero. In cases where the patient has imperfect information about the product characteristics and relies on provider advice to make a decision, the sign of α is ambiguous ex-ante.

Component (2) is the term that results from the provider altruism. Therefore, this term influences the slope of the demand curve if the provider is altruistic with regards to the patient's expenditure, i.e. if $\kappa < 0$, and if the patient cares about the provider's advice when making a choice, i.e. $\delta > 0$. This component should be negative unless the provider does not internalize the patient's expenditure or the patient disregards the provider's advice.

Finally, component (3) summarizes the effect of changes in the provider's financial incentives on

the patient's demand for SI[40]. If the provider's advice is influenced by their financial incentives, i.e. $\lambda > 0$, and the patient takes into account the provider's advice, then we expect (3) to be positive.

Ex-ante, it is not clear how a price change that is correlated with the provider's financial incentives will impact the demand curve. The total slope of demand will be determined by the distinct effects summarized by components (1), (2) and (3) in equation 8. It is even possible for the slope of demand with respect to price to be positive (at least locally) if the provider financial incentives component is relatively larger than the other components.

5.5 Model results

We focus on the full structural estimates, but first note that a linear probability (2SLS) version of the model recovers the same qualitative conclusions while offering directly interpretable marginal effects and a transparent check on the instruments[41]. The full linear results are reported in appendix tables A.16 and A.17, and the structural estimates below match each of these patterns.

5.5.1 Model parameter estimates

The parameter estimates of the model align with the linear probability results. Panel B of table 4 presents the parameter estimates in the provider counseling model and again find evidence that providers weight their own financial incentives heavily. The provider model is estimated through IV probit (Rivers and Vuong, 1988) as described in section 5.1. The coefficient on the provider's financial incentives to recommend ($f(p,c)$) is $\lambda = 0.111$ ($p < 0.01$). This parameter implies a marginal effect of roughly 5 percentage points in the probability of recommending SI for a 1KES increase in $f(p,c)$, matching the estimated marginal effect with linear probability (4.4 percentage points; LPM column of Panel B). On the other hand, the price coefficient is $\kappa = -0.017$ ($p = 0.03$). The implied marginal effect is roughly -0.8 percentage points, which matches the direct estimate using linear probability (LPM column of Panel B). When comparing the relative magnitudes of the coefficients we find that for each 1KES change in p_{SI} or $f(p,c)$ providers weight their financial incentives 6.5 times more than the patient's expenditure.

Column 1 of Panel A in table 4 shows the main parameter estimates of the demand equation. The primary parameters of interest are the coefficients for price and information (α and δ). Column 1 presents the results for the main estimation strategy described in section 5.2 using a mixed multinomial logit model. The specification includes an alternative-specific indicator for the new technology, reported in the vector means block. This indicator allows the baseline level for SI to differ from IMI's baseline at similar price and incentive levels. The indicator is estimated at -2.2562 ($p = 0.01$), so the implied patient value on the new technology before accounting for the provider's advice is low. The price parameter α is estimated to be 0.0025 ($p = 0.24$), so we find that

[40] Assuming, for expositional purposes, that the marginal costs to the provider are held constant.

[41] An advantage of linear probability models is that they can directly recover marginal effects from the model components which can aid in the interpretation of the results, avoid parametric assumptions on the error terms of the model, and provide relevant summary statistics (Angrist and Pischke, 2009). Moreover, the properties of a linear 2SLS estimator are well understood and robustness checks testing the validity of the instruments are easily implementable.

patients do not respond to price changes in SI conditional on the recommendation of the provider (LPM estimates in column 6 are more easily interpretable and show that the direct price response is not economically meaningful: a subsidy similar to T1 would lead to less than a 5 p.p. increase in demand). Parameter δ, which summarizes how patients respond to the provider's advice, is estimated to be 3.5326 ($p < 0.01$). Therefore, we again find that patients weight the provider's advice heavily when deciding whether to purchase the new technology.

The model in column 1 includes taste parameter estimates for two product characteristics which are modeled as normal random variables: an indicator for whether the product is a long-term method and the failure rate of the method under normal use. Unsurprisingly, the estimates imply a distaste for both product characteristics. The estimated standard deviations of these random coefficients give an intuition for the substitution patterns induced by these product characteristics. The standard deviation for the long-term indicator is very close to zero, so this suggests that there is not much substitution across long-term methods conditional on the failure rate. The standard deviation for the failure rate is roughly 0.2, suggesting that patients are likely to substitute across products that are near each other in this metric. Injections, emergency contraceptives, and oral contraceptives are closer to each other along this dimension, while condoms are much further. This implies that condoms are not close substitutes to SI in the model, a feature that matches the patterns in table A.3.

Columns 2, 3, 4, and 5 show the robustness of the results to different modeling assumptions. Column 2 uses the observed value of $\theta_{d,k}$ instead of the fitted probabilities from the provider model $\hat{\theta}_{d,k}$. Column 3 shows the same model estimation strategy as in column 1, but excluding the SI alternative in cases where the site did not observe any sales of the new technology, despite the product being available[42]. Column 4 shows the results from a multinomial logit model without random coefficients. Finally, Column 5 shows a multinomial logit estimate including fixed effects for each product alternative, which span the new-technology indicator and so subsume it. Column 6 reports the linear probability (2SLS) benchmark reproduced from column 5 of table A.17, which includes product fixed effects – the linear model's counterpart of the alternative-specific intercept carried by the structural columns – and whose marginal effects align with the structural estimates.

Decomposition of the demand for SI. — As shown in equation 8, the total slope of demand in this model with respect to price is not fully summarized by α since the price vector appears inside of $\hat{\theta}$. This equation decomposes the patient's value for SI into three components: (1) a direct price effect, (2) an indirect effect driven by the provider's altruism, and (3) an indirect effect driven by the provider's financial incentives. The main model parameters in table 4 can be used to estimate the magnitudes of each component in equation 8[43].

Figure 3 summarizes the magnitudes and significance levels of each component in the decomposition of the price effect. The direct price effect is given by α, which is not significantly different from

[42] More details on how the price variable is constructed can be found in table A.12.

[43] We evaluate this equation at the observed value of each study site and report the average across sites as a summary statistic.

zero (p = 0.24). The linear probability analogue in table **??** implies a non-statistically significant 4.4 p.p. response in demand to a price reduction comparable to T1. Therefore, patient demand for SI is locally flat conditional on the provider's recommendation.

The indirect effect driven by the provider's altruism has a value of -0.017 in terms of choice utils, 7 times greater than the direct patient effect. The test for whether this component is negative is significant at the 10% level (p = 0.09). Finally, the indirect effect from the provider's financial incentives has a value of 0.015 in choice utils, roughly 6 times higher than the direct patient effect. The bootstrap test for whether this component is positive is significant in the structural model (p = 0.04)Therefore, the only statistically significant and economically meaningful components of the demand curve are those that relate to the provider's behavior.

5.5.2 Own-price elasticity and external validity

These results highlight the importance of controlling for the financial incentives of the provider when estimating the demand curve with the goal of studying patient welfare. Figure 4 shows the impact on elasticity estimates from ignoring the financial incentives of the provider. First, the green histogram implies the usual downward sloping demand curve when financial incentives are held constant, with a mean elasticity of -1.13 and a median of -0.91 (97% of sites have a negative conditional elasticity). This elasticity is being driven by the direct patient response and the provider's altruism, and is informative of patient welfare. This estimate is also not far off from the shift in demand observed in T1, where the implied midpoint elasticity is -1.96 using only two price points (C vs T1).

However, if one does not condition on $f(p, c)$, the estimated total price elasticity collapses towards zero and turns positive at most sites (mean +0.02, positive at 57% of sites), so the estimated demand curve is flat to upward sloping. This is because the effect on the provider's financial incentives roughly offsets the price response driven by the patient and the provider's altruism in our study sample's distribution of prices and incentives. The intuition for this result aligns with the conceptual example in figure 1.

Since the financial incentives of the provider are not welfare-relevant to the patient, failing to control for these will lead to biased welfare estimates when observing the demand curve for a health product, even when one has access to exogenous supply-side cost-shifters. Therefore, this exercise highlights that markets with expert intermediaries are settings where traditional exclusion restrictions widely used in the economic literature do not always hold, particularly if one's goal is to assess the welfare impact on patients. In settings where financial incentives and prices are positively correlated, such as with pay-per-service models, one would expect less elastic unconditional estimates of demand relative to the welfare relevant estimates.

6 Welfare effects and policy counterfactuals

6.1 The impact of θ on the patient's welfare

As discussed in the conceptual framework, the welfare impact of the provider's recommendation (θ) is ambiguous: it is welfare-enhancing if it accurately updates the patient's valuation (even if partially), or it could be welfare-decreasing if it distorts that valuation (e.g. through misrepresentation or pressure).

The reduced form evidence from the mystery shopper activity and provider survey suggests that provider advice is more likely to correctly update the patient's valuation: providers inform patients about alternative options at similar rates across arms while sharing more information about SI in treated arms (section 4.2, with additional outcomes in appendix table A.11).

We provide further evidence that θ improves the accuracy of the patient's valuation by examining how counseling characteristics relate to the provider's financial incentives $f(p, c)$, whose shocks identify the role of advice. Using 2SLS (table A.18), $f(p, c)$ is positively correlated with the SI information index, the use of educational tools during counseling, and being perceived as more knowledgeable about FP, while the coefficient on whether the provider pressured the patient to purchase SI is negative and insignificant[44]. Since mystery shoppers have above-average FP knowledge, these positive perceptions likely reflect more accurate information diffusion, with no evidence that higher incentives distort counseling.

6.2 Welfare estimation

We estimate the welfare effects for the patient by calculating the expected compensating variation (CV) for each policy (Small and Rosen, 1981; Bockstael and McConnell, 2007) by simulation (McFadden, 2001; Bockstael and McConnell, 2007).

In our preferred analysis, we assume the provider's recommendation θ accurately updates the patient's valuation of SI to its true value, so that this true value is implied by the model at $\theta = 1$. This aligns with the reduced form evidence, and results are robust to a wide range of assumptions about the true value of SI which we also present to illustrate how provider counseling can impact patient welfare more broadly. We simulate 5,000 patients per study site and compute their changes in utility under each counterfactual policy.

As we argued before, the welfare relevant parameter in the price response equation in the model excludes the provider's financial incentives. We therefore normalize the welfare estimates using $\hat{\alpha} = 0.0022 + (-0.005) = -0.0028$, the sum of the direct price effect and the provider-altruism component from the demand decomposition (section 5.5.1). This $\hat{\alpha}$ captures the patient's price response conditional on the provider's financial incentives, and is consistent with other experimental estimates in the health economics literature (for instance, Manning et al. (1987) estimated the widely

[44] While not reported, the coefficients of $f(p, c)$ for outcomes such as general FP information index, non-SI information index, trust indicator from the mystery shopper, and the indicator for allowing patient opinions are also positive.

cited elasticity from a large-scale health insurance experiment of -0.2 which matches the elasticity implied by this normalization).

Finally, we assume these small independent pharmacies are price takers when computing counterfactuals, consistent with the RCT results and field activities where there are minimal to no price responses to the experimental cost-shifters (see appendix B).

6.3 Welfare and counterfactual results

Table 5 presents the counterfactual analysis. The key takeaway is that providers are crucial in the new health technology adoption process and to the success of subsidy programs, regardless of whether these subsidies result in lower prices for patients or higher financial incentives for pharmacies. Without the provider's role as an expert intermediary, the subsidies would not have significantly impacted the adoption of the new technology compared to the control group.

Columns 1-4 display the welfare effect estimates and SI choice probabilities, depending on whether the provider advice is active or not. Panel A examines the counterfactual impact of introducing SI into the patient's choice set. The first row shows the welfare effect of introducing SI at treated sites. We find that the estimated welfare gain from introducing the new health technology into patient's choice sets is 3.5 times higher when provider advice is allowed to respond to prices and financial incentives. Therefore, most of the welfare gains come from providers informing patients about the value of this new option.

