Appendix A (Main Online Appendix)

(February 25, 2024)

A1. The Reducing Stock-outs Impact Calculator (RSIC) Tool

Converting our estimates on contraceptive availability into public health outcomes is a two-step approach (RHSC 2022). In the first step, we convert the estimated reductions in contraceptive stock-outs in our study to changes in the contraceptive prevalence rate (CPR). In the second step, we evaluate the impact of changes in CPR on public health outcomes.

Step 1. Converting Contraceptive Availability into Contraceptive Usage

Our initial step in measuring the public health impact of the informed push model is to convert the estimated reductions in stock-outs into additional number of contraceptive users. To this end, we employ the Reducing Stock-outs Impact Calculator (RSIC) tool developed by the Reproductive Health Supplies Coalition (RHSC 2022). The tool is built upon estimates derived from previous research which demonstrate that the availability of one additional contraceptive method type on the shelf is associated with an increase of between 4 to 9 percentage points (hereafter "p.p.") in CPR. Next, the conversion of contraceptive availability into contraceptive usage relies on the assumption by the RSIC tool that the *stock-out* of a contraceptive method is equivalent to the *partial removal* of that method from the shelf. In what follows, we provide a thorough description of the three studies that serve as the foundation for the RSIC tool, along with a detailed explanation of the methodologies employed and the limitations.

- ***Methodology.*** We begin by delving into the methodology employed in the three studies that underlie the conversion of contraceptive availability into contraceptive usage by the RSIC tool:

- *Karim et al. (2008)*. This report is commissioned by the United States Agency for International Development's (USAID) DELIVER PROJECT. The authors collect facility-level data on method-mix availability and country-level data on CPR from 12 countries, including Bangladesh, Bolivia, El Salvador, Ghana, Honduras, Malawi, Mali, Nicaragua, Nigeria, Paraguay, Rwanda, and Uganda. Using correlation analysis, the paper finds a strong positive association between contraceptive availability and CPR ($\rho = 0.78, p < 0.05$). The paper, however, falls short of conducting a rigorous analysis to determine the exact slope coefficient for this relationship. The subsequent studies help address this limitation.

- *Wang et al. (2012)*. This paper, commissioned by USAID's DELIVER PROJECT and prepared by ICF International, is part of the Demographic and Health Survey's (DHS) Analytical Studies Series. The authors utilize nationally representative data from the DHS and Service Provision Assessment (SPA) surveys conducted in four East African countries: Kenya, Rwanda, Uganda, and Tanzania. Based on bivariate and multivariate random effects logit regression models, they find that the offering of one additional contraceptive method type on the shelf is associated with a 9 p.p. increase in CPR. These results are further confirmed by the authors through simulation analyses.

- *Ross and Stover (2013)*. Published in the journal *Global Health: Science and Practice*, this paper presents the most comprehensive quantitative evidence across the three studies on the link between contraceptive availability and usage. The study utilizes nationally representative longitudinal data from 113 countries spanning a period of 27 years. Data from various sources, including the DHS and the United Nations Population Division, are used to obtain national CPRs for the respective countries. Additionally, data on the number of contraceptive methods available in national family planning programs is collected from the Family Planning Effort (FPE) Index. The FPE index indicates the percentage of the population with access to specific contraceptive methods in a country. Sensitivity analyses are conducted to assess the robustness of the findings by examining different levels of access based on the FPE index. Leveraging these data, the authors conduct four different analyses:

(i) *Time-trend Analysis*. To examine the temporal trends in mean CPR and the mean number of available methods in a country over the period of 1982 through 2009.

(ii) *Variability Analysis*. To evaluate cross-sectional variation in CPR and contraceptive availability across countries.

(iii) *Correlation Analysis*. To examine the temporal and cross-sectional correlation coefficients between the two measures across all countries and over the years.

(iv) *Fixed Effects Regressions*. To conduct a more rigorous analysis of the relationship between CPR and availability by eliminating time-invariant unobserved confounding factors across countries.

Collectively, these analyses provide robust evidence for the relationship between contraceptive availability and usage. The findings indicate that an increase of one contraceptive method being available to the majority of clients in a country is associated with a statistically significant increase in CPR. Specifically, the increase in CPR ranges between 4 to 9 p.p.

- ***Limitations.*** The first study's limitation lies in its inability to estimate a slope coefficient, thus only confirming the relationship between contraceptive availability and usage. The second study has limitations due to the small number of countries included in the analysis, the cross-sectional nature of the data, and the lack of adjustments for potential confounding factors. Although the third study improves upon the previous ones by analyzing a large panel of 113 countries over 27 years of data, it is not without its own limitations. For instance, the models used in this study do not account for potential unobserved confounding variables (e.g., client awareness), which restricts the ability to draw causal interpretations. Further, the estimates assume a linear and homogenous relationship between the increase in contraceptive availability and the corresponding increase in CPR across different methods.

Despite the mentioned limitations, the collective evidence from the three studies provides support for the positive relationship between contraceptive availability and usage in developing countries. These estimates have been cited by the academic community and various global health organizations, highlighting their relevance and significance in the field.

- ***Application in Our Study.*** Based on the findings of the three studies, we observe that the inclusion of one additional contraceptive method type on the shelf is associated with an increase of between 4 to 9 p.p. in CPR. Consistent with the RSIC tool, we utilize an average estimate of 6.50 p.p. increase in CPR to convert our estimated reductions in stock-outs resulting from the informed push model into changes in CPR. However, regardless of which values are used as the basis for the conversion (i.e., ranging from 4 to 9 p.p.), it is evident that the supply chain intervention has a substantial public health impact.

