Online Appendix

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

We first note that estimating the direct impact of the inventory management training program on public health outcomes, such as unintended pregnancies and maternal and newborn mortalities, is fraught with challenges (e.g., due to the presence of unobserved confounding variables, concerns related to data quality and availability, etc.) To circumvent these challenges, we draw upon existing literature to convert our estimates on contraceptive availability into public health outcomes in a two-step process (see RHSC 2022). In the first step, we convert the estimated reductions in contraceptive stock-outs to changes in modern contraceptive prevalence rate (CPR), defined as the percentage of women or their partners using a modern contraceptive. In the second step, we evaluate the impact of changes in CPR on the following key public health outcomes: (i) unintended pregnancies; and (ii) maternal and newborn mortalities.[1]

Step 1. Converting Contraceptive Availability into Contraceptive Usage. To measure the public health impact of the inventory management training program, our first step is to translate the estimated reductions in stock-outs into the corresponding increase in the CPR. To that end, we use the Reducing Stock-outs Impact Calculator (RSIC) tool developed by the Reproductive Health Supplies Coalition (RHSC 2022). This tool is informed by research findings (i.e., Karim et al. 2008, Ross and Stover 2013, Wang et al. 2012), which indicate that the presence of one additional contraceptive method on the shelf is associated, on average, with an increase of 6.50 percentage-points (hereafter "p.p.") in the CPR. Of note, this estimate has been cited by both academic studies (see Haakenstad et al. 2022, OlaOlorun and Casterline 2021) and global health organizations (PATH 2020, USAID 2014), highlighting its relevance and validity. Next, the RSIC tool converts contraceptive availability into usage based on the assumption that the stock-out of a contraceptive method is equivalent to its *partial* removal from the shelf (Ross and Stover 2013).

Step 2. Converting Contraceptive Usage into Public Health Outcomes. The second step involves converting the changes in CPR into measurable public health outcomes (i.e., unintended pregnancies, maternal and newborn mortalities). To achieve this, we follow the methodology outlined by the RSIC, which utilizes various demographic and reproductive health estimates by the Guttmacher Institute (see Darroch 2017). These estimates have proven valuable in measuring the public health impacts of contraceptive availability, as evidenced by their usage across the academic (Bhutta et al. 2014, Sawyer et al. 2012) and practitioner community (WHO 2016).

While the RSIC tool draws on estimates from the 2008 version of the Guttmacher Institute report, our analysis utilizes the more recent estimates from the 2017 version (see Darroch 2017). This choice is motivated by the following reasons. First, the timeframe of the estimates from the 2017 report aligns more closely with the period during which the benefits of the inventory management training program are anticipated to be realized. Second, unlike the 2008 estimates used by RSIC—which represent data from the entire pool of low- and middle-income countries (LMICs)—we focus on estimates that correspond specifically to "South-Eastern Asia." This ensures that the conversion process is representative of our study setting, Indonesia. Finally, the updated report includes methodologically refined estimates, offering a more accurate and reliable basis for analysis compared to the 2008 version.

Leveraging this approach, we calculate how an increase in contraceptive usage translates into public health outcomes in the context of Indonesia. Specifically, we conclude that the addition of 2.65

[1] Maternal mortality is defined as the death of a woman while pregnant or within 42 days of termination of pregnancy, from any cause related to or aggravated by the pregnancy or its management but not from accidental or incidental causes. Newborn or neonatal mortality is defined as the death of a newborn within 28 days of birth.

contraceptive users corresponds to averting one unintended pregnancy, while 5,762 and 546 additional users are required to prevent one maternal death and one newborn death, respectively.[2]

A2. Accounting for the Selection of Health Facilities into the MyChoice Project

As mentioned in the paper, the MyChoice Project was implemented in a subset of provinces and districts within Indonesia. We posit that the size of the catchment population served by health facilities in the treated areas is a relevant factor that explains the rollout of the MyChoice Project (see Cavallaro et al. 2016, Iyer et al. 2017, Lauria et al. 2019). In particular, the catchment population size refers to the total number of women of reproductive age residing in an area who intend to prevent or delay pregnancies and have a need for contraception.

To address potential endogeneity concerns associated with this unobserved variable, Freyaldenhoven et al. (2019) recommend identifying a suitable proxy variable that can reasonably approximate the catchment population size. Since we do not have direct access to the catchment population data used by the program, we utilize data on the total population districts across Indonesia as a reasonable proxy for the catchment population size. To this end, we collected additional data from The World Bank's Indonesia Database for Policy and Economic Research (World Bank 2023a) and Statistics Indonesia (2023) which compile a range of demographic and economic indicators at the subnational level in the country.

An examination of these data validates our conjecture that the catchment population size was a significant factor in the selection of the treatment provinces and districts across Indonesia. Notably, we observe that the four treated provinces are among the seven most populous provinces in the country, placing them within the top 80th percentile by population size. A similar pattern is evident when examining population data at the district level. To visually represent these patterns, we have included Figure A1 in the Online Appendix, which displays the population data across treated and non-treated areas in Indonesia. These visualizations show that the treated areas in Indonesia are generally characterized by larger populations, providing support for the impact of catchment population size in determining the intervention's rollout.

Following Freyaldenhoven et al. (2019) and to account for potential selection bias arising from the effect of catchment population size, we incorporate into our main model the following control variables:

- *Province Population*. Measured as the total number of people residing in a specific province.
- *District Population*. Measured as the total number of people residing in a specific district.

Incorporating these variables into our main model helps address potential endogeneity concerns arising due to the selection of health facilities into the MyChoice Project across geographic areas in Indonesia.

A3. Cost Estimation Strategy

We follow the guiding framework provided by Burns et al. (1985, p. 469) to calculate facility-level costs of administering each training modality, onsite and offsite. Specifically, Burns et al. (1985) develop models for calculating transportation costs under two scenarios: (i) "direct shipping" which involves "shipping separate loads to each customer," and (ii) "peddling" involving "dispatching trucks that deliver items to more than one customer per load." The *direct shipping* resembles *offsite training*, where health workers

[2] These calculations are based on an estimated 23,990,000 unintended pregnancies averted, 116,462 newborn mortalities averted, and 11,027 maternal mortalities averted, per 63,545,000 modern contraceptive users in the "South-Eastern Asia" region (see Tables 22, 31, and 33 of the "methodology tables" in Darroch 2017).

need to travel to a central training location. This is in contrast to the *peddling* scenario which parallels the delivery of *onsite training*, where a trainer travels to multiple locations and delivers training to more than one health facility "per load."

Cost of Onsite Training. Burns et al. (1985, p. 477) consider different factors in calculating the transportation cost under the "peddling" scenario (equivalent to onsite training), including (i) the roundtrip distance between the supplier and the customer—in our context, the central office from which trainers are dispatched and the health facility where health workers are located; (ii) the transportation cost per unit distance; (iii) the number of customers visited per dispatch load; (iv) the density of customer locations; and (v) the time spent at each customer stop. We collected these pieces of information from a variety of sources.

First, we undertook the task of collecting additional data on the approximate GPS coordinates of health facilities in Indonesia. This was not straightforward, as no readily available databases capture the GPS coordinates of health facilities in the country. To overcome this challenge, we rely instead on information regarding the specific village where each health facility is located. In Indonesia, the village, or "Desa" in the local language, represents the lowest administrative boundary. We then retrieved the GPS coordinates of the centroid of each village from Google Maps to serve as the approximate location for each health facility. Using this approach, we were able to gather approximate GPS coordinate data for nearly 80% of all health facilities in Indonesia and close to 95% of facilities that were treated with *Training*. Using this data, we calculated the roundtrip distance between each health facility and its corresponding district office in Indonesia, and the total number and density of health facilities in each district.

We then gathered data from the MyChoice Project and publicly available sources on the transportation costs per kilometer (Indonesia Ministry of Transportation 2015, Numbeo 2025).[3] We assume that a trainer spends an average of two hours per health facility including the necessary time required for administering the training, commuting to the next health facility, and taking potential breaks. This sets the number of health facilities that can receive onsite training during an 8-hour workday to a maximum of four.