SI choice probabilities are markedly different when θ is inactive. Columns 3 and 4 of row 1 show that the likelihood of patients choosing SI nearly halves when providers do not counsel patients in treatment arms (from 0.17 to 0.02). Thus, provider counseling is critical to patient choice and likely has significant implications for patient welfare, even if the assumptions used to compute consumer surplus do not hold. Without provider counseling, SI demand in treated arms (0.02) would resemble the control group's (0.01). Rows 2 through 5 show that this pattern holds for every treatment arm, regardless of whether the policy targets the patient or the provider's incentives.

Panel B of table 5 estimates the monetary value of the information signal from the provider's advice. Specifically, it measures the change in the patient welfare from having accurate beliefs about SI compared to when patients are not counseled and retain their ex-ante beliefs. We find a 23KES increase in patient welfare from being informed. This implies that the information shared by providers is highly valuable, representing roughly welfare gains that are double the direct subsidy program costs.

There are (rapidly) decreasing marginal returns to incentivizing providers. Panel C estimates consumer surplus changes in treated sites due to shocks in the provider financial incentives while holding patient prices constant. We find that, at observed levels, a 75KES decrease in markups has a welfare effect 3 times larger in absolute terms than a 75KES increase.Thus, changes in SI profitability relative to other FP products impact patient's welfare and SI demand, albeit with diminishing returns.

Provider advice leads to most welfare gains from a price reduction to the patient, and price

reductions are twice as effective at increasing patient welfare than equivalent provider incentives. Panel D in table 5 assesses welfare effects from consumer subsidies. Using data solely from the consumer subsidy arm, we compare patient welfare at subsidized (50KES) versus market (125KES) prices, holding provider financial incentives at 0 KES to isolate the price effect on patient welfare, consistent with the study design. In the first column, where the providers counsel the patient, reducing prices from 125 KES to 50 KES increases patient welfare by 13 KES, which is roughly 3/4 the welfare effect of introducing the new technology to patient's choice set. Note as well, that this effect is twice as much as the effect of a provider's financial incentives shock suggesting that patient welfare responds much more strongly to T1 than T2 since pharmacies do not absorb the subsidy. Therefore, while both policies have similar effects on adoption, if one aims to maximize patient welfare T1 dominates T2.

When there is no counseling, as in column 2, patients become insensitive to changes in the price of SI, eliminating 95% of the welfare effect from the price reduction. This aligns with model findings that SI price sensitivity is mediated through provider counseling.

Finally, figure 5 shows how patient welfare from a price reduction varies as a function of the underlying true value of the new technology, ranging from the case where providers perfectly inform the patient, to a case where the provider's advice is completely distorting the patient's valuation for SI. We find that provider advice is welfare enhancing to the patient provided that at least 30% of the advice-induced shift in the valuation of SI reflects genuine information rather than distortion. Below that threshold the price subsidy distorts patient choices such that the welfare effect turns negative. Therefore, for much of the range of assumptions provider advice is welfare enhancing due to their altruism. We believe that in this setting we are in this range, given that the mystery shopper data does point to higher accurate information diffusion across all arms. Similarly, our headline result that much of the welfare effect from a price subsidy is the result of the provider's advice survives if at least more than 30% of the advice-induced shift reflects genuine information.

7 Conclusion

This study examines how policies targeting provider and patient incentives for a new health technology influence its diffusion and adoption, and quantifies the role of medical providers in their effectiveness. The cluster randomized controlled trial compares direct consumer price reductions against marginal cost reductions to the pharmacy. There are large and comparable effects on adoption for both subsidy structures. The structural model results suggest that provider advice is the key mechanism behind the effectiveness of both interventions and welfare increases to the patient. Moreover, we find that ignoring the role of the provider when studying the demand for a new health technology can lead to incorrect policy conclusions, such as understating the impact of price reductions to the patient.

There are caveats to this study. Since individual patient characteristics are not observed, we can only estimate the average causal effect of each mechanism across all patients. It is likely that patients exhibit heterogeneity in their responses to provider advice. For instance, current users

of modern family planning methods may react differently than new users. Additionally, our data does not allow us to study how provider advice varies as a function of patient characteristics. The sample size of the RCT further limits our ability to conduct heterogeneity analysis based on average differences in patient populations across regions.

Moreover, we caution that provider advice may not always lead to welfare improvements, especially when it is influenced by changes in financial incentives. Previous literature has documented cases where providers distort patient choices in ways that produce harm (Currie et al., 2014; Compton et al., 2015). Therefore, it is important to consider how policies targeting either patient out-of-pocket costs or provider incentives may influence provider behavior and, ultimately, patient outcomes.

The study's findings have additional policy implications. First, although pharmacies absorbed most of the incentives in the pharmacy cost reduction arm, patient demand for the new technology increased at similar rates as in the consumer price reduction arm. This suggests that provider incentives can serve as a viable alternative to increasing adoption of a new health technology, particularly in contexts where monitoring retailer fraud—such as the inappropriate absorption of patient discounts—is challenging.

The findings from this paper also contribute to important policy discussions in various areas of healthcare. Traditional estimates of demand for health products capture the reduced form effect of the patient-provider interaction. However, the designs of policies—such as insurance contracts, subsidy programs, and information campaigns—often incorporate elements that influence both patient and provider preferences. Understanding the distinct roles of each agent in the decision to purchase a health product is critical for crafting policies that maximize welfare. If providers are the primary drivers of product uptake, targeting the wrong agent's incentives could lead to unintended welfare losses. For instance, policies aimed at preventing moral hazard could inadvertently harm low-income patients by raising prices, even if the provider's behavior drives the observed price response and moral hazard.

Lastly, given that the study results and counterfactual analysis highlight the importance of advice and information channels in the uptake of new health technologies, it is crucial to consider how policies targeting patient or provider incentives interact with the relevant information channels in a given setting. For instance, the lack of effective information diffusion mechanisms or misaligned incentives with the medical provider may explain why some health product subsidy programs are unsuccessful. These dynamics are key for policies in healthcare markets, but also apply to other settings where expert intermediaries might influence consumer choices such as in the case of financial advisors (Gennaioli et al., 2015).

References

Tashrik Ahmed, Aneesa Arur, Damien de Walque, and Gil Shapira. Incentivizing quantity and quality of care: Evidence from an impact evaluation of performance-based financing in the health sector in tajikistan. Economic Development and Cultural Change, 71(2):667–707, 2023. doi: 10.1086/715579.

Michael L Anderson. Multiple inference and gender differences in the effects of early intervention: A reevalu-

ation of the abecedarian, perry preschool, and early training projects. Journal of the American statistical Association, 103(484):1481–1495, 2008.

Joshua D Angrist and Jörn-Steffen Pischke. Mostly harmless econometrics: An empiricist's companion. Princeton University Press, 2009.

Kenneth Arrow. Uncertainty and the welfare economics of medical care. The American Economic Review, 53(5):941–973, 1963.

Alexandre Belloni, Victor Chernozhukov, and Ying Wei. Post-selection inference for generalized linear models with many controls. Journal of Business & Economic Statistics, 34(4):606–619, 2016. doi: 10.1080/07350015.2016.1166116. URL https://doi.org/10.1080/07350015.2016.1166116.

Gunther Bensch and Jörg Peters. One-off subsidies and long-run adoption—experimental evidence on improved cooking stoves in senegal. American Journal of Agricultural Economics, 102(1):72–90, 2020.

James Berry, Greg Fischer, and Raymond Guiteras. Eliciting and utilizing willingness to pay: Evidence from field trials in northern ghana. Journal of Political Economy, 128(4):1436–1473, 2020.

Steven T Berry and Philip A Haile. Foundations of demand estimation. In Handbook of industrial organization, volume 4, pages 1–62. Elsevier, 2021.

David Besanko, Jean-Pierre Dubé, and Sachin Gupta. Own-brand and cross-brand retail pass-through. Marketing Science, 24(1):123–137, 2005.

Samir Bhatt, DJ Weiss, E Cameron, D Bisanzio, B Mappin, U Dalrymple, KE Battle, CL Moyes, A Henry, PA Eckhoff, et al. The effect of malaria control on plasmodium falciparum in africa between 2000 and 2015. Nature, 526(7572):207–211, 2015.

Isaac Boadu. Coverage and determinants of modern contraceptive use in sub-saharan africa: further analysis of demographic and health surveys. Reproductive Health, 19(1):1–11, 2022.

Nancy E. Bockstael and Kenneth E. McConnell. Measuring Welfare in Discrete Choice Models, pages 101–150. Springer Netherlands, Dordrecht, 2007. ISBN 978-1-4020-5318-4. doi: 10.1007/978-1-4020-5318-4_5. URL https://doi.org/10.1007/978-1-4020-5318-4_5.

Bart J Bronnenberg, Jean-Pierre Dubé, Matthew Gentzkow, and Jesse M Shapiro. Do pharmacists buy bayer? informed shoppers and the brand premium. The Quarterly Journal of Economics, 130(4):1669–1726, 2015.

Holly M Burke, Monique P Mueller, Brian Perry, Catherine Packer, Leonard Bufumbo, Daouda Mbengue, Ibrahima Mall, Bocar Mamadou Daff, and Anthony K Mbonye. Observational study of the acceptability of sayana® press among intramuscular dmpa users in uganda and senegal. Contraception, 89(5):361–367, 2014.

Deron C Burton, Brendan Flannery, Bernard Onyango, Charles Larson, Jane Alaii, Xingyou Zhang, Mary J Hamel, Robert F Breiman, and Daniel R Feikin. Healthcare-seeking behaviour for common infectious disease-related illnesses in rural kenya: a community-based house-to-house survey. Journal of health, population, and nutrition, 29(1):61, 2011.

Meghan Busse, Jorge Silva-Risso, and Florian Zettelmeyer. $1,000 cash back: The pass-through of auto manufacturer promotions. American Economic Review, 96(4):1253–1270, 2006.

Undral Byambadalai, Ching-to Albert Ma, and Daniel Wiesen. Changing preferences: An experiment and estimation of market-incentive effects on altruism. Journal of Health Economics, 92:102808, 2023. doi: 10.1016/j.jhealeco.2023.102808.

Lawrence P. Casalino, Shachar Kariv, Daniel Markovits, Raymond Fisman, and Jing Li. Physician altruism and spending, hospital admissions, and emergency department visits. JAMA Health Forum, 5(10):e243383, 2024. doi: 10.1001/jamahealthforum.2024.3383.

Amitabh Chandra, David Cutler, and Zirui Song. Chapter six - who ordered that? the economics of treatment choices in medical care. In Mark V. Pauly, Thomas G. Mcguire, and Pedro P. Barros, editors, Handbook of Health Economics, volume 2 of Handbook of Health Economics, pages 397–432. Elsevier, 2011. doi: https://doi.org/10.1016/B978-0-444-53592-4.00006-2. URL https://www.sciencedirect.com/science/article/pii/B9780444535924000062.

Victor Chernozhukov, Denis Chetverikov, Mert Demirer, Esther Duflo, Christian Hansen, Whitney Newey, and James Robins. Double/debiased machine learning for treatment and structural parameters, 2018.

Dawn Chin-Quee, Kelly L'engle, Conrad Otterness, Sarah Mercer, and Mario Chen. Repeat use of emergency contraceptive pills in urban kenya and nigeria. International perspectives on sexual and reproductive health, 40(3):127–134, 2014.

Jeffrey Clemens and Joshua D. Gottlieb. Do physicians' financial incentives affect medical treatment and patient health? American Economic Review, 104(4):1320–49, April 2014. doi: 10.1257/aer.104.4.1320. URL https://www.aeaweb.org/articles?id=10.1257/aer.104.4.1320.

Jessica Cohen and Pascaline Dupas. Free distribution or cost-sharing? evidence from a randomized malaria prevention experiment. The Quarterly Journal of Economics, 125(1):1–45, 2010. doi: 10.1162/qjec.2010.125.1.1.

Wilson M. Compton, Maureen Boyle, and Eric Wargo. Prescription opioid abuse: Problems and responses. Preventive Medicine, 80:5–9, 2015. ISSN 0091-7435. doi: https://doi.org/10.1016/j.ypmed.2015.04.003. URL https://www.sciencedirect.com/science/article/pii/S0091743515001036. Special Issue: Behavior change, health, and health disparities.

