Designing Public Health Supply Chains:
Towards Improving Health Commodity Availability in Developing Countries

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DEDICATION

To My Parents

Irandokht Kargar & Morteza Karimi

&

To My Wife

Jessica Stuart

ABSTRACT

In developing countries, significant resource constraints (e.g., funding and human resource limitations) hamper the effective delivery of health commodities from upstream suppliers to the last-mile, leading to supply chain failures such as "stock-outs." For individuals who are deprived access to basic health commodities due to stock-outs, the consequences can be dire. For example, without reliable access to contraceptives, women may suffer unintended pregnancies, imposing economic and psychological burden, and unsafe abortions that often cause death. While the prevalence of health commodity stock-outs and the consequent repercussions for clients in developing countries are well-documented, there is a paucity of rigorous empirical research into the factors that drive such stock-outs. Focusing on this context, this dissertation aims to (i) empirically evaluate and uncover the factors that contribute to health commodity stock-outs in developing countries by leveraging field data collected from health facilities and using a combination of rigorous econometric and predictive modeling techniques; (ii) generate actionable insights that public health organizations, governments, and donors can use to mitigate the risk of stock-outs in developing countries. Toward addressing these objectives, the first dissertation study focuses on the effect of factors at the *upstream* level of the public health supply chain and explores the impact of the distribution model (i.e., pull vs. push) on the likelihood of stock-outs. At the *downstream* level, the second study investigates the role of practices that health facilities can use to mitigate the likelihood of stock-outs. The third dissertation study also focuses on the *downstream* level of the public health supply chain by examining how the provision of training to frontline healthcare providers can help reduce the likelihood of stock-outs. Taken together, the three dissertation studies serve as the first systematic attempt in the literature to conduct a rigorous empirical evaluation of the factors driving the stock-outs of health commodities in developing countries

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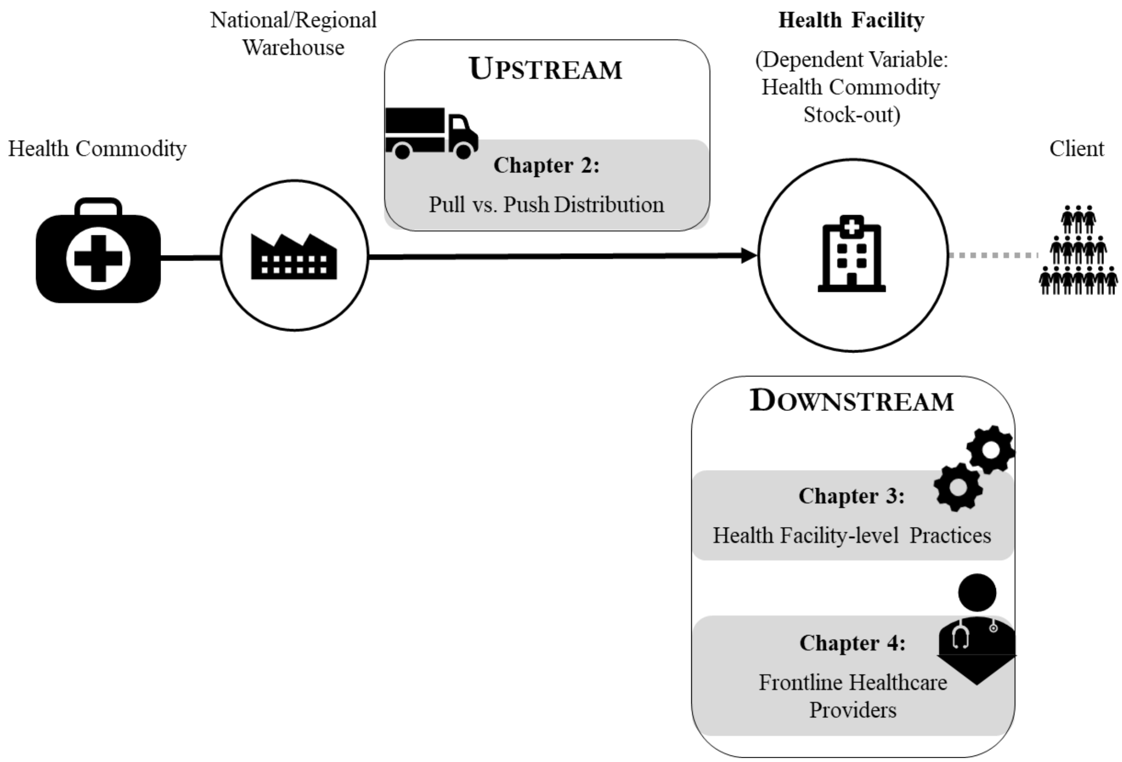
Chapter 1:
Introduction

1.1. Overarching Motivation for the Dissertation

Public health supply chains in developing countries are channels through which health commodities (e.g., antiretrovirals, contraceptives, antimalarials) are distributed from national/regional/district warehouses to health facilities in the last-mile (e.g., hospitals, clinics), with the end objective of improving health outcomes (Rosen 2014, p. 1). In this setting, significant resource constraints (e.g., funding and human resource limitations) hamper the effective delivery of health commodities to the last-mile, leading to supply chain failures such as "stock-outs." For individuals who are deprived access to basic health commodities due to stock-outs, the consequences can be dire. For example, without reliable access to contraceptives, women may suffer unintended pregnancies, imposing economic and psychological burden, and unsafe abortions that often cause death (Darroch et al. 2011). HIV patients unable to obtain antiretrovirals may face delays in treatment initiation and interruptions during the treatment process, subsequently increasing the risk of viral resistance, treatment failure and mortality (Gils et al. 2018).

Evidence from developing countries suggests that stock-outs are a common problem for various types of health commodities (e.g., contraceptives, antiretrovirals, antimalarials) and across geographical contexts from Sub-Saharan Africa to Southeast Asia (see JSI 2016, MSPA 2014, Speizer 2014, Speizer et al. 2012, USAID 2014a, 2016). While the prevalence of health commodity stock-outs and the consequent repercussions for clients in developing countries are well-documented, there is a paucity of rigorous empirical research into the factors that drive such stock-outs. Focusing on this context, this dissertation aims to (i) empirically evaluate and uncover the factors that contribute to health commodity stock-outs in developing countries by leveraging field data collected from health facilities and using a combination of rigorous econometric and predictive modeling techniques; (ii) generate actionable insights that public health organizations, governments and donors can use to mitigate the risk of stock-outs in developing countries. Toward these ends, the first dissertation study focuses on the effect of factors at the *upstream* level of the public health supply chain and explores the impact of the distribution model (i.e., pull vs. push) on the likelihood of stock-outs. At the *downstream* level, the second study investigates the role of practices that health facilities can employ to mitigate the likelihood of stock-outs. The third dissertation study also focuses on the *downstream* level of the public health supply chain by examining how the provision of training to frontline healthcare providers can help reduce the likelihood of stock-outs. Figure 1.1 positions the three dissertation studies within the public health supply chain context. The findings and policy implications from this dissertation are summarized below.

Figure 1.1. An Integrated View of the Dissertation Positioned within the Public Health Supply Chain Context



1.2. Impact of Distribution Model on Health Commodity Stock-outs

In this study, I investigate (i) *the performance implications of two types of distribution models, namely pull and push distribution*, that are used in developing countries to distribute health commodities from upstream locations to health facilities in the last-mile; (ii) *the role of facility-level infrastructural characteristics that can moderate the relationship between distribution model and commodity availability*. In short, pull distribution is defined by the United States Agency for International Development (USAID) as one where health facilities are responsible for monitoring and recording inventory data (*data collection*); transmission of data upstream in the form of resupply orders (*order fulfillment*); and travelling upstream to pick up orders from suppliers (*transportation*). By contrast, a push model is one where the above components are delegated to an external entity that takes responsibility for the delivery of health commodities from suppliers to health facilities, in addition to assisting with the collection and transmission of data upstream.

Focusing on the staggered expansion of a supply chain intervention in Senegal, this research leads to actionable insights for public health supply chains in developing countries:

(a) A transition from pull to push distribution mitigates the likelihood of health commodity stock-outs by 12 percentage points across all health facilities. However, these benefits increase to a 22 percentage point reductions in stock-outs for facilities with *less developed* logistics infrastructure[1]. In the case of health facilities with *less mature* Logistics Management Information System (LMIS) practices[2], the benefits of a transition to push distribution equate to 27 percentage point reductions in stock-outs.

(b) The results indicate that facilities with both *less developed* logistics infrastructure and *less mature* LMIS practices obtain the largest gains following a transition to push distribution. These benefits equate to approximately 60 percentage point reduction in health commodity stock-outs. On the other hand, I find no statistically significant benefits of a transition to push distribution for health facilities with both *more developed* logistics infrastructure and *more mature* LMI*S* practices.

(c) Finally, I examine whether, and to what extent, the benefits of the intervention carry over to the demand-side, where I find that the introduction of push distribution can increase the probability of client satisfaction by 8 percentage points.

Taken together, the findings from this study show that the benefits associated with transitioning from pull to push distribution vary significantly depending upon a health facility's infrastructural characteristics. Given the significant start-up investments and operating costs associated with the push distribution models, these results can be used to inform resource allocation strategies in developing countries.

1.3. Managing Stock-outs Using Health Facility-level Practices

In this study, I use data collected across five developing countries, namely Bangladesh, Haiti, Malawi, Senegal, and Tanzania to address the following research questions: (i) *What factors affect the likelihood of commodity stock-outs at health facilities?* (ii) *What facility-level mitigation mechanisms can be employed to minimize the likelihood of stock-outs?* The findings from empirical analyses indicate that:

[1] Measured in terms of the distance between a facility and its nearest primary road

[2] LMIS refers to a system for reporting inventory data across the public health supply chain. Less mature LMIS is defined in terms of facilities engaged in neither frequent LMIS updating nor the use of electronic LMIS.

(a) Expanding the *range* of commodities (defined as the total number of contraceptive methods offered by a facility) increases the likelihood of stock-outs at both urban and rural health facilities. However, the marginal increase in stock-outs is greater at the resource-constrained rural health facilities, relative to urban facilities.

(b) The implementation of *frequent LMIS updating* leads to a significant reduction in the likelihood of stock-outs at urban facilities, while pairing this practice with *electronic LMIS* does not lead to any additional benefits. However, in rural health facilities, the use of *frequent LMIS updating* and *electronic LMIS* leads to a significant reduction in stock-outs only when these practices are implemented concurrently, and not as standalone practices.

Taken together, the above findings offer nuanced insights into the effects of previously unexplored health facility-level factors that contribute to commodity stock-outs. Further, the results suggest that the impact of the different facility-level practices can vary significantly depending on the type of health facility. Hence, funding allocation strategies need to be tailored to the specific facility type, i.e., urban vs. rural facilities, when undertaking initiatives to reduce the likelihood of stock-outs in public health supply chains.

1.4. Mitigating Stock-outs through Healthcare Provider Training

One major challenges faced by public health supply chains in developing countries is that the frontline healthcare providers (e.g., midwives, nurses) who are primarily in charge of providing clinical services, are also responsible for managing inventories, for which they have not received sufficient training (Wiedenmayer et al. 2015). The lack of adequate training on inventory management could increase the risk of inaccuracies in the inventory data, negatively impact the replenishment process, and drive up the likelihood of stock-outs. Given these challenges, I raise and investigate the following research questions: *Does an improvement in the inventory management skills of healthcare providers, through formal training programs, lead to a meaningful and sustained reduction in health commodity stock-outs at health facilities in developing countries? What factors moderate the relationship between training programs and health commodity stock-outs?* Focusing on the staggered expansion of a supply chain intervention in Indonesia, I evaluate the effect of initial and refresher trainings aimed at improving the inventory management skills of healthcare providers (e.g., using classroom training, paper-based job aids, and video tutorials), and establishing recording procedures that are consistent with the standard operating procedures. The findings from difference-in-differences estimations indicate that:

(a) The provision of *initial trainings* to healthcare providers reduces the likelihood of health commodity stock-outs by an average of 5 percentage points. However, I find that health facilities with higher levels of inventory data inaccuracies experience additional reductions of up to 20% percentage points in stock-outs, when compared to health facilities with lower levels of data inaccuracies prior to the provision of initial trainings.

(b) The provision of *refresher trainings* leads to reductions in the likelihood of stock-outs by an average of 6 percentage points, although the majority of these benefits are obtained by health facilities with lower magnitudes of learning. Particularly, the findings indicate that facilities with lower magnitudes of learning after the provision of initial trainings experience additional reductions of up to 7 percentage points in stock-outs, when compared to health facilities with higher magnitudes of learning.

Taken together, the findings from this study signal significant opportunities to reduce the likelihood of stock-outs in developing countries by allocating resources toward the expansion of training programs at the healthcare provider-level. The remainder of the dissertation is structured as follows. Chapters 2, 3, and 4 provider further details on the separate studies comprising the dissertation. In Chapter 5, I delineate the key theoretical contributions and policy implications for public health supply chains in developing countries.

Chapter 2:
Impact of Distribution Model on Health Commodity Stock-outs

> *"The [United Nations] Sustainable Development Goals cannot be achieved without full provision of sexual and reproductive health for all, including the vital [health] commodities necessary to save lives, and make rights and choices accessible in the most remote and underserved communities"*
>
> *Dr. Natalia Kanem, United Nations Population Fund Executive Director (UNFPA 2018)*

> *"[Push distribution of health commodities] was incredibly promising, but to launch it nationwide would be a massive undertaking. Was it logistically and financially possible? And would we be able to maintain the system after the conclusion of donor support?"*
>
> *Dr. Bocar Mamadou Daff, Senegalese Ministry of Health and Social Action (Daff 2015)*

2.1. Introduction[3]

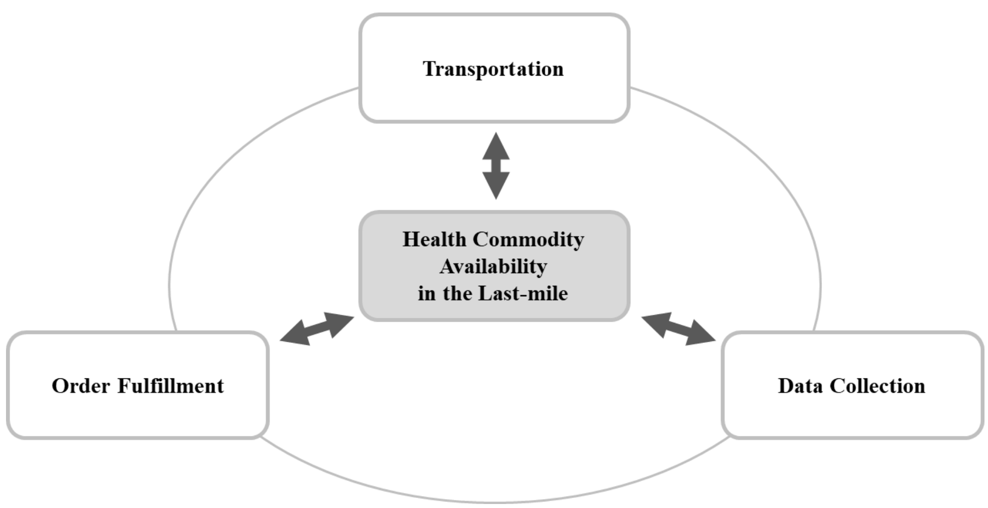
The 2030 Agenda for Sustainable Development calls for ensuring "universal access to sexual and reproductive healthcare services" as well as "access to safe, effective, quality and affordable essential medicines and vaccines for all" (see UN Sustainable Development Goals 3.7 and 3.8, United Nations 2015). While progress has been made over the last two decades toward expanding access to reproductive health supplies (e.g., contraceptives) and other essential health commodities (e.g., antimalarials, HIV medication), significant challenges remain to exist. For example, as of 2019, 190 million women of reproductive age worldwide (or roughly 10% of this population group) have an unmet need for contraceptive methods (United Nations 2019). The problem is particularly acute for countries in Sub-Saharan Africa, with several countries facing upwards of 20% unmet need for contraceptive methods. This presents a substantial barrier to achieving many of the UN Sustainable Development Goals (SDGs) since access to family planning is not only essential to women's reproductive rights and preventing unintended pregnancies, but also to improving the health and well-being of children (UN SDG 3.2) and reducing maternal mortality rates (UN SDG 3.1).

The lack of access to health commodities in developing countries is driven by factors related to both the demand-side (e.g., awareness issues) and the supply-side. On the supply-side, the focus of this study, one critical barrier to access is the stock-outs of health commodities at health facilities

[3] A paper based on this study is co-authored with Dr. Anant Mishra, Dr. Karthik Natarajan, and Dr. Kingshuk Sinha from the Carlson School of Management, University of Minnesota.

in the last-mile (e.g., at hospitals and health clinics; see Kraiselburd and Yadav 2013, Yadav 2015). For example, a majority of surveyed health facilities in Kenya, Nigeria and Senegal experienced the stock-out of at least one contraceptive method in the year preceding the survey visits (Speizer et al. 2012). In this context, an important factor that could affect the physical availability of health commodities is the *distribution model (pull vs. push)* used to deliver health supplies from upstream locations to the last-mile. As noted in Chapter 1, the most commonly used distribution model across developing countries is what is known as a *pull* distribution in the public health sector (Yadav et al. 2011). Under this distribution model, health workers at health facilities are responsible for carrying out the key administrative elements of the *logistics cycle*, a framework developed by the United States Agency for International Development (USAID) that outlines the building blocks of health commodity management in the last-mile (see Figure 2.1). The elements of the logistics cycle include (i) tracking and recording inventory data (*data collection*), (ii) transmission of resupply orders upstream (*order fulfillment*), and (iii) picking up supplies from upstream locations (*transportation*) (USAID 2011c, Yadav et al. 2011). In this context, an important drawback of pull distribution is that the health workers, whose primary roles are to provide clinical services, are not equipped with the necessary skills and resources to effectively and efficiently carry out the administrative elements of the logistics cycle framework.

