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 for the patient from the introduction of demand- and supply-side incentives to adopt the new technology. This approach lets us study the 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 up to 95% of the consumer surplus of a policy that reduces the price to the patient, as well as all of the reduction in expected failure rates. To be effective, incentive policies need to account for the central role that the provider plays in medical decision-making.

Draft version: November 3, 2026

*All authors contributed to the conception and design of the experiment, as well as funding acquisition. CP conceptualized the theoretical framework and the model, accessed the underlying data, conducted analysis, and drafted the paper. All authors reviewed the draft. We thank Benjamin Handel, Edward Miguel, Jonathan Kolstad, Matthew Grennan, Kei Kawai, Nicholas Ryan, Rohini Pande, Michael Whinston, Paul Niehaus, Matthew Backus, Yuki Ito, Daniel Maggio, Liana Woskie, Mattia Fracchia, the conference and seminar audiences at Boston University, MIT Sloan, Yale, University of Pittsburgh, California Health Economics Conference, the LIFT-IPA-CEGA Research Gathering, the 2024 ASHEcon Conference, and the CSAE 2024 Annual Conference for helpful comments and discussion. We thank Maisha Meds, especially Ruth Namai, Veronica Njeri, Jessica Vernon, and Michael Liang. REMIT Kenya, Carolyne Nekesa, Nettah Isavwa, and Leah Adero provided excellent research assistance and field management support. This study was approved by the UC Berkeley Committee for the Protection of Human Subjects, Strathmore University Ethics Review Board in Kenya, and the Kenyan National Commission for Science, Technology and Innovation. A pre-analysis plan was registered at the AEA registry for randomized controlled trials (AEARCTR-0009020). This study was funded by the Children's Investment Fund Foundation and by The Weiss Fund for Research in Development Economics at the University of Chicago.

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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). 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.

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 counseling 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 provide advice on to patients or to have financial incentives (or opportunity costs) 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 shape patients' response, or lack of response, to such policies (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 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 well suited to this question: every option in our setting is sold over the counter, so the patient makes the final choice, yet patients rely on providers' information to make it. We study how the mechanisms of provider counseling, 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, and identifying these mechanisms lets us carry lessons from this setting to other contexts.

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). Licensed pharmacists in Kenya hold a post-secondary degree that includes patient counseling and clinical training, and pharmacies routinely offer family planning counseling, injections, and malaria and HIV testing[1]. However, Kenyan pharmacists are likely to have financial incentives tied to the product counseling they give to patients. This is because most pharmacies in Kenya (and in many other LMIC settings) are small independent businesses (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*

[1]In our context, FP counseling in pharmacies is based on informed choice where patients are encouraged to make a decision themselves across options using the information presented by the provider. National clinical guidelines available at: https://media.tciurbanhealth.org/wp-content/uploads/2017/07/12124654/2022Kenya-National-Family-Planning-Guidelines-6th-Edition.pdf

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.

We combine reduced-form evidence from the RCT with a structural model of patient demand and provider advice. Taken together, the results show that provider counseling is the key to adoption of the new technology, whether the intervention targets patient prices or provider incentives: counseling responds to both subsidy types, and patient demand responds strongly to counseling. The outweigh role of provider counseling, particularly for a price subsidy to the patient, is surprising in a setting where all options are out-of-pocket and over-the-counter.

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 welfare-relevant demand elasticity for the new technology and could understate the potential impact of direct price reductions for the patient and lead to biased welfare estimates.

The reduced-form results show large adoption effects, increased FP protection, and reductions in method failure rates in every treated arm, with no significant differences between consumer and provider subsidies: the share of FP transactions that include SI rises by 21 percentage points (p.p.) at treated sites, against 2% in the control group. The effect operates mainly at the intensive margin rather than through greater availability of SI. Patients substitute away from short-term methods within the study sites, reducing expected method-failure rates by 10%.

Prices and incentives, however, differ sharply across arms. Pharmacies in the provider arms pass a third or less of the marginal cost reduction through to patients, who therefore pay about twice as much for SI as patients in the consumer arm, so price changes alone cannot explain adoption in every 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 prefer recommending the new technology to patients interested in injectables, and pharmacists in the provider subsidy arms (T2 and T3) are much more likely to share information about SI, with increases of up to 0.82 SD relative to the control group. Provider knowledge about SI increases across all arms. Providers in treated arms discuss alternative options with the patient at rates similar to those in 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' counseling. In fact, in this setting we do not find evidence that patients respond

to changes in the price of the new technology conditional on the provider's counseling (estimates suggest patients are perfectly inelastic). Providers, on the other hand, respond both to patients' out-of-pocket costs and to their own financial incentives to share information and advise on 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 advise on the new technology when patient cost-reduction subsidies are in place, thus increasing adoption. However, providers also respond to their own financial incentives, so positive shocks to the pharmacy incentives motivate them to share more information and advice on the new technology, raising patients' willingness to pay for SI.

Neglecting provider agency can thus lead to incorrect policy and welfare conclusions and violates exclusion restrictions commonly assumed in demand estimation. Providers' financial incentives are often positively correlated with the price the patient pays, and higher incentives lead providers to share more information about the new technology. As a result, studying patient choices in isolation, even with exogenous supply-side cost shifters such as those generated by T2 and T3, can make the demand curve look flat or upward-sloping. This understates the welfare-relevant elasticity and the effect of price reductions, and it biases welfare estimates.

Finally, we use the model and the mystery shopper data to study patient welfare under counterfactual policies. Because adoption runs through counseling, the subsidies could in principle be distortionary. We find that patient subsidies raise welfare as long as at least 29% of the advice-induced shift in the valuation of SI reflects genuine information rather than distortion, and the mystery shopper evidence and the fall in expected failure rates suggest that this is the case. Roughly 95% of the welfare gain from a price reduction to the patient, and all of the gains in family planning protection and failure rates, come from the change in providers' counseling. Without these information channels, changes in the price of SI would barely affect patient 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). We contribute to this literature by considering the role of expert intermediaries and how they respond to the presence of patient price reduction policies. The paper 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 observed measures and proxies for 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, and instead directly measure the causal impact of provider counseling on patient demand.

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 providers 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 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 limited pass-through.

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 counseling, 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). When patients receive counseling from providers, these implications are not immediately clear, since counseling can inform

patients' choices but it can also distort them (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 holds a prior belief about its value, $\hat{v}_{n,i}$.

The patient seeks counseling from a medical provider d before making a purchase decision. Providers differ in how they approach the new technology during counseling, which we summarize by $\theta \in \{0, 1\}$. A *receptive* provider ($\theta = 1$) engages with the new technology: they might be more knowledgeable about the product, be more likely to share information about it, or be willing to spend the effort of discussing its differences relative to products patients might be more familiar with. A non-receptive provider ($\theta = 0$) could be less willing to spend the effort of discussing the product (or learning about its attributes) and leave the new technology largely out of the conversation. After counseling with a receptive provider, the patient updates their perceived value of the new technology to $\bar{v}_{n,i}$. After counseling with a non-receptive provider, the patient's perceived value is unchanged, so $\bar{v}_{n,i} = \hat{v}_{n,i}$. The provider therefore shapes the information available to the patient, but the purchase decision remains the patient's: a counseled patient buys the new technology if they believe it offers enough value relative to its price, that is, if $\bar{v}_{n,i} - v_{o,i} > p_n - p_o$.

Welfare effects of provider counseling — The welfare effect of receptive counseling is ambiguous because it depends on whether the belief update moves the patient closer to or further from the true value of the new technology. Consider two extremes. If receptive counseling fully informs the patient ($\bar{v}_{n,i} = v_{n,i}$), it raises the welfare of patients who buy the new technology only because of it, that is, those with $\hat{v}_{n,i} - v_{o,i} < p_n - p_o < v_{n,i} - v_{o,i}$. If instead the patient's prior was correct and counseling overstates the new technology's value, for example through selective framing or pressure ($\bar{v}_{n,i} > v_{n,i} = \hat{v}_{n,i}$), it lowers the welfare of patients with $v_{n,i} - v_{o,i} < p_n - p_o < \bar{v}_{n,i} - v_{o,i}$, who buy the new technology only because of the distorted belief. In both cases, the welfare of other patients is unchanged.

Evidence points both ways: provider incentives are the main driver of antibiotic overuse in China (Currie et al., 2014) but do not explain inappropriate child diarrhea treatment in India (Wagner et al., 2024), and US prescribing and counseling patterns have had both positive and negative welfare effects on patients (Compton et al., 2015; Grennan et al., 2025). Section 6 parameterizes the range between these extremes, letting the true value be a weighted average of the prior and the counseled valuation, and uses evidence on the content of counseling and on patient outcomes to assess where our setting falls.