Janet Currie, Wanchuan Lin, and Juanjuan Meng. Addressing antibiotic abuse in china: An experimental audit study. Journal of Development Economics, 110:39–51, 2014. ISSN 0304-3878. doi: https://doi.org/10.1016/j.jdeveco.2014.05.006. URL https://www.sciencedirect.com/science/article/pii/S0304387814000704. Land and Property Rights.

Jacqueline E Darroch, Elizabeth Sully, and Ann Biddlecom. Adding it up: investing in contraception and maternal and newborn health, 2017—supplementary tables. New York, NY: The Guttmacher Institute, 2017.

Jishnu Das, Alaka Holla, Aakash Mohpal, and Karthik Muralidharan. Quality and accountability in health care delivery: Audit-study evidence from primary care in india. American Economic Review, 106(12):3765–99, December 2016. doi: 10.1257/aer.20151138. URL https://www.aeaweb.org/articles?id=10.1257/aer.20151138.

Anusua Datta and Dhaval Dave. Effects of physician-directed pharmaceutical promotion on prescription behaviors: longitudinal evidence. Health economics, 26(4):450–468, 2017.

Damien de Walque, Paul J. Gertler, Sergio Bautista-Arredondo, Ada Kwan, Christel Vermeersch, Jean de Dieu Bizimana, Agnès Binagwaho, and Jeanine Condo. Using provider performance incentives to increase hiv testing and counseling services in rwanda. Journal of Health Economics, 40:1–9, 2015. ISSN 0167-6296. doi: https://doi.org/10.1016/j.jhealeco.2014.12.001. URL https://www.sciencedirect.com/science/article/pii/S0167629614001489.

Michael Dickstein. Physician vs. patient incentives in prescription drug choice. 2017.

Michael J. Dickstein, Jihye Jeon, and Eduardo Morales. Patient costs and physicians' information. Working Paper 32014, National Bureau of Economic Research, 2024.

David Dranove. Chapter ten - health care markets, regulators, and certifiers. In Mark V. Pauly, Thomas G. Mcguire, and Pedro P. Barros, editors, Handbook of Health Economics, volume 2 of Handbook of Health Economics, pages 639–690. Elsevier, 2011. doi: https://doi.org/10.1016/B978-0-444-53592-4.00010-4. URL https://www.sciencedirect.com/science/article/pii/B9780444535924000104.

Pascaline Dupas. Getting essential health products to their end users: Subsidize, but how much? Science, 345(6202):1279–1281, 2014a.

Pascaline Dupas. Short-run subsidies and long-run adoption of new health products: Evidence from a field experiment. Econometrica, 82(1):197–228, 2014b.

Randall P. Ellis and Thomas G. McGuire. Provider behavior under prospective reimbursement: Cost sharing and supply. Journal of Health Economics, 5(2):129–151, 1986. doi: 10.1016/0167-6296(86)90002-0.

Veronica Escamilla, Lisa Calhoun, Jennifer Winston, and Ilene S Speizer. The role of distance and quality on facility selection for maternal and child health services in urban kenya. Journal of Urban Health, 95:1–12, 2018.

Nicola Gennaioli, Andrei Shleifer, and Robert Vishny. Money doctors. The Journal of Finance, 70(1):91–114, 2015. doi: https://doi.org/10.1111/jofi.12188. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12188.

Matthew Grennan, Kyle Myers, Ashley Swanson, and Aaron Chatterji. No free lunch? welfare analysis of firms selling through expert intermediaries. The Review of Economic Studies, 92(4):2537–2577, 2025.

Jonathan Gruber and Maria Owings. Physician financial incentives and cesarean section delivery. The RAND Journal of Economics, 27(1):99–123, 1996.

Martin B. Hackmann, R. Vincent Pohl, and Nicolas R. Ziebarth. Patient versus provider incentives in long-term care. American Economic Journal: Applied Economics, 16(3):178–218, 2024.

Benjamin Handel and Joshua Schwartzstein. Frictions or mental gaps: what's behind the information we (don't) use and when do we care? Journal of Economic Perspectives, 32(1):155–178, 2018.

Toshiaki Iizuka. Physician agency and adoption of generic pharmaceuticals. American Economic Review, 102(6):2826–2858, 2012.

Jill Keesbury, Gwendolyn Morgan, and Benter Owino. Is repeat use of emergency contraception common among pharmacy clients? evidence from kenya. Contraception, 83(4):346–351, 2011. ISSN 0010-7824. doi: https://doi.org/10.1016/j.contraception.2010.08.010. URL https://www.sciencedirect.com/science/article/pii/S0010782410004737.

Mathew V Kiang, Keith Humphreys, Mark R Cullen, and Sanjay Basu. Opioid prescribing patterns among medical providers in the united states, 2003-17: retrospective, observational study. bmj, 368, 2020.

KNBS. Kenya demographic and health survey 2014. 2015.

KNBS. Kenya demographic and health survey 2022. 2022.

Jonathan T Kolstad. Information and quality when motivation is intrinsic: Evidence from surgeon report cards. American Economic Review, 103(7):2875–2910, 2013.

Michael Kremer and Rachel Glennerster. Improving health in developing countries: Evidence from randomized evaluations. In Mark V. Pauly, Thomas G. McGuire, and Pedro P. Barros, editors, Handbook of Health Economics, volume 2 of Handbook of Health Economics, pages 201–315. Elsevier, 2011. doi: 10.1016/B978-0-444-53592-4.00004-9.

Michael Kremer and Edward Miguel. The illusion of sustainability. The Quarterly journal of economics, 122 (3):1007–1065, 2007.

Willard G Manning, Joseph P Newhouse, Naihua Duan, Emmett B Keeler, and Arleen Leibowitz. Health insurance and the demand for medical care: evidence from a randomized experiment. The American economic review, pages 251–277, 1987.

Daniel McFadden. Economic choices. American economic review, 91(3):351–378, 2001.

Daniel McFadden and Kenneth Train. Mixed mnl models for discrete response. Journal of applied Econometrics, 15(5):447–470, 2000.

Bruno Meessen, Agnès Soucat, and Claude Sekabaraga. Performance-based financing: just a donor fad or a catalyst towards comprehensive health-care reform? Bulletin of the World Health Organization, 89(2): 153–156, 2011.

Jennifer Meredith, Jonathan Robinson, Sarah Walker, and Bruce Wydick. Keeping the doctor away: Experimental evidence on investment in preventative health products. Journal of Development Economics, 105:196–210, 2013.

John W Molyneaux and Paul J Gertler. The impact of targeted family planning programs in indonesia. Population and Development Review, 26:61–85, 2000.

Amil Petrin and Kenneth Train. A control function approach to endogeneity in consumer choice models. Journal of marketing research, 47(1):3–13, 2010.

Chelsea Polis, Sarah EK Bradley, Akinrinola Bankole, Tsuyoshi Onda, Trevor N Croft, and Susheela Singh. Contraceptive failure rates in the developing world: an analysis of demographic and health survey data in 43 countries. 2016.

Chelsea B Polis, Gertrude F Nakigozi, Hadijja Nakawooya, George Mondo, Fredrick Makumbi, Ronald H Gray, Rakai Health Sciences Program Sayana Press study team, et al. Preference for sayana® press versus intramuscular depo-provera among hiv-positive women in rakai, uganda: a randomized crossover trial. Contraception, 89(5):385–395, 2014.

Douglas Rivers and Quang H Vuong. Limited information estimators and exogeneity tests for simultaneous probit models. Journal of econometrics, 39(3):347–366, 1988.

Yogesh D Sabde, Vishal Diwan, Vivek S Saraf, Vijay K Mahadik, Vinod K Diwan, and Ayesha De Costa. Mapping private pharmacies and their characteristics in ujjain district, central india. BMC health services research, 11:1–8, 2011.

Vikas Saini, Sandra Garcia-Armesto, David Klemperer, Valerie Paris, Adam G Elshaug, Shannon Brownlee, John PA Ioannidis, and Elliott S Fisher. Drivers of poor medical care. The Lancet, 390(10090):178–190, 2017.

Lhamo Yangchen Sherpa, Bhim Singh Tinkari, Popular Gentle, Ram Kumar Sah, Amul Shrestha, Sanjeev Kumar Sahani, Kabita Aryal, Jagdishwor Ghimire, and Deepak Kumar Karki. A prospective cohort study to assess the acceptability of sayana press among 18–49-year-old women in nepal. Contraception, 104(6):623–627, 2021.

Kenneth A Small and Harvey S Rosen. Applied welfare economics with discrete choice models. Econometrica: Journal of the Econometric Society, pages 105–130, 1981.

Alessandro Tarozzi, Aprajit Mahajan, Brian Blackburn, Dan Kopf, Lakshmi Krishnan, and Joanne Yoong. Micro-loans, insecticide-treated bednets, and malaria: evidence from a randomized controlled trial in orissa, india. American Economic Review, 104(7):1909–1941, 2014.

UN-DESA. Contraceptive use by method. 2019. URL https://www.un.org/development/desa/pd/sites/www.un.org.development.desa.pd/files/files/documents/2020/Jan/un_2019_contraceptiveusebymethod_databooklet.pdf.

UNAIDS. Global aids update 2021. 2021.

United Nations General Assembly. Transforming our world: the 2030 agenda for sustainable development, September 2015. URL https://documents-dds-ny.un.org/doc/UNDOC/GEN/N15/291/89/PDF/N1529189.pdf?OpenElement.

USAID. Sources of family planning: Kenya. 2018. URL https://shopsplusproject.org/resource-center/sources-family-planning-kenya.

Francis Wafula, Chima Onoka, Anita Musiega, Arnold Okpani, Dosila Ogira, Ufuoma Ejughemre, Rosalind Miller, Catherine Goodman, and Kara Hanson. Healthcare clinic and pharmacy chains in kenya and nigeria: A qualitative exploration of the opportunities and risks they present for healthcare regulatory systems. The International Journal of Health Planning and Management, 37(6):3329–3343, 2022.

Zachary Wagner, Manoj Mohanan, Rushil Zutshi, Arnab Mukherji, and Neeraj Sood. What drives poor quality of care for child diarrhea? experimental evidence from india. Science, 383(6683):eadj9986, 2024. doi: 10.1126/science.adj9986. URL https://www.science.org/doi/abs/10.1126/science.adj9986.

Rockney G Walters. An empirical investigation into retailer response to manufa. Journal of Retailing, 65 (2):253, 1989.

Kim Ward, David Sanders, Henry Leng, and Allyson M Pollock. Assessing equity in the geographical distribution of community pharmacies in south africa in preparation for a national health insurance scheme. Bulletin of the World Health Organization, 92:482–489, 2014.

WHO. Family planning - a global handbook for providers. 2022. URL https://www.who.int/publications/i/item/9780999203705.

WHO. Atc classification index with ddds. 2024. URL https://atcddd.fhi.no/atc_ddd_index/.

Joseph K Wulifan, Stephan Brenner, Albrecht Jahn, and Manuela De Allegri. A scoping review on determinants of unmet need for family planning among women of reproductive age in low and middle income countries. BMC women's health, 16:1–15, 2015.

Jia Xiang. Physicians as persuaders: Evidence from hospitals in china. Available at SSRN 3906909, 2021.

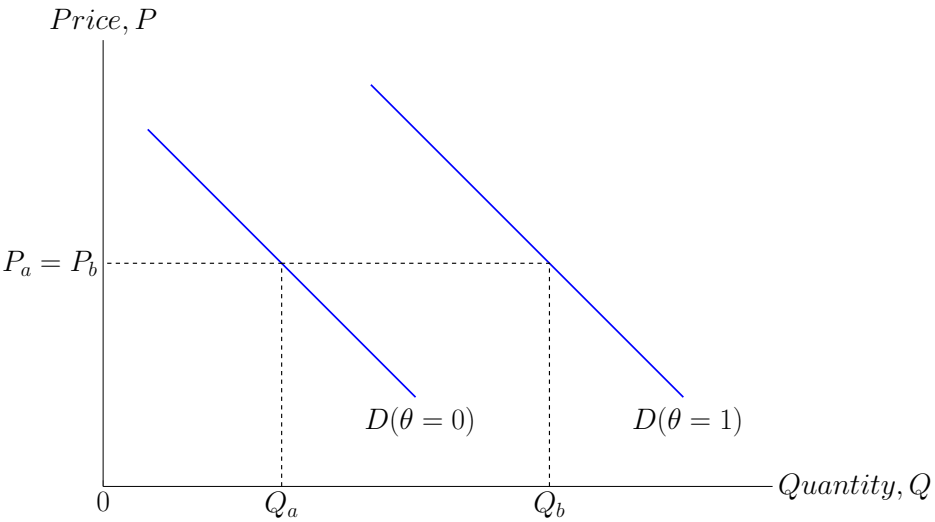
Yang Ye, Qingpeng Zhang, Xuan Wei, Zhidong Cao, Hsiang-Yu Yuan, and Daniel Dajun Zeng. Equitable access to covid-19 vaccines makes a life-saving difference to all countries. Nature human behaviour, 6(2): 207–216, 2022.