Figure 2.1. The "Logistics Cycle in the Last-mile" Framework; Adapted from USAID (2011c)

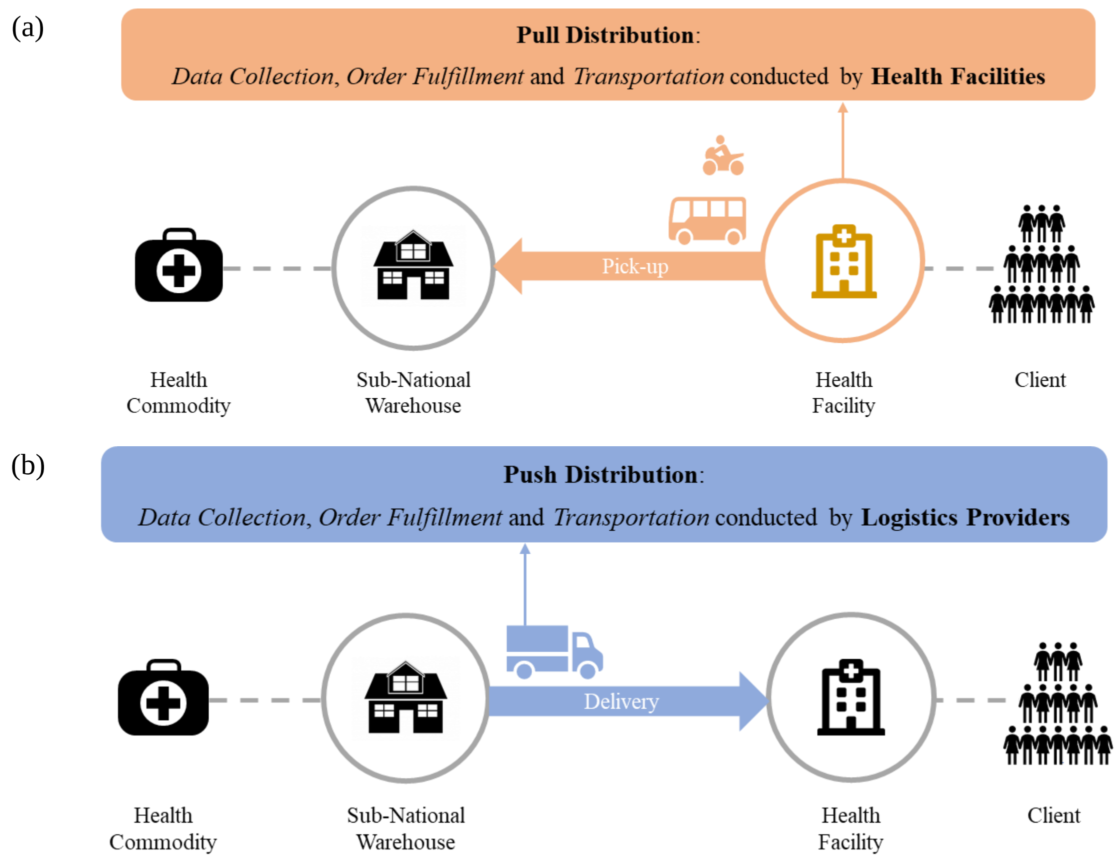


For instance, health workers in developing countries are typically not well-trained in the inventory management of health commodities (Waako et al. 2009, WHO 2006). The lack of sufficient training can negatively impact the *data collection* process and lead to inaccuracies in inventory records and ordered supply amounts, thereby increasing the risk of a supply-demand mismatch. In addition, health facilities in developing countries often use paper-based systems to keep track of available inventory, and the information contained in such hardcopy reports is typically transmitted to upstream supply locations either by mail or in-person (USAID 2011a). Given the inherent infrastructural challenges in developing countries (e.g., lack of access to roads), this often leads to uncertainty and delays in the *order fulfillment* process, exacerbating the supply-demand mismatch. Finally, health facilities in developing countries frequently rely on ad-hoc modes of transport (e.g., bikes, public transport) in order to pick-up supplies from upstream locations. This, combined with other resource constraints faced by health facilities such as a limited access to developed logistics infrastructure (e.g., well-maintained roads) can negatively impact the effectiveness and efficiency of the *transportation* process (Berenguer et al. 2016, McCoy and Lee 2014). Taken together, the above challenges associated with pull distribution in developing countries lead to inaccuracies in the inventory records and increased supply lead times, both of which could contribute to the stock-outs of health commodities at last-mile facilities.

To mitigate these challenges and ensure reliable access to essential health commodities as outlined in UN SDGs 3.7 and 3.8, an alternative distribution model has been introduced in the public health supply chains of several developing countries. This model, referred to as *push* distribution within the public health sector, utilizes trained logistics providers (LPs) to carry out the different elements of the logistics cycle framework, i.e., data collection, order fulfillment and transportation (Daff et al. 2014, USAID 2011c). As a result, health workers are not required to travel upstream to pick up health supplies since these supplies are delivered to the health facilities by the LPs. Upon visiting a facility to deliver supplies, LPs also check the accuracy of data collected by health workers, followed by recording and transmitting the data upstream (Agrawal et al. 2016). In essence, through the use of LPs, the push distribution model has the potential to alleviate some of the difficulties faced by health facilities under pull distribution with respect to executing the different elements of the logistics cycle framework (see Figure 2.2).

Although the transition to a push distribution offers potential benefits, such a distribution model is capital-intensive due to the substantial start-up investments (e.g., obtaining delivery vehicles, optimizing delivery routes) and operating costs (e.g., fuel and maintenance, see USAID 2008). For instance, Daff et al. (2014) estimated that the operating costs associated with the push distribution of contraceptive methods in Senegal was equivalent to 11% of the annual national spending on contraceptive procurement. Given the severe resource constraints faced by the public health sector in developing countries (Kazaz et al. 2016), it is critical to ensure that the resources allocated towards transitioning to and operating a push distribution model yield commensurate benefits that justify the substantial financial commitments. Hence, for policymakers and health facilities in developing countries, identifying the circumstances under which the transition to push distribution is beneficial (and when it is not) is particularly important. However, a review of prior studies — relating to operations management in public health and not-for-profit settings (e.g., Gallien et al. 2017, Natarajan and Swaminathan 2014, Taylor and Xiao 2014) as well as healthcare delivery in underserved communities (e.g., Kohnke et al. 2017, Rowe et al. 2005, 2018) — provides limited understanding of the relative performance of pull vs. push distribution models in the context of public health supply chains in developing countries, and the conditions under which the performance differences are amplified or attenuated. This study fills these gaps in the extant literature as described below.

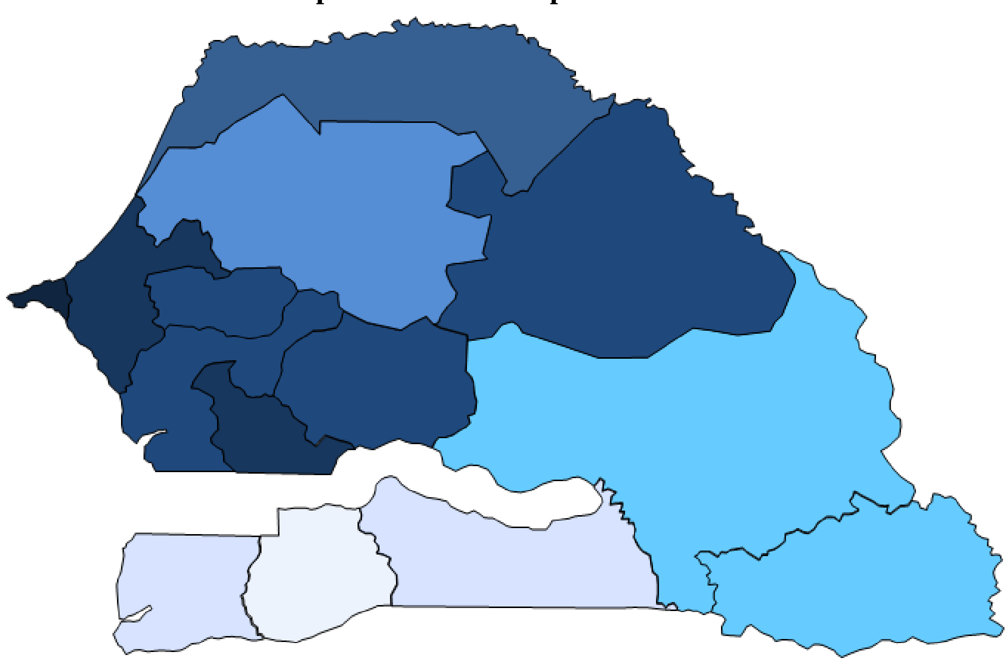
Figure 2.2. Public Health Supply Chains: (a) Pull Distribution vs. (b) Push Distribution



First, *I examine how and to what extent a transition to push distribution (from pull distribution) impacts the likelihood of health commodity stock-outs in public health supply chains in developing countries*. Second, *I evaluate how a health facility's infrastructural characteristics moderate the extent to which the transition to push distribution affects the likelihood of health commodity stock-outs*. In particular, I explore the impact of a health facility's LMIS practices (where LMIS refers to a system used to track and report inventory data) and access to logistics infrastructure on the potential benefits derived from a transition to a push distribution model. I classify a health facility's LMIS practices as *more mature* when the facility engages in either the frequent updating of the inventory records or the use of electronic LMIS, while *less mature* LMIS pertains to facilities engaged in neither of those two practices. A health facility's access to logistics infrastructure is classified as *more developed* when it is located in closer proximity of a primary road (i.e., lower than the median distance in the sample) and *less developed* when it is located farther away from the nearest road (i.e., higher than the median distance in the sample).

Toward addressing the study objectives, I focus on a public health supply chain initiative in Senegal, West Africa where the distribution model used for delivering reproductive health commodities to the last-mile transitioned from pull distribution to push distribution. I use the intervention's staggered expansion across geographic regions and time (Cavallaro et al. 2016) to identify the effect of the distribution model on health commodity stock-outs (see Figure 2.3). Using data collected from health facilities across Senegal, I conduct difference-in-differences (DID) estimations. The results provide strong empirical evidence that a transition from pull to push distribution significantly lowers the likelihood of health commodity stock-outs in developing countries. I observe a 12-percentage point reduction, on average, in the probability of commodity stock-outs across all health facilities following a transition from pull to push distribution. However, this effect varies considerably based on the maturity of a health facility's LMIS practices and access to developed logistics infrastructure.

Figure 2.3. Staggered Expansion of Push Distribution across Senegal, West Africa. Darker-shaded Areas Correspond to Earlier Expansion of the Intervention



In particular, I find that the transition to push distribution leads to significantly larger benefits for facilities with less mature LMIS practices (27 percentage point reduction in the likelihood of stock-outs), compared to those with more mature LMIS practices (8 percentage point reduction in the likelihood of stock-outs). With regards to the moderating role of logistics infrastructure, the results suggest that the transition to push distribution is associated with significant reductions in the likelihood of stock-outs only at health facilities with access to less developed logistics infrastructure (22 percentage point reduction in the likelihood of stock-outs). I observe no significant reductions in the likelihood of stock-outs for facilities that have access to more developed logistics infrastructure. Finally, my investigation into the existence of potential complementarity between the moderating variables reveals that there are no statistically significant benefits of a transition to push distribution for facilities that have more mature LMIS practices and access to more developed logistics infrastructure. In contrast, the benefits proliferate for health facilities with less mature LMIS practices and less developed logistics infrastructure, equating to a 59-percentage point reduction in health commodity stock-outs.

I complement the main analyses with a battery of robustness checks that include the use of relative time models to test for pre-treatment trends, matching technique to create a similar control group for DID analysis, hazard-based duration models to assess the potential for the endogeneity of the intervention, and placebo tests to rule out alternative plausible explanations. The results yield several important insights to public health supply chain managers and policy makers in developing countries, especially as it relates to the effective allocation of limited resources to expand access to essential health commodities and achieve progress towards the UN SDGs 3.7 and 3.8. Particularly, I find that when faced with severe resource constraints, public health managers and policy-makers should allocate the limited resources to transition health facilities with less mature LMIS practices and less developed logistics infrastructure to push distribution. That is, facilities that are severely disadvantaged with respect to data management and logistical capabilities should be given priority. The transition of such health facilities to push distribution has significant implications for expanding access to reproductive health supplies since a 59 percentage point reduction in the likelihood of stock-outs translates into a 38% increase in contraceptive prevalence rate[4], which is one of the key performance indicators tied to UN SDG 3.7. In contrast, I find no benefits of a transition to push distribution for facilities with more mature LMIS practices and more developed

[4] The estimate is based on the "Reducing Stock-outs Impact Calculator" and assumes that a health facility offers nine contraceptive methods, which is the median number of methods offered by a facility in the sample. See https://www.rhsupplies.org/activities-resources/tools/reducing-stockouts-impact-calculator/

logistics infrastructure. Hence, it may not be prudent to allocate scarce resources to transition such facilities to a push distribution model. Finally, the findings also have far-reaching implications that carry over to the demand-side. Specifically, I find that the increased commodity availability owing to the transition to push distribution contributes towards a significant increase in client satisfaction. This could consequently lead to increased commodity use, improved confidence in the public health delivery system and ultimately, better health outcomes in developing countries (Penfold et al. 2013, Rosen 2014).

The remainder of the study is structured as follows. In section 2.2, I review the relevant literature. In section 2.3, I lay the theoretical foundation to develop the study hypotheses. Section 2.4 delineates the empirical approach used in the study including identification strategy, model specification, data and variables. I present the results of the empirical analysis and robustness checks in section 2.5. In section 2.6, I discuss the results of a post hoc analysis that extends the findings of the study to the demand-side. Finally, in section 2.7, I delineate the contributions of the study, discuss the limitations, and highlight avenues for future research.

2.2. Literature Review

This study builds upon two main streams of literature: (i) the literature on managing operations in public health and not-for-profit settings (e.g., Berenguer et al. 2016, Gallien et al. 2017, Kazaz et al. 2016, Leung et al. 2016, Natarajan and Swaminathan 2014, Taylor and Xiao 2014), and (ii) the literature on healthcare delivery in underserved communities (e.g., Githinji et al. 2013, Kohnke et al. 2017, Ngo et al. 2017, Rowe et al. 2005, 2018, Zurovac et al. 2011) where access to quality health commodities and services is hindered by a number of demand-side and supply-side barriers. I review these literature streams below.

2.2.1. Managing Operations in Public Health and Not-for-Profit Settings

The first stream related to this study is the literature on managing operations in public health and not-for-profit settings. In this stream, Berenguer et al. (2016) focus on supply chains for delivering reproductive health commodities in Africa and compare the managerial efficiency of country-level healthcare programs. They conclude that socioeconomic factors at the national level (e.g., public health expenditure and logistics capability) can significantly influence program outputs in terms of supply lead times. Focusing on supply chains for delivering essential health commodities in Zambia, Leung et al. (2016) utilize simulation-based models to explore how changes in the inventory management practices can influence health commodity stock-outs. Relatedly, Kazaz et al. (2016) study the effect of supply-side interventions aimed at increasing the availability of artemisinin-based malaria medicine in Sub-Saharan Africa. Other papers in this literature have investigated the relationship between funding constraints and health commodity availability. For example, Gallien et al. (2017) utilize simulation-based models to analyze the impact of disbursement and procurement variability on national drug stock-outs in Africa. Taylor and Xiao (2014) study how a budget-constrained donor should design sales and purchase subsidies in order to improve the sales of a socially-beneficial product (e.g., antimalarial drugs). Natarajan and Swaminathan (2014) model the effect of funding constraints on operating costs and fill rates in the context of inventory management for ready-to-use therapeutic food products in Africa and find that funding delays can have a significant negative impact on service levels and operating costs.

My research fills two important gaps in this literature. First, the vast majority of operations management literature has focused on the performance indicators of public health supply chains at a macro-level. Little attention has been paid to the performance outcomes at the health facility-level and how health supplies are distributed from the national level to the peripheral level. Investigating the link between supply chain distribution strategy (push vs. pull distribution) and product availability at the health facility level is critical since the availability of supplies at the national level does not directly translate into supply availability in the last-mile. For instance, Leung et al. (2016, p. 1) report the widespread prevalence of stock-outs at the health facility level "despite ample inventory being simultaneously available at the national warehouse." Similarly, Lee and Tang (2017) identified the "last-mile delivery" of health products and services in developing countries as a bottleneck hindering the achievement of better health outcomes. Second, the majority of papers in this body of literature are based on either analytical or simulation-based models. The above gaps can be primarily attributed to the historical absence of large-scale, granular, and reliable data at the health facility-level in developing countries. However, this trend has begun to change in recent years with increased appetite for data-driven health policy-making and new developments in data collection technologies (e.g., using mobile devices). Utilizing novel field data collected from health facilities in a developing country, this study addresses these gaps by uncovering empirically-grounded insights into the magnitude of potential benefits derived by transitioning from pull distribution to push distribution.

2.2.2. Healthcare Delivery in Underserved Communities

With regards to research on healthcare delivery, while both demand-side and supply-side factors play a vital role in determining the quality of healthcare services, my focus in this study is on the supply-side. Hence, I restrict the discussion to the papers that address the supply-side barriers. In this domain, the existence of provider-related barriers (e.g., absenteeism, lack of skills) can hinder clients' access to quality healthcare services. For example, Kohnke et al. (2017) discuss a variety of short-term (e.g., lecture sessions) and long-term training schemes (e.g., residency programs) aimed at promoting the skills of healthcare providers. Rowe et al. (2018) and Rowe et al. (2005) provide extensive reviews of the strategies that can be used in order to mitigate provider-related barriers in resource-constrained settings and find that the adoption of multifaceted interventions (e.g., training and supervision combined) might be more effective than single interventions (e.g., training only). Focusing on Kenya, Zurovac et al. (2011) find that the use of text messaging reminders can significantly improve the adherence of healthcare providers to national malaria treatment guidelines. Ngo et al. (2017) study the Rwandan national pay-for-performance (P4P) intervention, which incentivizes healthcare providers to deliver quality services and achieve targeted outcomes, and find that the intervention was successful in increasing staff presence at health facilities.

Another key supply-side barrier is related to the physical unavailability of services and commodities at health facilities. The physical unavailability of health commodities, frequently manifested in the form of stock-outs, can be primarily attributed to last-mile challenges associated with the distribution of health commodities to health facilities in developing countries. Examples of these challenges include logistics infrastructure issues (e.g., lack of access to roads) and poor data management practices across the public health supply chain. Toward addressing the physical availability barriers, Githinji et al. (2013) explore the impact of an intervention in rural Kenya surrounding the use of SMS messaging in order to electronically transmit data from health facilities to upstream warehouses. They find that the intervention successfully reduced antimalarial stock-outs in the last-mile due to the increased visibility of downstream consumption. Toward addressing physical availability barriers, Daff et al. (2014) compare the performance of pull and push distribution models in Senegal using a combination of descriptive statistics and field interviews. They conclude that a transition to push distribution has the potential to increase the availability of health commodities. Relatedly, Bukuluki et al. (2013) use data from field interviews and conclude that a transition from pull to push distribution can mitigate medicine stock-outs in Ugandan health facilities.