Cost of Offsite Training. Burns et al. (1985) identify several factors for calculating transportation costs under the "direct shipping" scenario, which corresponds to offsite training in our context. These factors include (i) the roundtrip distance between supplier and customer—in our context, the health facilities where health workers are located and the central office to which they need to commute to receive the training; (ii) transportation cost per unit distance; and (iii) the time spent at each customer stop (see p. 472). We rely on the same sources and assumptions as described earlier to obtain an estimate for these parameters. Additionally, we assume that offsite training requires an average of two hours to administer, including preparation time, and it is delivered to a batch of 30 health workers at the same time. Beyond the transportation costs of offsite training, we account for two additional non-transportation expenses related to logistical arrangements (e.g., room rental), which were directly provided by the MyChoice Project.[4]

Using this methodology, our calculations yield an average cost of $9.72 USD for onsite training and $30.01 USD for offsite training. Notably, these estimates align closely with figures provided directly by the

[3] These include an average daily wage of $23 for a trainer as obtained from the MyChoice Project; an average commuting speed of 40 km per hour, and a cost of $0.18 per kilometer to account for fuel expenses and vehicle depreciation. All cost values are in USD.
[4] This includes a meeting venue cost of $19.23 per health facility (e.g., room rental, electricity, sound and visual equipment, meals, etc.), and a supply cost of $3.85 per facility (e.g., printed handouts, scrap papers, markers, pens, etc.).

MyChoice Project—$10 USD for onsite training and $32 USD for offsite training—differing by only about 2% to 6%. This consistency validates the accuracy of our cost calculation approach. However, unlike the MyChoice project costs, which are only observable as *average* values, we can calculate the cost of administering each training modality per health facility.

Lastly, we calculate the counterfactual cost of administering onsite training to health facilities that had originally received offsite training. This calculation accounts for potential differences in the density of health facilities in a region and the average roundtrip distance between facilities and the district office, as these factors may vary between facilities retrospectively reassigned to onsite training and those that originally received it.

A4. An Exploratory Analysis of the Underlying Mechanisms

In this section, we report the results of an exploratory analysis that helps illuminate the underlying pathways through which the inventory management training program may have reduced stock-outs. To this end, we examine the post-training changes in facility-level operational outcomes across the main training components introduced in section 2.3 of the paper: (i) improving stock card usage; (ii) conducting a physical count of inventory; (iii) improving dispensing and storage practices; and (iv) reporting inventory data upstream. We leverage the MyChoice Project's Magpi dataset to evaluate the impact of the training program on training components (i) through (iii) and the Baseline-Endline surveys to assess its impact on training component (iv), as elaborated below.

Specifically, the Magpi data includes information on over 1,000 health facilities that received onsite training as part of MyChoice project. The data is repeated cross-sectional in that the performance of the health facilities were measured sporadically whenever a trainer conducted an onsite visit.[5] To analyze these data, we compare the performance of health facilities during the first onsite visit (control) to their performance during the subsequent, second visit (treatment). The first visit serves as a baseline, capturing the facility's performance before any training impact is realized, while the second visit measures the immediate impact of the training.

Our empirical approach is justified for the following reasons: First, given the absence of any control units in the sample, this method allows us to restrict the treatment window to a short period of time, thereby reducing the risk of confounding variables and external shocks that are more likely to arise over a longer horizon (note that the median time interval between the first and second visits is only about four months.) Second, by focusing on the effect of a single training session, we can capture a clean baseline effect, ensuring that no facility in the sample has received training prior to the first visit. Third, it is important to note that under both control and treatment conditions, health facilities had already received the district- and province-level components of the MyChoice Project which were rolled out during the initial phase. As a result, any potential effects attributable to such factors will be "differenced out." Together, these factors help in isolating the impact of the training on various outcomes. Nonetheless, it is noteworthy that the primary objective of the exploratory analysis is to compare and contrast the impact of the training program across various outcomes, rather than to estimate unbiased treatment effects within each outcome.

Next, we perform *t*-tests to compare the performance of a health facility during the first onsite visit at

[5] We acknowledge that these data are only available for onsite training and *not* for offsite training. This limitation restricts our ability to directly compare the performance of offsite and onsite training modalities across the analyzed dimensions. Further, the dataset does not include any information on health facilities in Indonesia that were not a part of the MyChoice project.

the baseline (control) to its performance at the second visit (treatment). In essence, this approach is equivalent to a pre–post design, where we would have regressed our dependent variable, *Stock-Out*, on health facility fixed effects and the treatment variable, *Training*.

Further, we utilize the MyChoice Project's Baseline-Endline surveys to evaluate the impact of the program on training component (iv). These data were collected through a baseline survey conducted in late 2015 before the MyChoice project was launched, and an endline survey in 2018 after the project was rolled out. Similar to before, we employ a pre–post design by applying *t*-tests to compare the performance of health facilities at the endline survey (treatment) to their performance at the baseline survey (control). This approach is equivalent to regressing our dependent variable, *Stock-Out*, on health facility fixed effects and the treatment variable, *Training*. One limitation of these data is that performance was measured at only two time points, which are relatively far apart. However, this concern is mitigated for the following reasons. First, the measured outcome—routine monthly reporting of inventory data upstream—is highly specific and is unlikely to be influenced by factors other than the training program. Second, as will be shown in the results section, more than 97% of health facilities were already compliant with this practice at baseline. In other words, the outcome was nearly maxed out, leaving little room for further improvement during the training program. Hence, the potential for under- or over-estimating the impact of the training program is low in this context.

The results of our exploratory analysis are presented in Figure A5, where we find improvements in outcomes across all training components: (i) stock card usage, (ii) physical counting of inventory, (iii) dispensing and storage practices, and (iv) reporting inventory data upstream.

(i) ***Improving Stock Card Usage.*** Starting with Figure A5(i), we observe a substantial increase in stock card usage post-training, with a rise of 19.14 p.p. Within the subset of health facilities utilizing stock cards, there are also improvements in the proper use of stock cards in accordance with standard operating procedures post-training (point estimates ranging from 1.31 p.p. to 4.05 p.p.).

(ii) ***Conducting a Physical Count of Inventory.*** Figure A5(ii) shows improvements in the routine physical count of inventory by health facilities, with an increase of 3.45 p.p. Additionally, there is a 2.72 p.p. increase in the likelihood that the inventory level on the stock card matches the physical count.

(iii) ***Improving Dispensing and Storage Practices.*** Figure A5(iii) highlights improvements in various dispensing and storage practices post-training. Specifically, we observe that health facilities are more likely to adhere to the first-expire, first-out inventory protocol, with an increase of 4.96 p.p. They are also 2.43 p.p. more likely to follow appropriate storage practices, keeping supplies in clean dry areas and away from sunlight and hazardous materials. Further, improvement in the proportion of health facilities that had a plan for handling expired products was relatively modest, increasing by just 0.58 p.p. Finally, the proportion of health facilities reporting no damaged or expired products increased slightly by 2.17 p.p. post-training, although this effect is statistically insignificant. The relatively small size of this increase suggests that the improvements in dispensing and storage practices may not have had a material impact on the risk of damaged/expired supplies and, consequently, stock-outs.

(iv) ***Reporting Inventory Data Upstream.*** The results in Figure A5(iv) indicate that 97.19% of health facilities in Indonesia were submitting timely reports of inventory data upstream pre-training, which increased only slightly to 98.12% post-training. Given the high reporting rates in both periods, it is unlikely that this component of the training played a major role in reducing stock-outs.

A5. An Exploratory Mediation Analysis of the Underlying Mechanisms

In this section, we conduct additional exploratory analyses to examine how different components of the inventory management training program may have contributed to reductions in contraceptive stock-outs. To that end, we conduct a series of mediation analyses following the framework of Baron and Kenny (1986), where the inventory management training program is treated as the primary independent variable, and various training components (e.g., stock card usage) are considered potential mediating variables. To assess mediation, we estimate three sets of regression models: (i) the direct effect of the training program on contraceptive stock-outs; (ii) the direct effect of the training program on each mediating variable; and (iii) the joint effect of the training program and the mediating variables on contraceptive stock-outs. A reduction or disappearance of the training program's effect on stock-outs after accounting for the mediating variables would suggest the presence of partial or full mediation.[6]

Figure A6 presents the results of our mediation analyses, with bar charts illustrating the proportion of the inventory management training program's effect on contraceptive stock-outs that is mediated by each component of the training program. As shown, stock card usage emerges as the most influential mediator, accounting for 25.19% of the training program's total effect, followed by routine physical inventory counting (13.42%). In contrast, the contributions of the remaining components appear relatively modest. For instance, routine reporting of inventory data upstream accounts for less than 1% of the training program's effect on stock-outs, suggesting a more limited role in driving the observed outcomes.