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[2]. Let patient i's perceived utility for alternative k (given by $\bar{v}_{i,k,d}$) be a function of product characteristics, as well as an "expert advice" component $\theta_{d,i,k} \in \{0, 1\}$ (a proxy for the provider's behavior during counseling), which results from the patient's interaction with the provider d:

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

In equation 1, p_k is the price of alternative k which is observed by the patient, and x_k are characteristics observable to both the patient and the researcher. When a patient interacts with a provider, $\theta_{d,i,k}$ indicates whether the provider is receptive to product k during counseling, and δ is the weight of that counseling on the patient's perceived value. The provider's counseling is modeled as an additional product attribute, which can be interpreted as the impact on product k's perceived utility from the provider's behavior during the counseling interaction. In other words, the provider's counseling type updates the patient's perceived value of a product depending on δ, analogous to the two-product model presented above. Parameters α and β are coefficients for the patient's preferences over other product characteristics observed by the researcher *conditional* on the provider's counseling. Let $\epsilon_{i,k}$ be a random component of the patient's preferences, unobserved by the researcher. This random component can include the patient's prior knowledge about the product, product characteristics unobserved by 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 counseling model

Since the main aim of this exercise is to study the introduction of SI, let the provider counseling component $\theta_{d,i,k}$ be active only for the new technology ($k = SI$)[3]. Therefore, the provider's problem becomes a binary choice of counseling type: whether to be an SI-receptive provider ($\theta_{d,i,SI} = 1$), engaging with SI when counseling patients as described in Section 1.1, or not ($\theta_{d,i,SI} = 0$). This is a choice about how the provider counsels, not about which product the patient buys, which remains the patient's decision through equation 1.

Being SI-receptive is costly, since counseling on an unfamiliar product likely takes more effort. Costs related to counseling on SI might include knowledge acquisition costs, the time and effort of administering the product itself if it is chosen by the patient (relative to options that the patient takes home), and the effort of explaining this new option relative to more familiar alternatives to the patient. Providers plausibly weigh this effort against two considerations: the patient's welfare and the pharmacy's financial return. Let provider d's counseling approach be given by:

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

[3] 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.

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

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[4]. $W(p_{SI})$ 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. The term $f(p,c)$ is the pharmacy's expected financial return to SI counseling, where p and c are vectors for prices and marginal costs for family planning products available at the site. The parameter $\lambda \geq 0$ measures how responsive the provider's counseling approach is to this return, relative to what they think is best for the patient. Given the potential endogeneity of the $e_{i,d}$ shock, which may reflect 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 SI-receptive counseling:

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

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[5]. Because SI-receptive counseling changes the information available to the patient, it shifts the probabilities with which the patient chooses each product, $P[k \mid \theta = 1] - P[k \mid \theta = 0]$. The function $f(p,c)$ is the markup-weighted sum of these shifts, where $m = p - c$. It is therefore large when receptive counseling moves patients toward higher-margin products and small, or even negative, when it moves them away from the pharmacy's more profitable alternatives.

1.4 Framework implications for demand estimation

The framework implies that both patient subsidies and provider incentives can have an effect on both patient demand and provider behavior. 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 counseling to the patient will have an impact on the patient's willingness to pay for the new technology. If the provider's counseling approach toward the new technology 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 provider's counseling approach toward the new technology is a function

[4]For the purposes of this paper, altruism relates to what the provider believes might benefit the patient's welfare. A fixed effort cost of SI-receptive counseling enters equation (2) as a constant; it is not separately identified from any constant in $W(\cdot)$.

[5]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.

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 are two reasons θ may not be orthogonal to the price vector in the framework presented above. First, if $\lambda \neq 0$, then the provider's counseling 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 lead to 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 the effectiveness of well-designed price reduction policies. 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. In turn, failing to control for the financial incentives of the provider can lead to biased welfare estimates that use the estimated demand curve since the financial incentives of the provider are not part of the patient's welfare.

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 (USAID, 2018; Escamilla et al., 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 accessing 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). Meanwhile, 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[6]. 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 needle, 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 one-third 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).

3 Experimental design and study sample

The data and main exogenous variation for analysis come from a cluster randomized controlled 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 are concentrated in western Kenya, but there is also a sizable number near Nairobi and Mombasa.

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

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 (and provide injections), which is typical of regulation-compliant pharmacies in the country. 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-sale (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 were the following: a minimum distance of 0.5 km 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.[7]

3.2 Randomization

Randomization was done at the site level[8] 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. 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[9]. The treatment arms consist of the following: consumer price reduction (n=35), pharmacy cost reduction (n=33), and pharmacy incentive (n=36).

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

[7] Appendix Table A.1 reports balance tests; joint tests of orthogonality fail to reject balance across arms.

[8] 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.

[9] 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.

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 at no cost through the Maisha Meds program. Prices to the consumer are fixed at a subsidized rate of 50 KES in the POS system (roughly a 60% price reduction). The pharmacy keeps the 50 KES paid by the patient for SI. The 50 KES 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[10].

Pharmacy cost-reduction arm (T2): Sites in the pharmacy cost-reduction arm receive SI stock at no cost through the Maisha Meds program, a 75 KES reduction in marginal cost (Table 1). 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 cost-reduction arm, except that the pharmacy also receives a 50 KES transfer per SI sale.

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 Figure A.2), including the control arm. Any site in the RCT could also stock SI from other suppliers and sell it at its chosen price.

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.[11]

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

[11] While all arms can affect the price paid by the consumer $p(T)$ (by design in T1, and endogenously in T2 and T3), the $t = 50$ KES pharmacy incentive in T3 shifts the relationship between prices and markups by 50 KES: 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 include product characteristics, prices to the patient, cost of the product to the facility, and quantities sold. The POS system data include 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 were 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[12]. 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 sites' treatment assignments. Data were 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[13] 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[14], 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 the main 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.

[12]The final mystery shopper activity sample includes 83% 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.2.

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

[14]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). Each arm raises the share of family planning transactions that include SI by at least 18 p.p., and we cannot reject that the effects are equal across arms ($p \geq 0.50$; see appendix Table A.3 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 those of the other arms, suggesting diminishing returns. Pooling the treated arms, the increase is 21 p.p. 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 consist of non-injectables: condoms, EC, and OC. Overall, the analysis finds evidence of large substitution effects away from short-term methods across all treated arms.

Given that only 8% of transactions in the control group include IMI sales, there is limited room for substitution away from this option. In Column 2 we observe only a small, statistically insignificant 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 p.p.), but not significant for the pharmacy cost-reduction and consumer price reduction arms (1 percentage point in both cases). Appendix Table A.4 presents additional pooled results across arms and statistical tests. Pooled together, there is no significant reduction in IMI sales in treated sites (3 p.p.). However, the estimated effects are all negative across arms, and represent 13%-50% reductions relative to the control group's average, so there is still suggestive evidence of substitution even though we are not powered for this product due to the low baseline level of IMI.

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 p.p. in treated arms relative to the control group in the share of transactions that include a short-term method. Columns 3-5 of appendix Table A.4 show the effects on specific short-term methods and additional statistical tests. There are no significant differences across arms. Substitution is strongest away from oral contraceptives, which fall significantly in every arm; emergency contraceptive sales also fall, significantly so in T3 and, when arms are pooled, at the 10% level. The shifts move the product mix toward national patterns: injectable shares rise while EC and OC shares fall (KNBS, 2022). The reduction in emergency contraceptive sales is 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.

To illustrate how these substitution patterns impact the effectiveness of family planning products purchased by patients, Columns 4 and 5 detail the per-transaction effects on pregnancy protection and expected failure rates. Column 4 shows the effect on couple-years of protection (CYP), a standard family planning metric that adjusts the years of protection for failure rates, discontinuation (including those due to side effects), and wastage[15]. Protection per transaction rises by roughly 35% in all arms. Column 5 shows the effects on expected failure rates under typical use, which can be interpreted as unintended pregnancies averted per 100 women. We find that patients shift toward products with lower average failure rates, reducing expected failures by almost one unintended pregnancy per 100 women or a 10% improvement relative to control group levels. Appendix Tables A.9 and A.10 show additional results on family planning effectiveness.

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 2 km), 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 6-8 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 medium- to long-term methods (Column 6; IRR$-1 = -0.41$, SE $= 0.20$), an effect concentrated in injectables (Column 7), although results are imprecise. 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 may be partly 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.5, Column 1). Treatment effects on availability are nonetheless large, as essentially all treated sites stock SI[16].

Intensive margin effects appear to drive the higher adoption of SI. Conditional on availability, the pooled treatment effect is 18 p.p. (Columns 2-3 of Table A.5; see also Table A.7), only 3 p.p. 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

[15]We use the weights used in the evaluation of USAID programs, archive copy available at: https://usaid.com/global-health/health-areas/family-planning/couple-years-protection-cyp.

[16]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.

4) confirms intensive-margin effects of 21-26 p.p., consistent with the main adoption estimates in Table 2[17].