This study is different from the above papers in two important ways. First, most studies investigating the performance implications of pull vs. push distribution are conducted in small-scale settings (e.g., pilot studies) or based on qualitative and anecdotal insights. Therefore, whether the transition from pull to push distribution has a transformational impact on public health supply chains in developing countries, and if so, the magnitude of potential benefits provided by such a transition, remains unknown. Second, the extant literature has not rigorously examined the contingencies at the facility level (e.g., the quality of logistics infrastructure surrounding a health facility, data management practices of facilities) that could affect the performance implications of transitioning to push distribution. This study addresses each of the above-mentioned gaps in the literature on healthcare delivery in underserved communities. To the best of my knowledge, this study represents an important first step within this stream of literature to carry out a rigorous empirical evaluation using large scale data from health facilities within a developing country.

2.3. Hypotheses Development

2.3.1. Pull vs. Push Public Health Supply Chains

As highlighted earlier, under pull distribution, the main components of the logistics cycle framework, i.e., *data collection*, *order fulfillment* and *transportation*, are carried out by health facilities. *Data collection* deals with the tracking of inventory data on what are known as "stock cards," (Leung et al. 2016) with the purpose of maintaining a continuous and accurate record of health commodities. This includes updating of the records (i.e., stock cards) any time there is a change in the quantity of supplies (e.g., when commodities are received from upstream supply locations or when they are dispensed to clients). The inventory records maintained by health facilities form the basis for resupply calculations when placing orders with upstream locations. However, health facilities in developing countries may not be equipped with the required resources to collect and track inventory data in an effective and efficient manner. For example, in pull distribution, inventory data are collected and maintained by the same health workers who are primarily in charge of providing clinical services and typically lack sufficient training in managing inventory data (Bradley and McAuliffe 2009). More importantly, the use of paper-based inventory records, the most common form of data collection at health facilities in developing countries, can make the data aggregation and resupply calculations time-consuming and prone to human error (Leung et al. 2016). This, in turn, could lead to a mismatch between supply and demand and increase the risk of health commodity stock-outs.

With regards to the *order fulfillment* component, inventory and resupply orders data are typically transmitted to upstream locations using hardcopy reports that are either hand-delivered or sent via mail (USAID 2011a). Following order fulfillment, the *transportation* component of the logistics cycle framework comes into play wherein health facilities need to travel upstream to "pick up" the ordered commodities. Under pull distribution, health workers are responsible for both order fulfillment and transportation, creating significant challenges to the timeliness and predictability of supply refills. For example, given the severe resource constraints faced by health facilities in developing countries (e.g., lack of access to roads, reliable transportation options), facilities often find it difficult to identify and allocate the required transportation means to travel upstream in order to deliver inventory reports and collect the ordered supplies. In addition, health workers might also need to reconcile the opportunity costs of commuting upstream with the provision of clinical services (USAID 2011c). These challenges can reduce the visibility of downstream consumption and amplify supply lead-times, thereby increasing the potential for commodity stock-outs at health facilities.

In contrast to pull distribution, the key responsibilities of data collection, order fulfillment and transportation are delegated to trained logistics providers (LPs) in a push distribution model. The LPs are tasked with the transportation and delivery of commodities to health facilities on a scheduled basis, thereby eliminating the need for health facilities to pick up supplies from upstream locations. Upon arrival at a health facility, the LPs verify the accuracy of information recorded on stock cards and make necessary adjustments to improve the accuracy of data collection. This is followed by transmitting the verified inventory data to upstream supply locations, enhancing the visibility of downstream consumption. The LPs also calculate the resupply amounts and "top up" the inventories at the health facilities based on preset max-min levels for each commodity (Leung et al. 2016, Purcell 2015). Taken together, the activities carried out by the LPs under push distribution can lead to improved data accuracy, enhanced supply chain visibility and more timely replenishments, resulting in the increased availability of commodities at health facilities. Based on these arguments, I propose that a transition from pull distribution to push distribution in public health supply chains is likely to be associated with a reduction in the stock-outs of health commodities:

HYPOTHESIS 2.1 (H2.1): *Push distribution of health commodities in public health supply chains, vis-a-vis pull distribution, is associated with a decrease in the likelihood of stock-outs.*

Notwithstanding the potential benefits of push distribution in reducing stock-outs in public health supply chains, one particular drawback of such a distribution is the need for considerable start-up investments (e.g., acquiring delivery vehicles, training) and operating costs (e.g., fuel, maintenance, supervision, see Sarley et al. 2010). Given the tight funding constraints faced by the public health sector in developing countries (Kazaz et al. 2016, RHSC 2015), the significant costs associated with push distribution need to be considered by public health managers when evaluating whether to transition health facilities from pull distribution to push distribution. Hence, the subsequent hypotheses are aimed at identifying facility-level infrastructural characteristics under which the benefits of a transition from pull to push distribution are likely to be larger. I first explore how a health facility's LMIS practices (as a reminder, the LMIS is a platform used by health facilities to record and report inventory data across the public health supply chain) and access to logistics infrastructure moderate the relationship between the distribution model and health commodity stock-outs. In addition, I analyze whether there are complementarities between the LMIS practices and logistics infrastructure in terms of their moderating effects.

2.3.2. Role of Logistics Management Information System (LMIS) Practices

Health facilities are considered the "originating point" for collecting inventory data in public health supply chains (data collection), before these data are transmitted upstream in the form of resupply orders (order fulfillment, see USAID 2011c). In order for such data to translate into informed resupply calculations and order refills, inventory data need to be accurate and transmitted upstream in a timely manner (Githinji et al. 2013). However, anecdotal evidence from developing countries suggests that health facilities reliant on pull distribution face significant difficulties in ensuring the accuracy of data collection and the timeliness of order fulfillment. For example, the proportion of health facilities that had fully accurate LMIS records, when matched against physical inventory counts, was on average below 50% across sampled facilities in Indonesia (JSI 2016) and Nigeria (Bock et al. 2011). In addition, Bock et al. (2011) found that health facilities faced significant difficulties when transmitting their inventory reports upstream, attributable in part to a lack of access to developed logistics infrastructure and reliable transportation options.

In order to enhance the accuracy and timeliness of inventory data under pull distribution, two LMIS-related practices namely, (i) the frequent updating of LMIS records and (ii) the use of electronic LMIS, have been advocated in the public health domain. First, health facilities are encouraged to update their LMIS records as soon as there is a change in the inventory level of health commodities, either due to dispensing of products to clients or the replenishment of supplies. Frequent updating of the LMIS records ensures that facilities have access to more up-to-date inventory information and do not lose track of the amount of stock on-hand (see JSI 2015). The second LMIS practice advocated in pull distribution is the utilization of an electronic LMIS, vis-à-vis paper-based LMIS, to manage inventories. Paper-based LMIS involves aggregating data and performing resupply calculations manually, which can be time-consuming and prone to human error. In contrast, an electronic LMIS enables automated resupply calculations and rapid aggregation of data while ensuring mathematical precision (USAID 2011b). An added benefit of electronic LMIS is that it shifts the burden of order fulfillment away from health facilities by enabling the rapid transmission of inventory and order data upstream, which would otherwise have been transmitted in hardcopy format (either via mail or through direct hand delivery).

The adoption of the two LMIS-related practices discussed above has the potential to improve the accuracy and timeliness of inventory information under a pull distribution. It is worth noting that transitioning health facilities from pull distribution to push distribution can also lead to qualitatively similar benefits, i.e., improved accuracy and timeliness of inventory information. This is because, under push distribution, the delivery teams verify the accuracy of information recorded on stock cards and make necessary adjustments, thereby enhancing data accuracy. Furthermore, the delivery teams document and transmit the inventory data in electronic form, ensuring visibility and timely transmission of data across the public health supply chain. As a result, I argue that facilities that implement the two LMIS practices mentioned above (i.e., defined as more mature LMIS practices) may not benefit as much by transitioning to push distribution, relative to health facilities that are engaged in neither of the above LMIS practices (i.e., defined as less mature LMIS practices). Formally, I state the following hypothesis:

HYPOTHESIS 2.2 (H2.2): *Push distribution of health commodities in public health supply chains is associated with a greater decrease in the likelihood of stock-outs at health facilities with less mature LMIS practices, relative to facilities with more mature LMIS practices.*

2.3.3. Role of Logistics Infrastructure

Logistics infrastructure refers to physical components such as roads and transportation resources that can facilitate the effective and efficient distribution of health commodities within a country/region (Berenguer et al. 2016, World Bank 2018). In general, health facilities in developing countries suffer from a lack of access to adequate logistics infrastructure (Lee and Tang 2017), and this can pose significant hurdles to the order fulfillment and transportation of commodities under pull distribution (Yadav et al. 2011). For instance, public transportation is the most common form of transport used by health facilities in developing countries to carry hardcopy inventory reports upstream and pick up supplies from those locations (Bock et al. 2011, Kolapo et al. 2009). While public transportation is generally not considered reliable for connecting with upstream locations, the challenges are compounded for health facilities located in remote areas since access to public transportation is often more restricted for such facilities.

In addition to public transportation, health facilities might also utilize their own vehicles (e.g., ambulance, motorbikes, etc.) to connect with upstream locations (Kamunyori and Stewart 2013). These vehicles are likely to be shared across different health services and are not specifically designated for the transportation of health commodities. As such, the vehicles may not be available as and when needed to transport health commodities from upstream locations, resulting in uncertainty and delays in replenishment. Even when the vehicles are available, due to the insufficient logistics infrastructure surrounding health facilities in developing countries, health workers often travel upstream on roads that are in poor condition (i.e., dirt roads), leading to a substantial increase in the travel times (Lee and Tang 2017, McCoy and Lee 2014). Finally, one of the unique aspects of the last-mile in developing countries is that "road infrastructure typically worsens as one travels farther from the point of resupply" (USAID 2011c, p. 2). Consequently, health workers at remote facilities not only commute on roads that are in poor condition, but they might also have to travel longer distances on such roads to access the resupply locations, exacerbating the delays and uncertainty in supply lead times. In sum, under a pull distribution model, health facilities that do not have access to adequate logistics infrastructure face substantial challenges with respect to the effective order fulfillment and transportation of supplies. This has the potential to amplify supply lead times and increase the risk of health commodity stock-outs. In contrast, health facilities that have access to more developed logistics infrastructure are likely to face fewer challenges in connecting with and transporting supplies from upstream locations. As such, these facilities are unlikely to benefit as much from a transition to push distribution, relative to health facilities that do not have access to well-developed logistics infrastructure. I summarize the above discussion in the following hypothesis:

> HYPOTHESIS 2.3 (H2.3): *Push distribution of health commodities in public health supply chains is associated with a larger decrease in the likelihood of stock-outs at health facilities with less developed logistics infrastructure, relative to facilities with more developed logistics infrastructure.*

2.3.4. Complementarity of LMIS Practices and Logistics Infrastructure

As discussed earlier, facilities served using pull distribution experience significant hurdles in carrying out the activities associated with the logistics cycle framework (i.e., data collection, order fulfillment and transportation), which can adversely influence the availability of health commodities. However, I discussed the potential of two LMIS practices, namely frequent updating of LMIS records and the use of electronic LMIS, to attenuate the shortcomings faced by health facilities under pull distribution when executing the *data collection* and *order fulfillment* of health commodities. Moreover, I also argued that having access to developed logistics infrastructure can dampen some of the limitations experienced by facilities with respect to *order fulfillment* and *transportation* of commodities under pull distribution (see section 2.3.3). Taken together, the concurrent implementation of the above LMIS practices and accessibility of developed logistics infrastructure can help facilities served using pull distribution to weather some of the challenges associated with *data collection*, *order fulfillment* and *transportation* of supplies. As a result, facilities with more mature LMIS practices and access to more developed logistics infrastructure are not likely to benefit as much from transitioning to push distribution (relative to health facilities with less mature LMIS practices and less developed logistics infrastructure). For these health facilities, a transition from pull to push distribution is likely to be less effective in reducing the likelihood of stock-outs. I formalize the above discussion in the following hypothesis:

HYPOTHESIS 2.4 (H2.4): *Push distribution of health commodities in public health supply chains is associated with a larger decrease in the likelihood of stock-outs at health facilities with less mature LMIS practices and less developed logistics infrastructure, relative to facilities with more mature LMIS practices and more developed logistics infrastructure.*

2.4. Empirical Approach

2.4.1. Difference-in-Differences (DID) Estimation

In order to empirically test the hypotheses proposed in this chapter, I focus on a public health supply chain intervention in Senegal, West Africa where the distribution of health commodities switched from pull distribution to push distribution. The supply chain intervention was rolled-out starting in 2012. Between 2012 and 2015, the intervention expanded in a staggered manner to more than 1,400 public health facilities across different regions of Senegal, serving 85% of the population (see Table 2.1, Cavallaro et al. 2016). The intervention is not likely to be endogenous to health facilities for two main reasons. First, the decision to switch from pull to push distribution is not made by health facilities themselves, but rather by a higher authority, i.e., the Senegalese Ministry of Health. In other words, facilities cannot self-select into the intervention (e.g., based on their operational performance). Second, all health facilities were transitioned from pull to push distribution, regardless of their operational performance, LMIS practices and the availability/quality of logistics infrastructure surrounding a facility. Hence, the staggered expansion of the intervention across regions is not likely to be endogenous in the empirical estimation.

In this study, I exploit the staggered exogenous expansion across regions and time as the basis for identifying the effects of push distribution (vs. pull distribution) on health commodity stock-outs. This setting allows for the application of a generalized DID specification (Angrist and Pischke 2008). Consistent with prior research utilizing DID models in the context of staggered exogenous expansions (e.g., Dhanorkar 2019, Greenwood and Agarwal 2016), I model the likelihood of health commodity stock-outs using the following specification:

$$Ln\left[\frac{Pr\left(Stock-Out_{ijrt}=1 \mid X_{ijrt}\right)}{1-Pr\left(Stock-Out_{ijrt}=1 \mid X_{ijrt}\right)}\right] = \beta_0 + \lambda.X_{CL} + \alpha.Region\ FE_r + \gamma.Time\ FE_t + \beta.Push_{rt} + \varepsilon_{ijrt} \tag{2.1}$$

The specification in Equation (2.1) is based on a logistic regression model (binary outcome; see section 2.4.2 for a detailed discussion), where ε_{ijrt} is the error term, and i, j, r, and t denote commodity type *i* at health facility *j* located in region *r* and time *t*. $Region\ FE_r$ is a vector of region fixed effects. $Time\ FE_t$ pertains to the vector of year and month fixed effects, accounting for common variability in stock-outs over years and across seasons. I incorporate additional control variables in the vector X_{CL} (see section 2.4.2. for details). $Push_{rt}$ is the binary indicator for the presence of the intervention, taking the value of 1 following push expansion within a geographic area, and 0 otherwise. I consider all facilities in a given region as treated after the push intervention is rolled-out to that specific region. On the other hand, all facilities in a given region serve as the control group before the intervention's expansion to that region.

Table 2.1. Staggered Expansion of Push Distribution across Senegal, West Africa

Push Expansion Date	**Region**
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	*Sediou*

The coefficient β is the DID estimate of the overall effect of the push intervention on health commodity stock-outs (i.e., testing for H2.1). I test the rest of the hypotheses in this chapter (i.e., H2.2 through H2.4) by running subgroup analyses. Particularly, in order to test for H2.2, I create subgroups of less mature vs. more mature LMIS practices and compare the coefficients of $Push_{rt}$

across the subgroups using a Wald test. With respect to H2.3, I compare the coefficients of $Push_{rt}$ across the subgroups of less developed vs. more developed logistics infrastructure. Finally, I pursue a similar procedure to test for H2.4 by building two subgroups representing facilities with (i) more mature LMIS and more developed logistics infrastructure vs. (ii) less mature LMIS and less developed logistics infrastructure, followed by a Wald test to compare the coefficients across the subgroups. To account for correlated standard errors across commodity types within a facility, I use robust standard errors clustered at the facility-level for all specification models.

Throughout the analysis, I weight the observations using the survey weights (detailed description of the survey data used in this study provided below) corresponding to the "inverse probability of selection" to account for potential under-representation or over-representation of certain types of health facilities in the sample (Solon et al. 2015).[5] This approach limits the potential for selection bias that might arise during the sampling procedure. Additionally, I check the sensitivity of the results to identifying assumptions of DID estimation and complement the main analyses with multiple robustness checks that include relative time models, matching techniques, expansion endogeneity tests and a validation check.

2.4.2. Data and Variables

I perform the empirical analysis using data collected by the Demographic and Health Surveys (DHS) program. The DHS program is funded by USAID and implemented by ICF International. ICF's main objective is to assist decision-makers in developing countries with the collection and use of nationally representative data to monitor population, health, nutrition, and service delivery outcomes (ICF International 2014). Toward this end, the DHS program utilizes a range of qualitative and quantitative data collection tools, each designed to capture specific indicators at different levels. At the household and individual level, surveys and interviews are used to capture key indicators related to demographic characteristics, childhood mortality, fertility preferences, and maternal health, among others (DHS 2014). At the health facility level, which is the focus of this study, the program utilizes the Service Provision Assessment (SPA) survey to obtain a comprehensive understanding of the general and specific service readiness of health facilities. General readiness is defined as the availability of basic amenities and equipment at the facility such as water, electricity, stethoscopes, and weighing scales. Specific readiness pertains to the availability of essential supplies specific to a particular health service (e.g., contraceptives in the context of reproductive health; see MSPA 2014 and SPA 2016).

[5] Note that the results remain consistent even when observations are not weighted.

The SPA readiness indicators are a reliable source of data frequently used by public health organizations including USAID and the WHO to inform decision-making and policy-making (ICF International 2014, WHO 2013). SPA surveys are pre-tested to identify potential problems before they are administered in the field using mobile devices. Following the pre-test, survey administrators go through extensive training including lectures, role-plays, and mock interviews. This is done to ensure that they fully understand the survey contents and procedures. Once the survey is administered, program managers review the collected data to identify potential errors and missing information before the data is sent to the country's central office for final review (SPA 2016). Further, facilities are chosen to be included in the survey based on stratified random sampling, making them nationally representative. My study sample consists of 6,285 observations from health facilities located in all regions of Senegal.