Taken together, these results provide additional supporting evidence for the underlying mechanisms through which the inventory management training program reduces contraceptive stock-outs.

A6. Synthetic Control Method to Create a Synthetic Group of Almost Identical Counterfactuals

As shown in the paper, our results are robust to the inclusion of a range of district- and province-specific year-month fixed effects and time trends to absorb the effect of district- and province-level components of the MyChoice Project. Notwithstanding this robustness, we employ the synthetic control method as an alternative identification strategy to achieve the same objective, while enforcing the parallel trends assumptions in a non-parametric manner (Abadie et al. 2010). Specifically, the synthetic control method extends the conventional DiD framework adopted in the main model, "allowing that the effects of unobserved variables on the outcome *vary with time*" (Abadie et al. 2010, p. 494). An important implication of this extension in our context is that one can effectively estimate the treatment effect of the inventory management training program (i.e., facility-level), while allowing for the effect of unobserved confounding variables to vary over time (i.e., district and province-levels). Such unobserved confounding variables at the district- and province-levels will simply be differenced out of the treatment effect.

In explaining the underlying logic, Abadie et al. (2010) assert that "only units that are alike in both observed and *unobserved* determinants of the outcome variable […] should produce similar trajectories of the outcome variable over extended periods of time." Therefore, any discrepancy in the outcomes of treated and control units after the roll-out of the supply chain initiative can be "interpreted as produced by the intervention itself" and not something else (Abadie et al. 2015, p. 498). In practical terms, this implies that

[6] In these analyses, we measure stock-outs directly through the Magpi dataset ($\textit{Stock-Out}_{\textit{Magpi}}$). This dataset includes information on over 1,000 health facilities that received onsite training as part of MyChoice project. During onsite visits, the trainers evaluated the stock-out status of contraceptives on their own by inspecting and verifying historical documents available at the health facility. More detailed information surrounding the data, analysis approach, and limitations is provided in Appendix A4.

the synthetic control method would identify counterfactual units that have experienced similar, if not identical, stock-out trends to those of the treated units prior to the rollout of the inventory management training program.

However, the original version of the synthetic control method was designed to handle only a single treated unit and a fixed treatment timing, rendering it unsuitable for our study setting—where the treatment variable involves multiple units that are treated in a staggered manner. To circumvent this challenge, we employ the generalized synthetic control method developed by Xu (2017), which can effectively accommodate multiple treated units and variable treatment timing. The results of this analysis are presented in Figure A7. As can we be seen, these results are consistent with those of the main model, further supporting the impact of the inventory management training program in reducing contraceptive stock-outs.

A7. Gaussian Copula Correction to Account for the Differential Rollout Timing of Inventory Management Training Program

One potential source of selection bias in our study is related to the differential rollout timing of the inventory management training program. To understand the reasons behind this differential timing, we consulted with the program managers and technical advisors of the MyChoice Project. Our discussions revealed that due to the relatively large number of health facilities requiring training, a staggered approach was implemented, leading to some health facilities receiving the training earlier than others. However, our discussions did not reveal specific criteria or preferences driving the selection of health facilities for the staggered rollout. In other words, the differential timing of the training was primarily based on the limited capacity of the project team to accommodate many health facilities.

Nonetheless, we apply a class of estimators known as "instrument-free" approaches (Park and Gupta 2012) to address concerns of bias arising from the differential rollout timing of training. Of note, these estimators are not subject to the stringent identifying assumptions of instrumental variable estimation, which are often difficult to satisfy in many situations. 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 term using a Gaussian copula" (Becker et al. 2022, p. 47). The Gaussian copula approach provides consistent estimates and has been previously used by researchers to handle similar endogeneity issues (see Atefi et al. 2018, Deshpande and Pendem 2022, Gielens et al. 2018, Roy et al. 2022).

In line with Park and Gupta (2012), we construct the Gaussian copula endogeneity correction term using the following equation:

$$\widetilde{\boldsymbol{Copula}}_{jdt} = \emptyset^{-1}[H\ (Training\ Time\ Trend_{jdt})] \tag{A1}$$

Where j, d and t represent health facility j and district d at time t. Additionally, $\emptyset^{-1}$ is the inverse of the normal cumulative distribution function, and $H()$ is the empirical cumulative distribution function corresponding to the rollout timing of training. Further, *Training Time Trend* is a variable derived by multiplying the *Training* indicator in our main specification with a monthly *Time Trend*. This modification serves the following key objectives. First, by incorporating a time trend into our training variable, we are not only accounting for whether training was provided at health facilities (vs. no provision), but also directly modeling the timing of the training. This allows us to capture the temporal aspect of the training rollout and its potential impact on the outcome. Second, this modification helps establish the identifying assumption of the Gaussian copula correction approach, which requires endogenous variables to be *non*-binomially and *non*-normally distributed (Park and Gupta 2012). By transforming our binary *Training* variable using a time trend, we ensure that this variable is non-binomially distributed. Lastly, consistent with prior literature, we also tested the non-normality assumption of the endogenous regressors by running a Shapiro-Francia normality test. This test provides statistical evidence that the endogenous variables are non-normally distributed ($p < 0.01$). Therefore, the identifying assumption of the Gaussian copula correction approach is satisfied, ensuring the validity of our analysis. Next, we incorporate the copula correction term $\widetilde{Copula}_{jdt}$ into our main specification, correcting for potential endogeneity issues similar to the idea of a control function approach:

$$Stock\text{-}Out_{ijdpt} = \beta_0 + \beta_1.Training\ Time\ Trend_{jt} + \widetilde{\boldsymbol{Copula}}_{\boldsymbol{jt}} + \theta.Health\ Facility\ FE_j \\ + \psi.Month\text{-}Year\ FE_t + \lambda.X_{jdpt} + \alpha_i + u_{dt} + \gamma_{dt} + \nu_{pt} + \varepsilon_{ijdpt} \qquad \text{(A2)}$$

Where the subscripts i, j, d, and p denote a contraceptive method i offered by health facility j, which is located in district d and province p. The subscript t denotes the specific month-year when an observation was collected, ε_{ijdpt} is the error term, and X_{jdpt} is the vector of control variables. The results of the Gaussian copula endogeneity correction approach are presented in Table A6 of the Online Appendix. These results are consistent with those from our main model, suggesting that our coefficients are not biased by the differential rollout timing of training across health facilities. Further, we find that the coefficients of $\widetilde{Copula}_{jt}$ are small and statistically indistinguishable from zero, providing additional evidence that the rollout timing of the training is not likely to be a source of bias in our estimates.

A8. Alternative Measures of Stock-Out beyond the LMIS Dataset

In this section, we verify the validity of our dependent variable in the main analysis by collecting data on two additional indicators of stock-outs beyond the LMIS database.

(i) We collected additional data from Magpi database which includes information on over 1,000 health facilities that received onsite training as part of MyChoice. A key feature of the Magpi data is that the trainers evaluated the stock-out status of contraceptives independently by reviewing and verifying historical documents available at the health facility and observing the physical storage area where contraceptives were stored. To ensure the reliability of data collection, the trainers followed established procedures to distinguish between contraceptives that were genuinely out-of-stock and those never offered by a health facility, excluding the latter from stock-out reporting.

To analyze these data, we compare the performance of health facilities during the first onsite visit (control) to their performance during the subsequent, second visit (treatment). The first visit serves as a baseline, capturing the facility's performance before any training impact is realized, while the second visit measures the immediate impact of the training program. Next, we perform t-tests to compare the performance of a health facility during the first onsite visit at the baseline (control) to its performance at the second visit (treatment). In essence, this approach is equivalent to a pre–post design, where we would have regressed the new binary dependent variable, $Stock\text{-}Out_{Magpi}$, on health facility fixed effects and the treatment variable, *Training* (see Appendix A4 for more details surrounding data, analysis approach, and limitations).

Our analysis shows that the rollout of the inventory management training program is associated with a 7.19 p.p. reduction in contraceptive stock-outs, on average (β = –0.0719; 95% CI: –0.1156, –0.0282; n = 764).

(ii) We collected additional data from the MyChoice Project's "Baseline-Endline" surveys. This data was collected through a baseline survey conducted in early 2016 before the MyChoice project was launched, and an endline survey in 2018 after the project was rolled out.