4.2 Mechanisms: Prices, markups, and counseling

Price pass-through: 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.8 reports the full set of price specifications and tests). In the consumer price reduction arm (T1), the price of SI falls by 74 KES relative to the control-group mean of 129 KES (essentially equal to the 75 KES subsidy design benchmark), so patients received 100% of the subsidy as intended[18]. Because the average cost of stocking SI is 75 KES, the benchmarked 50 KES 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 (26 KES, T2) and 18% in the pharmacy incentive arm (22 KES, T3), pooling to a 23 KES reduction. We strongly reject equal pass-through ($p < 0.01$), 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 counseling responds to all treatment arms, with the response concentrated where providers' financial incentives are largest. Providers in treated pharmacies report higher preferences for counseling on 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 report a preference for recommending SI over the old injectable to patients interested in injectables (29 to 44 p.p., 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

[17] In the first stage, a probit regression models whether a site stocks SI as a function of pre-RCT SI stock, a ward wealth index, the ward's population, the number of surrounding competitors, and urbanicity indicators. The first-stage p-value is 0.05.

[18] 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.8 for details.

smaller, insignificant 0.34 SD in the consumer arm (Column 4). Consistent with this, providers in the pharmacy arms are significantly more likely to report recommending SI for medical reasons (Column 3), although the T1 estimate is similar in size to T2's and the arms are not statistically different. 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 in only 1 of 228 visits did the shopper report feeling pressured to purchase SI (in T1). Finally, provider knowledge improves across arms: providers become 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.11). 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 are SI-receptive comes from the provider survey, where providers reported which product they recommend to patients interested in injectables and why. This measure captures both provider counseling preferences and knowledge about SI, since SI weakly dominates IMI in terms of its product characteristics (conditional on price), so low values of this measure could reflect either a lack of knowledge of its relative characteristics, a low perceived value relative to the price, or other counseling preferences. We set $\theta = 1$ if half or more of the providers interviewed in a site reported a preference for recommending SI when counseling on injectables (Column 2 of Table 3)[19]. 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, so it should be interpreted as a provider counseling type. 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

[19]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, so there is no comparable measure. Furthermore, the mystery shopper activity excluded sites in Coastal Kenya due to implementation costs. Table A.12 shows how model components correlate with measures from the mystery shopper activity, finding similar patterns.

with SI availability[20]. Therefore, shifts in probability from the counseling type are held constant across sites and act as a scaling parameter for the product-category markups.

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[21] 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. Parameter κ summarizes how providers respond to changes in the patient's out-of-pocket costs.

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 jointly normal, i.e., $(e_d, \boldsymbol{v_d}) \sim N(\boldsymbol{0}, \boldsymbol{\Sigma_v})$, with $Var(e_d)$ normalized to 1 and the remaining elements of the covariance matrix estimated[22]. 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[23].

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 probability of being SI-receptive 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[24]. Again, this can be interpreted as patients encountering a provider type $\hat{\theta}_{d,k} \in [0, 1]$ that relates to the provider's

[20] See Table A.13 for the estimates of the shifts in probabilities. Results are robust to various definitions of θ.

[21] C absorbs both the altruism constant and any effort costs that are associated with explaining or learning about the new technology. This could be extended to include patient characteristics observed by the researcher if patient-level counseling data were observed.

[22] 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.

[23] Kisumu is where the implementation team was based. Results are robust to including all strata as controls, but bootstrap inference then performs poorly because the maximum likelihood estimator converges less often.

[24] An alternative approach is to plug in the site-level information measure $\theta_{d,SI}$ directly rather than the fitted probabilities. Parameter estimates are not sensitive to either choice, but measure $\hat{\theta}_{d,k}$ offers some advantages. For instance, because it is continuous, it 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 SI-receptiveness probabilities. Moreover, it allows for the derivation of a simple closed-form decomposition of the demand curve, which is discussed in Section 5.4.

openness to counseling on the new technology.

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 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 for which we assume consumer taste heterogeneity. 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 typical use failure rate of the family planning method from the World Health Organization's global handbook for family planning providers (WHO, 2022).

The outside option (utility normalized to zero) represents buying a medium- to long-term method elsewhere. Its market size is defined using the average number of such methods sold at the four nearest census sites[25]. The outside option thus summarizes alternative sources of care for medium- to long-term methods, motivated by the reduced-form patterns observed (Table 2).

The data used for the demand and provider advice model estimation come from a subset of the RCT site sample. First, only sites that stock SI are included since we will focus on patient adoption of SI. Moreover, only sites for which provider data and census data are available are included in order to have measures for θ and the outside option. This leads to a sample size of 24,640 patient-choice cases across 98 sites. A patient-choice case is defined as a patient encounter in the administrative data or a medium- to long-term method sale in the surrounding market. For transactions where multiple products were purchased, each transaction-category is considered as a separate case in order to keep the dimension of the product-space low[26].

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 multivariate 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 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)[27]:

[25] 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.14 for more details on the definition and comparisons with alternative definitions.

[26] Less than 9% of transactions in the data include multiple categories.

[27] Maximum likelihood estimation of this model offers the advantage that it explicitly controls for differences in

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

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

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 $\hat{\theta}_{d,SI}$.

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 two 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 that this component summarizes the provider's outside option when being SI-receptive 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 non-SI family planning products, 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 the provider equation directly (equation 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.

In the interest of tractability, the model reduces provider counseling to a single proxy; Section 5.5.1 shows that results are similar with alternative proxies.

The main motivation for using variation in provider financial incentives as an 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

the choice sets across patient encounters and allows market zeros and small shares to enter estimation efficiently.

technology through multiple dimensions of the provider counseling. Insofar as we interpret θ as a one-dimensional proxy for the counseling behavior of the provider with regard to the new technology, the instruments allow us to estimate δ and α capturing the distinct counseling channels that are correlated with the proxy being used.

5.4 Decomposition of the slope of the demand curve

A price effect on patient choice operates not only through a direct patient response, but also through changes in the counseling 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:

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

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

Component (1) is the direct effect of price on the patient's perceived value of SI, holding the provider's counseling fixed. It would be negative for a fully informed patient deciding alone and zero if the provider made the choice; when the patient relies on imperfect information and the provider's advice, its sign 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 regard 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 counseling on SI.

Finally, component (3) summarizes the effect of changes in the provider's financial incentives on the patient's demand for SI. 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.

The total slope of demand is the sum of components (1), (2), and (3), so it can even be positive, at least locally, if the incentives component dominates.

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. 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

In Panel B of Table 4, we find that providers are highly responsive to both their financial incentives and the patient's out-of-pocket costs. The provider model is estimated through IV probit (Rivers and Vuong, 1988) as described in Section 5.1. The coefficient on $f(p, c)$ is $\lambda = 0.111$ ($p < 0.01$). An analogous linear probability model implies a marginal effect of about 4.4 p.p. in the probability of being SI-receptive for a 1 KES increase in $f(p, c)$ (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 -0.7 p.p. in the linear probability model (LPM column of Panel B). When comparing the relative magnitudes of the coefficients we find that for each 1 KES change in p_{SI} or $f(p, c)$ providers weight their financial incentives 6.5 times more than the patient's expenditure in determining their type of counseling.

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 price parameter α is estimated to be 0.0025 ($p = 0.24$), so we find that patients do not seem to respond to price changes in SI conditional on the counseling 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 3.53 ($p < 0.01$). Therefore, we 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 typical use. 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 additional substitution across long-term methods conditional on other characteristics. 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. Injectables, 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.4.

The specification includes an alternative-specific indicator for the new technology. 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 perceived value on the new technology before accounting for the provider's advice is low, which aligns with the low levels of adoption observed absent an intervention and might capture patient's lack of familiarity with the product.

Columns 2-5 re-estimate the model under different 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. In this specification δ falls to 1.44 and is no longer significant (p = 0.25), and the new-technology indicator is close to zero (p = 0.65), because the excluded observations are the ones that identify it (when we exclude this indicator from estimation, the θ coefficient is significant and nearly identical with models that include market zeros). This highlights the advantage of estimation methods that are compatible with market zeros when data are sparse. Column 4 shows the results from a multinomial logit model without random coefficients. Column 5 shows a multinomial logit estimate including fixed effects for each product alternative. Column 6 reports the linear probability (2SLS) benchmark reproduced from Table A.17, which includes product fixed effects.

Our results are robust to several alternative specifications, all reported in Tables A.19 and A.20. First, they remain stable when using alternative measures of θ. One version to highlight is that when we include indicators for provider knowledge about SI the estimates barely move - suggesting that our current measure of θ is an information response from the provider rather than providers shifting their advice independently of their knowledge. Second, they are robust to allowing pharmacies with prior SI availability to exhibit distinct SI demand patterns, which controls for selection in stocking decisions. Finally, the findings are consistent with a model that excludes control group data, relying instead on variation in prices and financial incentives across treatment arms. This allows us to test whether anything other than changes in price and $f(p, c)$ due to the interventions drives the results. While this approach reduces statistical power, since most variation in θ stems from the control versus treatment arms, the relative coefficient magnitudes (and welfare effects discussed in a later section) lead to the same conclusions as our main result that provider counseling is the main driver of demand responses, suggesting that salience or related non-pecuniary elements from the interventions are unlikely to drive our primary conclusions.