Dependent Variable. I focus on the stock-outs of contraceptive methods as the dependent variable of interest. This choice is motivated by three main reasons. First, contraceptives are commonly offered by many last-mile health facilities in developing countries and sought by clients across different socioeconomic and demographic characteristics, therefore forming an integral part of public health supply chains. Second, increasing access to contraceptives is a key focus of the UN SDG 3.7 and furthermore, as mentioned earlier, ensuring reliable access to reproductive health supplies is critical not only to women's sexual health and reproductive rights, but also to improving the health and well-being of children (UN SDG 3.2) and reducing maternal mortality rates (UN SGD 3.1). Finally, within the study timeframe, the push intervention was rolled out primarily to the distribution of contraceptive supplies, for which I was able to obtain accurate roll-out dates as specified in Table 2.1. I capture *Stock-Out* as a binary variable, indicating whether or not a particular contraceptive method was out-of-stock on the day of survey visit. The SPA surveyors assess the availability of health commodities in an objective manner by directly observing them on the shelf, mitigating concerns pertaining to self-reported information. I coded *Stock-Out* as 0 (i.e., in-stock) for contraceptive methods for which surveyors noted that "at least one valid item was observed" or "reported as available, but not observed" (e.g., due to the storage area being inaccessible).[6] I coded *Stock-Out* as 1 (i.e., out-of-stock) for contraceptive methods for which surveyors noted "no valid items observed" (i.e., expired or damaged commodities) or "not available today." Finally, commodities reported to be "never available" were dropped from the sample as they were never offered by the facility.

[6] These cases comprised less than 2% of the observations.

The process of observing the available stock increases the reliability of the data and alleviates potential concerns related to self-reported information (Choi and Ametepi 2013). Furthermore, the approach used in this study to capture stock-outs, i.e., stock-out on the day of assessment, is approved by WHO (Choi and Ametepi 2013, WHO 2013), and is commonly used in surveys that focus on measuring the availability of products and services in public health supply chains within developing countries. Examples of such surveys include the Logistics Indicators Assessment Tool (LIAT) survey administered by USAID (see USAID 2014a, 2016), the Performance Monitoring and Accountability (PMA) program funded by the Gates Foundation (see PMA2020 2017b), and the Access, Bottlenecks, Costs, and Equity (ABCE) project (see ABCE 2017).

Moderating Variables. A facility's LMIS practices is represented using two metrics: (i) *LMIS updating frequency* which takes the value of 1 when facilities update their records on a daily basis, and 0 otherwise; (ii) *electronic LMIS* taking the value of 1 when facilities utilize an electronic LMIS to manage and report inventory data, and 0 in case of paper-based LMIS. I classify a facility's LMIS practices as less mature when the facility employs neither of the above practices (i.e., no frequent updating and no electronic LMIS) and more mature when the facility employs at least one of the mentioned practices.

Further, I measure logistics infrastructure as the Euclidean distance (in kilometers) between each facility and its nearest primary road. To construct this measure, I obtained the Senegalese road network data from OpenStreetMap and paired those data with the GPS coordinates of health facilities collected from the SPA surveys. The choice of *distance to road* to capture logistics infrastructure is grounded in the extant academic (e.g., Gabrysch and Campbell 2009) and practitioner literature (USAID 2014b). I use the median value of distance to split the samples into more developed logistics infrastructure (i.e., lower than median value of 7 km) vs. less developed logistics infrastructure (i.e., higher than median value of 7 km).

Control Variables. In addition to *Region*, *Month* and *Year* fixed effects, I control for multiple facility-level and commodity-level factors that have the potential to impact the likelihood of stock-outs. Accordingly, I include *Commodity Type* dummies representing male/female condoms, combined pills, progestin-only pills, combined injectables, progestin-only injectables, intrauterine devices (IUD), implants, emergency contraceptives and cycle beads. Another commodity-level factor that I control for in the models is *Commodity Range* fixed effects which captures the total number of contraceptive methods offered by a health facility, ranging from a minimum of 1 method to a maximum of 10 methods. In addition, I incorporate *Facility Type* dummies into the models, indicating whether facilities are classified as primary (e.g., dispensaries) or secondary facilities (e.g., hospitals). This accounts for systematic differences in supply availability that might exist across the different levels. In order to control for basic infrastructural attributes available within health facilities, I include a *Piped Water* dummy in the models. This variable takes the value of 1 when facilities have access to piped water, and 0 otherwise. I also include two management-related variables in the regression models. The first variable is *External Supervision*, a binary variable which takes the value of 1 if facilities receive supervision from external managers, and 0 otherwise. The second variable is *Management Meetings*, a binary variable pertaining to the frequency of management meetings within facilities which takes the value of 1 for routine management meetings, and 0 otherwise. Table 2.2 displays the correlation matrix and summary statistics for the main variables used in the study.

Table 2.2. Descriptive Statistics and Pairwise Correlations

	Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	*Push*	1.00						
2	*Primary Facility*	-0.20	1.00					
3	*Piped Water*	-0.03	-0.04	1.00				
4	*External Supervision*	-0.04	0.01	0.18	1.00			
5	*Management Meetings*	0.01	0.16	0.03	0.09	1.00		
6	*LMIS Practices*	-0.02	0.18	0.02	0.00	-0.06	1.00	
7	*Logistics Infrastructure*	0.13	-0.11	-0.11	-0.08	-0.02	-0.05	1.00
	Mean	0.53	0.78	0.83	0.96	0.94	0.73	13.73
	Std. Dev.	0.50	0.41	0.38	0.19	0.24	0.44	16.17
	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Max	1.00	1.00	1.00	1.00	1.00	1.00	70.51

Notes. See section 2.4.2 for a description of these variables.

2.5. Results

2.5.1. Main Findings

I begin by presenting the DID estimation results pertaining to the main effects of the push intervention on health commodity stock-outs (Table 2.3, Column 1), followed by results related to the moderating effects (Table 2.3, Columns 2-7). The regression results in Table 2.3, Column 1 show that a transition from pull to push distribution leads to a statistically significant decrease in the likelihood of stock-outs (β = -2.37, $p < 0.01$). This effect is equivalent to 12 percentage-point reduction in the probability of stock-outs across all health facilities (marginal effect = -12.27). These results provide support for H2.1.

Next, I investigate how a health facility's LMIS practices and logistics infrastructure moderate the relationship between push distribution and health commodity stock-outs. I estimate Equation (2.1) across the subgroups of less mature vs. more mature LMIS practices. The results presented in Table 2.3 Columns 2 and 3, demonstrate that a transition from pull to push distribution leads to significant reductions in stock-outs at facilities with more mature LMIS practices (Column 2, β = -1.64, $p < 0.05$) as well as those with less mature LMIS practices (Column 3, β = -4.48, $p < 0.01$). The difference between the two coefficients was statistically significant ($\chi^2 = 3.93$, $p < 0.05$), indicating that the benefits derived from a transition to push distribution are larger for facilities with less mature LMIS practices relative to the ones with more mature LMIS practices. These results provide support for H2.2. With respect to the magnitude of benefits, I find that a transition from pull to push distribution reduces the probability of stock-outs by about 27 percentage points at facilities with less mature LMIS practices (marginal effect = -26.58), compared to a reduction by about 8-percentage points at more mature LMIS facilities (marginal effect = -8.16).

I now turn my attention to how the potential benefits of transitioning to push distribution are moderated by a health facility's access to logistics infrastructure. To this end, I estimate the specification in Equation (2.1) across the subgroups of less developed logistics infrastructure vs. more developed logistics infrastructure, the results of which are shown in Table 3.3, Columns 4 and 5. These results demonstrate that the relationship between push distribution and stock-outs is negative and statistically insignificant (Column 4, β = -1.00, $p > 0.10$) under more developed logistics infrastructure but negative and statistically significant (Column 5, β = -4.03, $p < 0.01$) under less developed logistics infrastructure. The magnitude of benefits derived from a transition to push distribution under less developed logistics infrastructure is equivalent to an approximately 22 percentage-point reduction in the probability of stock-outs (marginal effect = -21.77). I tested the difference between the coefficients across the subgroups using a Wald test which was statistically significant ($\chi^2 = 6.69$, $p < 0.01$). These findings demonstrate that a transition from pull to push distribution leads to larger benefits for facilities that are disadvantaged with respect to access to logistics infrastructure, thereby providing support for H2.3.[7]

[7] As a robustness check, I also estimate the coefficients across the subgroups of less developed vs. more developed logistics infrastructure using a different criteria to split the samples, i.e., by using *top-bottom quartiles* of distance to the nearest road instead of the *median* value. The results are consistent with those presented in the main analyses; therefore, providing additional support for H2.3.

Table 2.3. Difference-in-Differences Estimation Results: Effects of Push Distribution on Health Commodity Stock-Outs

DV: Stock-Out	All (H2.1)	LMIS Only (H2.2)		Logistics Infrastructure Only (H2.3)		LMIS and Logistics Infrastructure (H2.4)	
		More Mature	Less Mature	More Developed	Less Developed	More Mature and More Developed	Less Mature and Less Developed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Push	-2.37***	-1.64**	-4.48***	-1.00	-4.03***	-0.53	-18.74***
	(0.60)	(0.75)	(1.22)	(0.78)	(0.87)	(1.08)	(1.82)
Primary Facility	-0.35*	-0.45*	-0.14	-0.41	0.04	-0.25	0.99
	(0.21)	(0.25)	(0.47)	(0.29)	(0.35)	(0.33)	(0.68)
Piped Water	-0.33	-0.63**	0.22	0.27	-0.65**	1.06*	0.67
	(0.23)	(0.30)	(0.32)	(0.39)	(0.28)	(0.63)	(0.44)
External Supervision	-0.78*	-0.87*	-0.22	-1.06*	-0.60	-1.43**	0.92
	(0.42)	(0.49)	(0.73)	(0.59)	(0.48)	(0.67)	(0.93)
Management Meetings	-0.59**	-0.53	-0.75*	-0.27	-0.95***	-0.08	-0.40
	(0.28)	(0.37)	(0.45)	(0.56)	(0.30)	(0.66)	(0.68)
Commodity Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodity Range FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	4.25***	4.71***	2.78	12.49***	7.25***	11.25***	-30.78***
	(1.48)	(1.68)	(2.30)	(1.14)	(1.85)	(1.38)	(5.00)
Marginal Effect (%)	-12.27	-8.16	-26.58	-4.94	-21.77	-2.57	-59.27
Pseudo R-Squared	0.23	0.25	0.31	0.24	0.29	0.30	0.45
Log Likelihood	-1341	-961	-314	-605	-660	-448	-162
Observations	6,285	4,640	1,619	3,118	3143	2,460	982

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$. *Notes*: All models are estimated using a logistic regression specification. FE = Fixed Effects. Robust standard errors clustered at the facility level in parentheses.

Finally, I investigate whether, and to what extent, the potential benefits of transitioning to push distribution are *jointly* moderated by the employment of LMIS practices and availability of logistics infrastructure. Accordingly, I estimate the model specified in Equation (2.1) across the subgroups of less mature LMIS and less developed logistics facilities (i.e., severely disadvantaged) vs. more mature LMIS and more developed logistics infrastructure facilities (i.e., not disadvantaged). The results are presented in Table 2.3, Columns 6 and 7. I find no statistically significant benefits of a transition to push distribution in the "not disadvantaged" group (Column 6, β = -0.53, $p > 0.10$). However, the results indicate that the "severely disadvantaged" health facilities can benefit significantly from the transition to push distribution (Column 7, β = -18.74, $p < 0.01$) — these benefits equate to a 59 percentage-point reduction in the probability of stock-outs (marginal effect = -59.27). The above findings provide support for H2.4 (χ^2 = 101.19, $p < 0.01$).

2.5.2. Robustness Checks

In this section, I document the results of robustness checks to test the sensitivity of the main analysis results to identifying assumptions and help rule out alternative explanations.

2.5.2.1. Alternative Specification Using Relative Time Models

My empirical strategy thus far has been focused on estimating Equation (2.1), which is based on aggregate DID estimates between the treated and untreated health facilities. Producing unbiased estimates in DID models is dependent upon the identifying assumption of parallel trends, i.e., the assumption that the outcomes in the treated and untreated groups would follow the same trajectory in the post-treatment period in the absence of the intervention (Daw and Hatfield 2018). Although the parallel trends assumption is fundamentally untestable because of the unobservability of the counterfactual (Imbens and Wooldridge 2009), I follow recommendations in the prior econometrics literature (Angrist and Pischke 2008, Autor 2003) to check for diverging trends by using a *relative time* model specification, as shown below (Burtch et al. 2018):

$$Ln\left[\frac{Pr\left(Stock-Out_{ijrt}=1 \mid X_{ijrt}\right)}{1-Pr\left(Stock-Out_{ijrt}=1 \mid X_{ijrt}\right)}\right] = \beta_0 + \lambda.X_{CL} + \alpha.Region\ FE_r + \gamma.Time\ FE_t + \beta_{t-T}\ .Push_{r,\ t-T} + \beta_{t+T}\ .Push_{r,\ t+T} + \varepsilon_{ijrt} \tag{2.2}$$

Where the index T denotes the time difference from the introduction of the intervention. Particularly, β_{t-T} and β_{t+T} represent pre-treatment effects (leads) and post-treatment effects (lags), respectively. I estimate the above model for the entire sample of health facilities, as well as the sub-samples pertaining to the effects of the moderators. In general, I expect little to no significant negative effects in the pre-treatment leads and significant estimates in the post-treatment lags.

Table 2.4. Relative Time Model Results: Effects of Push Distribution on Health Commodity Stock-Outs

DV: Stock-Out	All (H2.1)	LMIS Only (H2.2)		Logistics Infrastructure Only (H2.3)		LMIS and Logistics Infrastructure (H2.4)	
		More Mature	Less Mature	More Developed	Less Developed	More Mature and More Developed	Less Mature and Less Developed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Push $_{t-1}$	-0.16	-0.21	-0.64	-0.49	-0.14	-0.42	-2.78
	(0.39)	(0.43)	(1.02)	(0.57)	(0.50)	(0.69)	(1.74)
Push $_{t+1}$	-3.02***	-2.61***	-4.06***	-1.21	-4.24***	-0.97	-15.49***
	(0.53)	(0.74)	(1.23)	(0.82)	(0.68)	(0.94)	(1.62)
Push $_{t+2}$	-4.51***	-4.27***	-4.27**	-2.27	-5.83***	-2.30	-13.61***
	(0.89)	(1.17)	(1.76)	(1.48)	(1.22)	(1.64)	(2.91)
Primary Facility	-0.32	-0.33	-0.27	-0.35	-0.05	-0.26	1.00
	(0.20)	(0.24)	(0.42)	(0.27)	(0.35)	(0.31)	(0.90)
Piped Water	-0.31	-0.68**	0.26	0.10	-0.56**	0.71	0.56
	(0.23)	(0.30)	(0.32)	(0.37)	(0.28)	(0.59)	(0.46)
External Supervision	-0.85**	-0.88*	-0.84	-0.99	-0.72	-1.18	-1.10
	(0.41)	(0.49)	(0.79)	(0.67)	(0.50)	(0.72)	(1.01)
Management Meetings	-0.52*	-0.53	-0.45	-0.29	-0.78**	-0.28	-0.39
	(0.28)	(0.37)	(0.40)	(0.55)	(0.32)	(0.67)	(0.64)
Commodity Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodity Range FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.31*	3.14**	3.67*	-0.60	4.42***	-1.32	-5.98
	(1.19)	(1.45)	(2.14)	(1.01)	(1.63)	(1.15)	(5.69)
Pseudo R-Squared	0.22	0.25	0.27	0.24	0.27	0.29	0.40
Log Likelihood	-1343	-952	-337	-601	-681	-444	-178
Observations	6,329	4,630	1,699	3,114	3,191	2,429	1,015

**p* < 0.10; ***p* < 0.05; ****p* < 0.01. *Notes*: All models are estimated using a logistic regression specification. FE = Fixed Effects. Robust standard errors clustered at the facility level in parentheses. Month FE were excluded to avoid severe multicollinearity.

The results of the relative time models presented in Table 2.4 corroborate the previous findings and alleviate concerns related to diverging trends. First, I find the pre-treatment coefficients to be statistically insignificant in all models (Columns 1 through 7) indicating that there are no systematic differences in the pre-treatment trends across the treated and control groups. Second, by ruling out potential confounding in the pre-treatment periods, the results substantiate my claim that the introduction of the intervention is not likely to be endogenous (Angrist and Pischke 2008). This is true across the full sample (Column 1) as well as the subgroups (Columns 2 through 7). Third, the coefficients of the push intervention in the post-treatment periods are consistent with those estimated earlier. Notably, among the subgroups, I find the largest post-treatment coefficient to belong to the less mature LMIS and less developed logistics subgroup (Column 7), further ensuring the robustness of the study findings.[8]

2.5.2.2. Application of Propensity Score Matching

I argued theoretically in section 2.4.1 that selection bias is unlikely to influence the estimated coefficients of interest due to the following reasons: (i) the decision to transition health facilities from pull to push distribution is taken by the government, i.e., facilities cannot self-select into the intervention; and (ii) all health facilities are transitioned from pull to push distribution irrespective of their operational performance, LMIS practices or availability/quality of logistics infrastructure surrounding a facility. Therefore, I expect treatment and control facilities to exhibit similar pre-intervention trends with respect to the likelihood of stock-outs across the full sample and the subgroups. Further, as demonstrated empirically in section 2.5.2.1, I observe no systematic and significant differences in pre-intervention trends, across treated and control health facilities. Nevertheless, in order to bolster my claim that potential imbalance between treated and control groups is not biasing the estimated coefficients, I generate a matched sample of facilities using propensity score matching. The propensity score is defined in terms of "the conditional probability of assignment to a treatment" given a set of observed variables (Rosenbaum and Rubin 1983). The basic notion behind this approach is that each treated facility is matched with control facilities that are very similar to the treated facility in terms of their propensity of being treated. Prior research has utilized propensity score matching to reduce imbalance across treated and control facilities in DID settings (e.g., Dhanorkar 2019, Oh et al. 2018).

In this study, I calculate the propensity scores using covariates at the facility-level, commodity-

[8] The results remain robust to the application of coarsened exact matching (CEM).

level and region-level.[9] I use these variables in order to predict the conditional probability of a facility being assigned to the treatment group. Utilizing the nearest-neighbor matching with a caliper of 0.20, each treated health facility is then matched with control facilities that have similar propensity scores. Table 2.5 shows the balance diagnostics before and after the application of propensity score matching, where I find that the matching procedure has significantly reduced the amount of imbalance between treated and control health facilities. Table 2.6 presents the results of DID models based on samples that were matched using propensity score matching. These results are consistent with those of the main models, demonstrating the robustness of the study findings.

Table 2.5. Balance Diagnostics for Propensity Score Matching

	Before Matching		**Propensity Score Matching**		
	Difference in Means	**Standardized Bias (%)**	**Difference in Means**	**Standardized Bias (%)**	**Bias Reduction (%)**
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Facility Type	0.02	2.40	0.00	-0.60	75.40
Piped Water	0.12	31.80	0.00	1.30	95.90
External Supervision	0.01	5.70	-0.01	-7.70	-34.70
Management Meetings	0.04	17.90	-0.01	-3.40	81.20
Commodity Range FE		46.70		-6.60	86.00
Commodity Type FE		-8.00		0.90	89.30
Region FE		-43.10		-5.10	88.10
Rubin's B		65.10		14.40	
Rubin's R		0.72		1.44	

Notes: FE = Fixed Effects. The propensity score matching process was based on the nearest ten neighbors estimator, where a caliper of 0.20 was used. Rubin's B and Rubin's R measure the extent of sample imbalance with respect to mean and variance, respectively. For samples to be considered sufficiently balanced, Rubin (2001) recommends that B be less than 25 and R between 0.5 and 2.