A key feature of the Baseline-Endline survey data is that the survey administrators conducted a thorough inspection of the contraceptive storage areas and performed a physical count of actual inventory during their visits to health facilities (see Figure A8), thereby identifying and recording instances of contraceptive stock-outs. Similar to Magpi data, and to enhance the reliability of data collection, the trainers adhered to standardized protocols to distinguish between contraceptives that were truly out-of-stock and those never offered by a health facility, excluding the latter from stock-out reporting.

Similar to before, we employ a pre–post design by applying *t*-tests to compare the performance of health facilities at the endline survey (treatment) to their performance at the baseline survey (control). The new outcome variable, $\textit{Stock-Out}_{\textit{Baseline-Endline Survey}}$, is measured as a binary variable (see section A4 of the Online Appendix for more details surrounding data, analysis approach, and limitations.)

Our analysis shows that the rollout of the inventory management training program is associated with a 10.50 p.p. reduction in contraceptive stock-outs, on average (β = –0.1050; 95% CI: –0.1772, –0.0328; n = 697).

Together, these alternative measures yield treatment effects ranging from a 7.19 to 10.50 p.p. reduction in stock-outs following the implementation of the training program (see Table A8 for a side-by-side summary), reinforcing the consistency of our findings.

Table A1: Detailed Description of Inventory Management Training Program
(continued on next page)

(i)	***Improving Stock Card Usage***	The inventory management training program placed significant emphasis on the utilization of stock cards by frontline health workers to monitor and track the inflows and outflows of contraceptive supplies at health facilities. This includes tracking information regarding the receipt of contraceptive supplies from upstream warehouses, their distribution to clients, or any potential losses due to expiration or damage. In addition to promoting stock card usage, the training emphasized the proper use of stock cards in accordance with standard operating procedures. This component was designed to improve the real-time visibility of stock balance information for frontline health workers, allowing them to take appropriate action when supplies are running low to avert stock-outs (e.g., placing emergency orders). Further, the inventory data forms the basis for calculating the resupply quantities by upstream warehouses. In the Indonesian context, the resupply quantities for contraceptives are determined by the district warehouses based on a health facility's consumption data. The following provide illustrative examples of this component of the training: – *"Recording of transactions in the stock card starts from the first row. For example, when you issue a contraceptive [e.g., to a client], write down the date, quantity, and destination of the product. Next, complete the adjacent columns by recording the batch number and expiry date. Remember to sign or initial your name in the 'note' column."* – *"Similarly, when you receive a supply of contraceptives [e.g., from the district office], record the date of receipt, quantity received, and the source of the supply. Ideally, each individual transaction should be documented on the stock card."* – *"To maintain an accurate record, ensure that the column for stock balance reflects the total stock on hand."* – *"You can calculate the quantity for the emergency order point and reallocation point by looking at the F/2 report. Write these quantities on the stock card using a pencil."*
(ii)	***Conducting a Physical Count of Inventory***	The training program emphasized the importance of conducting a physical count of inventory on a regular basis. The purpose of a physical count is to verify that the stock balance quantity recorded on the stock card accurately reflects the physical quantity of inventory available on shelf. In the event of discrepancies between the two, health workers are instructed to adjust the stock card information accordingly. The following provide an overview of the guidance shared during the training: – *"Physical counting is performed routinely every month. Prior to conducting the physical count, ensure that the stock card has been updated, separate any damaged products, and gather all usable products in one place. This will facilitate the counting process."* – *"Begin by counting the number of unopened boxes for each contraceptive method. Multiply the number of boxes by the quantity of products contained in each box. Next, count the quantity of products in opened boxes. Add the quantity from the unopened boxes to the quantity from the opened boxes. Next, record the result of the physical count in the stock card, along with the date of the count."* – *"As you perform physical counting, also examine the physical condition of contraceptives. Separate the damaged/expired products."*

Table A1: Detailed Description of Inventory Management Training Program (continued from previous page)

(iii) Improving Dispensing and Storage Practices	The training program provided guidance on proper storage practices for contraceptives to preserve their quality and extend their shelf life. For instance, it emphasized the dispensing of products using the first-expire first-out protocol and highlighted the importance of storing contraceptives in appropriate conditions, such as keeping them away from direct sunlight and moisture. These practices help prevent damage to the products and maintain their effectiveness. Additionally, the training covered the management of expired and damaged products. Health facilities were instructed to separate any expired or damaged products from the rest of the inventory. These products were not to be counted or included in the main stock cards where the useful inventory was being tracked. This ensures that accurate records are maintained and that only usable contraceptives are accounted for in the inventory management process. The following quotes provide an overview of the guidance shared during the training to ensure appropriate storage conditions: – *"Contraceptives should be organized according to FEFO system (First Expired First Out). That is, place the product with the nearest expiration dates in the front for prioritized use."* – *"Damaged or expired contraceptives should be recorded on a separate stock card specifically designated for tracking such products [as these products cannot be used to satisfy demand.]"* – *"Ensure the cleanliness of the storage room where contraceptives are stored at the health facility. For example, contraceptives should be stored away from insecticides, chemicals, hazardous materials, and direct sunlight. The storage area should be dry and free of water penetration."* – *"The area where contraceptives are stored should have a functioning temperature control mechanism in place (e.g., air conditioning, fans, or passive ventilation.)"*
(iv) Reporting Inventory Data Upstream	The resupply quantities for contraceptives are determined by the district warehouses based on the information recorded on stock cards including a health facility's consumption data. The training program covered relevant materials to ensure the effective reporting of such data to the upstream entities. The following highlight examples of the training on effective reporting practices: – *"Transfer the stock card record to the F/2 report by the end of each month after physical counting is completed. This month's report has to be received by the district family planning office before the 5th day of the following month."* – *"Ensure that you submit your stock report to the district office on time, so that supplies are received by your facility in a timely manner and match the actual needs [avoiding supply-demand mismatch]."*

Notes: The inventory management training program was aimed at improving the knowledge and skills of frontline health workers in managing inventory at the health facility level. This was achieved through different focus areas of the MyChoice Project including "logistics recording and reporting (LRR)," "inventory management (IM)," and "mentorship and on-the-job training (MOT)." LRR emphasized, at the facility-level, the proper use of stock cards for managing inventory (i.e., "recording") and ensuring timely reporting of inventory data upstream (i.e., "reporting"). This focus area is embedded within the components (i) and (iv) of the training program. IM was primarily implemented at the district and province-levels. However, its only component at the facility-level was focused on the delivery of training to frontline health workers to ensure better adherence to minimum-maximum inventory policies and better use of emergency orders when supplies are running low. This focus area is embedded within component (i) of the training program. MOT emphasized, at the facility-level, delivering the training materials through onsite training, complementing the traditional offsite training format. In particular, both onsite and offsite modalities were designed to cover relevant information pertaining to all components of the training. As noted by one of the senior managers involved in the MyChoice Project during our discussion, the training components across the two modalities were "exactly the same." (i.e., component (i), (ii), (iii) and (iv) of the training program).

Table A2. Description of Control and Matching Variables

	Variable Name	Description	Data Source
1	*Quantity Received*	Number of contraceptive supplies received by a health facility from upstream locations. This variable is log-transformed after adding the value of 1 to reduce skewness.	Indonesian Family Planning LMIS
2	*Quantity Issued*	Number of contraceptive supplies issued to clients by a health facility. This variable is log-transformed after adding the value of 1 to reduce skewness.	
3	*Contraceptive Variety*	Total number of different contraceptive types offered by a health facility (i.e., condoms, implants, injectables, intrauterine devices, and oral pills). This variable is log-transformed to reduce skewness.	
4	*District & Province Population*	Total number of people residing in a specific district/province.	The World Bank, Statistics Indonesia, Indonesian Ministry of Finance
5	*Health Function Expenditure (per capita)*	Per capita budget allocated to health expenditures including "all expenditures for the provision of health services, family planning activities, nutrition activities and emergency aid designated for health" (WHO 2023).	
6	*Number of Frontline Health Workers (per 100K people)*	Per capita number of frontline health workers providing health services and commodities to clients.	
7	*Skilled Birth Attendance (%)*	Proportion of "deliveries that are attended by frontline health workers trained to give the necessary supervision, care, and advice to women during pregnancy" (World Bank 2023c).	
8	*Households with Access to Safe Sanitation (%)*	Proportion of households with access to safely managed sanitation services.	
9	*Household Health Expenditure (per capita)*	Per capita monthly expenditures incurred by households for various healthcare-related services.	
10	*Villages with Asphalt Road (%)*	Proportion of villages with access to asphalt road, serving as a proxy for the logistics infrastructure.	
11	*Literacy Rate*	Proportion of people "aged 15 and over who can both read and write … and understand a short simple statement about their everyday life" (World Bank 2023b).	
12	*Poverty Rate*	Proportion of the population living below the national poverty line.	