Richard Zeckhauser. Medical insurance: A case study of the tradeoff between risk spreading and appropriate incentives. Journal of Economic theory, 2(1):10–26, 1970.

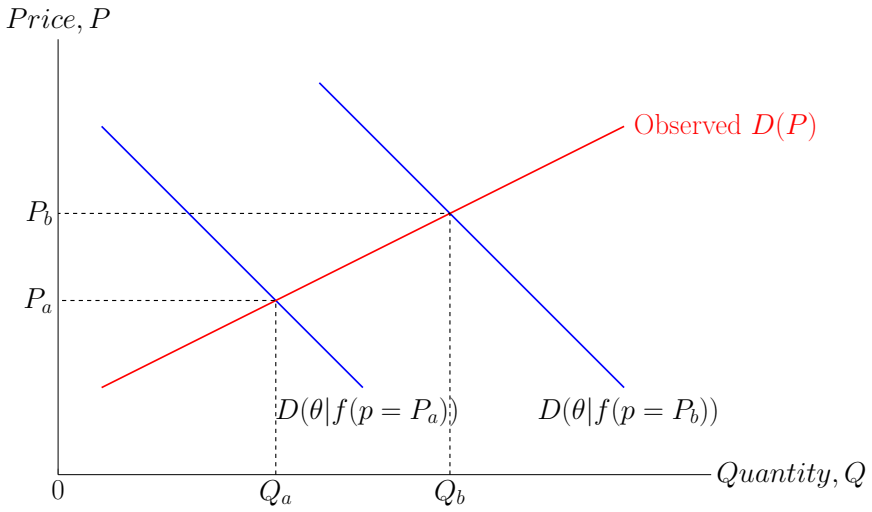
8 Tables and Figures

Figure 1: Role of advice (θ) in the conceptual framework

(a) Provider advice (θ) could shift the demand curve

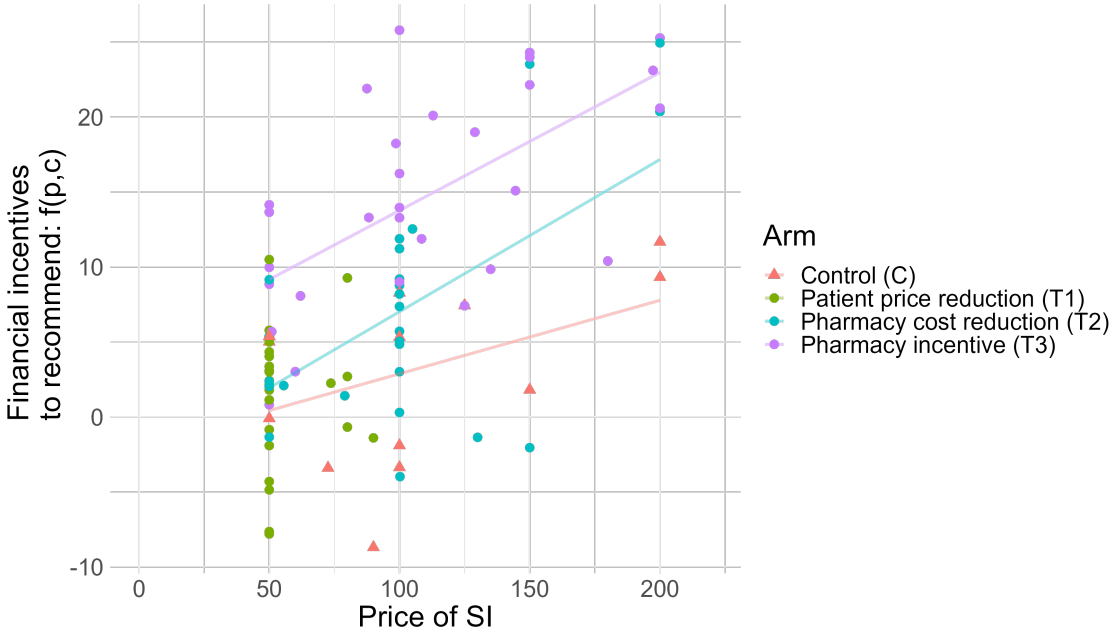


(b) Endogeneity of advice (θ) could lead to misleading policy conclusions



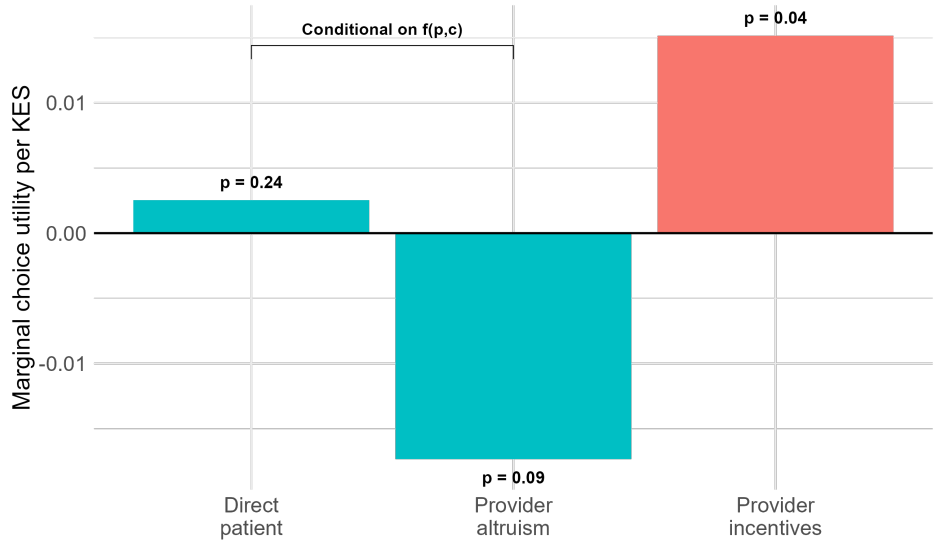
This figure shows how some parameters in the conceptual framework could influence the shape of the demand curve. Panel (a) shows that the provider's advice θ can potentially shift the demand curve for the new technology outwards, since the patient's perceived value for the new technology could increase. Panel (b) shows a scenario where the financial incentives of the provider ($f(p, c)$) are positively correlated with the price paid by the patient (p). Therefore, the provider's advice could respond to a price change through changes in the financial incentives of the provider to recommend the new technology. This in turn can downplay the effectiveness of policies that target the patient's prices if appropriate controls for financial incentives are excluded from the analysis.

Figure 2: Relationship between the price of SI and $f(p, c)$



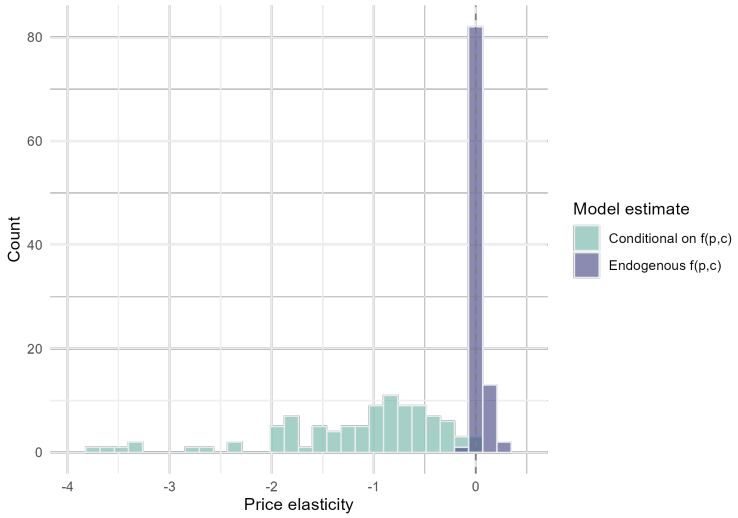
This figure plots the prices of SI against the financial incentive function defined with the primary measure of θ described in section 5. Both variables are positively correlated, but treatment status generate exogenous shifts in their relationship. Sample is restricted to sites used for estimation of the structural model as described in section 5. N = 98.

Figure 3: Decomposition of the price effect on the patient's perceived value (demand) of SI



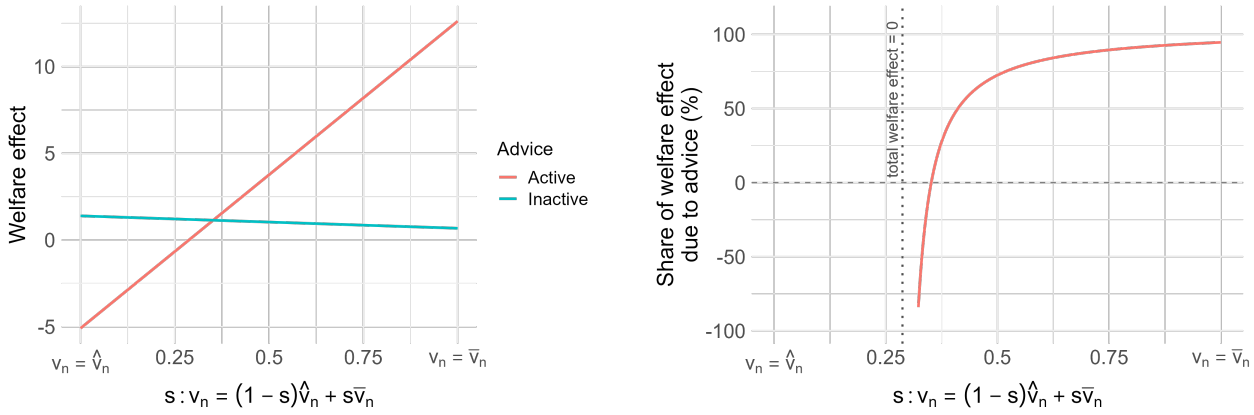
This figure decomposes the effect of a price change on the patient's perceived value of SI into three components, using the structural parameters in column 1 of table 4 and equation 8, measured in marginal utility per KES. The figure reports the effect of a price increase. The p-value on the direct patient effect is the asymptotic p-value on α from the demand model; the p-values on the provider altruism and provider incentives components are computed by inverting BCa confidence intervals over the joint bootstrap of the demand and provider models, and are one-sided, in the directions implied by the framework in section 1. The direct patient effect relates to the price response conditional on the provider's advice. The provider altruism component relates to the effect from the advice response to the patient's out-of-pocket costs. The provider incentives component relates to the effect from an advice response to changes in the financial incentives of the provider. The first two bars represent the effect of a price change conditional on the provider's financial incentives. The linear probability analogue of this decomposition can be read off appendix table A.17, where we are more powered to reject the null for the provider channels since they are direct estimates.

Figure 4: Own-price elasticity of demand for SI: controlling for vs. ignoring $f(p, c)$



The histogram in green shows the distribution of own-price elasticity estimates for SI conditional on the provider's financial incentives $f(p, c)$, so that price changes are orthogonal to $f(p, c)$; the estimated demand curve slopes downward (negative elasticity). The purple histogram is analogous, but allows the provider's financial incentives to respond endogenously to the price change (i.e., $f(p, c)$ is not held constant); the resulting total own-price elasticity is positive, so the estimated demand curve slopes slightly upward. The distributions of elasticities together illustrate that failing to control for $f(p, c)$ reverses the sign of the estimated price response, which can lead to biased welfare estimates.

Figure 5: Welfare estimates under different assumptions about the true value of SI to the patient.