Decomposition of the demand for SI. — Because price also enters through $\hat{\theta}$, α alone does not summarize the slope of demand. We use the estimates in Table 4 to compute each of the three components in equation 8[28].

We find that provider channels completely drive the price response in this setting. Figure 3 reports the magnitude and significance of each component. The direct price effect is given by α, which is not significantly different from zero (p = 0.24). The linear probability analogue in Table 4 implies a statistically insignificant 4.4 p.p. response in demand to a price reduction comparable to T1. Therefore, we do not find evidence that patients respond to price changes conditional on the provider's advice.

The indirect effect driven by the provider's altruism is −0.017 choice utils, about seven times the magnitude of the direct patient effect. The bootstrap test for whether this component is negative is significant at the 10% level (p = 0.09). The price coefficients in Column 2 of Tables A.17 and

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

A.18 also show that only the combined patient-provider component (columns 2) is significant (at p $< 1\%$ and p $= 5\%$), while the direct patient effect is not (columns 1). Finally, the indirect effect from the provider's financial incentives is 0.015 choice utils, about six times the direct patient effect. The bootstrap test for whether this component is positive is significant in the structural model (p $= 0.04$) and analogous tests in the linear probability tables show similar significance.

Therefore, the only statistically significant and economically meaningful components of the demand curve are those that include the provider's behavior.

5.5.2 Own-price elasticity

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 a 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 since it excludes the role of provider profits in the price response. 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 toward zero and turns positive at most sites (mean $+0.02$, positive at 57% of sites), so the estimated total slope of the 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. The conceptual model predicts that omitting financial incentives introduces a positive bias in the slope of the demand curve (as observed), and a bootstrap test rejects the null that there is no positive bias at p $= 5\%$.

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 economics literature do not always hold, particularly if one's goal is to assess the welfare impact on patients by estimating consumer surplus. In settings where financial incentives and prices are positively correlated, such as with fee-for-service models, one would expect less elastic unconditional estimates of demand relative to the welfare relevant parameters.

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 counseling type (θ) is ambiguous: encountering SI-receptive providers is welfare-enhancing if they accurately update the patient's perceived value (even if partially), or it could be welfare-decreasing if they distort that valuation (e.g., through misrepresentation or pressure).

The reduced-form evidence from the mystery shopper activity, provider survey, and failure rates 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.21). Moreover, results from Table 2 show reductions in failure rates from purchased products and increased family planning protection (using CYP as a measure, which accounts for failure rates, discontinuation risk due to side effects, wastage, among other factors that impact use). The effectiveness of a family planning method is welfare relevant, since preventing unintended pregnancies is most likely the main motivation of FP users to purchase a contraceptive method.

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.12), we find that $f(p, c)$ 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[29]. 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.

These results are consistent with the robustness checks in Table A.19, which show that adding measures of provider knowledge to alternative definitions of θ does not change the parameter estimates. This stability implies that patient demand is likely driven by changes in the information providers give them, rather than by provider advice that is disconnected from actual knowledge of product characteristics.

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). We index the true value of SI by $s \in [0, 1]$, with $v = (1-s)\hat{v} + s\bar{v}$, where $s = 0$ means the advice-induced shift in demand is pure distortion and $s = 1$ means it is fully informative. We report thresholds of s under which our main conclusions hold, as

[29] 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.

well as estimates under our preferred assumption. We also show counterfactual effects on expected failure rates and amount of FP protection (CYP) to contrast our consumer surplus results with traditional proxies for welfare and program effectiveness in the family planning literature (Stover et al., 2000).

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 $\hat{\alpha} = 0.0025 + (-0.017) = -0.0145$, 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 the elasticity implied by the price response in T1 (which holds provider incentives constant). This parameter is also analogous to the elasticity parameter recovered in the RAND health insurance experiment where provider incentives were held constant (Manning et al., 1987), so it relates to a parameter commonly used in the literature to normalize welfare effects.

Finally, we assume that prices for non-SI products do not change in response to SI cost shifters (this assumption would hold, for instance, if pharmacies were price-takers), 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 and Figure 5 present the counterfactual analysis. The key takeaway is that providers are crucial in the new health technology adoption process and to the success and cost-effectiveness of subsidy programs, regardless of whether these subsidies result in lower prices for patients or higher financial incentives for pharmacies. Without the provider's response to patients' out-of-pocket costs and their own financial incentives, the subsidies would not have significantly impacted the adoption of the new technology, consumer surplus, expected failure rates, or FP protection (CYP) compared to the control group. These conclusions hold regardless of the value of s.

6.3.1 Decomposition of welfare effects from a price subsidy

We begin by showing the welfare implications to the patient from the model without imposing an assumption on whether provider advice distorts or improves patient decision making. To do so, we take two approaches. First, panels (a) and (b) in Figure 5 show how patient welfare effects from a price reduction vary as a function of the underlying true value of the new technology, ranging from the case where providers perfectly inform the patient ($v = \bar{v}$), to a case where the provider's advice is completely distorting the patient's valuation for SI ($v = \hat{v}$). Second, in panel (c) we show the structural model's implications for the impact of price reductions on family planning protection (as measured by CYPs) and expected failure rates.

Panel (a) of Figure 5 plots the consumer surplus under two different counterfactuals for a 75 KES price reduction subsidy analogous to T1: when provider counseling endogenously responds to prices and incentives as measured in our data, and when providers do not counsel on SI ($\theta = 0$). This allows us to understand the value that provider counseling for the new technology brings to the patient. We

find that provider advice is welfare enhancing to the patient provided that at least 35% of the advice-induced shift in the valuation of SI reflects genuine information rather than a distortion. Below that threshold, distortions of patients' choices make the provider's counseling welfare-decreasing. Moreover, below 29%, even a price subsidy could harm patient welfare if the provider response leads to substantial distortions. Nevertheless, for much of the range of assumptions provider counseling is welfare enhancing. We believe our setting falls in this range, given the mystery shopper evidence of more accurate information diffusion in all arms.

Panel (b) shows that regardless of the assumption, the welfare implications to the patient from a price subsidy appear to be almost completely determined by the provider's response. This holds even though all FP products in the study are sold over the counter and the provider's financial incentives are held constant. The share of the provider's response contribution to patient welfare reaches 95% when providers increase patient information ($v = \bar{v}$), and can turn negative when less than 35% of the shift in demand is representative of the true value of SI to the patient.

Panel (c) shows the effects from a price subsidy on FP protection (CYP) and expected failure rates under both counterfactual scenarios, where again we find that these effects would disappear absent a provider counseling response to the intervention. We would generally expect that patient welfare increases when failure rates are lower and FP protection increases since our sample only includes patients who self-selected into purchasing birth control methods. In fact, the effectiveness of FP interventions is often assessed using both CYP and failure rates (Stover et al., 2000). Therefore, the treatment effects on welfare-relevant patient outcomes from the interventions are also determined by the provider's response to the price subsidy, consistent with the consumer surplus analysis in panels (a) and (b).

6.3.2 Cost-effectiveness implications

Information channels have the potential to make subsidy interventions cost-effective from a consumer-surplus perspective. The area above the dashed line in panel (a) of Figure 5 represents cases where the welfare effect is higher than the expected costs of the subsidy program. We find that if at least 75% of the shift in demand reflects genuine information rather than a distortion, a conditional price subsidy for SI is more cost-effective than an unconditional transfer from a consumer surplus perspective. If $s = 1$, the consumer-surplus gain exceeds the expected subsidy cost by about 50%, so the SI price subsidy generates more consumer surplus than an equivalent cash transfer would.

Similarly, the cost effectiveness of these policies as traditionally measured through unintended pregnancies and CYPs per unit of program cost is also almost completely determined by the provider's counseling response. This follows from panel (c), where the effects on these outcomes are completely driven by the provider's counseling response to the price subsidy.

6.3.3 Comparisons between patient and provider interventions

In order to make cross-arm comparisons in counterfactual analysis, one needs to hold constant the value of v. Given our reduced-form evidence from the mystery shopper activity (increase in accurate information diffusion), provider surveys (increase in provider knowledge), and effects on

expected failure rates and FP protection (CYP), we believe that the observed shift in demand reflects accurate information diffusion that helps patients make more informed choices ($v = \bar{v}$). Therefore, we proceed under this assumption in Table 5.

First, we study the implications of introducing the new health technology into the patient's choice set across the different treatment arms, and the role of provider counseling. Columns 1-4 in Table 5 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 patients' choice sets is more than three times as large when provider counseling impacts patient's preferences. This pattern holds across all treatment arms. Therefore, most of the welfare gains come from providers informing patients about the value of this new option rather than from the expansion in the patient's choice set itself.