Notes: Variables 1–3 are measured at the health facility-level; these were not directly incorporated into the models but rather indirectly through matching to avoid potential collider bias (see Frake et al. 2024). Variables 4–12 were directly incorporated into all models as control variables. Variables 6–12 are measured at the district level, aiming to capture the demographic, socioeconomic, and infrastructural characteristics of the environments where health facilities are located. For these variables, a regression-based imputation was applied to handle any missing observations. Lastly, the following variables were used to match treated and control health facilities: *Quantity Received*, *Quantity Issued*, *Contraceptive Variety*, and *District Population* (see section 3.3.3 of the manuscript for details surrounding our matching approach). Matching was conducted on the population of districts rather than provinces, as districts represent a more granular unit of analysis and more precisely define the geographic scope of the intervention.

Table A3. Pairwise Correlations

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	*Stock-Out*	1.00																	
2	*Training*	–0.03	1.00																
3	*Onsite Training*	–0.02	0.82	1.00															
4	*Offsite Training*	–0.01	0.56	–0.01	1.00														
5	*MyChoice Initial Phase*	–0.02	0.62	0.51	0.35	1.00													
6	*Quantity Received*	0.03	0.00	0.00	0.00	–0.01	1.00												
7	*Quantity Issued*	0.00	0.00	0.00	0.00	0.00	0.52	1.00											
8	*Contraceptive Variety*	–0.14	–0.01	0.02	–0.04	0.00	0.02	0.02	1.00										
9	*District Population*	–0.01	0.00	–0.01	0.02	0.04	0.00	0.00	0.05	1.00									
10	*Province Population*	–0.01	–0.08	–0.07	–0.05	–0.15	0.04	0.03	0.02	0.55	1.00								
11	*Health Function Expenditure (per capita)*	–0.04	–0.02	–0.01	–0.02	–0.08	–0.02	–0.02	–0.06	–0.42	–0.15	1.00							
12	*Number of Frontline Health Workers (per 100K people)*	0.04	–0.01	0.01	–0.03	–0.01	0.01	0.00	–0.05	–0.64	–0.42	0.39	1.00						
13	*Skilled Birth Attendance (%)*	–0.16	0.05	0.04	0.03	0.09	–0.08	–0.06	0.02	0.15	0.13	0.01	–0.27	1.00					
14	*Household Access to Safe Sanitation (%)*	–0.09	0.06	0.04	0.05	0.10	–0.04	–0.03	–0.01	0.21	0.15	–0.11	–0.24	0.37	1.00				
15	*Household Health Expenditure (per capita)*	–0.16	0.04	0.03	0.03	0.05	–0.07	–0.05	0.05	0.45	0.25	–0.10	–0.52	0.46	0.52	1.00			
16	*Villages with Asphalt Road (%)*	–0.11	0.02	0.00	0.02	0.03	–0.05	–0.04	0.04	0.40	0.33	–0.08	–0.56	0.48	0.24	0.55	1.00		
17	*Literacy Rate (%)*	0.02	0.01	0.00	0.02	0.03	–0.01	–0.01	0.01	0.43	0.18	–0.12	–0.19	0.06	0.42	0.42	0.18	1.00	
18	*Poverty Rate (%)*	0.07	–0.06	–0.03	–0.05	–0.09	0.04	0.03	–0.04	–0.52	–0.23	0.12	0.45	–0.21	–0.41	–0.65	–0.41	–0.64	1.00

Table A4. Summary Statistics

	Variable	Mean	Std. Dev.	Min	Max
1	*Stock-Out*	0.2182	0.4130	0.0000	1.0000
2	*Training*	0.0228	0.1493	0.0000	1.0000
3	*Onsite Training*	0.0167	0.1280	0.0000	1.0000
4	*Offsite Training*	0.0061	0.0782	0.0000	1.0000
5	*MyChoice Initial Phase*	0.0565	0.2309	0.0000	1.0000
6	*Quantity Received*	57.7688	294.5711	1.0000	115,201
7	*Quantity Issued*	60.4985	397.5171	1.0000	115,201
8	*Contraceptive Variety*	4.8060	0.5439	1.0000	5.0000
9	*District Population*	1,547,269	844,488	112,976	3,775,279
10	*Province Population*	27,900,000	17,500,000	871,510	49,300,000
11	*Health Function Expenditure (per capita)*	322,051	196,901	0.0000	2,810,272
12	*Number of Frontline Health Workers (per 100K people)*	50.1232	39.0347	2.5306	326.3677
13	*Skilled Birth Attendance (%)*	96.9096	5.4285	43.3308	100.0000
14	*Household Access to Safe Sanitation (%)*	79.6503	10.7508	26.1918	98.3759
15	*Household Health Expenditure (per capita)*	33,519	15,788	2,231	121,933
16	*Villages with Asphalt Road (%)*	85.4016	16.3082	2.7513	100.0000
17	*Literacy Rate (%)*	95.9783	4.4589	75.4873	100.0000
18	*Poverty Rate (%)*	9.3125	5.0411	1.6700	34.1300

Notes: As noted in Table 1 of the paper, a total of 1,020 health facilities were treated with inventory management *Training* in the unmatched sample. Within this group, 185 health facilities were treated with *Offsite Training*, and the remaining 835 health facilities received *Onsite Training*.

Table A5. Instrumental Variable Estimation Results: Effect of Onsite Training and Offsite Training on Contraceptive Stock-outs

	First-Stage Regression		Second-Stage Regression
	DV: Onsite Training	**DV: Offsite Training**	**DV: Contraceptive Stock-Out**
	(1)	**(2)**	**(3)**
Onsite Training	—	—	**–0.0916** [–0.1594, –0.0239]
Offsite Training	—	—	**–0.0267** [–0.1305, 0.0771]
Onsite Training Instrument	0.7875 [0.7390, 0.8360]	–0.0457 [–0.1018, 0.0105]	—
Offsite Training Instrument	–0.0900 [–0.1366, –0.0433]	0.7102 [0.5884, 0.8319]	—
Health Facility FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
Contraceptive Type FE	Yes	Yes	Yes
MyChoice Initial Phase	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes
CEM Weights	Yes	Yes	Yes
District & Province × Month-Year Linear Trends	Yes	Yes	Yes
Kleibergen-Paap Wald F-statistic	—	—	82.29
Observations	1,127,977	1,127,977	1,127,977
R-squared	0.55	0.63	0.27

Notes: 95% confidence bounds are presented in brackets and are two-way clustered at health facility and month. Descriptions of control variables, and their pairwise correlations and summary statistics are presented in Tables A2, A3, and A4 of the Appendix, respectively.

Table A6: DiD Estimation Results with Copula Correction to Account for the Staggered Rollout Timing: Effect of Inventory Management Training Program on Contraceptive Stock-Outs

	Dependent Variable: Contraceptive Stock-out	
	(1)	**(2)**
Training × Time Trend	**–0.1896** [–0.3069, –0.0723]	**–0.2162** [–0.3469, –0.0856]
Copula Correction	0.0014 [–0.0003, 0.0031]	0.0015 [–0.0002, 0.0031]
Health Facility FE	Yes	Yes
Year-Month FE	Yes	Yes
Contraceptive Type FE	Yes	Yes
MyChoice Initial Phase	Yes	Yes
Control Variables	Yes	Yes
CEM Weights	Yes	Yes
District & Province × Month-Year Linear Trends	No	Yes
Observations	1,132,376	1,132,376
R-squared	0.26	0.27

Notes: 95% confidence bounds are presented in brackets and are two-way clustered at health facility and month. Descriptions of control variables, and their pairwise correlations and summary statistics are presented in Tables A2, A3, and A4 of the Appendix, respectively.