Step 2. Converting Contraceptive Usage into Public Health Outcomes

The second step in assessing the public health impact of the informed push model involves converting the changes in CPR into public health outcomes. To accomplish this, we adopt the approach outlined by the RSIC tool, which utilizes estimates developed by the Guttmacher Institute (see Darroch 2017). These estimates provide insights into how an increase in the number of contraceptive users translates into reductions in unintended pregnancies, and maternal and newborn mortalities. In what follows, we provide a thorough description of the above study that serves as the foundation for converting contraceptive usage into public health outcomes, along with an explanation of the methodologies employed and the limitations.

- ***Methodology.*** The study by Darroch (2017) is part of an ongoing series of projects named “Adding It Up” by the Guttmacher Institute, a leading research and policy organization committed to advancing women’s sexual and reproductive health worldwide. The project offers three key sources of information that are relevant to the conversion of the number of contraceptive users into public health outcomes:

(i) *Number of women of reproductive age who are using a modern contraceptive method*. To estimate the number of contraceptive users, the study utilizes nationally representative surveys conducted in developing countries. The use of nationally representative surveys ensures that the findings are applicable to a wide range of populations and contexts within developing countries. The sources of data include the DHS, U.S. Centers for Disease Control and Prevention Reproductive Health Surveys (RHS), United Nations Children’s Fund (UNICEF) Multiple Indicator Cluster Surveys (MICS), and Performance Monitoring and Accountability 2020 (PMA2020) surveys. Across these sources, the study identifies the distribution of women of reproductive age by contraceptive need and use of modern contraceptives for 80% of the respective populations in developing countries.

(ii) *Number of unintended pregnancies averted by the current use of modern contraceptives*. The first step to estimate the number of unintended pregnancies averted is to estimate the total number of births in each country by utilizing data from the UN World Population Prospects (United Nations 2015). Using these data, the study applies the findings from a Bayesian analysis conducted by Bearak et al. (2018) to calculate the proportion of births that are planned or unplanned. By considering this proportion, the study estimates the total number of unintended pregnancies by summing the occurrences of unplanned births, induced abortions, miscarriages, and stillbirths among women who desired to avoid a pregnancy.

Next, Darroch (2017) incorporates adjusted use-failure rates from Bradley et al. (2019) to develop estimates on the additional number of unintended pregnancies that would occur if no women were using contraceptives. By comparing the actual number of unintended pregnancies with this hypothetical scenario, the study quantifies the number of unintended pregnancies *averted* through contraceptive use.

(iii) *Number of maternal and newborn deaths averted by current use of modern contraceptives*. Estimates of the total numbers of maternal deaths worldwide and their causes were obtained from the WHO (2015). To develop country-specific estimates, the study uses the ratio of maternal deaths per 100,000 live births in each country. These estimates were then used as the basis to calculate the estimated number of maternal deaths averted due the current use of modern contraceptives by women.

Additionally, the study estimated the number of newborn deaths by multiplying the median country-specific estimates from the UN Interagency Group for Child Mortality Estimation (IGME) of newborn mortality rates by the number of live births in each country (Healthy Newborn Network 2023). The estimates from IGME, along with data on live births, were used to calculate the estimated number of newborn deaths averted attributable to the current use of modern contraceptives by women.

- ***Limitations.*** It is important to acknowledge that the methodology used to estimate the number of contraceptive users and the number of maternal and newborn mortalities averted is not without limitations. For example, Darroch (2017) acknowledge that some countries lacked recent national surveys, which posed challenges in developing accurate estimates. In such cases, the study made assumptions by using data from other countries within the same subregion or region, or countries that were demographically or socioeconomically similar. Further, the estimates regarding maternal and newborn mortalities averted assume only the direct physical health consequences that results from unintended pregnancies, excluding other indirect and long-term consequences (e.g., impact on mental health, unfulfilled career/educational aspirations of mothers and children).

Despite these limitations, the estimates by the Guttmacher Institute have proven to be valuable in measuring the public health impacts of contraceptive availability, as evidenced by their usage across the academic (e.g., Bhutta et al. 2014) and practitioner community (e.g., WHO 2016).

- ***Application in Our Study.*** While the RSIC tool relies on estimates from the 2008 version of the Guttmacher Institute report to convert contraceptive usage into public health outcomes, our analysis utilizes the more recent estimates from the 2017 version of the report (see Darroch 2017). This choice is motivated by the following reasons. First, unlike the RSIC's estimates from the 2008 report—which are based on the entire pool of developing countries—the estimates from the 2017 report allow us to specifically focus on the subset of estimates for the "least developed countries." This ensures that the numbers used in the analysis are more representative of our specific setting, i.e., Senegal. Second, the timeframe of the estimates from the 2017 report aligns more closely with the time period during which the benefits of the informed push model are anticipated to be realized. Additionally, the more recent report encompasses updated estimates that have undergone methodological refinements.

Using these estimates as the basis, we calculate how an increase in contraceptive usage would translate into public health outcomes in Senegal. Specifically, the addition of 2.81 contraceptive users in the country is associated with one unintended pregnancy averted. Further, the addition of 1,518 and 132 contraceptive users is associated with averting one maternal death and one newborn death, respectively.[1] In summary, our approach to converting estimates of contraceptive stock-outs to public health outcomes is based on established tools and methodologies that are accepted in the academic community and widely applied in practice.

A2. Estimating the Cost of Transitioning from the Pull Model to the Informed Push Model

We refer to the output of Equation (4) in the paper as the *Modified Health Facility Cost* (see Table B4 in Appendix B for a summary of the average cost numbers at different levels)[2] where the facility-level costs of transitioning to the informed push model are calculated by progressively allocating upstream costs to the next downstream level in a proportional fashion. For example, the cost incurred at the national level under the informed push model is allocated equally to the different regions within the country (i.e., $\frac{National\ Cost}{No.\ of\ Regions}$). By adding this "National-to-Regional Cost" allocation to the average costs incurred directly at the regional level (i.e., *Regional Cost*), we estimate the costs incurred at the national and regional levels combined, which we refer to as the *Modified Regional Cost* (i.e., $\left(\frac{National\ Cost}{No.\ of\ Regions}\right) + Regional\ Cost$).