Panels B and C provide additional counterfactuals for patient and provider-style interventions. Provider advice accounts for most of the welfare gains from a price reduction to the patient, and price reductions are three times as effective at increasing patient welfare as equivalent provider incentives. Panel B in Table 5 assesses welfare effects from consumer subsidies, analogous to the exercise in Figure 5. In Column 1, where providers counsel the patient, reducing prices from 125 KES to 50 KES increases patient welfare by 13 KES. Note also that this effect is three times as much as the effect of a provider's financial incentives shock in Panel C, where the effect of an equivalent SI markup increase only rises patient surplus by 4 KES. While in both cases the policies increase overall social welfare by similar amounts relative to the cost of the program (since providers keep 75 KES markup increases), patient welfare responds much more strongly to p reductions than $f(p, c)$ increases since pharmacies do not absorb the subsidy. Therefore, while both policies have similar effects on adoption, if the aim is to maximize patient welfare, T1-style interventions are the preferred policy in this context where providers respond to patient prices through their counseling.

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. This 95% in consumer surplus contribution is consistent with the implied relative contributions in CYP and expected failure rates from the provider's counseling (panel c of Figure 5), which are traditional proxies for patient welfare in cost-effectiveness analyses in the family planning literature. Similarly, this share of the provider counseling is robust to estimating the model when excluding control group data, suggesting that this conclusion is robust to any salience from the intervention arms (see Figure A.3).

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, and similar effects on reductions in expected unintended pregnancies. 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.

This study has limitations. 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. Future research can expand into the heterogeneity in demand responses by patient and provider characteristics, including mechanisms that influence patient trust in advice or baseline patient knowledge (e.g., new vs. existing FP users). Moreover, this study focuses on a new health technology where information channels during counseling might be particularly important, so future research could study the decomposition of the demand curve between patient and provider channels for other types of medical products and services and assess their implications for patient welfare.

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. In this paper we find that the cost-effectiveness of price subsidy policies in Kenyan pharmacies is determined by the provider's response.

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, and patient welfare increased beyond the direct effect of price pass-through, because providers conveyed more information during counseling. This suggests that provider incentives can serve as a viable way to increase adoption of a new health technology, particularly in contexts where monitoring retailer fraud—such as the inappropriate absorption of patient discounts—is challenging or where providers do not directly observe patient prices (e.g., insurance).

Second, the findings matter beyond family planning. Traditional demand estimates capture the reduced-form effect of the patient-provider interaction, yet insurance contracts, subsidy programs, and information campaigns often change the incentives of both agents. If providers are the primary drivers of uptake, targeting the wrong agent can lower welfare: policies aimed at preventing moral hazard could harm low-income patients by raising prices even when provider behavior drives the observed price response. Likewise, missing information channels or misaligned provider incentives may explain why some health product subsidy programs fail, and similar dynamics arise wherever expert intermediaries influence consumer choices, such as financial advice (Gennaioli et al., 2015).

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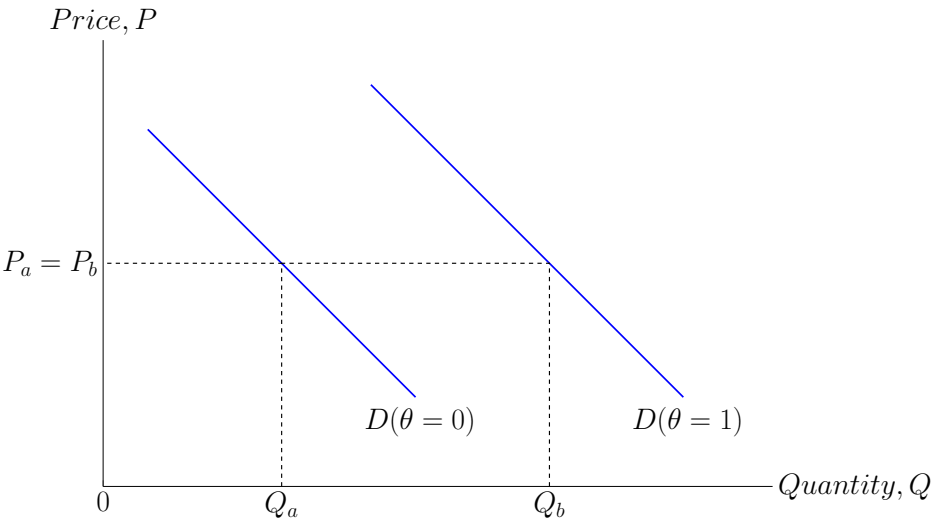
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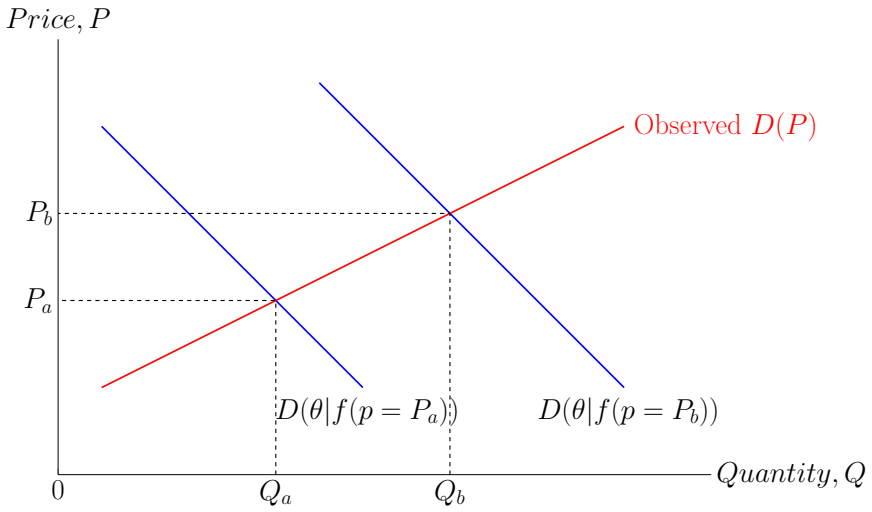
8 Tables and Figures