(a) Welfare effect from a price subsidy

(b) Relative contribution from advice

This plot shows how welfare estimates from the effect of a price reduction policy vary as a function of the true value of SI to the patient, ranging from the case where the provider perfectly informs the patient ($s = 1$), to the case where the provider is completely distorting the patient's belief about the value of SI ($s = 0$). The two lines in panel (a) compare the estimates between the case where providers counsel the patient on SI against the case where providers do not counsel the patient on SI. The advice-active effect crosses zero at $s = 0.29$, so at the distorting end of the range a price subsidy moves patients onto a product that is less valuable to them. Panel (b) shows the relative contribution to welfare from the provider's advice over the range where the total welfare effect is positive; the dotted line marks the zero of the total effect. Over that range the provider's advice accounts for most of the welfare effect, reaching 95% when the advice is taken to be fully informative.

Table 1: Summary of study arms in Kenyan Shillings

	C	T1	T2	T3
Cost of SI to site (c)	75	0	0	0
Pharmacy price incentive (t)	0	0	0	50
Price patient pays	$p(C)$	$p(T1) = 50$	$p(T2)$	$p(T3)$
Price pharmacy receives	$p(C)$	$p(T1) = 50$	$p(T2)$	$p(T3) + 50$
Pharmacy markup (m_{SI})	$p(C) - 75$	50	$p(T2)$	$p(T3) + 50$

Note: $p(T)$ for $T \in \{T2, T3, C\}$ is the price endogenously set by pharmacies in the control group, and the pharmacy subsidy arms. In T1, the price that the patient pays is set by the researcher, and a $75KES$ subsidy for the patient is used to guarantee the pharmacy a markup of $50KES$ which empirically matches the mean markup in the control group ($\hat{\mathbb{E}}[p(C) - 75] \approx 50KES$). T1 offers a large price reduction to the patient relative to the control group ($\hat{\mathbb{E}}[p(C)] \approx 125KES$). During the study period, 1USD $\approx$ 120KES. Realized prices are presented in table A.12.

Table 2: Effects on patient demand for family planning

	DML: RCT site shares			DS-Poisson: census quantities		
	SI	IMI	Short-term methods	Long-term methods	Injectables	Short-term methods
	(1)	(2)	(3)	(4)	(5)	(6)
T1: Consumer price reduction	0.21***	-0.01	-0.17***	-0.41	-0.38	-0.25
	(0.06)	(0.02)	(0.06)	(0.2)	(0.19)	(0.18)
T2: Pharmacy cost reduction	0.18***	-0.01	-0.16**	-0.05	0.08	0.2
	(0.06)	(0.03)	(0.07)	(0.24)	(0.28)	(0.23)
T3: Pharmacy incentive	0.23***	-0.04*	-0.19***	0.08	0.1	0.24
	(0.06)	(0.02)	(0.06)	(0.29)	(0.28)	(0.26)
Control mean	0.02	0.08	0.91	15.69	12.16	86.30
Observations	136	136	136	452	452	452
Clusters				115	115	115

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Columns 1, 2 and 3 are double-ML estimates (Chernozhukov et al., 2018), using cross-validated LASSO with randomization strata, ward demographic characteristics, and the characteristics of surrounding census sites. The outcome variables in columns 1, 2 and 3 are the shares of family planning transactions in a site that include a given product category (SI, IMI, and short term methods). Short term methods in column 3 include EC, OC, and condoms. Columns 4, 5 and 6 present the IRR-1 estimates of double-selection Poisson models following Belloni et al. (2016), using cross-validated LASSO with randomization strata and ward demographic characteristics. The outcome variable is the number of units sold in a given category in the past month. Long-term methods include SI, IMI, and implants. Short-term methods include OC, EC, and condoms. For additional outcomes, statistical tests, and pooled analysis see appendix tables A.2 and A.3. For OLS results see tables C.1 and C.2.

Table 3: Mechanisms

	Price channel	Information channels				
	Price (KES)	Recommend SI (θ)	Recommend SI medical	SI info.	General FP info.	Info. non-SI methods
	(1)	(2)	(3)	(4)	(5)	(6)
T1: Consumer price reduction	-73.75***	0.29***	0.41	0.34	0.14	-0.21
	(8.27)	(0.11)	(0.27)	(0.26)	(0.16)	(0.16)
T2: Pharmacy cost reduction	-25.78**	0.3***	0.49**	0.74***	0.23	0.2
	(10.95)	(0.1)	(0.24)	(0.26)	(0.16)	(0.19)
T3: Pharmacy incentive	-21.91*	0.44***	0.74***	0.82***	0.2	-0.07
	(11.23)	(0.1)	(0.23)	(0.28)	(0.18)	(0.18)
Control mean	129.6	0.28	0	0	0	0
Observations	131	123	123	228	228	228
Clusters				114	114	114
T1 = T2	0.00	0.96	0.83	0.28	0.68	0.09
T1 = T3	0.00	0.34	0.34	0.21	0.81	0.54
T2 = T3	0.80	0.35	0.44	0.83	0.88	0.29
Data source	POS	Provider	Provider	SP	SP	SP

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Double-ML estimates (Chernozhukov et al., 2018). Indices follow Anderson (2008). Column 1 is the price of SI in KES, constructed with POS and field data; appendix table A.12 reports the full set of price specifications and tests. Column 2 is an indicator for whether the provider recommends SI to patients interested in injectable contraceptives. Column 3 is an index for whether the provider reports that they recommend SI over IMI to patients interested in injectables due to medical reasons, including indicators for whether they recommend SI because it has less side effects, and whether they recommend SI because it is safer and easier to administer. Column 4 is an SI information index including whether the provider mentioned SI, discussed SI side effects, and the MM poster was visible in the site. Column 5 is an index of 7 variables summarizing general FP information shared with the patient. Column 6 is an index of indicators for whether the provider discussed non-SI family planning methods and their side effects. Provider knowledge outcomes are reported in appendix table A.13.

Table 4: Structural model parameter estimates

Panel A: Patient demand model						
	(1) Mixed	(2) Mixed	(3) Mixed	(4) Multinomial	(5) Multinomial	(6) LPM
Price and information						
α (var: p_k)	0.0025	0.0027	0.0015	0.0001	-0.0015	-0.0006
	p=0.237	p=0.213	p=0.514	p=0.938	p=0.753	p=0.283
	(-0.0014, 0.0072)					
δ (var: $\hat{\theta}_{d,i,k}$)	3.5326***	3.9390***	1.4436	3.0977***	3.2837***	0.3502**
	p<0.001	p=0.002	p=0.246	p=0.001	p<0.001	p=0.023
	(0.5042, 6.8961)					
Vector means: β						
New technology (SI)	-2.2562***	-2.5799***	-0.4295	-1.8913**		
	p=0.006	p=0.006	p=0.653	p=0.013		
	(-4.9649, -0.0982)					
Is Longterm	-0.7299***	-0.6839***	-0.7360***	-0.8526***		
	p=0.004	p=0.007	p=0.003	p<0.001		
Failure rate	-0.0492*	-0.0530**	-0.0427*	-0.0069		
	p=0.051	p=0.038	p=0.096	p=0.585		
Non-linear parameters: β						
SD(longterm)	0.0043	0.0020	0.0052			
SD(Failure)	0.2153	0.2290	0.1896			
Estimation:						
Alternative-cases	126,573	126,573	121,702	126,573	126,573	-
Cases	24,640	24,640	24,640	24,640	24,640	-
Clusters	98	98	98	98	98	98
Alternative FEs:	N	N	N	N	Y	Y
New tech. indicator:	Y	Y	Y	Y	-	-
Info. measure:	$\hat{\theta}$	θ	$\hat{\theta}$	$\hat{\theta}$	$\hat{\theta}$	$\hat{\theta}$
Filled-in market zeros	Y	Y	N	Y	Y	N

Panel B: Provider advice model		
	Recommend ($\theta_{d,SI}$)	
	IV probit	LPM
κ (var: p_k)	-0.017**	-0.007**
	(0.008)	(0.003)
λ (var: $f(p,c)$)	0.111***	0.044***
	(0.028)	(0.015)
Observations	98	98

Structural estimates of the patient demand model (Panel A) and the provider advice model (Panel B). **Panel A:** Parameters estimated through maximum likelihood. An alternative-case are the case-specific characteristics of an alternative and an indicator for whether that alternative was chosen. The estimation procedure weights observations so that sites have equal weights since model components in the data are only available at the site level. P-values use asymptotic formulas for the mixed and multinomial logit models, while 95% confidence intervals inside brackets are from the bootstrap distribution of the whole procedure including the provider model and control function estimation. **Panel B:** Model estimated through maximum likelihood, using treatment assignment as instruments. IV probit model follows Rivers and Vuong (1984). Asymptotic standard errors are shown in parenthesis. The demand linear probability column is a site-level regression with 336 observations and 98 clusters.

Table 5: Welfare estimates and counterfactual choice probabilities

Policy change	Consumer surplus (KES)		SI choice probability	
	θ active	θ inactive	θ active	θ inactive
	(1)	(2)	(3)	(4)
Panel A: Introduce SI to the patient's choice-set				
T: Treated arms	17	5	0.17	0.02
T1: Consumer price reduction	21	5	0.14	0.02
T2: Pharmacy cost reduction	16	6	0.16	0.02
T3: Pharmacy incentive	15	5	0.21	0.02
C: Control group	11	3	0.08	0.01
Panel B: Effect of patient being perfectly informed about SI				
Provider informs the patient	23		0.28	
Panel C: Shocks to the markup of SI holding p_{SI} constant				
75 KES increase	2	0	0.10	0
75 KES decrease	-6	0	-0.10	0
Panel D: Effects of price reductions with constant $f(p, c)$				
75 KES change in p_{SI}: 125 vs 50KES	13	1	0.08	-0.00

This table presents the estimated welfare effects per patient encounter and counterfactual choice probabilities using the main model parameters in table 4. "θ active" denotes counterfactuals where provider advice is endogenous and responds to changes in model components, whereas "θ inactive" denotes counterfactuals where providers do not counsel the patient on the new technology. Comparing both columns allows us to assess the role of the provider on patient welfare and choice probabilities. Panel A shows the effect of making SI available in the patient's choice set by treatment arm. Panel B shows the effect from the providers informing all patients about the value of SI. Panel C shows the effect of an increase and a decrease in the markup of SI in treated arms, holding prices constant. Panel D shows the effect of a price reduction holding the financial incentives of the provider constant. Model fit tests comparing observed and predicted probabilities are reported in appendix table A.14.

A Additional exhibits

A.1 Additional study sample details and balance

In terms of provider qualifications, 100% of the sites have either a pharmacist (in 84% of sites), pharmtech (93%), nurse (83%), or clinical officer (84%) on staff, meaning that at least one staff member can counsel patients on family planning. For the pharmacies in the study sample, the average age of client facing staff is 34, 43% of providers are female, and in 69% the owner is a provider. The average number of client facing staff per site is 3.5. Provider survey respondents have on average worked 4 years for the study pharmacy, and have over 9 years of experience in the health sector. According to provider surveys, the median family planning client that seeks care at participating pharmacies is 24 years old, more likely married than unmarried (58%), and has at least one child.

Table A.1: Balance table

Var	All	C	T1	T2	T3
FP revenues above median	0.372	0.455	0.371	0.394	0.278
Site sells DMPA-SC at baseline (%)	0.38	0.273	0.429	0.424	0.389
Urban site (%)	0.345	0.326	0.365	0.325	0.36
Ward population density (log)	7.36	7.28	7.29	7.38	7.49
Ward relative wealth index	0.47	0.541	0.485	0.428	0.428
Number of competing pharmacies within 30 minutes	12.9	10.8	10.1	16	14.8
Monthly average family planning sales (volumes)	72.9	84.3	57.2*	83.8	67.9
Share of FP transactions that are DMPA-SC (%)	0.158	0.0921	0.193	0.157	0.185
Share of FP transactions that are DMPA-IM (%)	0.0773	0.089	0.088	0.0613	0.0707
Share of FP transactions that are condoms (%)	0.206	0.239	0.191	0.171	0.221
Share of FP transactions that are emergency contraception (%)	0.439	0.436	0.426	0.467	0.429
Share of FP transactions that are oral contraceptives (%)	0.187	0.224	0.172	0.215	0.142**
Site active on Maisha Meds platform	0.883	0.879	0.886	0.879	0.889
Joint orthogonality test (p-value)			0.853	0.172	0.276

Notes: Stars denote significant differences between the control group and the treatment group for each baseline variable using the test from an OLS regression where the outcome is the baseline variable and the explanatory variables are the treatment indicators ($^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$). The test for joint orthogonality is from a regression where the outcome variable is treatment assignment and the explanatory variables are the baseline characteristics in this table.