The next step in the calculation is to allocate the *Modified Regional Cost* among the districts within each region (i.e., "Modified Regional-to-District Cost"). Next, by adding this "Modified Regional-to-District" cost allocation to the average costs incurred directly at the district level (i.e., *District Cost*), we obtain an estimate of the costs incurred at the national, regional, and district levels combined. We label this estimate as the *Modified District Cost*, which is represented by the numerator of the first term in Equation (4). Subsequently, the *Modified District Cost* is allocated to individual health facilities proportionally, based on the number of facilities within each district.[3] Finally, we add this "Modified District-to-Health Facility Cost" to the average costs incurred directly at the health facility level. For this purpose, we rely on the estimates from Lynch et al. (2020), who report direct average facility-level costs for primary and secondary facilities (see Table B4 in Appendix B). By adding these average costs incurred directly at the health facility level to the "Modified District-to-Health Facility Cost," we calculate the cost incurred under the informed push model at the individual health facility level (labeled as the *Modified Health Facility Cost*).

Similar to the costs of the informed push model, Lynch et al. (2020) also report the corresponding average cost numbers for the pre-transition pull distribution model (see Table B4 in Appendix B). Using these numbers and following the approach described above, we calculate the modified health facility costs for each last-mile facility under the pull distribution model. The difference in the *Modified Health Facility Cost* between the informed push model and the pull distribution model provides an estimate of the cost of transitioning to the informed push model at each health facility.

A3. Evaluating the Robustness of Cost Estimates to an Alternative Approach by Burns et al. (1985)

In this section, we evaluate the robustness of our cost estimates by re-estimating these values using an alternative costing approach outlined in Burns et al. (1985). Specifically, in calculating the *Modified Health Facility Cost* in Equation (4) of the paper, the same *Regional Cost* values were used across all regions in the country (equal to the average *Regional Cost* reported in Lynch et al. 2020 and in Table B4 in Appendix B). One limitation of this approach is that it does not take into account the economies of scale benefits of the informed push model. To develop more refined estimates of the *Regional Cost* values that take the such economies of scale into account, we leverage the costing methodology presented in Burns et al. (1985). They consider the transportation cost in a "peddling" scenario where a dispatch truck makes deliveries to more than one customer per load. This distribution strategy is similar to the informed push model.

In developing the transportation cost per load under "peddling," Burns et al. (1985) consider different factors including (a) the number of customers per dispatch load, (b) density of customer locations, (c) time spent at each customer stop, and (d) the transportation cost per mile (see p. 477). Using data on the GPS coordinates of public health facilities in Senegal collected from the Maina et al. (2019), we first calculate the number and density of customers (i.e., health facilities) within each region. Next, we combine these data with publicly available information regarding the transportation cost per kilometer in West Africa[4] (Bove et al. 2018) and the amount of time spent at a customer stop[5] (McElwee 2015) to develop more refined estimates of the *Regional Cost* values under the informed push model. Next, we recalculate the

Modified Health Facility Cost under the informed push by plugging in the unique *Regional Cost* values corresponding to the region where each health facility is located (see Equation (4) in the paper). The revised cost-benefit ratios corresponding to stock-out reductions are presented in Table B5 in Appendix B, where we find that the insights remain effectively unchanged compared to our main results in Figure 3a of the paper. We also find that the revised cost-benefit numbers corresponding to the public health outcomes remain effectively unchanged compared to the main models in Figure 4 of the paper (results not shown to save space but are available upon request).

In closing, we make a noteworthy observation. From our calculations, we observe that the total *Regional Cost* (aggregated across all regions) obtained using Burns et al. (1985) under the informed push model is similar to the total *Regional Cost* reported on p. 157 of Lynch et al. (2020) (the difference between the two cost values is roughly 7%). In a similar vein, our calculation of the total health facility level costs obtained using the "direct shipping" method presented in Burns et al. (1985)[6]—where individual facilities receive direct individual shipments from the regional warehouse, similar to the pull model—is in the same ballpark as the total health facility level cost estimate reported on p. 158 of Lynch et al. (2020) for the pull distribution model. This lends further credence to the cost-benefit analyses reported in this section.

A4. Estimating the Cost and Benefits of Upgrading LMIS Practices from Less Mature to More Mature

The cost of upgrading the LMIS practices from less mature (i.e., neither frequent LMIS updating nor electronic LMIS) to more mature (i.e., either frequent LMIS updating, electronic LMIS, or both) involves the following components: (i) costs associated with frequent updating of LMIS records, or/and (ii) costs associated with upgrading from paper-based LMIS to electronic LMIS. In terms of the latter, the costs of upgrading from paper-based to electronic LMIS are estimated to be roughly \$448 per health facility annually based on Mwencha et al. (2017). This estimate takes into consideration the expenses associated with the development, rollout, and maintaining/operating an electronic system in Tanzania.