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

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

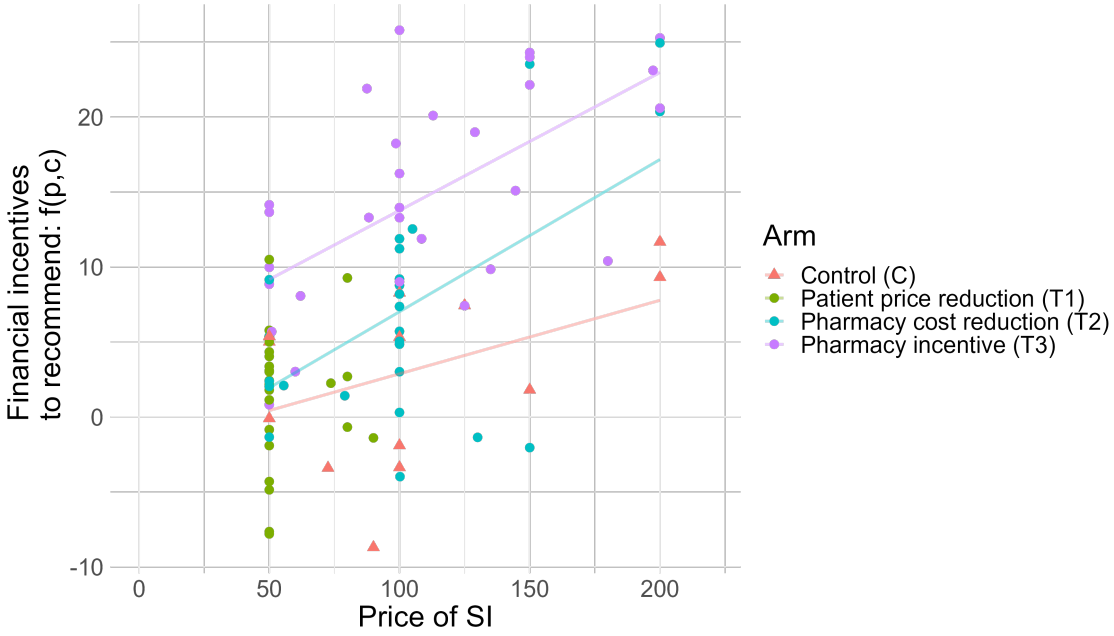


(b) Endogeneity of advice (θ) could lead to misleading policy conclusions



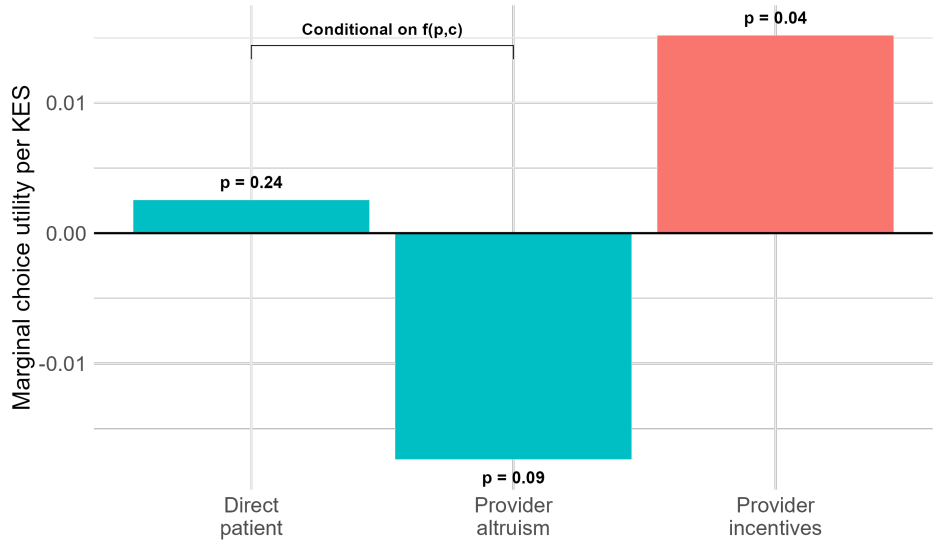
This figure shows how some parameters in the conceptual framework could influence the shape of the demand curve. Panel (a) shows that the provider's counseling type θ can potentially shift the demand curve for the new technology outwards, since the patient's perceived value for the new technology could 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), similar to our data. 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. Therefore, the total slope of the demand curve might not match the consumer-surplus relevant slope.

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



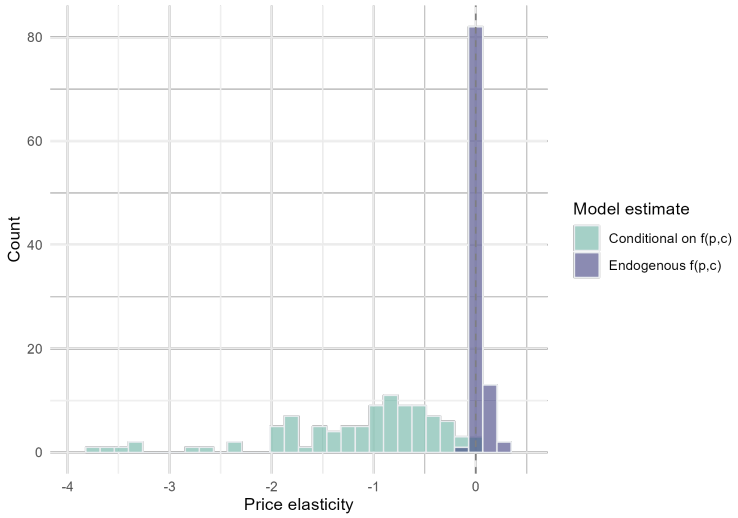
This figure plots the prices of SI against the financial incentive function defined with the primary measure of θ described in section 5. Both variables are positively correlated, but treatment status generate exogenous shifts in their relationship. Sample is restricted to sites used for estimation of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



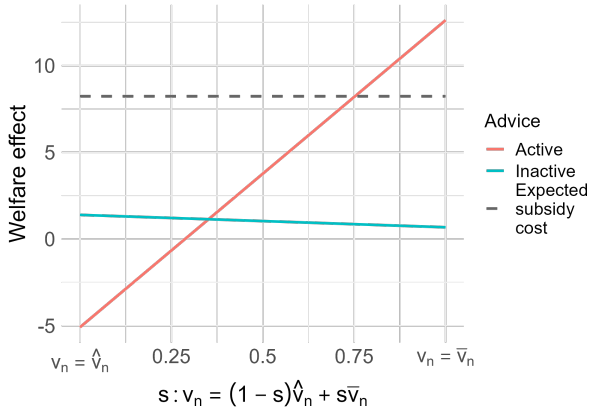
This figure decomposes the effect of a price change on the patient's perceived value of SI into three components, using the structural parameters in column 1 of table 4 and equation 8, measured in marginal utility per KES. The figure reports the effect of a price increase. The p-value on the direct patient 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.

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

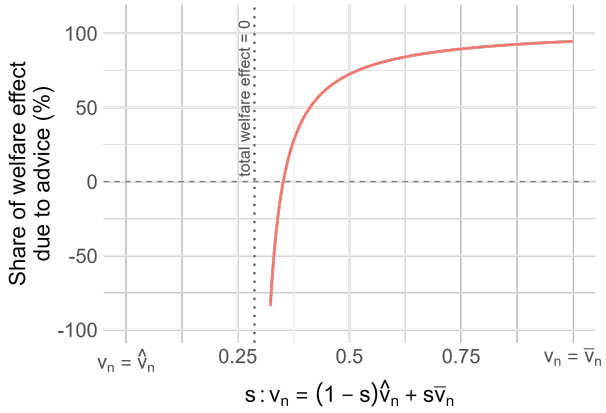


The histogram in green shows the distribution of own-price elasticity estimates for SI conditional on the provider's financial incentives $f(p, c)$, so that price changes are orthogonal to $f(p, c)$; the estimated demand curve slopes downward (negative elasticity). The purple histogram is analogous, 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 and close to zero, 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.

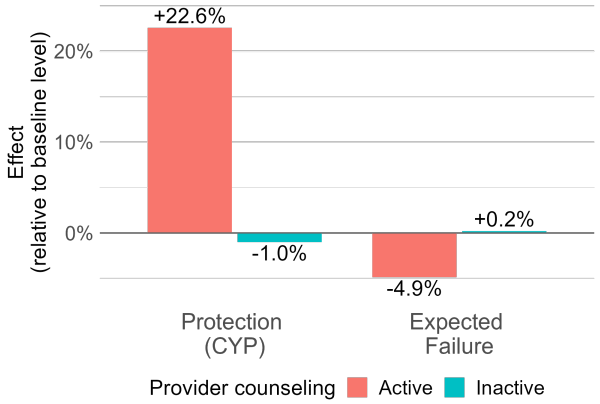
Figure 5: Welfare effects from a price subsidy under different assumptions about the true value of SI to the patient.



(a) Welfare effect from a price subsidy



(b) Relative contribution from advice



(c) Counterfactual effects on FP protection and failure rates

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.

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.8.

Table 2: Effects on patient demand for family planning

	DML: RCT site shares			FP Effectiveness		DS-Poisson: census quantities		
	SI	IMI	Short-term methods	Protection (CYP)	Expected Failure	Long-term methods	Injectables	Short-term methods
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1: Consumer price reduction	0.21***	-0.01	-0.17***	0.031**	-0.80**	-0.41	-0.38	-0.25
	(0.06)	(0.02)	(0.06)	(0.013)	(0.33)	(0.2)	(0.19)	(0.18)
T2: Pharmacy cost reduction	0.18***	-0.01	-0.16**	0.032**	-0.67	-0.05	0.08	0.2
	(0.06)	(0.03)	(0.07)	(0.015)	(0.41)	(0.24)	(0.28)	(0.23)
T3: Pharmacy incentive	0.23***	-0.04*	-0.19***	0.030**	-0.71*	0.08	0.1	0.24
	(0.06)	(0.02)	(0.06)	(0.013)	(0.37)	(0.29)	(0.28)	(0.26)
Control mean	0.02	0.08	0.91	0.085	8.17	15.69	12.16	86.30
Observations	136	136	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 and 5 show the effects on 2 product characteristics related to their effectiveness on preventing pregnancies: per-transaction expected couple-years-of-protection (a measure of protection coverage in family planning), and the expected failure rate of products sold in a transaction. Columns 6, 7 and 8 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.3 and A.4. 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.8 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.11.