Table A7: DiD Estimation Results with an Alternative Dependent Variable: Effect of Inventory Management Training Program on Ending Balance as a Continuous Variable

	Dependent Variable: Ln (Ending Balance)	
	(1)	**(2)**
Training	**0.0147** [–0.0818, 0.1112]	**0.0349** [–0.0471, 0.1169]
Health Facility FE	Yes	Yes
Year-Month FE	Yes	Yes
Contraceptive Type FE	Yes	Yes
MyChoice First Phase	Yes	Yes
Control Variables	Yes	Yes
CEM Weights	Yes	Yes
District & Province × Month-Year Linear Trends	No	Yes
Observations	881,138	881,138
R-squared	0.62	0.63

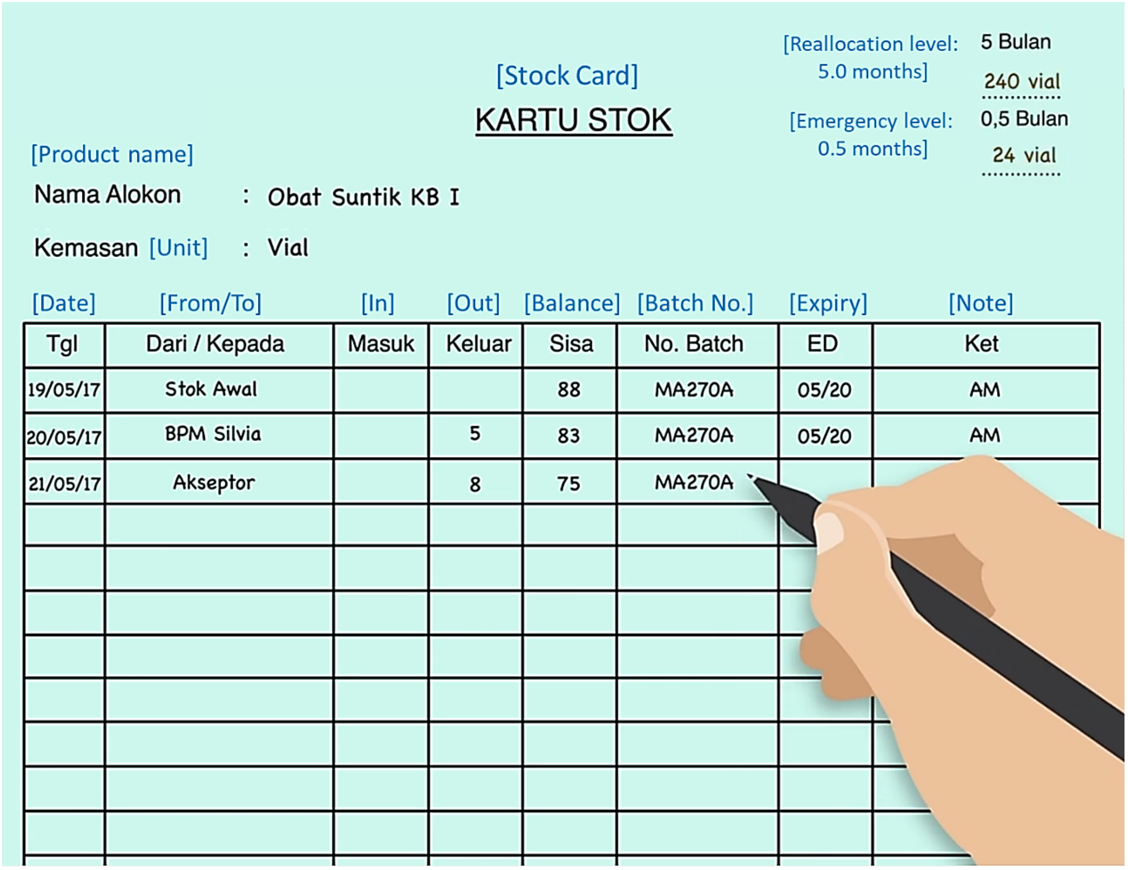
Notes: 95% confidence bounds are presented in brackets and are two-way clustered at health facility and month. The analysis excludes all observations where a stock-out was recorded. Descriptions of control variables, and their pairwise correlations and summary statistics are presented in Tables A2, A3, and A4 of the Appendix, respectively.

Table A8. Estimation Results Across Different Measurements of the Dependent Variable: Effect of Inventory Management Training Program on Contraceptive Stock-Outs

	Dependent Variable: Contraceptive Stock-Out		
	LMIS Data	**Magpi Data**	**Baseline-Endline Survey Data**
	(1)	**(2)**	**(3)**
Training	**–0.0652** [–0.1073, –0.0232]	**–0.0719** [–0.1156, –0.0282]	**–0.1050** [–0.1772, –0.0328]
Observations	1,132,377	764	697

Notes: 95% confidence bounds are presented in brackets. All models include Health Facility FE. See section 3 of the manuscript for details surrounding the estimation approach in column 1 (LMIS Data). See Appendix A8 for details surrounding the estimation approach in columns 2 and 3 (Magpi Data, Baseline-Endline Survey Data).

Figure A1. Example of a Stock Card Used by Frontline Health Workers in Indonesia


[Stock Card]
KARTU STOK

[Reallocation level: 5.0 months] 5 Bulan 240 vial
[Emergency level: 0.5 months] 0,5 Bulan 24 vial

[Product name]
Nama Alokon : Obat Suntik KB I

Kemasan [Unit] : Vial

Tgl [Date]	Dari / Kepada [From/To]	Masuk [In]	Keluar [Out]	Sisa [Balance]	No. Batch [Batch No.]	ED [Expiry]	Ket [Note]
19/05/17	Stok Awal			88	MA270A	05/20	AM
20/05/17	BPM Silvia		5	83	MA270A	05/20	AM
21/05/17	Akseptor		8	75	MA270A		

Source: John Snow Inc.

Figure A2. Visualized Populations of (a) MyChoice Provinces; and MyChoice Districts within (b) Jakarta Province, (c) Jawa Tengah Province, (d) Sulawesi Selatan Province, and (e) Sumatera Utara Province

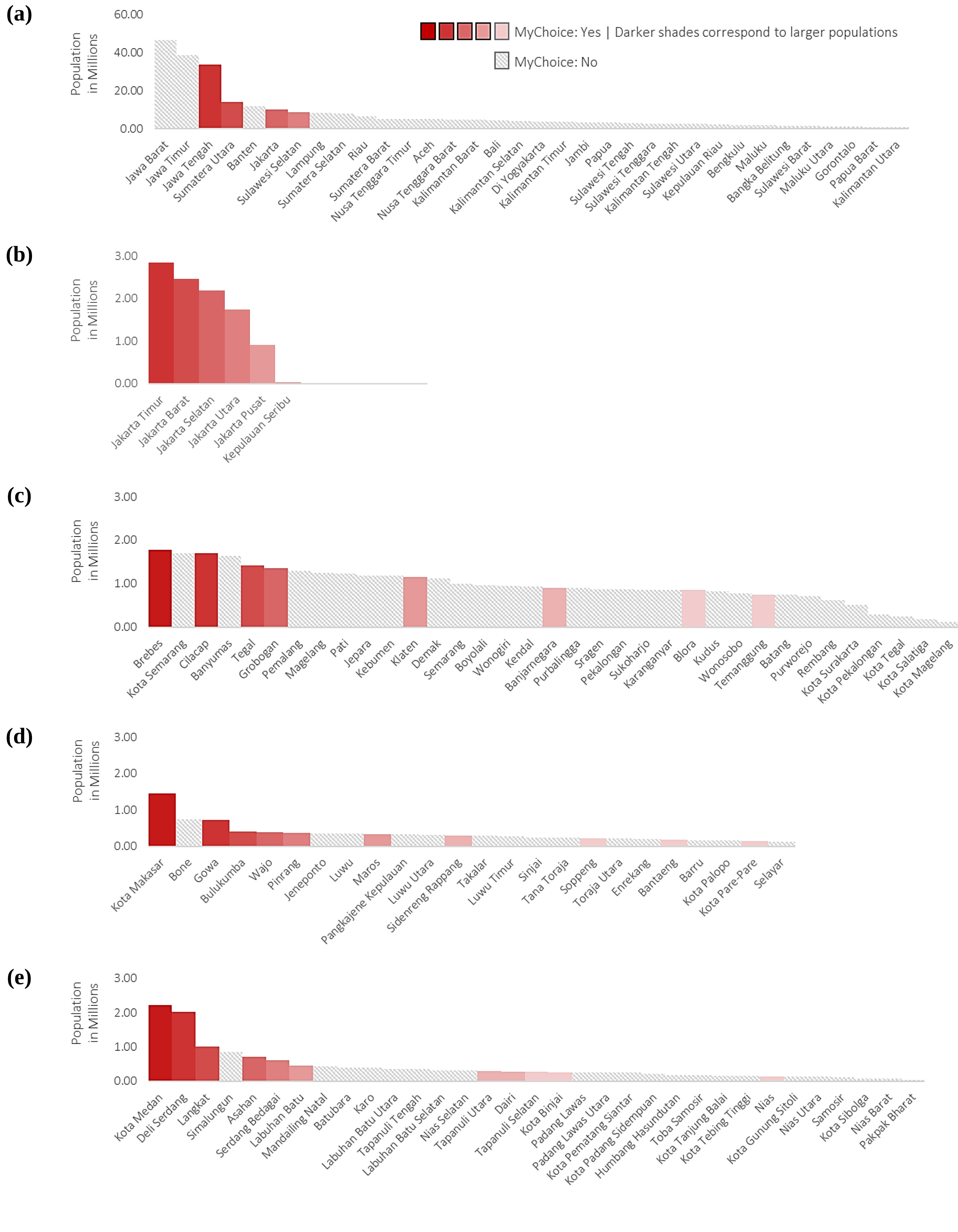


Figure A3. Balance Diagnostics by Treatment Status

Unmatched **Matched**

(a)