Further, the cost of frequent updating of the stock records is estimated to be approximately \$272 per health facility annually. This estimate is based on a minimum hourly wage of \$5.64 and assumes an additional hour of work per day by health facilities to verify and update the stock records, an additional trip per month to upstream locations to deliver inventory reports and/or pickup supplies (equal to half a day of work), and a \$40 fixed annual cost of providing training to a health facility. The cost of an additional trip to upstream locations is calculated based on the average time of 6 minutes per mile spent by a frontline health worker during their daily work schedule. This is derived by assuming an average roundtrip distance of 40 kilometers to an upstream warehouse based on our data, and using "public transportation" by the average health facility in Senegal (USAID 2020b) with an average speed of 16 kilometers per hour (USAID 2020a). Additionally, the fixed annual training cost is derived based on the expenses associated with rolling out a new inventory management system for managing health commodities in the context of least developed countries (LDCs, see USAID 2019), and is equal to 9% of the overall rollout costs of such a system (Mwencha et al. 2017). Lastly, we combine the estimated costs of implementing frequent LMIS updating and/or electronic LMIS by weighting each cost estimate based on the number of health facilities in the sample engaged in either frequent LMIS updating, electronic LMIS, or both. These calculations lead to an average annual cost of $306 for upgrading health facilities from less mature to more mature LMIS practices.

Next, to measure the impact of upgrading a facility's LMIS practices (from less mature to more mature under the pull distribution model) on stock-outs, we rely on variations in the maturity of LMIS practices across regions, time, and health commodities prior to the transition. Specifically, we estimate the following triple differences model for a subset of observations where the transition to the informed push model has not yet taken place (i.e., dropping all observations pertaining to the post-transition period).

$$Ln\left[\frac{Pr(Stock\text{-}Out_{ijrt}=1)}{1-Pr(Stock\text{-}Out_{ijrt}=1)}\right] \\ = \beta_0 + \lambda.X_{CL} + \alpha.Region_r + \gamma.Time_t \\ + \beta.LMIS\ Practices_{rt} \times Contraceptive_i + \varepsilon_{ijrt} \tag{A1}$$

Where i, j, r, and t denote health commodity i at health facility j located in region r at time t. In the above specification, $Region_r$ is a vector of region fixed effects. $Time_t$ pertains to the vector of year, month, and day-of-week fixed effects. We incorporate additional control variables in the vector X_{CL} (see Table A3 in Appendix A). The unit of analysis in this model is facility-health commodity. The variable $LMIS\ Practices_{rt}$ takes the value of 1 when the LMIS practices are more mature (i.e., either frequent LMIS updating, electronic LMIS, or both), and 0 otherwise (i.e., neither frequent LMIS updating, nor electronic LMIS). We adopt a two-pronged approach to alleviate concerns of bias due to observed and unobserved confounding variables in this model: (i) triple differences estimation, and (ii) matching techniques. First, we interact $LMIS\ Practices_{rt}$ with $Contraceptive_i$ which is a binary indicator for the type of health commodity. This variable takes the value of 1 for contraceptive methods, and 0 for deworming medications which serve as placebo units. Second, to ensure that sample imbalance is not biasing the coefficients, we utilize coarsened exact matching (CEM) to match treated (i.e., more mature LMIS practices) and control health units (i.e., less mature LMIS practices) using the same set of facility-level covariates in the paper.

A5. Goodman-Bacon Decomposition Test to Evaluate Bias in Staggered Rollout Designs

Recent econometrics papers have shown that the estimated treatment effects in staggered DiD designs may be prone to bias and even "obtain the opposite sign" (Goodman-Bacon 2021). The underlying mechanism behind such potential bias is that the units which are already treated can serve as effective controls for untreated units. Baker et al. (2022) argue that this bias is likely to be most pertinent in settings where (i) treatment timing varies across a long period of time, and (ii) there are not any *never-treated* units to serve as effective controls. However, these conditions are less relevant in our setting considering the relatively short duration of the informed push model rollout, as well as the availability of *never-treated* units in the sample (i.e., private facilities). Nevertheless, we apply the “Bacon Decomposition” diagnostic test to evaluate the potential for bias in our triple differences estimation (Goodman-Bacon 2021).[7] First, we find that the estimated treatment effect is negative and in the right direction across all the following comparison-groups: (i) earlier-treated units serving as control, (ii) later-treated units serving as control, and (iii) never-treated units serving as control. Second, we find that a small proportion of our treatment effect is driven by the first comparison-group. Together, the insights from this diagnostic test indicate that our estimated effects are not likely to be biased due to the staggered rollout of the informed push model.

A6. Placebo Falsification Tests to Rule Out the Presence of Facility-level Unobserved Confounders

We conduct placebo falsification tests by estimating DiD model models using an alternative outcome variable that was *unaffected* by the treatment. Specifically, we replace the original dependent variable (i.e., health commodity stock-outs) with an alternative variable, namely the unavailability of basic health supplies which were unaffected by the treatment.[8] We estimate the following DiD specification:

$$\begin{aligned} Ln\left[\frac{Pr(Basic\ Supply\ Unavailability_{bjrt}=1)}{1-Pr(Basic\ Supply\ Unavailability_{bjrt}=1)}\right] &= \beta_0 + \lambda.X_{CL} + Catch.Pop.Proxy_{rt} + \alpha.Region_r + \gamma.Time_t \\ &\quad + \beta.Informed\ Push\ Model_{rt} + \varepsilon_{bjrt} \end{aligned} \tag{A2}$$

Where ε_{bjrt} is the error term for basic health supply *b* at health facility *j* located in region *r* at time *t*. Table B6 in Appendix B presents the results of placebo falsifications tests where we find that the placebo rollout of informed push model to basic health supplies does not lead to any consistent and statistically significant reductions in the unavailability of these supplies. This suggests that our findings are not likely to be driven by facility-level time-invariant unobserved confounders, ruling out alternative explanations.