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 (1988) 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
Panel B: Effects of price reduction with constant $f(p,c)$				
75 KES change in p_{SI}: 125 vs 50KES	13	1	0.08	-0.00
Panel C: Effects of $f(p,c)$ increase with constant price				
75 KES increase in m_{SI}	4	0	0.10	0.00

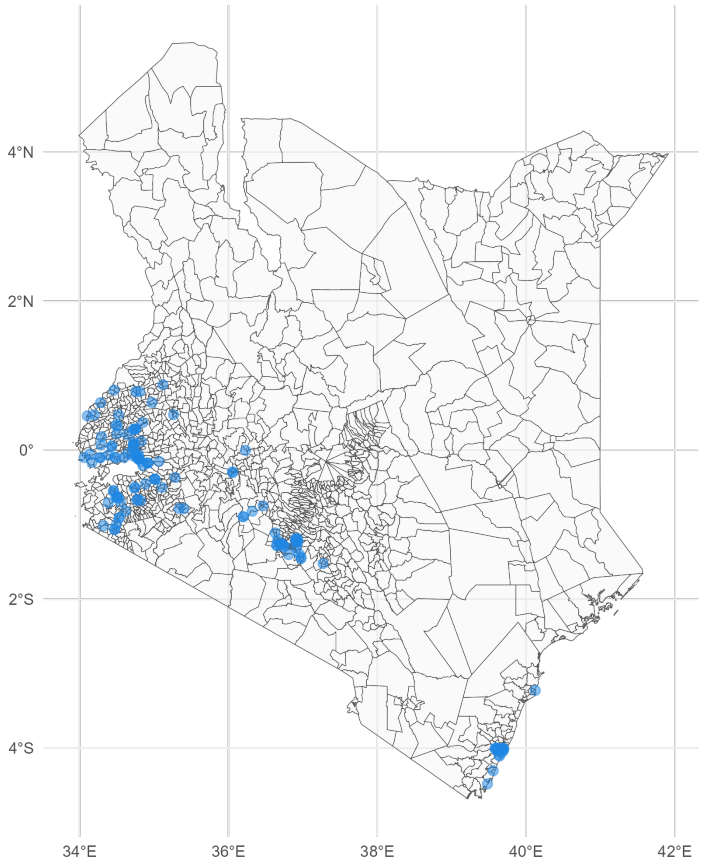
This table presents the estimated welfare effects per patient encounter and counterfactual choice probabilities using the main model parameters in table 4. "θ active" denotes counterfactuals where provider advice is endogenous and responds to changes in model components, whereas "θ inactive" denotes 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 of a price reduction in T1 holding the financial incentives of the provider constant. Panel C shows the effect of a 75KES increase in SI markups (and its associated $f(p,c)$ increase), holding the baseline case constant relative to Panel B to make the comparison directly interpretable.

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.

Figure A.1: RCT site locations in Kenya



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

The following table shows the balance of the arms for various baseline variables from administrative data. We present join tests of orthogonality where we find no evidence of imbalance relative to the control group. Altogether, only two coefficients in treatment arms are significantly different from the control group (out of 39 tests), likely due to random variation.

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 Mystery shopper 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.

Due to budget constrains, the mystery shopper activity excluded pharmacies in coastal (eastern) Kenya. The reduced form results are similar in the non-coastal sub-sample relative to the whole sample, and included as a robustness check in appendix A.2.

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

A.4 Construction of prices, markups, and $f(p, c)$

Prices. All prices enter the model at the site by product level, normalized in Kenyan shillings per dose. Since the definition of a unit varied from site to site for a given product, doses per unit were calculated in the following way: injectables and emergency contraception are one dose per unit since this is the standard package size, while pack sizes for oral contraceptives and condoms are inferred from the brand, product description, and the unit price (e.g. whether unit is a single pill, or a month of oral contraceptives; a single condom, or a pack of multiple). Per-dose prices are winsorized at the fifth and ninety-fifth percentiles across transactions and then averaged within site and product.

For the non-SI products, prices come from the point-of-sale system. A product enters a site's choice set only if that site transacted it during the study, so its price is always observed. SI enters a site choice set if it was transacted during the study period or the site reported availability in the provider survey.

[30] 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.

The SI price is assembled from four sources in a fixed priority order. Point-of-sale transactions are used wherever available. If missing, the price is first taken from the mystery shopper visits, or if otherwise unavailable from the pharmacy endline survey. For sites in the control group where none of these is available, the price is predicted from a site-level regression of the SI price on the price of IMI at the same site, estimated on pre-study transactions, control-group transactions during the study, and transactions from non-study pharmacies in the same cities. Absent a subsidy, pharmacies tend to price the two injectables at similar levels (appendix figure B.1), which is what makes this prediction informative. SI POS prices are drawn from the window ending in February 2023, since a bug in the software led to incorrectly recorded prices in T2 and T3 after an update that month (this only affected the last month of data).

Marginal costs and markups. The marginal cost of a product is the purchase price the pharmacy paid for the unit it sold, recorded transaction by transaction in the point-of-sale system. Neither survey instrument collects a per-unit purchase cost. Costs are normalized per dose, winsorized and averaged within site and product exactly as prices are.

The SI marginal cost follows a chain parallel to the price. Observed point-of-sale costs are used where available. For control-group sites without one, cost is predicted from a site-level regression of the SI cost on the cost of IMI, estimated on the same pooled sample of pre-study, control-group and non-study transactions. For treated sites without a recorded cost, marginal cost is set to zero, since subsidized stock was supplied to those pharmacies at no charge by design. Remaining control sites are assigned the average observed cost among control sites facing the same SI price.

For the non-SI products, missing costs and markups are filled with the sample mean for that product category instead, on the grounds that the treatments did not shift non-SI prices meaningfully.

The SI markup is the SI price net of SI marginal cost. Sites in the pharmacy incentive arm have the 50 KES per-sale transfer added to their markup. Any markup still missing in the control group takes the control-group mean. For non-SI products, the transaction margin is computed using prices and costs.

The financial incentive function. Equation 3 defines $f(p, c)$ as the change in the pharmacy's expected profit per encounter induced by the provider recommending SI,

$$f(p,c)_d = \sum_k m_{k,d} \left(P[k \mid \theta = 1] - P[k \mid \theta = 0] \right) \mathbf{1}\{k \text{ stocked at } d\}, \tag{9}$$

where $m_{k,d}$ are the product markups described above. The shift probabilities are estimated through DML. The resulting estimates are reported in appendix table A.13. Because they are

estimated once and applied to every site, the shift probabilities act as fixed weights that scale each site's product-category markups. A product contributes to $f(p, c)$ only where it is stocked.

Figure A.2: Information sheet about Sayana Press distributed to all study sites



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: 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.3: 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.4: 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.3.

Table A.5: 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.3. Pooled analysis results and additional statistical tests can be found in appendix tables A.6 and A.7.

Table A.6: Indicator for whether SI is available in a study site - extensive margin effects

	Sells SI (1)	Sells SI (2)	Sells SI (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.3.

Table A.7: Share of transactions in a study site that include SI controlling for 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.3.

Table A.8: 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.3. For OLS results, see table C.3.

Table A.9: Couple-years of protection sold per family planning transaction in a site

		By method		
	Total	SI	IMI	Short-term methods
	(1)	(2)	(3)	(4)
T1: Consumer price reduction	0.031**	0.053***	-0.003	-0.015**
	(0.013)	(0.015)	(0.006)	(0.007)
T2: Pharmacy cost reduction	0.032**	0.043***	-0.002	-0.009
	(0.015)	(0.016)	(0.009)	(0.007)
T3: Pharmacy incentive	0.030**	0.057***	-0.012*	-0.019***
	(0.013)	(0.014)	(0.007)	(0.007)
Control mean	0.085	0.007	0.020	0.058
Observations	136	136	136	136
T1 = T2	0.94	0.65	0.98	0.50
T1 = T3	0.96	0.81	0.31	0.74
T2 = T3	0.90	0.49	0.38	0.33

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. 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 is the average number of couple-years of protection (CYP) sold per family planning transaction in a site. CYP per dose were obtained using the 2022 USAID conversion table[31]. Columns 2-4 split the outcome in column 1 by the method that delivers the protection. Short-term methods include condoms, EC, and OC. We report the p-values from tests for significant differences in estimates across the three arms.

Table A.10: Expected failure rate of the family planning products sold in a site

	EC: trial rates		EC: CYP convention	
	Typical use (1)	Ideal use (2)	Typical use (3)	Ideal use (4)
T1: Consumer price reduction	-0.80**	-0.32	-1.19*	-1.01
	(0.33)	(0.24)	(0.68)	(0.96)
T2: Pharmacy cost reduction	-0.67	-0.20	-0.92	-0.27
	(0.41)	(0.26)	(0.78)	(1.05)
T3: Pharmacy incentive	-0.71*	-0.51**	-1.76***	-1.68*
	(0.37)	(0.23)	(0.68)	(0.90)
Control mean	8.17	2.78	13.11	8.65
Observations	136	136	136	136
T1 = T2	0.81	0.74	0.80	0.60
T1 = T3	0.85	0.57	0.56	0.61
T2 = T3	0.95	0.38	0.42	0.31

Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. 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 is the expected failure rate (pregnancies per 100 women in the first year of use) of the family planning products sold in a site: the mean rate of the products in each transaction, averaged over the site's family planning transactions. Failure rates are those of the demand model (WHO, 2022): typical (ideal) use 4 (0.2) for SI and IMI, 7 (0.3) for OC, and 13 (2) for condoms. For EC, the per-use rate is annualized. Columns 1 and 2 use rates from trials of repeated pericoital levonorgestrel as a primary method: 7.1 for typical use, the Pearl Index in Festin et al. (2016), and 5.0 for ideal use, the pooled Pearl Index in Halpern et al. (2014). Columns 3 and 4 instead use 18.2, the annual rate implied by a 1% failure per use (post-coital rate) and the 20 uses a year of the CYP convention. We report the p-values from tests for significant differences in estimates across the three arms.

Table A.11: 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.12: 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.8 being available.