A.2 Data sources: additional details

Mystery shopper profiles and training. Each mystery shopper visit presented one of two patient cases. The first was an unmarried young woman who recently graduated high school and has never had children. The second was a married woman who had a child one year ago and wants to prevent future pregnancies for now. In both profiles, the patient is sexually active with her partner and knows little about family planning methods. Mystery shoppers received two weeks of training on family planning and the cases prior to the activity, but were unaware of the study design and treatment assignments of study sites; they were, however, informed that all study sites were part of an RCT involving subsidies for family planning products. When consenting to participate, pharmacy owners were told that the implementing partner might conduct unannounced monitoring activities, but owners and providers were not explicitly informed about the mystery shopper activity.

A.3 Empirical strategy for the reduced form analysis

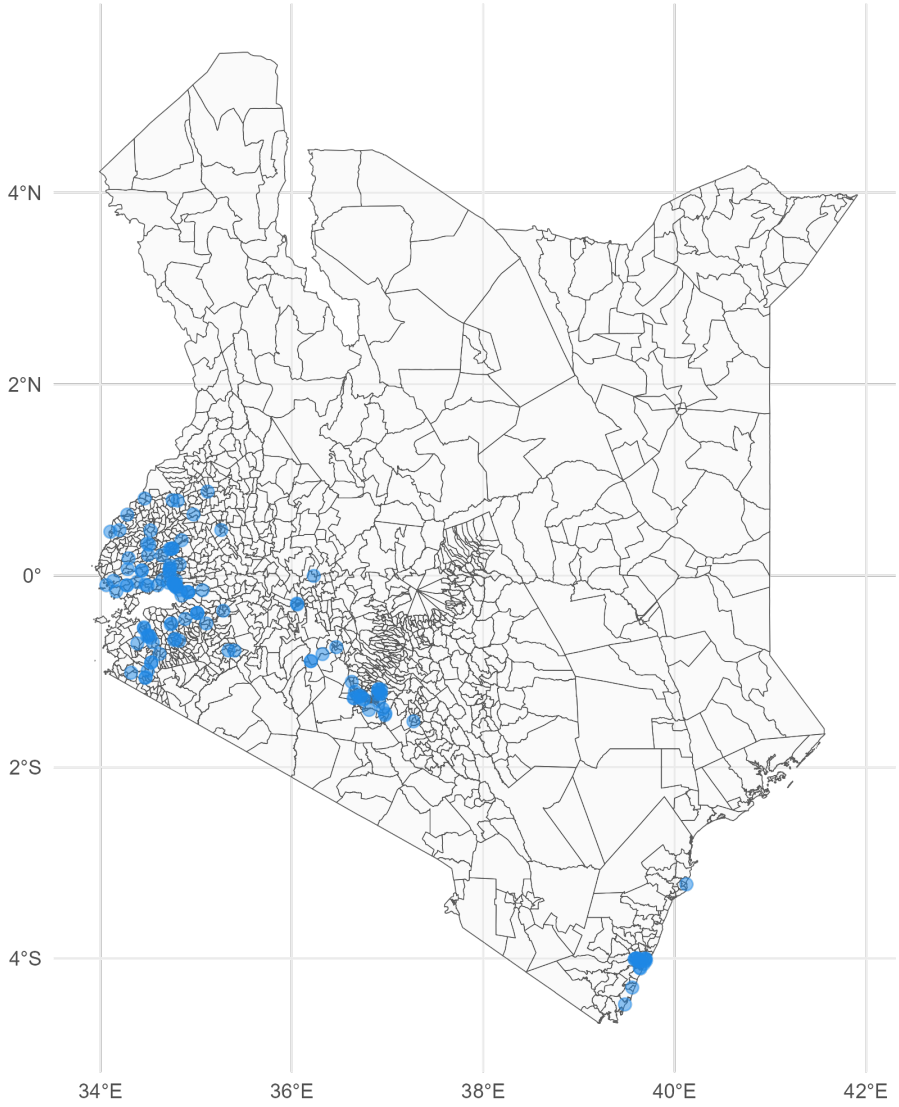
The reduced form results present comparisons across treatment arms and the control group. The POS data set is the main source for analysis to study effects on adoption of the new technology. The analysis focuses on transactions that include at least one family planning product when using this data source. For the supplementary data sources, which include the provider survey (n = 124) and the mystery shopper activity (n = 114), only a subset of the main sample of sites is observed.

Since study site representation varies by data source, there could be selection concerns on survey and mystery shopper activity participation. To address these concerns, we use the double/debiased machine learning (DML) approach described in Chernozhukov et al. (2018). This approach allows us to conduct robust covariate control in the presence of many candidate covariates. In particular, we estimate partially linear regressions using cross-validated LASSO as our learner. The potential set of covariates (control variables) includes stratification variables, ward demographic characteristics, and characteristics of surrounding sites[45] [46].

[45] In particular, covariates include the following types of variables: indicators for randomization wave, urbanicity, baseline level of sales, baseline availability of SI, number of competing pharmacies in the surrounding area, fixed features of surrounding sites, ward population density, and the relative wealth index of the ward where the facility is located.

[46] We include the main results on adoption using traditional OLS in appendix C, which are in line with our preferred results using DML.

Figure A.1: RCT site locations in Kenya



Study pharmacies and clinics are located across 21 counties in rural, peri-urban, and urban Kenya.

Figure A.2: Information sheet about Sayana Press



LEARN MORE ABOUT SAYANA PRESS

WHAT IS SAYANA PRESS?

- Sayana Press is a new long-term injectable contraceptive made by the same company as Depo-Provera (Pfizer).
- Unlike condoms, injectable contraceptives such as Sayana Press do not prevent sexually transmissible diseases. However, they are highly effective at preventing pregnancy.

WHAT ARE SOME DIFFERENCES BETWEEN SAYANA PRESS AND DEPO-PROVERA?

- Sayana Press is a reformulation of the popular injectable Depo-Povera, so it has the same active pharmaceutical ingredient.
- It is a subcutaneous injection, which means it is a smaller needle than Depo-Provera. Research studies have found that Sayana Press has slightly less side effects than Depo-Provera while being as effective.

WHAT ARE SOME POSSIBLE SIDE EFFECTS FROM USING SAYANA PRESS?

- Sayana Press should not be used if you believe you are pregnant or if you are planning to become pregnant within a year.
- Some common side effects include weight gain, abdominal pain (cramps), nausea, acne, irregular periods with higher or lower than usual bleeding, depression, tiredness, headache, among others.

Maisha Meds www.maishameds.org

Table A.2: Share of transactions in a site that include SI - take-up effects

	Share SI (1)	Share SI (2)	Share SI (3)
T1: Consumer price reduction	0.21***	0.22***	
	(0.06)	(0.06)	
T2: Pharmacy cost reduction	0.18***		
	(0.06)		
T3: Pharmacy incentive	0.23***		
	(0.06)		
Provider		0.21***	
		(0.04)	
Treated			0.21***
			(0.04)
Control mean	0.02	0.02	0.02
Observations	136	136	136
T1 = T2	0.67		
T1 = T3	0.80		
T2 = T3	0.50		
T1 = Provider		0.93	

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Double-ML estimates (Chernozhukov et al., 2018). The outcome variable is the share of family planning transactions in a site that include SI. Provider includes pharmacy cost reduction and incentive arms. Cross-validated LASSO was used with controls including randomization strata, ward demographic characteristics, and characteristics of surrounding census sites. We report the p-values from tests for significant differences in estimates across the three arms.

Table A.3: Share of transactions including the column's category in a study site - FP product substitution patterns

	Non-SI methods		Short-term methods		
	IMI	Short-term methods	Condoms	EC	Oral
	(1)	(2)	(3)	(4)	(5)
T1: Consumer price reduction	-0.01	-0.17***	-0.05	-0.06	-0.08**
	(0.02)	(0.06)	(0.04)	(0.06)	(0.03)
T2: Pharmacy cost reduction	-0.01	-0.16**	-0.03	-0.03	-0.12***
	(0.03)	(0.07)	(0.05)	(0.06)	(0.03)
T3: Pharmacy incentive	-0.04*	-0.19***	-0.02	-0.11**	-0.11***
	(0.02)	(0.06)	(0.05)	(0.05)	(0.04)
Treated	-0.03	-0.18***	-0.03	-0.09*	-0.1***
	(0.02)	(0.04)	(0.04)	(0.05)	(0.03)
Control mean	0.08	0.91	0.26	0.48	0.26
Observations	136	136	136	136	136
T1 = T2	1.00	0.89	0.80	0.73	0.41
T1 = T3	0.37	0.76	0.66	0.54	0.54
T2 = T3	0.45	0.67	0.86	0.35	0.88

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Double-ML estimates (Chernozhukov et al., 2018). The outcome variable is the share of family planning transactions in a site that include a given category of product. For other details see Table A.2.

Table A.4: Indicator for whether SI is available in a study site - extensive margin effects

	SI sold (1)	SI sold (2)	SI sold (3)
T1: Consumer price reduction	0.47***	0.5***	
	(0.08)	(0.08)	
T2: Pharmacy cost reduction	0.38***		
	(0.09)		
T3: Pharmacy incentive	0.45***		
	(0.09)		
Provider		0.42***	
		(0.09)	
Treated			0.47***
			(0.08)
Control mean	0.47	0.47	0.47
Observations	136	136	136
T1 = T2	0.49		
T1 = T3	0.86		
T2 = T3	0.63		
T1 = Provider		0.56	

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Double-ML estimates (Chernozhukov et al., 2018). The outcome is an indicator for whether a site stocked SI during the study period. For other details see Table A.2.

Table A.5: Share of transactions in a study site that include SI conditional on availability

	Share SI (1)	Share SI (2)	Share SI (3)
T1: Consumer price reduction	0.16**	0.17***	
	(0.06)	(0.06)	
T2: Pharmacy cost reduction	0.15**		
	(0.06)		
T3: Pharmacy incentive	0.19***		
	(0.06)		
Provider		0.18***	
		(0.05)	
Treated			0.18***
			(0.04)
Site sells SI	0.1**	0.11***	0.1**
	(0.04)	(0.04)	(0.04)
Control mean	0.02	0.02	0.02
Observations	136	136	136
T1 = T2	0.94		
T1 = T3	0.76		
T2 = T3	0.70		
T1 = Provider		0.94	

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Double-ML estimates (Chernozhukov et al., 2018). The outcome variable is the share of family planning transactions in a site that include SI. For other details see Table A.2.

Table A.6: Site-level take-up for sites in non-coastal Kenya

	Unpooled treatment	Pooled treatment	Pooled provider
Consumer price reduction	0.18***		0.18***
	(0.05)		(0.05)
Pharmacy cost reduction	0.21***		
	(0.07)		
Pharmacy incentive	0.26***		
	(0.06)		
Treated		0.21***	
		(0.04)	
Provider			0.23***
			(0.05)
Control mean	0.03	0.03	0.03
Num. obs.	113	113	113

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Stars denote significance using asymptotic inference $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. This table is equivalent to table C.1 but the sample is composed of sites in the Standardized Patient activity. Results are not significantly different from our main sample.