A7. Two-staged Least Squares Endogeneity-Corrected Event Study

The identifying assumption of our main triple differences estimation is that the stock-outs of the two types of health commodities (i.e., contraceptive methods and deworming medications) would have followed parallel trends in the post-treatment period in the absence of the informed push model. In this section, we report the results of a two-staged least squares (2SLS) event study which is robust to potential violations of the parallel trends assumption. Specifically, we estimate the following specification:

$$\begin{aligned} Ln\left[\frac{Pr(Stock\text{-}Out_{ijrt}=1)}{1-Pr(Stock\text{-}Out_{ijrt}=1)}\right] &= \beta_0 + \lambda.X_{CL} + Catch.Pop.Proxy_{rt,2SLS\ Instrumented} \\ &\quad + \alpha.Region_r + \gamma.Time_t \\ &\quad + \beta_{t-T}\ .Informed\ Push\ Model_{r,t-T} \times Contraceptive_i \\ &\quad + \beta_{t+T}\ .Informed\ Push\ Model_{r,t+T} \times Contraceptive_i + \varepsilon_{ijrt} \end{aligned} \tag{A3}$$

Where ε_{ijrt} is the error term, and i, j, r, and t denote health commodity i at health facility j located in region r and time t. The index T denotes the time difference from the rollout of the informed push model.

Following Freyaldenhoven et al. (2019), we incorporate the variable $Catch.\ Pop.\ Proxy_{rt,\ 2SLS\ Instrumented}$ to relax the parallel trends assumption. Specifically, we have identified *catchment population* as an important unobserved variable (η) that determines the rollout timing of informed push model. Controlling for this proxy variable (x) would correct for endogeneity issues as long as x is a reasonably accurate proxy for η. The authors propose an improved version of the above approach, where the assumption of x being a reasonably accurate proxy for the unobserved η is no longer required. Instead, they suggest finding a proxy variable x that is simply "related" to the unobserved variable η, but unaffected by the policy rollout z. Next, they suggest applying 2SLS estimation to instrument for the covariate x using the most recent pre-treatment lead of the policy rollout (i.e., z_{t-1}) as an excluded instrument. This 2SLS estimation differs from the conventional instrumental variable estimation in that the "requirement of an instrument that impacts the policy but not the outcome" is replaced with "requirement of a covariate that is related to the [unobserved variable] but unaffected by the policy" (Freyaldenhoven et al. 2019, p. 3311). Next, the instrumented covariate $x_{Instrumented}$ is included as a control variable to account for the effect of unobservable confounders. Importantly, the proposed method relaxes the parallel trends assumption, thereby allowing researchers to "conduct valid inference … whether or not pre-trends are detected" (Freyaldenhoven et al. 2019, p. 3307).

The results of 2SLS endogeneity-corrected event study model using coarsened exact matched samples are presented in Table B7 in Appendix B, allowing us to "conduct valid inference whether or not pre-treatment trends are detected" (Freyaldenhoven et al. 2019, p. 3308). We find that the coefficients of the informed push model in the post-treatment periods are consistent with those estimated from our main models. Notably, among the subgroups, we find the largest post-treatment coefficient to correspond to the subgroup with less mature LMIS practices and less developed road infrastructure (Column 7). Overall, these results alleviate concerns of bias due to the potential endogeneity of rollout timing and demonstrate the plausibility of the identifying assumption of triple differences estimation.

A8. Instrument-free Gaussian Copula Correction to Account for the Endogeneity of Rollout Timing

We apply a class of estimators known as "instrument-free" approaches to further alleviate endogeneity concerns due to the presence of unobserved confounding variables (Park and Gupta 2012). We utilize the Gaussian copula correction proposed by Park and Gupta (2012) which handles endogeneity by directly modelling the correlation between the potentially endogenous regressor and the error time using a Gaussian copula. We construct the Gaussian copula endogeneity correction term using the following equation:

$$\widetilde{Copula}_{rt} = \emptyset^{-1}[H\ (Informed\ Push\ Model_{rt,Continuous})] \tag{A4}$$

Where j and t represent the rollout timing of the informed push model in region j at time t, $\emptyset^{-1}$ is the inverse of the normal cumulative distribution function, and $H()$ is the empirical cumulative distribution function of the rollout timing. Next, the copula correction term $\widetilde{Copula}_{rt}$ is incorporated into the main specification, thereby correcting for endogeneity similar to the idea of a control function approach:

$$Ln\left[\frac{Pr(Stock\text{-}Out_{ijrt} = 1)}{1 - Pr(Stock\text{-}Out_{ijrt} = 1)}\right] = \beta_0 + \lambda.X_{CL} + Catch.Pop.Proxy_{rt} + \alpha.Region_r + \gamma.Time_t + \beta.Informed\ Push\ Model_{rt,Continuous} \times Contraceptive_i + \widetilde{Copula}_{rt} + \varepsilon_{ijrt} \quad \text{(A5)}$$

Where i, j, r, and t denote health commodity i at health facility j located in region r and time t. In this Equation, the rollout timing of the informed push model is assigned a continuous value, corresponding to the number of days elapsed since the initial rollout date. The variable takes the value of 0 in the absence of the rollout. This modification serves the following key purposes. First, it allows us to directly account for the potential endogeneity of differential rollout timing across regions. Second, it helps establish the identifying assumption of the Gaussian copula correction that requires endogenous variables that are non-binomially and non-normally distributed (Park and Gupta 2012). Consistent with prior literature, we also tested the non-normality assumption of the endogenous regressor by running a Shapiro-Francia normality test ($W = 0.93$, $p < 0.01$). The results, presented in Table B8 in Appendix B, are consistent with our main models, suggesting that our coefficients are not biased due to the potential endogeneity of rollout timing.

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[1] These calculations are based on an estimated 21,171,000 unintended pregnancies averted, 39,163 maternal mortalities averted, and 448,920 newborn mortalities averted per 59,447,000 modern contraceptive users in the least developed countries (see Tables 22, 31, and 33 of Darroch 2017).

[2] Appendix B is available for download through the following link: https://github.com/karimamiri/Senegal/blob/main/AppendixB.pdf

[3] This information was obtained from the World Health Organization (WHO)'s spatial database of health facilities managed by the public health sector in sub-Saharan Africa (Maina et al. 2019).