2.5.2.3. Evaluating the Potential for the Endogeneity of the Intervention

Thus far, I have argued theoretically and demonstrated empirically that the expansion of the push intervention is not likely to be endogenous. Furthermore, there are no a priori reasons to suggest that a reduction in stock-outs could be driving the expansion of the intervention. Nevertheless, I employ a hazard specification to alleviate potential concerns that reverse causality could be biasing the estimated coefficients. Particularly, I utilize the following Cox proportional hazard model to predict the hazard of a health facility being treated using *Stock-Out* as the main independent variable of interest (Cox 1972). In other words, the goal is to evaluate whether potential reverse causality could be driving the hypothesized relationships.

[9] These variables are as follows: facility type (primary vs. secondary), piped water, external supervision, management meeting, commodity type fixed effects, commodity range fixed effects, and region fixed effects.

$$h(t, X_{ij}) = h_0(t)\exp\,(\lambda.X_{CL} + \delta.Stock - Out_{ij} + \varepsilon_{ij}) \tag{2.3}$$

where *i* and *j* denote commodity type *i* at health facility j, $h(t)$ is the change in the treatment hazard at time *t* conditional on a set of variables, $h_0(t)$ is the baseline hazard rate, and X_{CL} is the vector of control variables. Table 2.7 presents the results for the hazard specifications, where I find that the coefficients of stock-outs as independent variables are statistically insignificant across all models. Therefore, I find no evidence that stock-outs are influencing the expansion of the intervention, further demonstrating that the intervention is not likely to be endogenous.

2.5.2.4. Placebo Tests Using Alternative Dependent Variable: Stock-Outs of Tuberculosis Drugs

Another potential concern with the results might be that the significant declines in the likelihood of stock-outs are not necessarily driven by push distribution. Rather, one could argue that systemic improvements at health facilities (e.g., funding availability) that are somehow concurrent with the expansion of push distribution are the primary drivers of the results. In order to eliminate this alternative explanation, I conduct placebo (falsification) tests by running regression models using an alternative outcome variable that was *unaffected* by the treatment (Abadie et al. 2010). The essential idea is that if systemic facility-wide improvements were indeed responsible for the findings, I would expect similar reductions in the likelihood of stock-outs for health commodities that did *not* transition to push distribution. Hence, I run the model in Equation (2.1) by substituting the original dependent variable (i.e., contraceptive stock-outs) with an alternative variable corresponding to the stock-out of tuberculosis drugs. Since the intervention did *not* involve the distribution of tuberculosis medications throughout the duration of the study, significant and systemic reductions in the stock-outs of tuberculosis drugs would signal potential issues with the main estimated coefficients. Table 2.8 presents the results of these analyses, where I find that the placebo expansion of push distribution to tuberculosis drugs does not lead to any consistent and statistically significant reductions in stock-outs. These results suggest that the main findings are not likely to be driven by alternative explanations.

2.6. Post Hoc Analysis: How Does the Intervention Impact Client Satisfaction?

The focus of this study has been on examining the impact of a transition from pull to push distribution on the supply-side performance outcome of health commodity availability, given that this outcome is a critical performance metric of public health supply chains in developing countries (Rosen 2014). Furthermore, prior research has identified stock-outs as a major source of client dissatisfaction that can consequently lead to other undesirable outcomes including diminished confidence in the public healthcare delivery systems and discontinuation of commodity use (Hutchinson et al. 2011, Penfold et al. 2013).

Table 2.6. Difference-in-Differences Estimation Results Using Propensity Score Matching: Effects of Push Distribution on Health Commodity Stock-Outs

DV: Stock-Out	All (H2.1)	LMIS Only (H2.2)		Logistics Infrastructure Only (H2.3)		LMIS and Logistics Infrastructure (H2.4)	
		More Mature	Less Mature	More Developed	Less Developed	More Mature and More Developed	Less Mature and Less Developed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Push	-2.39***	-1.55**	-4.11***	-0.94	-4.38***	-0.13	-17.55***
	(0.59)	(0.76)	(1.55)	(0.77)	(0.90)	(0.99)	(2.28)
Primary Facility	-0.54*	-0.62*	-1.02	-0.55*	-0.80	-0.31	0.00
	(0.29)	(0.32)	(0.67)	(0.31)	(0.64)	(0.38)	0.00
Piped Water	-0.63**	-0.80***	-0.37	-0.04	-0.85***	0.13	0.04
	(0.25)	(0.28)	(0.71)	(0.47)	(0.32)	(0.50)	(1.23)
External Supervision	-1.08**	-1.35***	0.56	-1.58***	0.63	-1.74***	2.57***
	(0.48)	(0.49)	(1.85)	(0.57)	(0.63)	(0.62)	(0.83)
Management Meetings	-1.19***	-0.83*	-2.36**	-1.04	-1.98***	-0.81	-2.63**
	(0.40)	(0.48)	(1.03)	(0.84)	(0.45)	(1.06)	(1.11)
Commodity Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodity Range FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.03*	1.67	-0.25	13.42***	2.88	11.95***	3.22
	(1.15)	(1.23)	(3.32)	(1.29)	(2.10)	(1.56)	(4.17)
Pseudo R-Squared	0.27	0.28	0.52	0.28	0.42	0.30	0.73
Log Likelihood	-1596	-1259	-209	-772	-648	-671	-78
Observations	5,342	4,192	1,080	2,689	2,635	2,282	541

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$. *Notes*: All models are estimated using a logistic regression specification. FE = Fixed Effects. Robust standard errors clustered at the facility level in parentheses.

Table 2.7. Hazard Models Predicting Push Expansion across Health Facilities in Senegal Conditional on Health Commodity Stock-Outs

DV: Push Expansion	All	LMIS Only		Logistics Infrastructure Only		LMIS and Logistics Infrastructure	
		More Mature	Less Mature	More Developed	Less Developed	More Mature and More Developed	Less Mature and Less Developed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Stock-out	0.14	0.24	-0.02	0.06	0.08	0.23	0.32
	(0.13)	(0.16)	(0.21)	(0.18)	(0.23)	(0.26)	(0.36)
Primary Facility	-0.01	-0.04	-0.08	0.02	-0.07	-0.02	-0.06
	(0.15)	(0.17)	(0.27)	(0.17)	(0.20)	(0.19)	(0.32)
Piped Water	-0.06	-0.06	-0.27	0.14	-0.26*	-0.19	-0.44*
	(0.11)	(0.16)	(0.18)	(0.20)	(0.14)	(0.28)	(0.23)
External Supervision	-0.42**	-0.21	-0.37	-1.03***	-0.12	-0.70**	-0.32
	(0.19)	(0.24)	(0.37)	(0.27)	(0.20)	(0.35)	(0.38)
Management Meetings	-0.11	-0.32	0.59**	0.23	-0.58*	-0.02	0.03
	(0.19)	(0.21)	(0.27)	(0.22)	(0.33)	(0.24)	(0.30)
Commodity Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodity Range FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,378	4,679	1,699	3,179	3,199	2,504	1,024
Log Likelihood	-24156	-16289	-5818	-10896	-10932	-8419	-3568

**p* < 0.10; ***p* < 0.05; ****p* < 0.01. *Notes*: FE = Fixed Effects. Robust standard errors clustered at the facility level in parentheses. More (less) mature LMIS practices correspond to facilities utilizing either (neither) frequent updating of the LMIS records or (nor) an electronic LMIS. More (less) developed logistics infrastructure correspond to facilities whose distance to their nearest road is smaller (greater) than the median value.

Table 2.8. Placebo (Falsification) Tests: Effects of Placebo Push Distribution on Stock-Outs of Tuberculosis Drugs

DV: Tuberculosis Stock-Out	All	LMIS Only		Logistics Infrastructure Only		LMIS and Logistics Infrastructure
		More Mature	Less Mature	More Developed	Less Developed	More Mature and More Developed
	(1)	(2)	(3)	(4)	(5)	(6)
Placebo Push	-0.74	1.45	-0.07	-0.99	-1.20	2.47
	(0.90)	(1.23)	(2.05)	(1.28)	(1.75)	(2.04)
Primary Facility	1.50***	2.00***	2.08***	1.04**	2.38***	1.33*
	(0.32)	(0.64)	(0.54)	(0.45)	(0.50)	(0.75)
Piped Water	-0.11	1.56	-2.06**	-0.55	0.44	15.81***
	(0.66)	(0.96)	(0.94)	(1.84)	(0.69)	(1.54)
External Supervision	-0.53	-1.39	0.03	-0.72	-0.94	-0.88
	(0.50)	(0.86)	(0.65)	(0.90)	(1.22)	(0.91)
Management Meeting	0.10	-1.10	2.83***	2.34**	-1.10	2.03*
	(0.58)	(0.72)	(0.95)	(1.08)	(0.79)	(1.13)
Commodity Type FE	Yes	Yes	Yes	Yes	Yes	Yes
Commodity Range FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-3.54*	-5.13*	-1.74	-1.00	-7.66***	-15.95***
	(2.02)	(2.90)	(2.93)	(2.68)	(2.61)	(2.84)
Pseudo R-Squared	0.57	0.52	0.66	0.66	0.59	0.70
Log Likelihood	-325	-149	-135	-93	-182	-70
Observations	1,348	682	648	600	678	434

*p < 0.10; **p < 0.05; ***p < 0.01. *Notes*: FE = Fixed Effects. Robust standard errors clustered at the facility level in parentheses. More (less) mature LMIS practices correspond to facilities utilizing either (neither) frequent updating of the LMIS records or (nor) an electronic LMIS. More (less) developed logistics infrastructure correspond to facilities whose distance to their nearest road is smaller (greater) than the median value. Due to a lack of sufficient sample size, I was not able to run the analysis on the less mature LMIS and less developed logistics infrastructure subgroup.

In this section, I empirically test whether the benefits associated with a transition to push distribution could translate into benefits on the demand-side. I consider an important demand-side outcome metric, namely *client satisfaction,* for which I have available data. Specifically, I utilize client exit interview data from the SPA surveys. The interview data include client satisfaction scores collected from two rounds of exit interviews that took place in a non-staggered manner: one set of interviews administered in 2012 before the intervention was expanded and another set of interviews administered in 2015 after the expansion of the intervention. Although this setting does not allow for the application of a generalized DID estimation model similar to the one specified in Equation (2.1), I run a conventional DID model using treatment/control dummies where the control group corresponds to clients attending health facilities that have access to more developed logistics infrastructure.

Note that the main results in Table 2.3 (Columns 4 and 5) indicate that the expansion of the intervention does not lead to any statistically significant reductions in health commodity stock-outs for facilities proximate to the nearest roads (Column 4: more developed logistics). Hence, I expect a negligible increase in client satisfaction, if any, after the expansion of the intervention to health facilities in closer proximity to roads (i.e., control group). On the contrary, I expect the potential growth in client satisfaction due to the push intervention to be stemming primarily from health facilities located farther away from primary roads (i.e., facilities that have access to less developed logistics infrastructure). These facilities serve as the treatment group in this analysis. Therefore, I specify the following model:

$$Ln\left[\frac{Pr\left(Client\ Satisfaction_{ijt} = 1 \mid X_{ijt}\right)}{1 - Pr\left(Client\ Satisfaction_{ijt} = 1 \mid X_{ijt}\right)}\right] = \beta_0 + \lambda.X_{CL} + \rho.Post_t + \pi.Treatment_j + \beta.Push_{jt} + \varepsilon_{ijt} \quad (2.4)$$

where *i*, *j* and *t* denote client *i* at facility *j* at time *t*, and ε_{ijt} is the error term. Client satisfaction is measured as a binary variable, taking the value of 1 when clients reported no major or minor complaints regarding the availability of health commodities, and 0 otherwise. X_{CL} is the vector of control variables. At the facility-level, I control for facility type (i.e., primary vs. secondary), commodity range fixed effects, piped water, external supervision and frequency of management meetings. I further control for region and month fixed effects to account for potential variability in client satisfaction across regions and seasons. In addition, I incorporate multiple client-level control variables including age, education, and the satisfaction level of clients with other aspects of the service (e.g., wait time, facility's cleanliness, hours of service, etc.). $Post_t$ takes the value of 1 when the surveys are administered after the intervention, and 0 otherwise. $Treatment_j$ is coded based on the median distance between each facility and its nearest primary road, therefore taking the value of 1 when the distance is larger than 7km (i.e., treatment group), and 0 otherwise (i.e., control group). $Push_{jt}$ is the DID coefficient of interest and is assigned the value of 1 when treatment facilities are surveyed post-intervention, and 0 otherwise. I cluster the robust standard errors at the facility-level.

Table 2.9 presents the results of this analysis, where I find a positive and statistically significant coefficient for the impact of push distribution on client satisfaction (Column 2: $\beta = 2.18$, $p < 0.05$). This effect is equivalent to a 9 percentage-point increase in the probability that a client leaves the facility with no complaints pertaining to stock-outs (marginal effect = 8.77). This finding not only indicates that the benefits of the intervention translate into improved client satisfaction on the demand-side, but also signals to policymakers about the practical significance of focusing on the availability of health commodities as a mechanism to achieve that end.

2.7. Discussion

2.7.1. Theoretical and Practical Implications for Public Health Supply Chains

Consistent availability of commodities at last-mile health facilities is critical to making progress towards meeting the UN Sustainable Development Goals and ultimately, advancing health outcomes in developing countries (Rosen 2014). Ensuring the availability of supplies in last-mile facilities, however, is fraught with challenges. Some of the challenges can be attributed to the use of pull distribution by public health supply chains in developing countries, where inventory data management is delegated to health workers who lack the required skills and resources for the effective and efficient execution of the elements of the logistics cycle framework (i.e., data collection, order fulfillment and transportation of health commodities). Several countries have, therefore, advocated for a transition to push distribution where external LPs are responsible for inventory and logistics data management. While the push distribution has the potential to alleviate some of the difficulties faced by health facilities in executing the different elements of the logistics cycle framework under the traditional pull model, there is a paucity of rigorous research comparing the relative performance of the two models in public health supply chains in developing countries. Further, the extant literature has not investigated the moderating impact of facility-level infrastructural characteristics that can moderate the above relationship. This study is aimed at filling these gaps in the literature.

Table 2.9. Difference-in-Differences Estimation Results: Effects of Push Distribution on Client Satisfaction (Post Hoc Analysis)

	Base Model	Full Model
DV: Client Satisfaction of Commodity Availability	**(1)**	**(2)**
Push = Post × Treatment		2.18**
		(0.91)
Post	1.69***	0.72
	(0.54)	(0.59)
Treatment	-0.88**	-1.21***
	(0.39)	(0.41)
Primary Facility	0.34	0.27
	(0.39)	(0.38)
Piped Water	-0.21	-0.32
	(0.41)	(0.42)
External Supervision	-0.67	-0.60
	(0.75)	(0.72)
Management Meetings	0.18	0.02
	(0.46)	(0.47)
Client's Age	-0.05***	-0.05***
	(0.02)	(0.02)
Client's Education	-0.58**	-0.62**
	(0.24)	(0.25)
Client's Other Satisfaction FE	Yes	Yes
Commodity Range FE	Yes	Yes
Month FE	Yes	Yes
Region FE	Yes	Yes
Constant	-2.11	-0.57
	(1.91)	(1.91)
Marginal Effect (%)		8.77
Pseudo R-Squared	0.33	0.34
Log Likelihood	-279	-275
Observations	1,355	1,355

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$. *Notes*: All models are estimated using a logistic regression specification. FE = Fixed Effects. Robust standard errors clustered at the facility level in parentheses. *Post* is a binary variable indicating whether observations belong to the post-intervention vs. pre-intervention group. *Treatment* is a binary variable indicating whether a health facility's access to more developed logistics infrastructure is (i.e., control group) vs. less developed logistics infrastructure (i.e., treatment group).

Toward this end, I focus on the staggered expansion of a supply chain intervention in Senegal where the distribution of health commodities transitioned from pull distribution to push distribution. Using novel field data collected from health facilities across Senegal, I find that a transition from pull to push distribution is associated with a statistically significant reduction in the likelihood of health commodity stock-outs. Moreover, I identify infrastructural characteristics of health facilities that can moderate the benefits provided by the transition to push distribution. First, I investigate the moderating role of two LMIS practices, namely daily LMIS updating and the use of electronic LMIS by facilities, and find that benefits of a transition from pull to push distribution are significantly larger for facilities engaged in neither of the above practices. Second, I explore the moderating role of access to logistics infrastructure, measured as the distance between a health facility and its nearest primary road. The findings indicate that facilities with access to less developed logistics infrastructure obtain larger gains from a transition to push distribution. Third, I examine the potential for complementarities between the moderating variables, and find that the severely disadvantaged health facilities (i.e., less mature LMIS and less developed logistics) reap the largest benefits from the implementation of push distribution. To the best of my knowledge, this is the very first study to quantify the magnitude of the above relationships in a rigorous empirical setting.

The study findings have actionable implications for resource allocation in public health supply chains in developing countries. As noted earlier, moving from a pull to a push distribution model is capital intensive, involving significant start-up investments (e.g., procuring delivery vehicles, establishing support systems) and operating costs (e.g., fuel and per-diems). Besides funding considerations, the implementation of a push intervention also requires the dedication of substantial resources for planning of scheduled deliveries and ongoing supervision. Given the significant resource constraints faced by public health systems in developing countries, it is imperative to understand how the benefits realized from transitioning to push distribution vary based on facility characteristics, so that the limited resources available can be allocated in the best way possible to increase access to health commodities in the last-mile — an important objective of UN SGDs 3.7 and 3.8. In this context, my key study results, summarized in Table 2.10, offer important takeaways in terms of the specific facilities that should be prioritized for resource allocation. From the table, health facilities that have less mature LMIS practices and access to less developed logistics infrastructure benefit the most from transitioning to a push distribution model, with a 59-percentage point reduction in the likelihood of stock-outs. As such, these severely disadvantaged facilities should receive *top* priority for resource allocation towards transitioning to a push distribution model so as to mitigate the challenges they face in terms of low data management capabilities, limited supply chain visibility, and constrained transportation capacity. For a health facility that offers nine contraceptive methods (the median commodity range in the sample), the above-specified 59-percentage point reduction in the likelihood of stock-outs roughly translates into a 38 percent increase in contraceptive prevalence, which is one of key indicators related to UN SDG 3.7.