Table A.7: Estimates of $P(k|\theta = 1) - P(k|\theta = 0)$, for various definitions of θ

θ	SI	IMI	Condoms	EC	OC	Short term
			Recommend (more than half)			
Recommend	0.13**	0	-0.18***	0.06	-0.09***	-0.14**
	(0.06)	(0.02)	(0.04)	(0.04)	(0.03)	(0.06)
			LDA			
Know and rec.	0.13**	-0.01	-0.16***	0.1**	-0.1***	-0.12**
	(0.06)	(0.02)	(0.04)	(0.04)	(0.03)	(0.06)
Recommend	0.12*	-0.03	-0.12***	0.06	-0.07***	-0.11*
	(0.06)	(0.02)	(0.04)	(0.05)	(0.03)	(0.06)
Recommend med.	0.2***	-0.03	-0.11**	0.02	-0.09***	-0.18**
	(0.08)	(0.02)	(0.05)	(0.06)	(0.03)	(0.07)
			PCA			
Know and rec.	0.11*	-0.01	-0.14***	0.09**	-0.09***	-0.11*
	(0.06)	(0.02)	(0.04)	(0.04)	(0.03)	(0.06)
Recommend	0.14**	-0.02	-0.14***	0.07	-0.07**	-0.13**
	(0.06)	(0.02)	(0.04)	(0.04)	(0.03)	(0.06)
Recommend med.	0.15**	-0.03	-0.16***	0.08*	-0.08***	-0.13**
	(0.06)	(0.02)	(0.04)	(0.04)	(0.03)	(0.06)
N	103	103	103	103	103	103

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Double-ML estimates (Chernozhukov et al., 2018). The first panel is the main measure of θ, defined as whether half or more of the providers in a site recommend SI. Panels two and three present robustness checks for various methods of aggregating variables into a single binary indicator. The different set of variables are: know and recommend (indicators for recommending SI for various reasons, knowledge about SI having less side effects, reporting being comfortable administering injectables), recommend (indicators for recommending SI for various reasons), and recommend medical (indicators for recommending SI for medical reasons). For the second panel, the Latent Dirichlet Allocation algorithm is used to partition the site sample into "high" vs "low" information types. PCA uses the first principal component of the variables, and defines "high" information sites as those above median values of PC1. The sample includes all RCT sites that participated in the provider survey and that had SI in stock.

Table A.8: Linear probability provider model estimates with alternative definitions of θ

	Recommend	Recommend LDA	Recommend PCA	Recommend and know LDA	Recommend and know PCA
f(p,c)	0.044^{***}	0.056^{***}	0.045^{***}	0.043^{**}	0.048^{**}
	(0.015)	(0.015)	(0.014)	(0.016)	(0.019)
P_{SI}	-0.007^{**}	-0.008^{**}	-0.010^{***}	-0.007^{*}	-0.007^{*}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Num. obs.	98	98	98	98	98

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. This table shows 2SLS estimates analogous to table A.16 for various alternative definitions of the information measure θ (and their implied $f(p, c) = f(p, c|\theta)$ function). For more details on the alternative definitions of θ see table A.7. For analysis using outcomes from the mystery shopper activity see table A.18.

Table A.9: Share of transactions including SI as a function of price and financial incentives

	Share SI	Share SI	Share SI
P_{SI}	0.000	-0.004^{*}	-0.000
	(0.001)	(0.002)	(0.001)
$f(p,c)$		0.021^{**}	
		(0.009)	
$\hat{\theta}$			0.530^{**}
			(0.221)
Num. obs.	98	98	98

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The outcome variable is the share of transactions that include SI in a site. Treatment assignment indicators were used as instruments for p_{SI} and $f(p,c)$. Stratification variables are included as controls.

Table A.10: Substitution patterns with the outside option

	Closest site		Closest 2 sites		Closest 3 sites		closest 4 sites	
	Share SI	Share OO	Share SI	Share OO	Share SI	Share OO	Share SI	Share OO
Consumer subsidy	0.12**	-0.08	0.12**	-0.13**	0.11**	-0.12*	0.11**	-0.1
	(0.05)	(0.06)	(0.05)	(0.06)	(0.04)	(0.07)	(0.04)	(0.07)
Pharmacy cost reduction	0.14***	0	0.15***	0	0.15***	0.05	0.15***	0.02
	(0.05)	(0.07)	(0.05)	(0.07)	(0.05)	(0.08)	(0.05)	(0.07)
Pharmacy incentive	0.18***	0	0.18***	-0.04	0.16***	-0.03	0.16***	-0.04
	(0.05)	(0.06)	(0.05)	(0.06)	(0.04)	(0.07)	(0.04)	(0.06)
Control mean	0.02	0.2	0.02	0.26	0.02	0.27	0.02	0.29

Each pair of columns are the shares for SI and the outside option respectively, for various definitions of the outside option. The outside option in all cases is the average number of long-term methods sold in surrounding sites in the month previous to the census, times the number of trimesters that each RCT site was enrolled. In each pair, the average is defined based on the closest 1, 2, 3, and 4 sites respectively.

Table A.11: Treatment effects on counseling characteristics

	(1)	(2)	(3)	(4)
	Trust	Knowledgeable	Used tools	Allowed opinion
T1: Consumer subsidy	0.08	0.08	-0.02	0.2**
	(0.1)	(0.1)	(0.07)	(0.1)
T2: Pharmacy cost reduction	0.24**	0.15	0.1	0.16*
	(0.09)	(0.1)	(0.07)	(0.09)
T3: Pharmacy incentive	0.11	0.09	0.1	0.1
	(0.1)	(0.09)	(0.07)	(0.09)
Control mean	0.52	0.22	0.12	0.31
Num. obs.	228	228	228	228
N Clusters	114	114	114	114

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Double-ML estimates (Chernozhukov et al., 2018). Outcome variables are from the mystery client activity. The outcomes for each column are: column 1 is an indicator for whether the mystery client would trust the provider to if they were seeking FP services. Column 2 is an indicator for whether the provider was perceived as highly knowledgeable about FP by the mystery client. Column 3 is an indicator for whether the provider used any tools or objects to explain things during their counseling to the patient. Column 4 is an indicator for whether the mystery client perceived that the provider allowed them to express their opinions during counseling.

Table A.12: Price of SI - subsidy passthrough to the consumer

	Price (KES) (1)	Price (KES) (2)	Price (KES) (3)
T1: Consumer price reduction	-73.75***	-75.31***	
	(8.27)	(8.59)	
T2: Pharmacy cost reduction	-25.78**		
	(10.95)		
T3: Pharmacy incentive	-21.91*		
	(11.23)		
Provider (T2, T3)		-23.25**	
		(10.15)	
Treated (T1, T2, T3)			-39.68***
			(10.05)
Control mean	129.6	129.6	129.6
Observations	131	131	131
T1 = T2	0.00		
T1 = T3	0.00		
T2 = T3	0.80		
T1 = Provider		0.00	

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Double-ML estimates (Chernozhukov et al., 2018). Outcome is SI price in KES constructed with POS data. Missing POS data was replaced with field data (standardized patient activity and the provider survey). For control group sites that stocked IMI, missing data from the POS system and field activities on the price of SI was replaced by predicted SI prices using a linear regression estimated on pre-study, control group, and non-RCT IMI and SI prices. Figure B.1 shows the relationship between SI and IMI prices, which tend to be set at similar levels by pharmacies absent any subsidies. Results are robust to using only POS data. For other details see Table A.2. For OLS results, see table C.3.

Table A.13: Provider knowledge about SI

	Comfortable administering (1)	Knows less side effects (2)	Knows unsuitable (3)
T1: Consumer price reduction	0	0.25**	-0.1
	(0.08)	(0.11)	(0.11)
T2: Pharmacy cost reduction	0.14**	0.26**	-0.05
	(0.07)	(0.1)	(0.11)
T3: Pharmacy incentive	0.13*	0.33***	-0.15
	(0.07)	(0.1)	(0.1)
Control mean	0.8	0.36	0.47
Observations	123	123	123
T1 = T2	0.16	0.93	0.73
T1 = T3	0.20	0.59	0.75
T2 = T3	0.93	0.65	0.49
Data source	Provider	Provider	Provider

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Double-ML estimates (Chernozhukov et al., 2018). Column 1 is an indicator for whether the provider feels comfortable administering an injectable contraceptive to a patient. Column 2 is an indicator for whether the provider knows that SI has less side effects than IMI on average. Column 3 is an indicator for whether the provider knows that injectable contraceptives are unsuitable for women that plan to become pregnant within a year. All outcomes come from the provider survey.

Table A.14: Model fit: observed vs. predicted probabilities

	SI choice probability		θ Probability	
	Observed (1)	Predicted (2)	Observed (3)	Predicted (4)
T: Treated arms	0.18	0.18	0.74	0.66
T1: Consumer price reduction	0.15	0.17	0.63	0.62
T2: Pharmacy cost reduction	0.21	0.19	0.78	0.60
T3: Pharmacy incentive	0.19	0.18	0.80	0.77
C: Control group	0.02	0.11	0.29	0.43

This table compares the predicted probabilities of the provider and patient models, using the main model parameters in table 4, against the observed probabilities in the data. The predictions correspond to the "Introduce SI to the patient's choice-set" counterfactual (Panel A of table 5), in which empirical product choice probabilities and provider recommendation probabilities $\hat{\theta}$ are observed due to randomized RCT treatment assignment. Columns 1 and 2 compare the observed and predicted probability that a patient chooses SI; columns 3 and 4 compare the observed and predicted probability that a provider recommends SI (θ).

Table A.15: Decomposition into extensive and intensive margin effects

	Extensive	Intensive: share of SI in site		
	Site sells SI (1)	Control for availability (2)	Conditional on availability (3)	Heckman model (4)
T1: Consumer price reduction	0.47***	0.16**	0.18**	0.23***
	(0.08)	(0.06)	(0.07)	(0.08)
T2: Pharmacy cost reduction	0.38***	0.15**	0.16**	0.21**
	(0.09)	(0.06)	(0.07)	(0.09)
T3: Pharmacy incentive	0.45***	0.19***	0.16**	0.26***
	(0.09)	(0.06)	(0.07)	(0.09)
Site sells SI		0.1**		
		(0.04)		
Inverse Mills Ratio				0.04
				(0.03)
Control mean	0.47	0.02	0.05	0.02
Observations	136	136	113	136
Censored observations				23
Observed shares				113
First stage p-val				0.05

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Columns 1, 2 and 3 show double-ML estimates (Chernozhukov et al., 2018). The outcome in column 1 is an indicator for whether a site stocked SI during the study period. The outcome in columns 2, 3, and 4 is the share of transactions in a study site that include a sale of SI. Column 4 estimates a Heckman selection model where the first stage estimates the probability of a site stocking SI as a function of whether the site stocked SI prior to the intervention, the relative wealth index of the ward, the ward's population, the number of competitors in the surrounding market, and urbanicity indicators. For other details on the ML estimation procedure see Table A.2. Pooled analysis results and additional statistical tests can be found in appendix tables A.4 and A.5.

Table A.16: Linear probability estimates of the provider model

	$\theta_{d,SI}$ (1)	$\theta_{d,SI}$ (2)	$\theta_{d,SI}$ (3)
Provider incentives: f(p,c)	0.044^{***}	0.047^{***}	0.022^{***}
	(0.015)	(0.012)	(0.008)
Price to the patient: P_{SI}	-0.007^{**}	-0.008^{***}	-0.003^{**}
	(0.003)	(0.002)	(0.001)
Num. obs.	98	98	98
RCT IVs	Y	Y	N
$p-c$ and c IVs	N	Y	N
First stage F: p_{SI}	20	5	
First stage F: $f(p,c)$	23	7	

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The outcome variable (θ) is an indicator for whether more than half of the providers in a site recommend SI over IMI. The component $f(p,c)$ is defined in section 1 as the financial incentives of the provider to recommend SI. For model 1, treatment assignment indicators were used as instruments for p_{SI} and $f(p,c)$. Stratification variables are included as controls. For model 2, average market markups from the census survey and marginal costs of non-SI FP products were used as instruments in addition to treatment indicators. Model 3 shows OLS results with no instruments. Stratification variables are included as controls in all models.