[4] That is, \$1.56 per kilometer based on trucking transportation costs in the Dakar-Bamako corridor (Bove et al. 2018).

[5] According to McElwee (2015), logistics providers spent an average of 21 minutes at each health facility for an average daily salary of \$5.64 as part of the informed push model.

[6] We rely on the following estimates: average daily salary of \$5.64 for a health worker conducting the following basic inventory management activities (McElwee 2015): An average of 1.20% of daily worktime spent on organizing shelves, an average of 1.90% of daily worktime spent on stocking shelves, an average of 3.30% of daily worktime spent on counting supplies, an average of 0.80% of daily worktime spent on recoding supplies dispensed, and an average of 0.20% of daily worktime spent on recording payment (the numbers are based on self-administered timesheets filled out by frontline health workers in Senegal, see McElwee (2015). In addition, the cost estimate assumes that health workers allocate an average of 6 minutes per mile of their daily worktime on activities related to ordering and picking up supplies from upstream that are conducted once per month for each activity. The amount of time spent per mile to connect with upstream is based on the assumption of reliance on "public transportation" by the average health facility in Senegal (USAID 2020b) with an average speed of 16 kilometers per hour (USAID 2020a).

[7] We note that the execution of Bacon Decomposition diagnostic test relies on a fully balanced panel data. To this end, we aggregate our observations using the following covariates: year, region, commodity type, and health facility type (i.e., public vs. private facility), leading to a panel of 429 observations.

[8] That is, adult/child/infant weighing scale, stadiometer, measuring tape, thermometer, stethoscope, digital/manual blood pressure apparatus, and light source.

References

Baker AC, Larcker DF, Wang CCY (2022) How much should we trust staggered difference-in-differences estimates? *J. financ. econ.* 144(2):370–395.

Bearak J, Popinchalk A, Alkema L, Sedgh G (2018) Global, regional, and subregional trends in unintended pregnancy and its outcomes from 1990 to 2014: estimates from a Bayesian hierarchical model. *Lancet Glob. Heal.* 6(4):e380–e389.

Bhutta ZA, Das JK, Bahl R, Lawn JE, Salam RA, Paul VK, Sankar MJ, et al. (2014) Can available interventions end preventable deaths in mothers, newborn babies, and stillbirths, and at what cost? *Lancet* 384(9940):347–370.

Bove A, Hartmann O, Stokenberga A, Vesin V, Yedan Y (2018) *West and Central Africa trucking competitiveness* (Washington, D.C.).

Bradley SEK, Polis CB, Bankole A, Croft T (2019) Global contraceptive failure rates: Who is most at risk? *Stud. Fam. Plann.* 50(1):3.

Burns LD, Hall RW, Blumenfeld DE, Daganzo CF (1985) Distribution strategies that minimize transportation and inventory costs. *Oper. Res.* 33(3):469–490.

Cavallaro FL, Duclos D, Baggaley RF, Penn-Kekana L, Goodman C, Vahanian A, Santos AC, et al. (2016) Taking stock: Protocol for evaluating a family planning supply chain intervention in Senegal. *Reprod. Health* 13:45.

Darroch J (2017) *Adding It Up: Investing in Contraception and Maternal and Newborn Health, 2017* (Washington, DC).

Freyaldenhoven S, Hansen C, Shapiro JM (2019) Pre-event trends in the panel event-study design. *Am. Econ. Rev.* 109(9):3307–3338.

Goodman-Bacon A (2021) Difference-in-differences with variation in treatment timing. *J. Econom.* 225(2):254–277.

Healthy Newborn Network (2023) Database: Global and National Newborn Health Data and Indicators – Healthy Newborn Network. Retrieved (July 14, 2023), https://www.healthynewbornnetwork.org/resource/database-global-and-national-newborn-health-data-and-indicators/.

Karim AM, Bieze B, Chimnani J (2008) *Measuring family planning logistics system performance in developing countries* (Arlington, VA).

Lynch C, Faye A, Cavallaro F, Cresswell J, Bradley J, Wong K, Gasparrini A, et al. (2020) *The informed push model for contraceptives in Senegal: How did it function, was it effective, in what context and at what cost?* (London, UK and Dakar, Senegal).

Maina J, Ouma PO, Macharia PM, Alegana VA, Mitto B, Fall IS, Noor AM, Snow RW, Okiro EA (2019)

A spatial database of health facilities managed by the public health sector in sub Saharan Africa. *Sci. Data* 6(1):1–8.

McElwee E (2015) *Time costs of the Informed Push Model (IPM): How has IPM in Senegal impacted health workers' time use at the service delivery level? A pilot study*. (London School of Hygiene and Tropical Medicine, London, UK).

Mwencha M, Rosen JE, Spisak C, Watson N, Kisoka N, Mberesero H (2017) Upgrading supply chain management systems to improve availability of medicines in Tanzania: Evaluation of performance and cost effects. *Glob. Heal. Sci. Pract.* 5(3):399–411.

Park S, Gupta S (2012) Handling endogenous regressors by joint estimation using copulas. *Mark. Sci.* 31(4):567–586.

RHSC (2022) Reducing Stockouts Impact Calculator - Reproductive Health Supplies Coalition. *Reprod. Heal. Supplies Coalit.* Retrieved (April 24, 2020), https://www.rhsupplies.org/activities-resources/tools/reducing-stockouts-impact-calculator/.

Ross J, Stover J (2013) Use of modern contraception increases when more methods become available: analysis of evidence from 1982–2009. *Glob. Heal. Sci. Pract.* 1(2):203–212.

SPA (2014) *Malawi service provision assessment 2013-14* (Lilongwe, Malawi, and Fairfax, VA).