The numbers in Table 2.10 further indicate that facilities that are moderately disadvantaged (i.e., those with either less mature LMIS practices, or with access to less developed logistics infrastructure, but not both) would also benefit from a transition to push distribution. For example, in the case of facilities that are only disadvantaged with respect to LMIS practices, a transition to a push distribution model reduces the likelihood of stock-outs by roughly 21 percentage points. The corresponding marginal effect for facilities that are only disadvantaged with respect to logistics infrastructure is 20 percentage points, or a roughly 12.5% increase in contraceptive prevalence rate for a health facility that offers nine contraceptive methods. The two marginal effects are not statistically different from one another and this suggests that between the two groups of health facilities, it might be beneficial to prioritize the transition of those health facilities to push distribution that are only disadvantaged with respect to logistics infrastructure. This is because health facilities often have limited control over the quality of logistics infrastructure, making logistical barriers a bigger hurdle to overcome, relative to LMIS practices. As a result, facilities that are disadvantaged with respect to logistics infrastructure should be given priority over those with less mature LMIS practices for a transition to push distribution. In the case of facilities that are only disadvantaged with respect to LMIS practices, a potentially cost-effective approach to lower the likelihood of stock-outs would be to make investments towards improving their LMIS practices, rather than committing to sweeping changes in the distribution strategy. Finally, the results indicate that there are no statistically significant benefits of a transition to push distribution for health facilities with superior data management capabilities, stronger supply chain visibility, and adequate transportation capacity (i.e., more mature LMIS and more developed logistics infrastructure). Hence, it may not be prudent to dedicate resources to transition such facilities to a push distribution model. Overall, the findings uncover resource allocation strategies that can be used to mitigate the risk of stock-outs in developing countries, therefore, contributing to improved access to reproductive health supplies and essential health commodities (UN SDGs 3.7 and 3.8).

Table 2.10. Changes in the Likelihood of Stock-Outs After a Transition from Pull to Push Distribution

More Mature LMIS Practices	**-20%*** **	**-3%**
Less Mature LMIS Practices	**-59%*** **	**-21%** **
	Less Developed Logistics Infrastructure	**More Developed Logistics Infrastructure**

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

The study findings also have far-reaching implications that carry over to the demand-side, where I illustrate through empirical analyses that a transition to push distribution has the potential to significantly increase demand-side client satisfaction owing to an increased availability of health commodities. This can have significant positive ramifications by contributing to increased health commodity use, and ultimately, improved health outcomes (Penfold et al. 2013, Rosen 2014).

2.7.2. Limitations and Future Research Directions

This study has some limitations that serve as avenues for future research. One potential limitation might be related to the dependent variable which captures stock-outs on the day the survey was administered at a health facility. Although this measure is well-accepted in both academic (e.g., Choi and Ametepi 2013) and practitioner literature (e.g., WHO 2015), one could argue that the measure might potentially underestimate or overestimate stock-outs depending on the particular date a health facility was surveyed. First, in section 2.5.2.3, I utilized Cox proportional hazard estimations which indicated that the expansion of the intervention is not likely to be endogenous, therefore, mitigating concerns of selection bias. That is, any potential measurement error in the dependent variable would likely be independent of the treatment status, thereby reducing bias in the treatment estimates (Wooldridge 2010). Second, given that the sampling procedure used to collect the data was based on stratified random sampling, I weight the observations by the inverse probability of selection. This approach minimizes any potential selection issues that might arise as a result of the sampling procedure, further reducing bias in the treatment estimates (Solon et al. 2015, Wooldridge 2010). Nevertheless, future research could replicate the findings using alternative measures of stock-outs (e.g., health commodity stock-outs over a period).

Further, the variables used to represent the utilization of LMIS practices by health facilities might be subject to limitations. For example, my measurements do not capture the specific frequency by which records are updated beyond “daily” updating, or the specific details surrounding how facilities use the LMIS platforms to make inventory decisions. Future research can benefit from using more granular measures of LMIS practices. Finally, I execute the empirical analysis by concentrating on the distribution of contraceptive commodities in the context of public health supply chains in Senegal, West Africa. Prospective studies can replicate the findings by focusing on alternative geographical and supply chain contexts. Notwithstanding the above limitations, this study provides novel empirically-grounded insights into how the type of distribution model used for delivering health commodities in public health supply chains influence the availability of supplies in the last-mile. The findings further shed light on facility-level infrastructural characteristics that can moderate the above relationship.

Chapter 3:
Managing Stock-outs Using Health Facility-level Practices

3.1. Introduction[10]

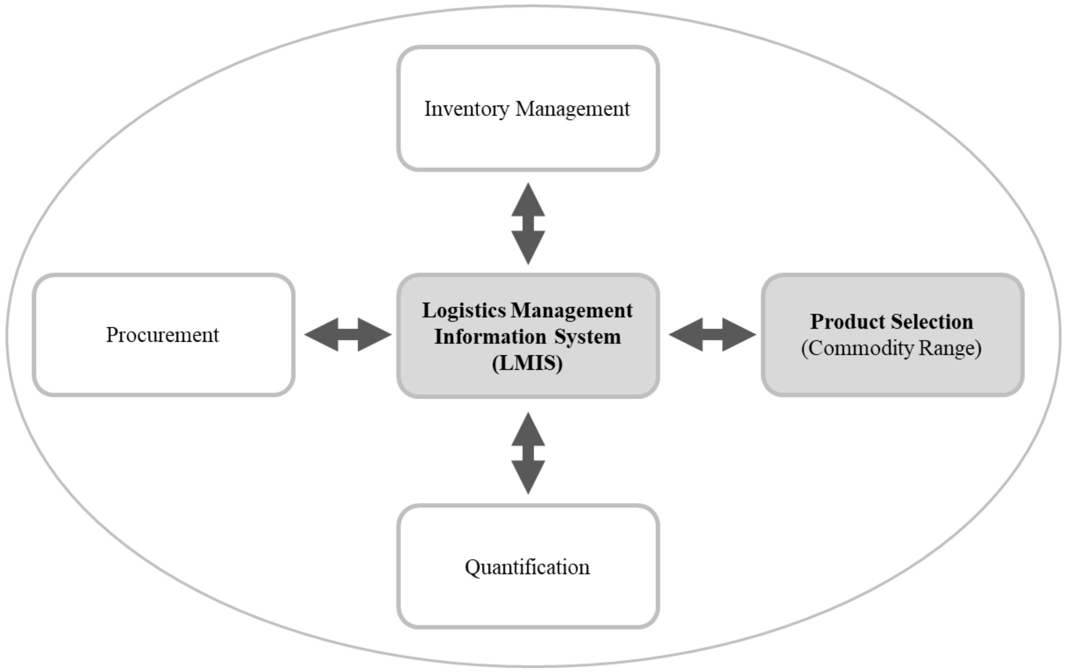
Having explored the impact of the distribution model on health commodity stock-outs in Chapter 2, I now turn my attention to the health facility-level practices that might drive stock-outs in developing countries. Particularly, I investigate the following questions of interest to different stakeholders involved in managing public health supply chains including national governments, donors, and policy-makers: (i) *What factors affect the likelihood of commodity stock-outs at health facilities in developing countries?* (ii) *What facility-level mitigation mechanisms can be employed to minimize the likelihood of stock-outs?*

I explore the factors impacting commodity stock-outs through the lens of the "logistics cycle" framework that is widely adopted by organizations involved in managing public health supply chains such as the World Health Organization (WHO) and the United States Agency for International Development (USAID). As shown in Figure 3.1, the key elements of the logistics cycle framework that serve as building blocks of public health supply chains include *product selection*, *quantification*, *procurement*, *inventory management*, and *logistics management information system (LMIS)* (USAID 2011b). Product selection refers to the range and type of health commodities made available to clients through the public health supply chain, with the goal of ensuring that the product mix offered aligns closely with the needs of clients. Quantification pertains to forecasting demand for health commodities and procurement deals with ordering and receiving products from suppliers. Inventory management refers to guidelines regarding when to place an order, how much to order, and how to maintain the appropriate level of stock to ensure consistent supply and avoid shortages and oversupply. At the center of the logistics cycle framework, as can be seen in Figure 3.1, is the LMIS that collects, organizes, and reports data to enable informed decision-making throughout the logistics cycle framework. The data collected using LMIS includes quantities of commodities received at health facilities, quantities issued to clients, and inventory available on-hand, among others. The LMIS data are central to the quantification process at the national level and also serve as the basis for inventory management at

[10] A paper based on this study is co-authored with Dr. Anant Mishra, Dr. Karthik Natarajan, and Dr. Kingshuk Sinha from the Carlson School of Management, University of Minnesota

downstream facilities in the public health supply chain including regional/district warehouses and health facilities.

Figure 3.1. The "Logistics Cycle" Framework; Adapted from (USAID 2011b)



In this study, I examine the operational implications of product selection by investigating how the range of health commodities offered by a health facility impacts the likelihood of stock-outs. Offering a wide range of commodities increases the likelihood that clients find a product that best meets their needs, but it also creates challenges due to the increased complexity of monitoring and managing the inventory of different health commodities. In addition to increased complexity, expanding the range of commodities offered also brings up other challenges that are unique to public health supply chains including the need for additional or more frequent trips to upstream facilities to collect supplies. Given these trade-offs, I investigate whether, and to what extent, increasing the range of commodities impacts the likelihood of stock-outs at health facilities.

With respect to other elements of the logistics cycle framework, decisions related to *quantification* and *procurement* are typically made by the Ministries of Health at the national level, and downstream health facilities are not directly involved in making those decisions. Hence, I do not directly investigate the impact of quantification and procurement on stock-outs at health facilities, but rather incorporate them into the empirical analysis by including administrative unit fixed effects (e.g., country fixed effects in the main model and region/district fixed effects as robustness checks in the Appendix) and month fixed effects. With respect to inventory management, the guidelines regarding when and how much to order are typically set at the national level and they are similar across facilities within any given administrative region. For example, health facilities within a specific administrative area utilize the same guidelines (based on average supply lead times to that region) to determine maximum-minimum inventory *levels* (specified in "number of months of stock") that form the basis for the replenishment decisions (USAID 2011b). Incorporating country/region/district fixed effects into the models would account for potential variations, if any, in inventory management guidelines across different administrative areas. In the same vein, in order to control for potential variations in maximum-minimum inventory *quantities* (specified in terms of "number of months of stock × demand"), I incorporate into the models multiple demand-related control variables at the health facility-level (i.e., facility size) and client-level (education, household size, wealth index).

Finally, I explore the inter-relationship between the *LMIS Practices* used by health facilities and stock-outs. Specifically, I focus on two key aspects related to a health facility's LMIS that have received significant attention within the public health sector: (i) encouraging health facilities to update their LMIS records on a frequent basis (i.e., daily) to accurately keep track of available supplies (MOH Malawi 2003, WHO 2006) and (ii) transitioning from paper-based records to electronic LMIS to reduce information transmission lead times and data aggregation errors (USAID 2006). While these two information management practices have the potential to reduce stock-outs, given the significant capital investments required for implementing these practices, it is imperative to rigorously analyze whether, and to what extent, the two LMIS practices reduce the likelihood of commodity stock-outs at health facilities in developing countries. In addition to testing the main effects, I also analyze how the impact of product selection and the potential effectiveness of the two LMIS practices vary across urban and rural health facilities, given the significant disadvantages faced by rural facilities with respect to the availability of logistics infrastructure (e.g., access to roads) and human resources (e.g., number of staff, workload, etc.) in developing countries.

To investigate how the different elements related to the logistics cycle framework impact stock-outs in public health supply chains, I estimate models using a novel field dataset (related to contraceptive availability) collected from 3,995 health facilities across five developing countries, namely Bangladesh, Haiti, Malawi, Senegal, and Tanzania. In order to reduce identification concerns and ensure that potential sample imbalance does not bias the results, I incorporate a rich set of control variables and estimate the models using the coarsened exact matching technique (Iacus et al. 2012). Although matching techniques are based on the identifying assumption of "selection on observables" (Ho et al. 2017), to the extent that the observable factors are correlated with unobservable factors, their application could reduce the possibility that the coefficients of interest are biased by unobserved heterogeneity (e.g., differences in funding availability, inventory management policies and demand patterns across facilities). The results yield the following consequential insights for stakeholders managing public health supply chains in developing countries:

(i) Expanding the range of health commodities offered increases the likelihood of stock-outs at both urban and rural health facilities. However, the adverse effect of increased commodity range is not the same across the two types of facilities, with the impact being more severe in rural health facilities. This result highlights the need for organizations managing public health supply chains to reconcile policy decisions (such as encouraging health facilities to expand the range of commodities offered) with the operational implications of those decisions. Without careful consideration, even well-meaning policy decisions could have a significant negative impact on the operational performance of public health supply chains and ultimately, health outcomes.

(ii) With respect to balancing the advantages (i.e., increased choice) and disadvantages (i.e., increased likelihood of stock-outs) of offering a wide range of contraceptive methods, the additional analyses conducted suggest that the appropriate range varies based on a health facility's location (urban vs. rural) and LMIS practices. For facilities with *less mature* LMIS practices (i.e., no daily updating of LMIS records, and no use of electronic LMIS), the appropriate range is around 8 contraceptive methods for urban locations and between 6 to 8 contraceptive methods for their rural counterparts. In the case of facilities with *more mature* LMIS practices (i.e., daily updating of LMIS records, or use of electronic LMIS, or both), the determination of the appropriate range is more involved and I explain the nuances in Section 3.5.3. By offering the appropriate number of methods, facilities would provide clients with a reasonable variety of methods so that they are likely to be able to access a contraceptive method of their choice, while still keeping stock-outs at a relatively low level.

(iii) Regarding the effect of individual LMIS practices, I find that urban health facilities are likely to realize a significant reduction in stock-outs with the implementation of daily updating of LMIS records. However, the use of electronic LMIS does not lead to a reduction in the likelihood of stock-outs at urban health facilities. This is a robust result, regardless of whether the use of electronic LMIS is implemented as a standalone practice or in conjunction with daily LMIS updating.

(iv) In rural health facilities, daily LMIS updating and the use of electronic LMIS do not lead to a significant reduction in stock-outs when they are implemented as standalone practices.

However, when the two practices are implemented together, their joint effect is significant in reducing the likelihood of stock-outs.

Taken together, the last two findings suggest that the impact of LMIS practices can vary considerably across rural and urban health facilities. Hence, the LMIS practices and the associated funding allocation strategies need to be tailored to the specific facility types when undertaking initiatives to reduce stock-outs in public health supply chains. These findings are significantly consequential in light of the growing demand for health commodities at a time when the future funding outlook is modest to weak for many developing countries. Implementing electronic LMIS and daily updating of LMIS records are both resource-intensive and as public health supply chains strive to do more with less, it is important to allocate the limited resources in the most effective way possible. The study results provide novel insights in this regard by shedding light onto how the effectiveness of the different LMIS practices vary across different types of health facilities.

In the empirical analyses, I supplement the matching technique used in the estimation of the main model with a diagnostic approach that tests the sensitivity of the coefficients of interest to potential unobserved heterogeneity (Altonji et al. 2005). The results of this diagnostic test provide strong evidence that the findings are not likely to be influenced by unobserved factors. Further, I conduct additional tests to evaluate the possibility that commodity substitution *within* (i.e., the stock-out of a particular contraceptive method leading clients to switch to a different method at the same facility) and *between* health facilities (i.e., the stock-out of a contraceptive method at a facility leading clients to switch to a "neighboring" facility) is affecting the coefficients of the estimated models. The results suggest that it is unlikely the case. In summary, through the empirical analyses discussed above, I rigorously establish the association between the independent variables of interest (commodity range and LMIS practices) and stock-outs.

Next, I conduct post hoc analysis to build on the insights gained from the above empirical analysis. Specifically, I develop predictive models to understand whether the same set of control and independent variables in the above empirical analysis can also be used to predict stock-outs with reasonable accuracy. I utilize a simple logistic regression classifier to predict commodity stock-outs and the results indicate that the predictive model can correctly forecast stock-outs 76% of the time. The application of alternative classification approaches, namely the "k-nearest-neighbors" (a non-parametric method) and "random forest" (an ensemble method) classifiers, leads to relatively similar prediction accuracies (74% and 82%, respectively), thereby establishing further confidence in the predictive power of my variables.

The remainder of the study is organized as follows. In section 3.2, I review the relevant literature to position this study and develop the study hypotheses. In section 3.3, I describe the data, variables, and the empirical research design. I present the results of the empirical analysis in section 3.4. In section 3.5, I discuss the checks performed to evaluate the robustness of the empirical analysis results to a number of alternative specifications. Section 3.6 contains a discussion on the post hoc analysis where I report the predictive model estimation results to understand whether the variables in the empirical analysis can also be used to reliably predict stock-outs with reasonable accuracy. In section 3.7, I present the concluding remarks, delineating the study's contributions and the implications of the study findings, highlight the limitations, and discuss potential avenues for future research.

3.2. Conceptual Foundation

3.2.1. Literature Review

This study primarily draws on and advances two streams of literature: (i) *impact evaluation of interventions to improve the performance of public health supply chains*, and (ii) *managing operations in public health and not-for-profit settings*.

3.2.1.1. Impact Evaluation of Interventions to Improve the Performance of Public Health Supply Chains

In this stream, the past literature has focused on a wide variety of interventions including the introduction of performance-based incentives, deployment of technology in public health supply chains, and changes to product distribution strategies. Among the relevant papers include Barrington et al. (2010) that documents a pilot study in Tanzania and analyzes how the introduction of SMS technology to transmit "stock counts" information from health facilities impacts the availability of antimalarial drugs in public health supply chains. The papers by Friedman et al. (2012) and Vledder et al. (2019) evaluate the impact of an intervention aimed at reducing the number of supply chain tiers within the public health system in Zambia. Based on the results of a quasi-randomized experiment that compares the performance of two different supply chain structures (treatment and control groups), they find that the structure with a smaller number of supply chain tiers had lower stock outs at the health facility level.

This study differs from the above-mentioned studies in two ways. First, the impact evaluation papers discussed above focus on how changes to one specific aspect of the public health supply chain (e.g., technology used to transmit stock-related information) influence commodity availability at health facilities in developing countries. In contrast, I take a more comprehensive view as captured by the logistics cycle framework and analyze how changes to multiple elements of the framework impact commodity availability in public health supply chains. Second, the impact evaluation studies typically use either qualitative or anecdotal evidence-based approaches while in my study, I employ a rigorous empirical analysis approach using data from nearly 4000 health facilities across five developing countries.