Table A.13: Estimates of $P(k|\theta = 1) - P(k|\theta = 0)$, for various definitions of θ

θ	SI	IMI	Condoms	EC	OC	Short term
			Recommend (half or more)			
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.14: 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.15: 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.13. For analysis using outcomes from the mystery shopper activity see table A.12.

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 half or more 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 $f(p,c)$, as in our main results. 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, showing similar estimates. 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.

Table A.18: 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

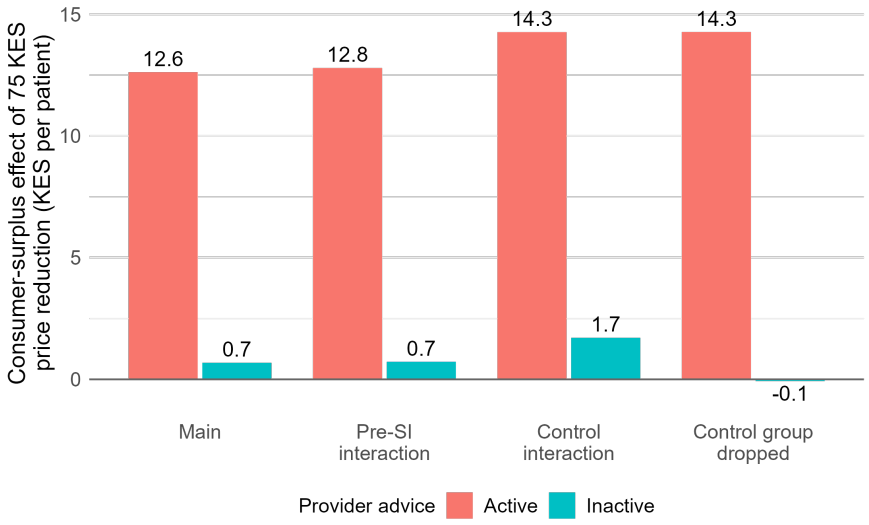
Stars denote significance $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The outcome variable is the share of transactions that include SI in a site. Treatment assignment indicators were used as instruments for p_{SI} and $f(p,c)$. Stratification variables are included as controls.

Table A.19: Structural estimates under alternative definitions of θ

	Recommend	Recommend LDA	Recommend PCA	Recommend and know LDA	Recommend and know PCA
	(1)	(2)	(3)	(4)	(5)
Panel A: Patient demand (mixed logit)					
α (var: p_k)	0.0025	0.0024	0.0026	0.0024	0.0025
	p=0.237	p=0.256	p=0.219	p=0.259	p=0.238
δ (var: $\hat{\theta}$)	3.5326***	2.8135***	3.3704***	3.8553***	3.7802***
	p<0.001	p=0.001	p=0.001	p<0.001	p<0.001
Panel B: Provider advice (IV probit)					
$f(p,c)$	0.1111***	0.1272***	0.0991***	0.0935**	0.1114***
	p<0.001	p<0.001	p<0.001	p=0.010	p=0.001
P_{SI}	-0.0166**	-0.0199***	-0.0226***	-0.0162*	-0.0173**
	p=0.035	p=0.004	p<0.001	p=0.076	p=0.011
Sites	98	98	98	98	98
Converged	Y	Y	Y	Y	Y

Each column re-estimates column 1 of table 4 under one of the definitions of θ reported in table A.15; column 1 here is that specification. A definition of θ implies a definition of the provider's financial incentive $f(p,c)$, so both move together across columns. Panel A reports the patient demand mixed logit with an alternative-specific constant for the new technology; Panel B reports the provider IV probit that generates the $\hat{\theta}$ entering the column above it. P-values are asymptotic and appear below each coefficient.

Figure A.3: Welfare estimates accounting for prior stock availability and SI salience in treatment arms



This plot shows welfare effects analogous to panel D of table 5 using model parameters in the robustness checks presented in table A.20. Estimating the model using only variation from treated arms leads to very similar welfare results to the ones from the main model.

Table A.20: Structural estimates: heterogeneity in demand for the new technology

	Main (1)	Pre-SI interaction (2)	Control interaction (3)	Control group dropped (4)
α (var: p_k)	0.0025 p=0.237	0.0025 p=0.244	0.0026 p=0.224	0.0040 p=0.106
δ (var: $\hat{\theta}$)	3.5326*** p<0.001	3.4417*** p<0.001	2.0529 p=0.183	2.1654 p=0.172
New tech. indicator	-2.2562*** p=0.006	-2.2644*** p=0.005	-1.1185 p=0.346	-1.2332 p=0.312
New tech. × pre-SI availability		0.1765 p=0.697		
New tech. × control group			-1.7617* p=0.065	
Sites	98	98	98	84

Column 1 is column 1 of table 4: the patient demand mixed logit with an alternative-specific constant for the new technology (SI). Column 2 adds that constant interacted with an indicator for sites where SI was available before the intervention, and column 3 adds it interacted with an indicator for control-group sites. Column 4 re-estimates column 1 on treated sites only. For additional details see table 4.

Table A.21: 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.

B Pharmacies as price-takers

For the counterfactual exercises we hold alternative product prices fixed, consistent with an assumption 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. 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.

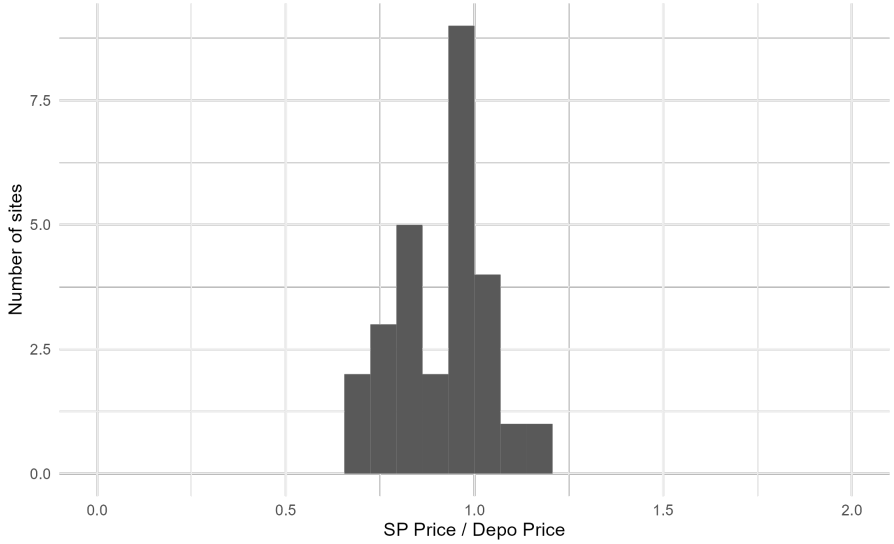
Furthermore, a price-taking assumption is consistent with the reduced form evidence from the RCT. There are no economically meaningful effects on the pricing of alternative family planning products due to the interventions (see table B.1).

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

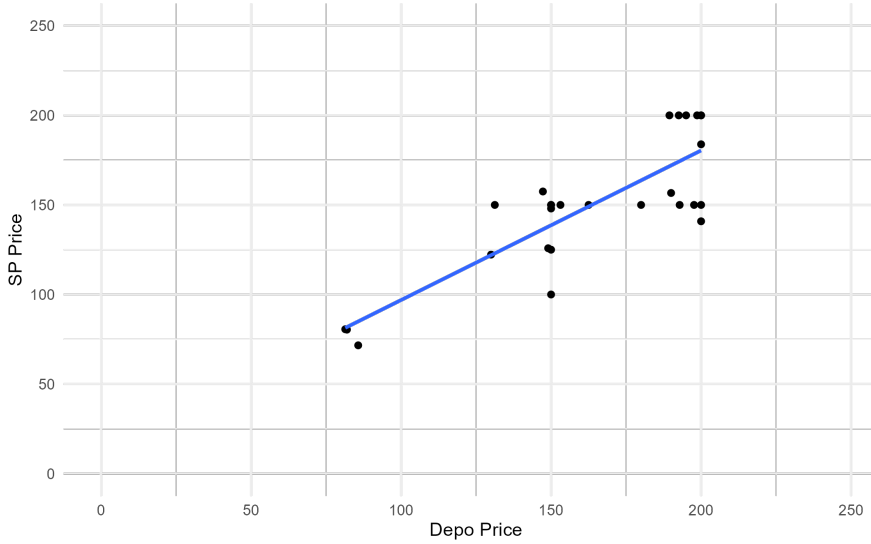
	IMI	Condoms	EC	Oral
Consumer subsidy	-0.28	-1.67	-7.81**	-10.65***
	(9.57)	(2.94)	(3.47)	(3.3)
Pharmacy cost reduction	-5.09	-1.06	-3.24	2.43
	(9.91)	(4.23)	(4.4)	(4.81)
Pharmacy incentive	13.49	8.11*	-3.33	0.18
	(12.67)	(4.65)	(4.34)	(5.16)
Control mean	156.81	57.08	118.36	73.41
Observations	51	90	123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

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

	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.