United Nations (2015) *The World Population Prospects: 2015 Revision* (New York, NY).

USAID (2019) *Electronic logistics management information system: Endline evaluation report* (Arlington, VA).

USAID (2020a) *Battery electric bus deployment considerations in developing countries* (Washington, D.C.).

USAID (2020b) *Political economy analysis of the drug and pharmaceutical supply chain in Senegal: A review of the literature* (Washington, D.C.).

Wang W, Wang S, Pullum T, Ametepi P, International I (2012) *How family planning supply and the service environment affect contraceptive use: Findings from four East African countries* (Calverton, MD).

WHO (2015) *Trends in maternal mortality: 1990-2015: estimates from WHO, UNICEF, UNFPA, World Bank Group and the United Nations Population Division* (Geneva, Switzerland).

WHO (2016) *Health workforce requirements for universal health coverage and the Sustainable Development Goals. (Human Resources for Health Observer, 17)* (Geneva, Switzerland).

Table A1. Staggered Rollout of the Informed Push Distribution Model across Senegal (Source: Cavallaro et al. 2016)

Rollout Date	Region Name
December 2012	*Dakar*
April 2013	*Thies*
April 2013	*Kaolack*
March 2014	*Diourbel*
March 2014	*Fatick*
March 2014	*Kaffrine*
March 2014	*Matam*
April 2014	*Saint louis*
July 2014	*Louga*
January 2015	*Tambacounda*
January 2015	*Kedougou*
February 2015	*Kolda*
February 2015	*Ziguinchor*
March 2015	*Sedhiou*

Table A2. Staggered Rollout of the Informed Push Distribution Model across Senegal and Characteristics of Health Facilities Surveyed in the Sample

Time	Number of Health Facilities Surveyed in the Sample			Primary Facility	Number of Full-time Health Workers	Number of Part-time Health Workers
	Informed Push: No	Informed Push: Yes	Total	Mean	Mean	Mean
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Oct-12	28	0	28	0.96	20.57	0.46
Nov-12	34	0	34	0.50	33.21	1.41
Dec-12	1	0	1	1.00	10.00	2.00
Jan-13	29	0	29	0.72	22.55	0.07
Feb-13	38	0	38	0.89	16.95	0.05
Mar-13	57	0	57	0.81	19.95	0.21
Apr-13	61	0	61	0.82	22.28	0.59
May-13	41	0	41	0.90	16.51	0.27
Dec-13	1	11	12	0.25	58.58	3.50
Jan-14	4	34	38	0.82	24.13	1.92
Feb-14	31	11	42	0.76	22.02	0.95
Mar-14	42	0	42	0.88	11.71	0.52
Apr-14	32	0	32	0.78	13.63	0.44
May-14	34	15	49	0.84	14.31	1.04
Jun-14	1	8	9	0.67	28.00	0.22
Jul-14	2	17	19	0.68	47.26	3.79
Aug-14	1	27	28	0.86	15.89	0.96
Sep-14	0	19	19	0.95	12.21	0.63
Dec-14	0	1	1	1.00	10.00	0.00
Feb-15	0	14	14	0.64	30.57	2.29
Mar-15	0	24	24	0.88	8.96	1.46
Apr-15	3	42	45	0.80	18.22	1.18
May-15	1	53	54	0.81	9.57	2.20
Jun-15	1	3	4	0.50	14.75	0.50
Jul-15	1	22	23	0.78	23.00	3.78
Aug-15	1	48	49	0.84	18.65	2.61
Sep-15	5	32	37	0.73	22.30	2.08
Oct-15	8	27	35	0.74	28.14	2.57

Notes: We apply a two-month lag after the starting rollout date to allow the informed push model to become fully operational and omit observations during this window to prevent treatment contamination issues (results remain consistent when we apply no lag, a one-month lag, and a three-month lag). In this table, we provide information on the number of sampled health facilities that received the informed push model over time (Columns 2–4) along with their characteristics (Columns 5–7). For example, as of October 2012, out of a total of 28 sampled health facilities, 0 had received the informed push model.

Table A3. Control Variables: Evaluating the Effect of Transition to the Informed Push Model on *Stock-Out*