In addition to the academic research-oriented papers, there is also a body of practitioner-oriented publications (in the form of white papers and reports published by leading global health organizations including USAID and the Reproductive Health Supplies Coalition) that focuses on the performance measurement and management of public health supply chains in developing countries (e.g., Allain et al. 2010, Aronovich et al. 2010, Hasselberg and Byington 2010, Rosen 2014, Sanderson et al. 2014). This body of publications is founded on the notion of "No product, no program!," where the central argument is that well-functioning supply chains that ensure product availability are critical to the success of public health programs and advancing health outcomes. The purpose of these practitioner-oriented publications is to serve as guiding documents for public health supply chain managers by outlining the key steps and processes involved in managing supply chains for health commodities. The following are some illustrative examples: Aronovich et al. (2010) describe the characteristics of "good" performance measures in the context of public health supply chains and offer detailed explanations regarding how to calculate the different performance measures associated with key elements of the logistics cycle framework including procurement, inventory management and logistics management information systems (LMIS). Hasselberg and Byington (2010) focus on community-based distribution (CBD) of health commodities and provide guidance regarding the design of key supply chain functions (e.g., *inventory management* and *LMIS*) for such programs. Allain et al. (2010) describe how "segmentation" can be a valuable tool to improve the performance of public health supply chains. Segmentation refers to grouping products with similar characteristics so that each group is managed using a supply chain strategy that best fits its requirements. The above-mentioned publications provide descriptive and qualitative guidance regarding the design of different elements of the logistics cycle framework. However, unlike my study, these publications are not based on rigorous empirical analysis of how specific supply chain strategies (e.g., increasing the range of health commodities offered or increasing the LMIS updating frequency) impact the performance of public health supply chains, and consequently, the availability of health commodities.

3.2.1.2. Managing Operations in Public Health and Not-for-profit Settings

In this stream of literature, published papers particularly relevant to this study include: Gallien et al. (2017), Leung et al. (2016), and Natarajan and Swaminathan (2014). I refer the reader to Section

2.2.1 for a detailed review of the studies in this literature. The above-mentioned papers analyze the effect of funding and inventory management policies on public health supply chain performance using simulation-based and analytical models. My study contributes to and complements this body of extant literature in the following ways. I empirically investigate the potential relationship between product selection (i.e., the range of health commodities offered) and stock-outs at health facilities in developing countries, a relationship that has not received attention in the prior literature. Next, I analyze how a health facility's LMIS practices including the LMIS updating frequency and the use of electronic LMIS impact stock-outs. The inter-relationship between LMIS practices and public health supply chain performance has not been explored before. Finally, I analyze the impact of the above-mentioned factors, i.e., commodity range, LMIS updating frequency and the use of electronic LMIS, using field data from developing countries to uncover novel, empirically-grounded drivers of health commodity stock-outs. In sum, my empirical study complements previous analytical and simulation-based works that focus on managing operations in public health and not-for-profit settings.

3.2.2. Hypotheses Development

3.2.2.1. Product Selection

Product selection, a key element of the logistics cycle framework, defines the range of health commodities procured and distributed through public health supply chains. Within the public health sector, there exists two contrasting perspectives with respect to the range of commodities offered to clients. The first perspective advocates for the adoption of a "supermarket approach," i.e., it suggests that public health supply chains should offer a "wide range" of commodities in order to best meet the needs of clients (see MOH Kenya 2010). The proponents of this approach argue for health facilities to offer a wide range of contraceptives since the preferred contraceptive method varies across population groups (e.g., depending on age, marital status, frequency of sexual activity; see Malawi DHS 2011). Similarly, in the case of antimalarial drugs, clients might have varying preferences for the different types of medications including antimalarial injectables, pills and suppositories. The rationale behind the above perspective is that offering a wider range of health commodities increases the likelihood of clients having access to a product that best meets their needs and preferences.

In contrast to the above perspective, there has also been a push within the public health sector to limit the range of health commodities offered to "as few as possible, while still providing an acceptable level of service" (USAID 2011b, p. 78). Proponents of this perspective argue that offering fewer health commodities enhances the manageability of public health supply chains, since a smaller number of items need to be stored, distributed, and monitored. Particularly, for every health commodity offered by a facility, staff personnel need to collect and record information regarding the item name, size, quantity issued or received, and quantity in-stock. The additional record-keeping requirements associated with the increased range of commodities may place a considerable strain on the health facilities, especially in light of the fact that public health supply chains in developing countries already operate under severe resource constraints (e.g., high workload; see Bradley and McAuliffe 2009). The increased complexity of record-keeping, combined with the resource constraints, has the potential to result in inaccurate inventory records, which in turn could lead to imperfect orders and supply-demand mismatches (Kolapo et al. 2009). In addition to the increased complexity, as the range of commodities offered increases, health facilities need to work with an increasing number of upstream facilities (or with the same number of facilities at an increased frequency) to secure supplies, creating significant challenges in terms of coordinating the ordering and delivery processes. Furthermore, in many developing countries, health facilities are responsible for collecting their supplies from upstream locations, and frequently, health workers need to take time away from providing care to perform this task (see Riders for Health 2018, Daff et al. 2014, and Allain et al. 2010). However, given the resource constraints, health facilities often find it difficult to allocate the necessary time and resources to collect supplies from upstream locations in a timely manner, resulting in supply interruptions and stock-outs. This problem is likely to be exacerbated as the range of health commodities increases since the frequency of supply pick-ups from upstream locations is likely to increase with the number of commodities offered.

In summary, offering a wide range of health commodities could be beneficial for clients but it also comes with potential downsides in the form of increased complexity of inventory record keeping and making additional trips to upstream facilities to collect supplies. These, in turn, could increase the likelihood of stock-outs at health facilities since public health supply chains often do not have buffer resources to deal with the increased complexity and additional resource requirements stemming from offering a wider range of commodities. Hence, I expect the range of health commodities offered through a public health supply chain to be associated with an increased likelihood of stock-outs.

In general, I expect the likelihood of stock-outs to increase with the range of commodities offered. However, the magnitude of the (negative) impact is not likely to be the same across different types of health facilities. The reasoning behind this is as follows. As the range of commodities offered increases, facilities need additional resources (e.g., funding, staff, vehicles) to manage the increased time and effort required to track supplies, coordinate orders with upstream facilities, and pick up the ordered supplies from the upstream locations. However, finding buffer capacity is challenging in resource-constrained environments that are typical of most public health supply chains in developing countries. These challenges are likely to be particularly acute for rural health facilities since they face more severe resource constraints relative to urban facilities (e.g., in terms of staff shortages and higher workload; see Bradley and McAuliffe 2009). In addition to resource constraints, there are also significant disparities in logistics infrastructure between urban and rural health facilities (Schöpperle and Woodburn 2013, USAID 2017). Given these disparities, rural facilities may find it more difficult to manage the increased complexity stemming from offering a wider range of health commodities. Consequently, I expect the negative impact of offering a wider range of commodities to be stronger in rural facilities when compared to facilities located in urban areas. Hence, I posit the following hypothesis:

HYPOTHESIS 3.1 (H3.1)

a) The range of health commodities offered through a public health supply chain is associated with an increase in the likelihood of stock-outs.

b) The increase in the likelihood of stock-outs is greater for rural facilities relative to urban facilities.

Beyond the impact of product selection on stock-outs, another key element of the logistics cycle framework is a health facility's LMIS practices. Specifically, I explore how different aspects related to LMIS including (i) the frequency with which health facilities monitor and update their LMIS records and (ii) the type of LMIS they use (electronic vs. paper-based) to store and transmit inventory-related information to upstream facilities impact the likelihood of stock-outs in public health supply chains.

3.2.2.2. Logistics Management Information System (LMIS) Practices

LMIS Updating Frequency. One of the fundamental activities in LMIS is stock tracking, aimed at keeping account of the in-flow and out-flow of commodities at health facilities. Stock tracking involves collecting and recording stock-related information including the amount received from suppliers, those dispensed to clients, and the quantity of usable stock available at the health facility (USAID 2011b). These LMIS data form the basis for procurement and resupply decision-making. For example, in many developing country health supply chains, facility staff utilize the LMIS information (specifically, the information recorded on stock cards) to determine order *quantities* based on pre-specified "max-min" inventory levels (Leung et al. 2016, USAID 2011b).

Since the LMIS records form the basis of procurement and resupply decisions at health facilities, it is critical that the information recorded on the stock cards is accurate and updated on a regular basis. Existing LMIS guidelines in the context of the public health sector recommend updating of the records as soon as there is a change in the quantity of available supplies either through replenishment or dispensing of products to clients (MOH Malawi 2003, WHO 2006). As mentioned in Section 2.3.2, frequent updating of the LMIS records increases the likelihood of the staff having access to accurate and reliable inventory information, which, in turn, could lead to better replenishment decisions and reduced probability of supply-demand mismatches. There is anecdotal evidence of the benefits of frequent and timely updating in the context of managing health commodities (see JSI 2015) but to the best of my knowledge, there is no empirical study that rigorously analyzes the relationship between LMIS updating frequency and stock-outs at health facilities in public health supply chains. I formally test this relationship in my study.

Next, I consider how a health facility's location might influence the benefits derived from more frequent updating of LMIS records. Intuitively, as discussed above, I expect more frequent updating of LMIS records to lead to lower stock-outs in both urban and rural health facilities. However, the benefits of frequent updating may not be uniform across the two types of facilities. This is because updating the LMIS stock-level information is only the first step in the replenishment process; this information must eventually be aggregated and transmitted to the upstream facilities in a timely manner for the replenishment process to be effective and efficient. In practice, health facilities record and update their LMIS information using either paper-based or electronic systems. With paper-based systems, the inventory and consumption pattern reports generated from the LMIS are either hand-delivered or sent via mail to the upstream facilities (USAID 2011a). Under both transmission methods, rural facilities experience significant hurdles, relative to their urban counterparts, in transmitting the LMIS information in a timely manner. The additional hurdles faced by rural facilities can be attributed to the significant disparities in logistics infrastructure across the two types of facilities (Schöpperle and Woodburn 2013, USAID 2017). For example, rural facilities are often located in remote, hard-to-reach areas with limited accessibility to well-maintained roads and in some cases, special off-road vehicles are required to access these facilities (Friedman et al. 2012). Hence, the potential benefits derived from the frequent updating of LMIS records are likely to be countered, at least, in part, by the infrastructural challenges faced by rural facilities. As a result, I expect the benefits from the frequent updating of LMIS records to be higher for urban facilities when compared to health facilities located in rural areas. Hence, I posit the following:

HYPOTHESIS 3.2 (H3.2)

a) *LMIS updating frequency of health commodities in a public health supply chain is associated with a decrease in the likelihood of stock-outs.*

b) *The decrease in the likelihood of stock-outs is greater for urban facilities relative to rural facilities.*

Use of Electronic LMIS. Paper-based LMIS is the most commonly used method of tracking supplies in public health supply chains within many developing countries (USAID 2011b). The primary advantage of a paper-based LMIS is that it does not require significant capital investments. However, as noted in Section 2.3.2, such systems suffer from a number of drawbacks that can adversely impact the efficiency and accuracy of record-keeping (USAID 2011a). Specifically, inventory management using paper-based LMIS tends to be cumbersome and time-intensive and it also requires manual aggregation of data across health facilities, increasing the potential for human errors (USAID 2011a, WHO 2006). Public health supply chains can mitigate some of the challenges associated with paper-based systems by moving to an electronic LMIS. For example, Bowser et al. (2014) found a positive association between the use of electronic LMIS by health facilities and the accuracy of their stock records.

In addition to increasing the accuracy of stock records, electronic LMIS also has the potential to reduce the information transmission lead times associated with sending inventory reports to upstream facilities. As noted earlier, in case of paper-based LMIS, the reports are either hand-delivered to the upstream facilities or sent via mail, significantly increasing the information transmission lead times (USAID 2011a). For example, OpenLMIS (2017) reported a lead time of greater than 15 days for paper-based inventory reports prepared by health facilities to reach the upstream supply locations. Paper-based reports submitted by facilities would then need to be manually processed for completeness by suppliers, further increasing the order processing times. The longer and highly unpredictable lead times can significantly increase the likelihood of commodity stock-outs at health facilities. The use of electronic LMIS can address this potential shortcoming of paper-based systems since they allow for data transmission to take place electronically, thereby increasing the speed and predictability of information transmission (OpenLMIS 2017, USAID 2012). For example, a pilot study conducted in Zambia found that the speed of information transmission in an electronic system used to manage various health commodities was substantially higher than paper-based systems (OpenLMIS 2017). Similarly, in Bangladesh, the implementation of an electronic system significantly increased the speed of data transmission between health facilities and the country's central warehouse (USAID 2012). Hence, an electronic LMIS can mitigate stock-outs by helping facilities avoid the delays and uncertainty associated with order submission and processing times. For example, OpenLMIS (2017) provides anecdotal evidence that the rate of stock-outs were reduced significantly for Tanzanian health facilities that moved from a paper-based LMIS to an electronic one. In light of this discussion, I expect the use of electronic LMIS by health facilities to reduce the likelihood of stock-outs (relative to paper-based LMIS).

Next, I consider the impact of a health facility's location on the benefits of using electronic LMIS. Consistent with the above discussion, I expect the use of electronic LMIS to lead to lower stock-outs in both urban and rural health facilities but the benefits of moving from paper-based LMIS to an electronic system may not be the same across the two types of facilities. In the earlier discussion leading up to H3.2b, I highlighted the information transmission challenges faced by rural facilities under a paper-based system due to infrastructural limitations. These challenges are likely to be less severe for urban facilities since they enjoy infrastructural advantages (e.g., access to well-maintained roads) over rural facilities and are also typically located in closer proximity to the upstream supply facilities (e.g., regional warehouses). As a result, the benefits of moving from paper-based LMIS to an electronic system are likely to be lower for urban facilities. Hence I posit the following hypothesis:

HYPOTHESIS 3.3 (H3.3)

a) The use of an electronic LMIS (vis a vis paper-based LMIS) to monitor inventory of health commodities in a public health supply chain is associated with a decrease in the likelihood of stock-outs.

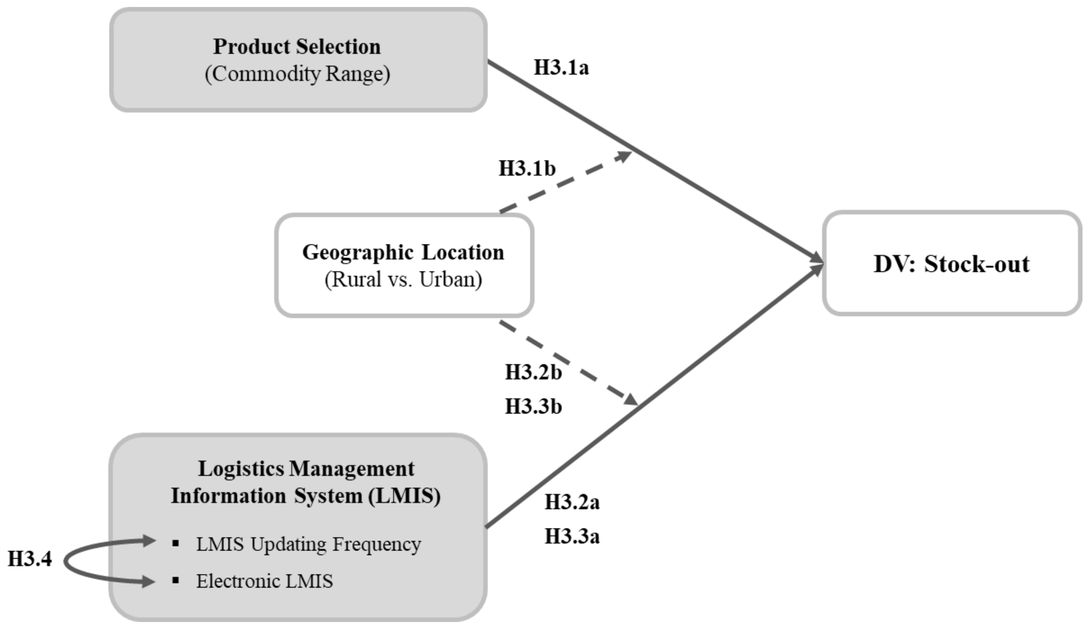
b) The decrease in the likelihood of stock-outs is greater for rural facilities relative to urban facilities.

Complementarity of LMIS Practices. Hypotheses H3.2a and H3.3a posit direct relationship between the two LMIS practices — namely, more frequent updating of the LMIS records and the adoption of an electronic LMIS — and stock-outs. However, it is conceivable that the impact of the two LMIS practices will be greater when they are implemented together. The intuitive reasoning for the greater impact is the following. While frequent updating of the LMIS records results in more up-to-date and reliable data, this information must eventually be aggregated and transmitted to the upstream facilities for resupply planning (Kolapo et al. 2009). The use of electronic LMIS can considerably facilitate the information transmission process by providing a platform for the rapid aggregation and transmission of collected data. As a result, I expect the benefits of frequent LMIS updating to increase when used in conjunction with electronic LMIS, and this is likely to hold across both urban and rural facilities. Earlier, I hypothesized that frequent LMIS updating has a larger impact on stock-outs in urban facilities when compared to their rural counterparts (see Hypothesis H3.2b), while I anticipate the opposite to be true with respect to the benefits of using an electronic LMIS (see Hypothesis

H3.3b). Therefore, depending on the type of facility (i.e., urban vs. rural), the effect of one LMIS practice is likely to be more dominating than the other in reducing stock-outs. Regardless, I expect the two practices to be complementary with respect to their impact on mitigating stock-outs. Hence, I posit Hypothesis 3.4 (H3.4). Figure 3.2 depicts an integrated view of the four hypotheses proposed in this chapter.

HYPOTHESIS 3.4 (H3.4): *The LMIS updating frequency and the use of an electronic LMIS to monitor the inventory of health commodities in a public health supply chain are complementary in their association with a decrease in the likelihood of stock-outs.*

Figure 3.2. An Integrated View of the Study Hypotheses



3.3. Empirical Analysis

3.3.1. Data Collection

I address the two research questions that motivate this study in the context of contraceptives, a health commodity. This choice is motivated by two important reasons. First, contraceptives are commonly offered by many last-mile facilities in the public health supply chains of developing countries, from those located in Africa to Western and Southeast Asia. Furthermore, contraceptives are also frequently sought and used by clients across a wide range of geographies and demographics, forming an important and integral part of the overall public health system in many developing countries. Second, the contraceptive methods offered by health facilities exhibit significant diversity along a number of dimensions including commodity value, shelf-life, and storage requirements. As such, contraceptives are representative of a broad array of health commodities offered through public health supply chains. Hence, the findings of this study have implications for managing public health supply chains for other types of commodities beyond reproductive health supplies.