Table A.17: Linear probability estimates of the patient demand model

	Share (1)	Share (2)	Share (3)	Share (4)	Share (5)
Price to the patient: P_{SI}	−0.0002	−0.0012***	0.0001	−0.0002	−0.0006
	(0.0007)	(0.0004)	(0.0006)	(0.0003)	(0.0005)
Provider's recommendation: $\hat{\theta}$	0.2270**		0.2494***	0.1470***	0.3502**
	(0.1024)		(0.0897)	(0.0533)	(0.1517)
Provider's incentives: $f(p, c)$		0.0075**			
		(0.0037)			
Is longterm	−0.1856***	−0.1014***	−0.2006***	−0.1497***	
	(0.0594)	(0.0297)	(0.0524)	(0.0299)	
Failure rate	−0.0070	−0.0124***	−0.0056	−0.0067**	
	(0.0045)	(0.0034)	(0.0040)	(0.0027)	
Num. obs.	336	336	336	336	336
N Clusters	98	98	98	98	98
RCT IVs and dose MC	Y	Y	Y	N	Y
Non-SI $f(p, c)$ IV	Y	Y	N	N	Y
$p - c$ and c IVs	N	N	Y	N	N
Product FEs	N	N	N	N	Y
First stage F: p_{SI}	43	43	27		195
First stage F: $\hat{\theta}$	32		17		58
First stage F: $f(p, c)$		20			

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The outcome variable is the site level share of patient encounters that result in a sale of each product category as defined in section 5. Column 1 shows that patients respond to the provider's advice but not to changes in prices conditional on the provider's advice. Column 2 shows that conditional on the financial incentives of the provider, the patient-provider unit responds to changes in prices, pointing to the role of the provider's altruism in the downward slope of the demand curve. Columns 3 and 4 are robustness checks of the estimates in column 1 with alternative instruments. Column 3 substitutes the non-SI component of $f(p, c)$ by the average markup of non-SI products in surrounding markets and the transaction-level marginal costs of non-SI products. Column 4 shows OLS results. Column 5 repeats column 1 with product fixed effects, which are the linear model's counterpart of the alternative-specific intercept for the new technology carried by the structural columns of table 4; it is the column reproduced as column 6 of Panel A in that table. The fixed effects span the long-term and failure-rate indicators, so those coefficients are not separately identified in column 5, and the first-stage F statistic on $\hat{\theta}$ rises from 32 to 58 once the product-level means are partialled out.

Table A.18: Relationship between financial incentitives and other counseling characteristics.

	SI info. (1)	Learning tools (2)	Knowledgeable (3)	Pressure SI (4)
P_{SI}	−0.0031	−0.0005	−0.0009	−0.0003
	(0.0037)	(0.0010)	(0.0013)	(0.0003)
f(p,c)	0.0375**	0.0086*	0.0113*	−0.0004
	(0.0172)	(0.0050)	(0.0066)	(0.0005)
Num. obs.	222	222	222	222
N Clusters	111	111	111	111

This table presents 2SLS regressions for various counseling characteristics where the independent variables are the financial incentives of recommending SI as defined in the main model, and the price paid by the patient. IVs are the RCT treatment indicators. Outcomes were measured by the mystery shopper activity. Column 1 is the SI information index described in table 3. Learning tools, in column 2, is an indicator for whether the provider used any learning tools during counseling with the patient. Knowledgeable, in column 3, is an indicator for whether the mystery client perceived the provider to be highly knowledgeable about FP. Pressure SI, in column 4, is an indicator for whether the mystery shopper reported feeling pressured to buy SI. The sample of sites included are all sites for which mystery shopper data was collected, conditional on the price measure from table A.12 being available.

B Pharmacies as price-takers

For the counterfactual exercises I assume that pharmacies are price takers in the family planning market. This is motivated by the fact that the interventions from the RCT were implemented at the site level, rather than at the market level, and pharmacies in the sample are small independent retailers. These small pharmacies do not have any meaningful bargaining power with suppliers, they have capacity and financial constraints limiting their ability to significantly expand their overall sales volumes, and they sell products widely available in competing pharmacies and government clinics. Furthermore, these pharmacies have few employees and limited specialization of roles, limiting the manager's attention on pricing decisions. For instance, pharmacy owners often act as both the manager of the site and the provider (69% of sites in the sample), and the pharmacies stock hundreds of products that need to be priced (family planning only accounts for less than 13% of sales on average). Therefore, assuming a more complicated pricing model would likely add little value and possibly lead to incorrect conclusions.

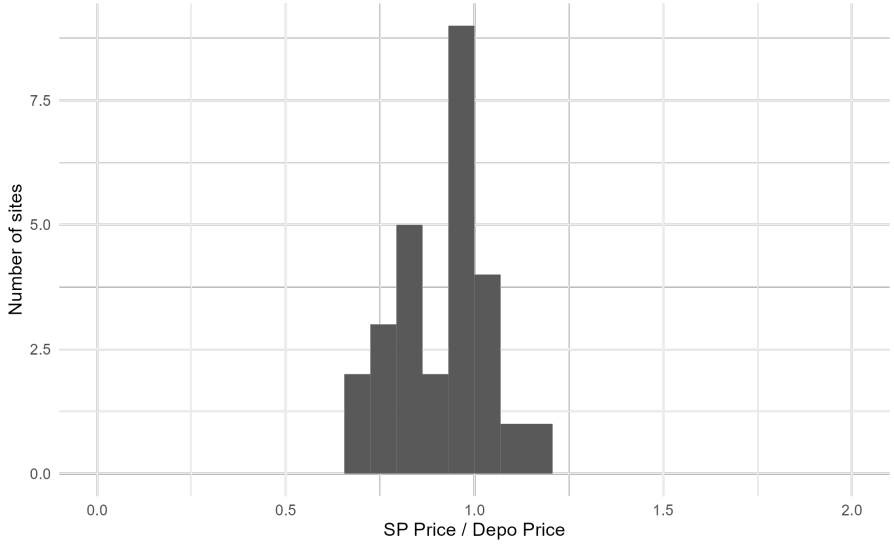
Furthermore, a price-taking assumption is consistent with the reduced form evidence from the RCT. There are no economically meaningful effects on the pricing of alternative family planning products due to the interventions (see table B.1), so pharmacies do not seem to re-optimize prices of alternative FP products after large shocks to the marginal costs and prices of SI. This is expected given that competing pharmacies and clinics sell these products as well, so deviating from the market price of these products is unlikely to be optimal given the pharmacy's constraints discussed above. In terms of the new technology, sites seem to benchmark the price of SI against the other injectable in the market (IMI) as seen in figure B.1. Moreover, prices for SI in the provider subsidy arms were similar to those of the control group, and in the consumer price-reduction arm the price of SI was set exogenously.

Table B.1: Estimates of price effects on non-SI FP alternatives in a site

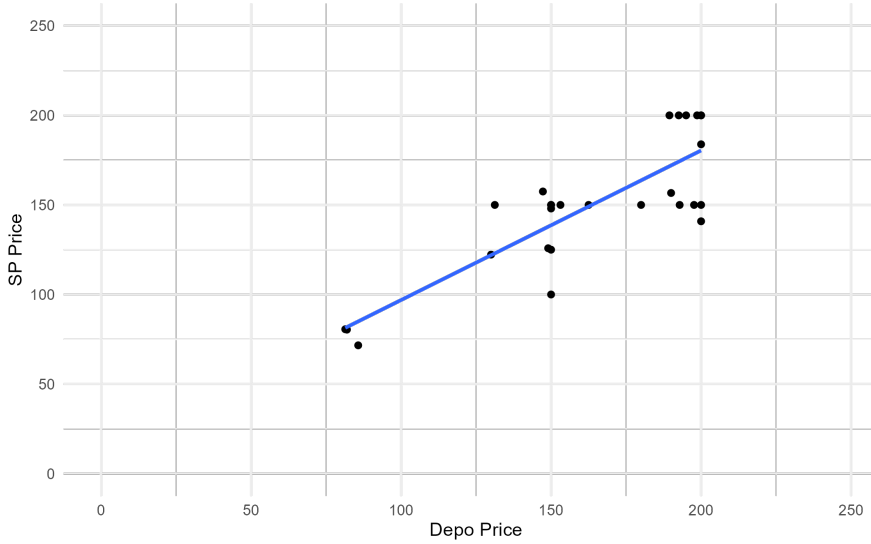
	IMI	Condoms	EC	Oral
Consumer subsidy	-0.28	-1.67	-7.81**	-10.65***
	(9.57)	(2.94)	(3.47)	(3.3)
Pharmacy cost reduction	-5.09	-1.06	-3.24	2.43
	(9.91)	(4.23)	(4.4)	(4.81)
Pharmacy incentive	13.49	8.11*	-3.33	0.18
	(12.67)	(4.65)	(4.34)	(5.16)
Control mean	156.81	57.08	118.36	73.41
Observations	51	90	123	94

Stars denote significance using asymptotic inference $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Outcome variables are the mean price in a site for each FP alternative, excluding SI.

Figure B.1: Relationship between SI and IMI prices



(a) Price ratio



(b) Relationship

This figure shows the relationship between IMI prices and SI prices for sites in the Maisha Meds network that stock both types of products. The sample includes control group data, pre-study RCT site data, and a sample of non-RCT site data from the MM network. Prices of IMI are highly predictive of prices for SI, with an adjusted $R^2 = 0.69$. In fact, marginal costs of SI are much less predictive of prices for SI with only an adjusted $R^2 = 0.12$. N = 27.

C Robustness checks on reduced form results

Table C.1: Take-up effects where the outcome variable is the share of transactions in a site that include SI

	Unpooled treatment	Pooled treatment	Pooled provider
Consumer Subsidy	0.24***		0.23***
	(0.06)		(0.06)
Pharmacy cost reduction	0.22***		
	(0.06)		
Pharmacy incentive	0.28***		
	(0.06)		
Treated		0.25***	
		(0.04)	
Provider			0.25***
			(0.05)
Control mean	0.02	0.02	0.02
Adj. R^2	0.26	0.27	0.26
Num. obs.	136	136	136
Stratification controls	Yes	Yes	Yes
Test: T1 = T2	0.85		
Test: T1 = T3	0.45		
Test: T2 = T3	0.38		
Test: T1 = Provider			0.75

Stars denote significance using asymptotic inference $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The outcome variable is the share of family planning transactions in a site that include SI. F-tests for arm differences are included, where T1 is the consumer arm, T2 is the pharmacy cost-reduction arm, and T3 is the pharmacy incentive arm. Provider includes pharmacy cost reduction and incentive arms. Stratification variables are included as controls.

Table C.2: Substitution patterns: site-level, outcome is share of transactions including the column's category using OLS

	IMI	Non-injectables	Condoms	EC	Oral
Control mean	0.08	0.91	0.26	0.48	0.26
Panel A: Unpooled treatment					
Consumer Subsidy	−0.01	−0.21***	−0.05	−0.10	−0.10***
	(0.03)	(0.06)	(0.05)	(0.07)	(0.04)
Pharmacy cost reduction	−0.03	−0.20***	−0.04	−0.08	−0.12***
	(0.03)	(0.06)	(0.06)	(0.07)	(0.04)
Pharmacy incentive	−0.04	−0.23***	−0.01	−0.14**	−0.10***
	(0.03)	(0.06)	(0.05)	(0.06)	(0.04)
Panel B: Pooled treatment					
Treated	−0.03	−0.21***	−0.03	−0.10*	−0.11***
	(0.03)	(0.04)	(0.04)	(0.06)	(0.03)
Num. obs.	136	136	136	136	136
Stratification controls	Yes	Yes	Yes	Yes	Yes

Stars denote significance using asymptotic inference $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The outcome variable is the share of family planning transactions in a site that include a given category of product. Panel A shows the treatment effects for each arm, while panel B shows the pooled effects across treatment arms. Stratification variables are included as controls.

Table C.3: Site-level pass-through of subsidies for SI using OLS

	Unpooled treatment	Pooled treatment	Pooled provider
Consumer Subsidy	-73.39^{***}		-73.60^{***}
	(10.08)		(10.03)
Pharmacy cost reduction	-26.15^{**}		
	(11.71)		
Pharmacy incentive	-18.35		
	(12.09)		
Treated		-41.83^{***}	
		(10.04)	
Provider subsidy			-22.29^{**}
			(10.32)
Control mean	129.60	129.60	129.60
Adj. R^2	0.32	0.14	0.33
Num. obs.	131	131	131
Stratification controls	Yes	Yes	Yes
Test: T1 = T2	0.00		
Test: T1 = T3	0.00		
Test: T2 = T3	0.50		
Test: T1 = Provider			0.00

Stars denote significance using asymptotic inference $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Outcome is SI price in KES constructed with POS data. Missing POS data was replaced with field data (standardized patient activity and the provider survey). For control group sites, missing data from POS system and field activities was replaced by predicted SI prices using a linear model trained on pre-study, control group, and non-RCT IMI and SI prices. Figure B.1 shows the relationship between SI and IMI prices.