(b)

(c)

(d)

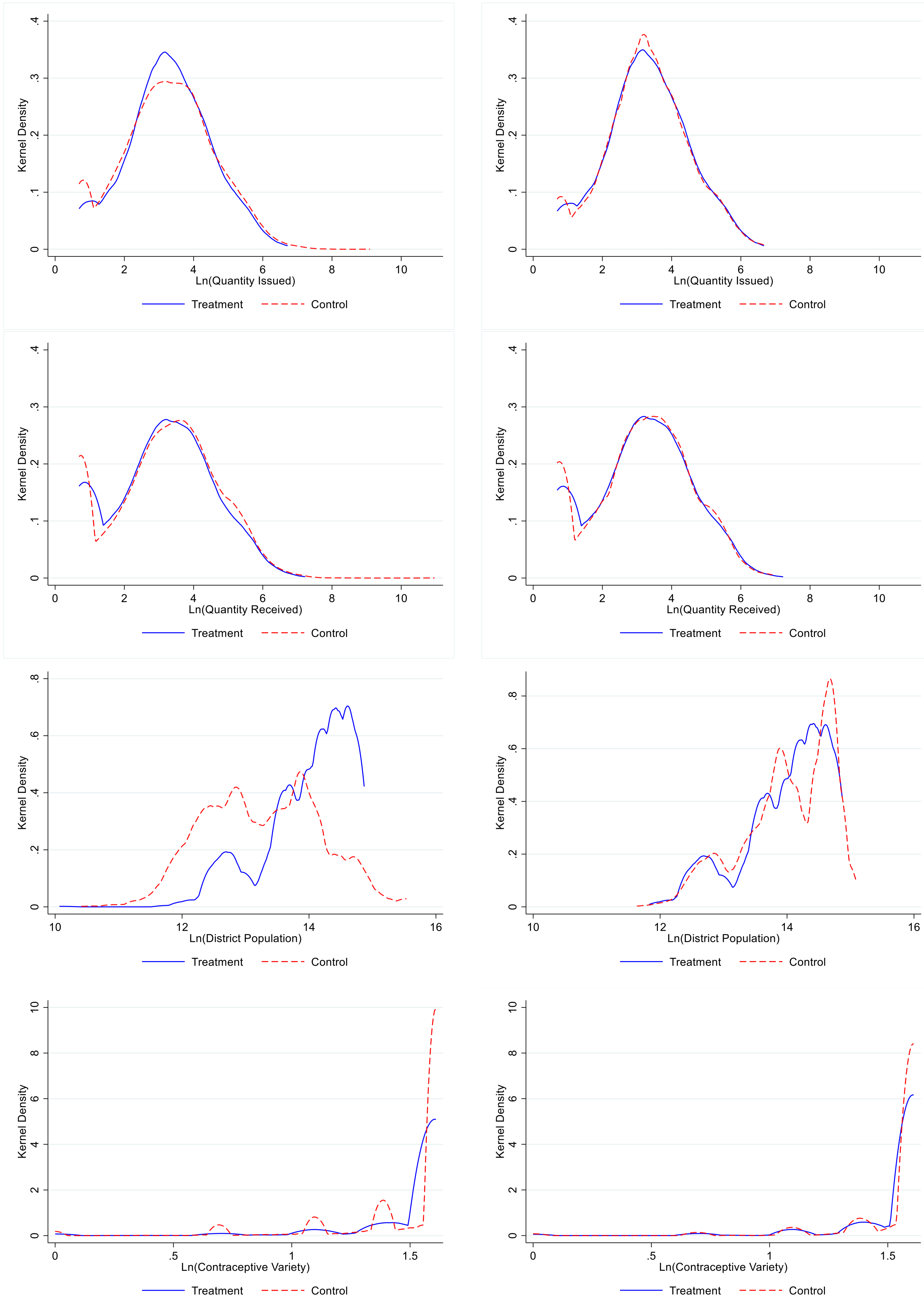


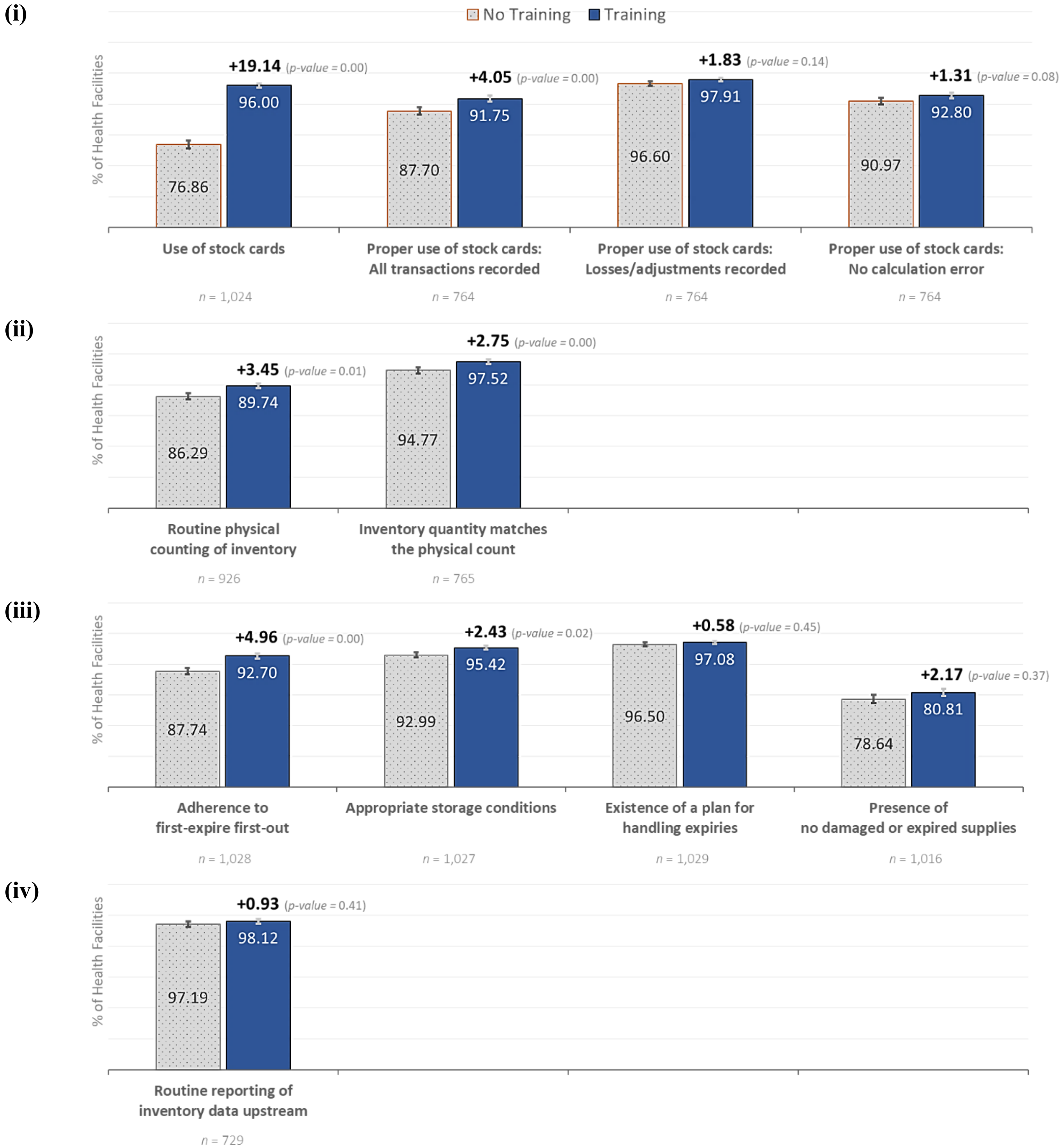
Figure A4. Administering Inventory Management Training to Frontline Health Workers in Indonesia during the MyChoice Project

(a) Onsite Training

(b) Offsite Training

Source: John Snow Inc.