Control Variable	Description	Data Source
Primary Facility	Taking the value of 1 when a health facility belongs to the primary level, and 0 for the secondary level. At the primary level (e.g., health posts), services are limited to mostly preventative/curative outpatient services. At the secondary level (e.g., health centers), the services provided include both outpatient and inpatient services, with a few larger facilities also serving as research institutions.	SPA's Inventory Questionnaire 2012-2013, 2014, 2015
Public Facility	Measuring the managing authority of health facility, taking the value of 1 when the facility is publicly operated, and 0 when it is privately operated.	
Number of Full-time Workers	A continuous variable measuring the total number of full-time health workers at a facility.	
Number of Part-time Workers	A continuous variable measuring the total number of part-time health workers at a facility.	
Piped Water	Takes the value of 1 when facilities have access to piped water as the most commonly used source of water, and 0 otherwise (i.e., access to alternative sources such as rainwater). This variable serves as a proxy for the availability of basic infrastructural components within health facilities that might be correlated with the outcomes of interest.	
Management Meetings	Takes the value of 1 when health facilities hold routine management meetings, and 0 otherwise. According to (SPA 2014, p. 38), a well-functioning health facility "must have a system in place for identifying and addressing management and administrative issues." To this end, facilities may conduct management meetings to "discuss day-to-day or broader management issues." As such, this variable serves as a proxy to capture facility-level managerial practices that might impact the outcomes of interest.	
External Supervision	Takes the value of 1 if a health facility receives supervisory visits from higher-level external managers (e.g., from regional or national offices), and 0 otherwise. According to SPA (2014, p. 40), external supervision ensures that "system-wide standards and protocols are followed at the facility level," while providing an opportunity to "expose staff members to a wider scope of ideas and relevant experiences." We control for this variable considering that facilities chosen for external supervision may have different characteristics and managerial practices compared to those not selected for such supervision.	
Commodity Variety FE	This variable captures the total number of contraceptive methods and deworming medications offered by a health facility. In our sample, a facility may offer up to 10 contraceptive methods (i.e., male/female condoms, combined pills, progestin-only pills, combined injectables, progestin-only injectables, intrauterine devices (IUD), implants, emergency contraceptives, and cycle beads). In addition, a facility may offer up to two deworming medications, serving as placebo units (i.e., albendazole and mebendazole).	
Day-of-Week FE	Captures the day of the week when the survey was administered to a health facility.	
Client Age (mean)	Measured in years. This variable is aggregated based on the proximity of clients to a focal health facility (i.e., within a 30 km range), thereby capturing the characteristics of the catchment population surrounding the facility.	DHS's Women Questionnaire 2012-2013, 2014, 2015
Client Education (mean)	Measured in years of cumulative education received. This variable is aggregated based on the proximity of clients to a focal health facility (i.e., within a 30 km range), thereby capturing the characteristics of the catchment population surrounding the facility.	
Client Household Size (mean)	Measured as the total number of people in a given household and capturing the characteristics of the catchment population surrounding a health facility (i.e., within a 30 km range).	DHS's Household Questionnaire 2012-2013, 2014, 2015
Client Wealth Index (mean)	Measured in terms of wealth quantile. The wealth index is developed by the DHS program and serves as a "proxy for measuring the long-term standard of living" (SPA 2014, p. 22). Specifically, a household's wealth falls within the following categories: "poorest", "poorer", "middle", "richer", and "richest". This variable is aggregated based on the proximity of clients to a focal health facility (i.e., within a 30 km range), thereby capturing the characteristics of the catchment population surrounding the facility.	

Notes: Unit of analysis is facility-commodity. FE = Fixed Effects. Client Age (mean), Client Education (mean), Client Household Size (mean), and Client Wealth Index (mean) were aggregated based on the proximity of clients to a focal health facility (i.e., within a 30 km range).

Table A4. Descriptive Statistics: Evaluating the Effect of Transition to the Informed Push Model on (a) *Stock-Out*, (b) *Frontline Health Worker Workload*, and (c) *Client Satisfaction*

		(a) Stock-Out				(b) Frontline Health Worker Workload				(c) Client Satisfaction			
	Variables	**Mean**	**St. Dev**	**Min**	**Max**	**Mean**	**St. Dev**	**Min**	**Max**	**Mean**	**St. Dev**	**Min**	**Max**
1	*Stock-Out*	0.11	0.32	0.00	1.00								
2	*Contraceptive*	0.82	0.38	0.00	1.00								
3	*Frontline Health Worker Workload*					0.21	0.41	0.00	1.00				
4	*Frontline Health Worker Education*					13.35	4.90	0.00	32.00				
5	*Client Satisfaction*									0.90	0.30	0.00	1.00
6	*Client Education*									0.46	0.50	0.00	1.00
7	*Client Other Satisfaction*									0.82	1.37	0.00	10.00
8	*Informed Push Model*	0.52	0.50	0.00	1.00	0.50	0.50	0.00	1.00	0.39	0.49	0.00	1.00
9	*LMIS Practices*	0.73	0.45	0.00	1.00	0.73	0.45	0.00	1.00	0.77	0.42	0.00	1.00
10	*Road Infrastructure*	0.50	0.50	0.00	1.00	0.38	0.49	0.00	1.00	0.42	0.49	0.00	1.00
11	*Primary Facility*	0.77	0.42	0.00	1.00	0.54	0.50	0.00	1.00	0.66	0.47	0.00	1.00
12	*Public Facility*	0.95	0.21	0.00	1.00	0.95	0.21	0.00	1.00	0.97	0.17	0.00	1.00
13	*Number of Full-time Workers*	22.64	30.69	1.00	497.00	36.71	44.57	1.00	497.00	30.33	31.92	1.00	236.00
14	*Number of Part-time Workers*	2.08	3.53	1.00	53.00	2.23	3.29	1.00	53.00	1.66	2.03	1.00	18.00
15	*Piped Water*	0.83	0.38	0.00	1.00	0.89	0.31	0.00	1.00	0.88	0.33	0.00	1.00
16	*External Supervision*	0.96	0.20	0.00	1.00	0.47	0.50	0.00	1.00	0.97	0.17	0.00	1.00
17	*Management Meetings*	0.93	0.25	0.00	1.00	0.94	0.24	0.00	1.00	0.94	0.24	0.00	1.00
18	*Client Age (mean)*	27.82	0.74	25.21	29.94	27.90	0.71	25.21	29.94	27.72	0.66	25.21	29.82
19	*Client Education (mean)*	3.15	1.26	0.15	6.60	3.36	1.31	0.15	6.60	3.26	1.30	0.16	6.60
20	*Client Household Size (mean)*	13.59	2.11	8.12	26.49	13.53	2.00	8.12	26.49	13.67	2.26	8.12	24.43
21	*Client Wealth Index (mean)*	2.87	0.85	1.00	4.54	3.04	0.89	1.00	4.54	3.04	0.88	1.00	4.54

Notes. Unit of analysis is facility-commodity, facility-health worker, and facility-client in (a), (b), and (c), respectively. Client Age (mean), Client Education (mean), Client Household Size (mean), and Client Wealth Index (mean) were aggregated based on the proximity of clients to a focal health facility (i.e., within a 30 km range). More (less) developed road infrastructure is represented using the value of 1 (0). More (less) mature LMIS practices are represented using the value of 1 (0).