Figure A5. Exploratory Analysis: Effect of Inventory Management Training Program on (i) Stock Card Usage; (ii) Physical Counting of Inventory; (iii) Dispensing and Storage Practices; and (iv) Reporting Inventory Data Upstream



Notes: Error bars are based on 95% confidence levels. Unit of analysis is a health facility. The Magpi data does not allow us to evaluate the impact of the inventory management training program on the fourth training component: reporting inventory data upstream. For this component, we rely instead on "Baseline-Endline" surveys. See Figure A1 for an example of a stock card used by frontline health workers in Indonesia. In Figure A5(iii), "appropriate storage conditions" are defined as health facilities ensuring that contraceptive supplies are stored in clean, dry areas free from insect and rodent infestations, while also keeping them away from sunlight and hazardous chemicals. In Figure A5(iii), the "existence of a plan for handling expiries" is defined as health facilities having at least one of the following plans in place: discarding expired supplies, reporting expiries to a higher authority, or separating and quarantining expired supplies.

Figure A6. Exploratory Mediation Analysis: Proportion of the Inventory Management Training Program's Effect on Contracptive Stock-outs Mediated by (i) Stock Card Usage; (ii) Physical Counting of Inventory; (iii) Dispensing and Storage Practices; and (iv) Reporting Inventory Data Upstream

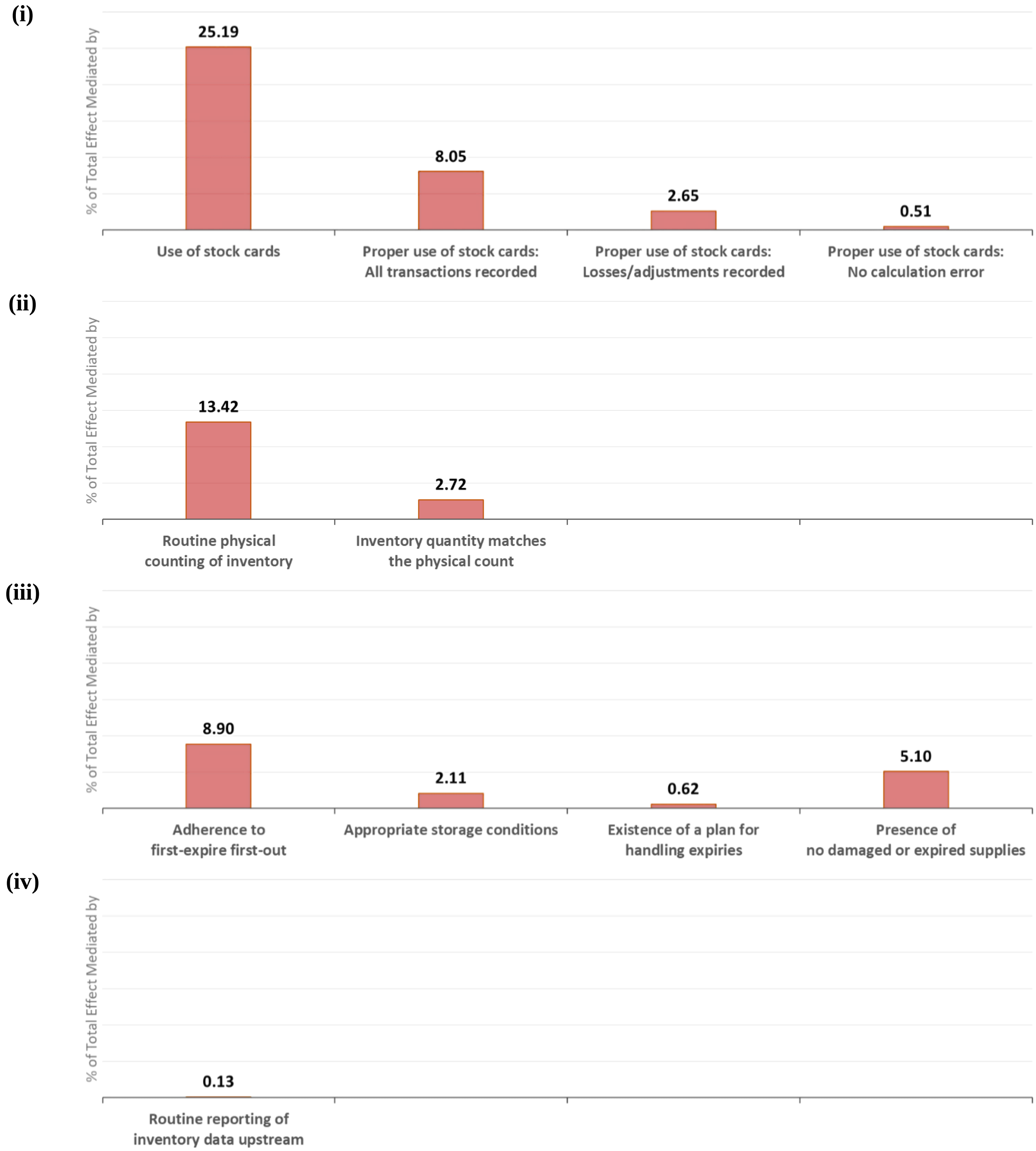
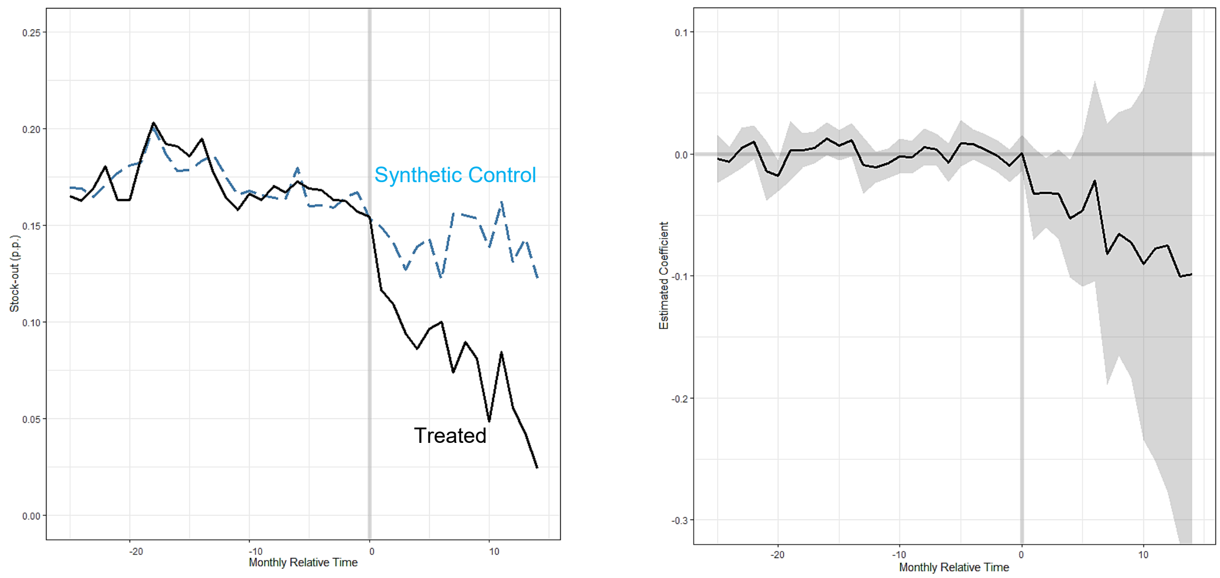


Figure A7. Generalized Synthetic Control Method Results (Xu 2017): Effect of Inventory Management Training Program on Contraceptive Stock-Outs



Notes: 95% confidence bounds are based on cluster-bootstrapped standard errors at the facility-level with 500 replications. The post-treatment window is restricted to time intervals in which at least 50 health facilities received the treatment.

Figure A8. Physical Counting of Inventory by Survey Administrators During Baseline-Endline Survey Data Collection

Source: John Snow Inc.

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