Similar to Chapter 2, I perform the empirical analysis using data collected through the SPA surveys. The DHS program has developed consistent procedures and methodologies to guide the SPA survey process, ensuring that the service readiness data are comparable across countries (Choi and Ametepi 2013, DHS 2017). This allows us to test the proposed hypotheses in the context of contraceptive methods in multiple developing countries. The DHS program has made the SPA survey data publicly available for nine countries: Bangladesh, Haiti, Kenya, Malawi, Namibia, Nepal, Senegal, Tanzania, and Uganda. The survey dates for the nine countries range from 2006 to 2015. For this study, I collect and aggregate SPA survey data from health facilities located in Bangladesh (survey year 2014), Haiti (survey year 2013), Malawi (survey year 2013), Senegal (survey year 2012), and Tanzania (survey year 2014).[11] These countries were chosen because their survey timings are relatively close to one another and also based on the fact that an identical survey instrument was used across the five countries over this time frame. I did not include the data from the SPA survey for Nepal (survey year 2015) since the survey questions are slightly different from the ones used in the five countries included in the sample. Finally, the SPA survey data from Kenya, Uganda, and Namibia are relatively old (2010 or prior) and hence, they are not included in the study sample. The data from the SPA survey across the five countries that is used in this study is cross-sectional in nature, i.e., each health facility represented in the sample was surveyed only once. Within each country in the sample, the health facilities included in the survey were identified either based on random sampling or stratified random sampling or in some cases a census, making the samples representative of the particular country (MSPA 2014, SPA 2016).

The unit of analysis is facility-method, i.e., a particular contraceptive method (e.g., condoms, implants, injectables, etc.) offered at a given health facility. I focus on stock-outs at the method level and not at the facility level since clients' preferences for the contraceptive methods are often specific and in many cases, they are reluctant to switch to other methods due to a variety of reasons including a lack of awareness of alternative contraceptive methods, concerns surrounding effectiveness and side-effects, and partner's reluctance to switch (RHSC 2016a, Sinha and Kohnke 2009). Furthermore, the methods themselves are not always substitutable. As a result, focusing on stock-outs at the overall facility level would not provide an accurate picture of the unmet demand for contraceptives. Nevertheless, in section 4.5.2, I consider potential substitution effects across

[11] For Malawi, Senegal and Tanzania, the survey timeline extends into the first half of the following year.

methods to examine the robustness of the findings. The study sample consists of 24,730 facility-method observations at 3,995 facilities across five countries: Bangladesh, Haiti, Malawi, Senegal, and Tanzania.

3.3.2. Variables

Dependent Variable: *Stock-outs*. The approach used to measure stock-outs in this study is similar to the one delineated in Chapter 2, Section 2.4, where I measure stock-outs as a binary variable indicating whether or not a specific type of contraceptive was out-of-stock on the day the survey was administered. Contraceptive methods for which "at least one valid item was observed" on the shelf are considered to be "in-stock." Products that are reported by the staff to be on the shelf but could not be observed for some reason (e.g., the storage area was locked) are recorded as "in-stock." Such cases are not common in the sample. Instances where the products are observed by the survey administrators, but none of the available products are valid (e.g., due to expiration or damage) are treated as "out-of-stock" since the non-valid items cannot be used to satisfy demand. Finally, products for which a "not available today" response was recorded are considered "out-of-stock" and those that received a "never available" response were dropped from the sample.

Independent Variables. Three independent variables are of interest in this study. The first is *Commodity Range* measured at the facility level, which captures the total number of contraceptive methods offered by a health facility. In the sample, health facilities offer anywhere from 1 to 10 contraceptive methods. These include male condoms, female condoms, combined pills, combined injectables, intrauterine devices (IUDs), implants, emergency contraceptives, cycle beads, Progestin-only pills, and Progestin-only injectables. The second independent variable is *LMIS Updating Frequency,* a binary variable that indicates whether health facilities update their LMIS records on a daily basis (variable equals 1 if records are updated on a daily basis and 0 otherwise). Finally, *Electronic LMIS* is a binary variable that indicates whether health facilities utilize an electronic LMIS to monitor their inventory of health commodities (variable equals 1 if the facility utilizes electronic LMIS and 0 otherwise). To test the moderating role of a health facility's location (i.e., rural vs. urban) on the three independent variables of interest, I perform a subgroup analysis by creating two sub-samples comprising urban and rural facilities.[12]

[12] The binary classification used in this study is directly based on the urban-rural classification recorded in the Demographic and Health Surveys (DHS). This dichotomous measure of geographic location has been widely used in prior research utilizing DHS data across various countries. Examples include the study of Wang et al. (2017) focusing on Haiti, White and Speizer (2007)'s study focusing on Zambia and research by Kanyangarara et al. (2018) who analyzed urban-rural disparities in the delivery of health commodities across 17 low and middle-income countries.

Control Variables. I control for a variety of country-, time-, product- and facility-specific factors. At the country-level, I include country fixed effects (*Country FE*) to account for variations in logistics infrastructure across the five countries included in the sample.[13] To account for potential supply chain shocks that could impact the availability of health commodities across different time periods, I incorporate month fixed effects (*Month FE*) corresponding to the month when the survey was conducted at a health facility. At the product-level, health facilities offer up to 10 different contraceptive methods which can be classified into three distinct groups:

(i) Long-acting contraception (IUD, implant);

(ii) Short-acting or emergency contraception (progestin-only pill or injectable, combined pill or injectable, emergency contraceptive); and

(iii) Barrier/fertility awareness contraception (male/female condom, cycle bead).

I include commodity type fixed effects, *Commodity Type FE,* (e.g., male condom, implant, etc.) to capture commodity-specific characteristics that might influence the availability of specific methods at health facilities. In addition, I also include *Commodity Assortment FE* to account for heterogeneity across health facilities in terms of the different combinations of contraceptive methods offered.[14]

Further, I control for multiple facility-specific characteristics that might impact the likelihood of health commodity stock-outs. In general, health facilities in developing countries are categorized based on *service delivery level* and *managing authority*. The service delivery level typically consists of the following three categories (see MSPA 2014):

(i) Primary level: health services at this level are provided by health posts and dispensaries and are limited to mostly preventative and some curative outpatient services;

(ii) Secondary level: services at this level are generally delivered by health centers and district hospitals and include both inpatient and outpatient services for the target populations; and

[13] In addition, as mentioned in the introduction, *procurement* and *quantification* are carried out at the national level and *inventory management* guidelines are also set at that level. Hence, the inclusion of *country fixed effects* would also account for potential variations in upstream supply availability (upstream from the perspective of health facilities) across the five countries that may arise due to differences in *procurement*, *quantification,* and *inventory management* guidelines across those countries. The results are robust to the inclusion of alternative administrative unit fixed effects as control variables (i.e., region/district fixed effects; see Table AP3.3 in the Appendix).

[14] For instance, I consider "long-acting methods only" as one combination and "long-acting and short-acting methods" as a different combination that could be offered by facilities. The inclusion of dummy variables would control for the possible combinations (i.e., seven combinations) of methods offered by facilities.

(iii) Tertiary level: health services are provided by regional and central hospitals that might also serve as research institutions.

In terms of the managing authority, health service providers in developing countries can be classified into the following groups:

(i) Public: includes providers across different service delivery levels that are run by the government;

(ii) Private non-profit: includes non-profit organizations (NGO) and faith-based organizations (FBO); and

(iii) Private for-profit: includes private providers that are not categorized as NGO or FBO.

I include relevant dummy variables corresponding to a health facility's *service delivery level* and *managing authority* in all models. In addition, I control for *Facility Size* that captures the total number of staff at a health facility. Further, I include the variable *Supervision,* which captures whether or not facilities receive external supervision from the upstream entities (equal to 1 if they receive external supervision and 0 otherwise). The storage conditions and product issuance protocols used at the health facilities could also impact the number of "useful" products (i.e., contraceptives that are not expired or damaged) available to satisfy demand and hence, I include two control variables in this regard: *First Expire First Out* and *Protection. First Expire First Out* refers to the practice of organizing and issuing health commodities based on their expiration dates. This is captured as a binary variable indicating whether some or all of the commodities on the shelf are sorted by expiration date. The control variable *Protection* is related to the storage conditions at health facilities. During their visit, survey administrators check the area where the health commodities are stored to determine whether adequate measures are in place to protect supplies from heat, moisture, and pests (e.g., are health commodities off the floor, are they protected from water? etc.) I define *Protection* as the number of protective measures (ranging from 0 to 4) taken by the health facility.

Finally, I incorporate multiple client-related variables into the main model that have the potential to drive contraceptive use among clients and subsequently impact demand patterns across health facilities. Using the "women and household" data from the DHS program, I collect more than 78,000 client-level observations pertaining to the characteristics of clients across the five countries in the sample. I first link the SPA survey (i.e., "health facility" data) in each country with the relevant "women and household" survey that had the closest date of administration: Bangladesh (survey year 2014), Haiti (survey year 2012), Malawi (survey year 2015), Senegal (survey year 2012), and Tanzania (survey year 2015). Next, I average client characteristics based on the proximity of clients to a focal health facility (i.e., clients located within 30 km range of a health facility). The client-level variables include *Client Education* (measured in years of cumulative education received), *Client Household Size* (measured as the total number of people in a given household), and *Client Wealth Index* (measured in terms of wealth quantile[15] where a household would fall into one of the following categories: "poorest," "poorer," "middle," "richer," and "richest").

3.3.3. Model Specification

The dependent variable in this study is *Stock-Out*. As mentioned earlier, the SPA survey data used in the empirical analysis captures the stock-outs of health commodities using binary values depending on whether or not a specific type of contraceptive was out-of-stock on the day of the survey assessment. Logistic regression is widely used to model such binary outcomes within the operations management literature (Jira and Toffel 2013, Powell et al. 2012). As such, I use the following model specification to test the hypotheses of this chapter:

$$Ln\left[\frac{Pr\left(Stock\text{-}Out_{ij} = 1\middle|X_{ij}\right)}{1 - Pr\left(Stock\text{-}Out_{ij} = 1|X_{ij}\right)}\right] \tag{3.1}$$
$$= \beta_0 + \beta_{CL}X_{CL} + \beta_1 Commodity\ Range_i + \beta_2 LMIS\ Updating\ Frequency_i$$
$$+ \beta_3 Electronic\ LMIS_i$$
$$+ \beta_4 LMIS\ Updating\ Frequency_i \times Electronic\ LMIS_i + \varepsilon_{ij}$$

In Equation (3.1), *i* and *j* denote health facility *i* and contraceptive method *j* respectively, and X_{CL} is the vector of control variables. As mentioned earlier, I test the moderating role of facility location on the three independent variables of interest by performing a subgroup analysis on the two sub-samples comprised of urban and rural health facilities, respectively. Throughout the analyses, I use robust standard errors clustered at the facility level.

One potential concern related to evaluating the impact of a facility's LMIS practices on commodity stock-outs is that the assignment of LMIS updating frequency and electronic LMIS to health facilities might not be random, i.e., they could be simultaneous with unobserved factors (e.g., funding) that are not accounted for in the specification. If the model fails to capture this endogeneity, then I might overestimate the benefits provided by those practices. To alleviate such concerns, I utilize the coarsened exact matching technique (CEM) in estimating the coefficients of interest (Iacus et al. 2012, Nandkumar and Srikanth 2016). Although matching techniques rely on the "selection on observables" assumption (Ho et al. 2017), to the extent that the unobservable and

[15] The wealth index is developed by the Demographic and Health Surveys (DHS) and serves as a "proxy for measuring the long-term standard of living" (MSPA 2014, p. 22).

observable parameters are correlated, they can reduce the possibility of the observed effects of interest being confounded by unobservable differences between the treatment and control groups (Nandkumar and Srikanth 2016). In addition, matching techniques can minimize the chances of the observed effects being model dependent since the results from matched samples are less sensitive to functional form assumptions of the regression models (Iacus et al. 2012). The CEM technique, which involves the *exact* matching of treatment and control facilities on categorical dimensions[16], tends to outperform other matching methods (e.g., propensity score matching) in terms of "its ability to reduce imbalance, model dependence, estimation error, bias, variance, mean square error, and other criteria" (Iacus et al. (2012, p. 2).

I conduct the matching process without replacement to assign each facility to a treated/untreated group, wherein a treatment facility may have no matched untreated facility, one matched untreated facility, or more than one matched untreated facility. The treatment group represents facilities utilizing at least one of the LMIS practices, (i.e., daily LMIS updating or electronic LMIS or both) and the untreated group represents facilities utilizing neither daily LMIS updating nor electronic LMIS. I use the following facility-level and client-level covariates in the matching process: facility type, facility size, managing authority, supervision, first expire first out, protection, client education, client household size, client wealth index and country fixed effects. In additional robustness checks, I use the same covariates described above to match health facilities based on their commodity range and obtain consistent results (see Table AP3.1 in the Appendix).

3.4. Results

Table 3.1 displays summary statistics related to the dependent variable conditional on the main independent variables of interest. Table 3.2 presents the summary statistics and pairwise correlations for the variables used in the models. Table 3.3 presents the logistic regression estimation results for Equation (3.1) using coarsened exact matched samples. Here, I discuss the association between the main variables of interest and health commodity stock-outs. From Table 3.3 (Model 3: Columns 3 through 6), *Commodity Range* is a significant contributor to stock-outs in both urban and rural health facilities ($\beta = 0.14$, $p < 0.01$, $e^{0.14} - 1 = 0.15$ for urban; and $\beta = 0.24$, $p < 0.01$, $e^{0.24} - 1 = 0.27$ for rural). Thus, H3.1a is supported across both urban and rural facilities. Notice, however, that the impact of *Commodity Range* is not the same across the two types of health facilities. As the range of commodities offered through the public health supply chain increases, the odds of experiencing a stock-out goes up by 27% in rural health facilities as opposed to a 15%

[16] For matching based on continuous dimensions, categories of the continuous variables are created.

increase in the odds at urban facilities. A Wald test rejected the null hypothesis that the difference between the two coefficients is zero ($\chi^2 = 3.27$, $p < 0.10$), confirming that the negative impact of the *Commodity Range* (in terms of its impact on health commodity availability) is more severe in rural facilities relative to facilities located in urban areas. This result provides support for H3.1b.

Table 3.1. Summary Statistics of Dependent Variable, *Stock-Out*, Conditional on the Main Variables of Interest

	Mean of *Stock-out*			St. Dev. of *Stock-out*		
	All	**Urban**	**Rural**	**All**	**Urban**	**Rural**
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Commodity Range (Low)	0.18	0.18	0.18	0.38	0.39	0.38
Commodity Range (High)	0.25	0.21	0.28	0.43	0.41	0.45
LMIS Updating Frequency (Low)	0.26	0.26	0.26	0.44	0.44	0.44
LMIS Updating Frequency (High)	0.21	0.18	0.22	0.41	0.38	0.42
Electronic LMIS (Low)	0.22	0.20	0.23	0.42	0.40	0.42
Electronic LMIS (High)	0.17	0.17	0.16	0.37	0.38	0.37

Notes: The median value of commodity range was used to split this variable into low vs. high commodity range.

I now turn my attention to another key element of the logistics cycle framework, namely a health facility's LMIS practices. I first examine how LMIS updating frequency (*LMIS Updating Frequency*) affects the likelihood of commodity stock-outs. The results in Table 3.3 (Model 3: Columns 3 and 5, urban) show that the odds of experiencing a stock-out decrease by 37% for urban health facilities that update their LMIS records on a daily basis, when compared to those that do not ($\beta = -0.47$, $p < 0.01$, $e^{-0.47} - 1 = -0.37$). However, daily updating of the LMIS records does not lead to a significant reduction in commodity stock-outs at rural facilities (see Table 3.3, Model 3: Columns 4 and 6, rural). Therefore, H3.2a is supported in the context of urban health facilities, but not for rural facilities. A Wald test also rejected the null hypothesis that the difference between these coefficients is zero ($\chi^2 = 9.28$, $p < 0.01$), thus lending support to H3.2b.

Table 3.2. Summary Statistics and Pairwise Correlations

Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
1. Primary Facility	1.00																
2. Secondary Facility	-0.74	1.00															
3. Tertiary Facility	-0.35	-0.38	1.00														
4. Facility Size	-0.45	-0.04	0.66	1.00													
5. Public Facility	-0.14	0.15	-0.01	0.02	1.00												
6. Private For-Profit	0.14	-0.15	0.02	-0.10	-0.59	1.00											
7. Private Non-Profit	0.06	-0.05	0.00	0.06	-0.71	-0.15	1.00										
8. Supervision	-0.03	0.02	0.02	0.07	0.11	-0.16	0.01	1.00									
9. First Expire First Out	-0.12	0.08	0.05	0.05	0.06	-0.06	-0.02	0.08	1.00								
10. Protection	0.04	-0.03	0.00	0.04	-0.01	0.01	0.00	0.02	0.14	1.00							
11. Client Education	-0.15	0.09	0.08	0.03	-0.19	0.16	0.09	0.00	0.08	-0.11	1.00						
12. Client Household Size	0.24	-0.17	-0.08	0.10	0.18	-0.11	-0.13	0.00	-0.15	0.10	-0.63	1.00					
13. Client Wealth Index	-0.04	-0.01	0.07	0.12	-0.11	0.12	0.03	-0.03	0.03	-0.02	0.61	-0.14	1.00				
14. Commodity Range	-0.13	0.03	0.14	0.35	0.00	0.00	-0.01	0.03	0.10	0.00	0.07	0.14	0.19	1.00			
15. LMIS Updating Frequency	-0.08	0.05	0.03	0.08	0.10	-0.11	-0.03	0.06	0.19	0.06	-0.03	0.01	0.08	0.09	1.00		
16. Electronic LMIS	-0.02	-0.03	0.07	0.04	-0.03	0.01	0.02	-0.01	0.06	0.01	0.00	-0.04	0.04	0.02	-0.09	1.00	
17. Stock-out	0.03	0.00	-0.04	-0.05	-0.07	0.09	0.01	-0.03	-0.05	-0.07	0.08	-0.05	0.03	0.14	-0.05	-0.03	1.00
Mean	0.40	0.45	0.15	2.49	0.74	0.11	0.15	0.96	0.85	3.59	5.63	6.44	3.07	6.87	0.76	0.06	0.22
Std. Dev.	0.49	0.50	0.36	1.19	0.44	0.31	0.36	0.20	0.36	0.69	1.22	2.49	0.57	1.92	0.43	0.25	0.41
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.16	4.11	1.00	1.00	0.00	0.00	0.00
Max	1.00	1.00	1.00	7.83	1.00	1.00	1.00	1.00	1.00	4.00	8.06	26.69	4.59	10.00	1.00	1.00	1.00

Notes: All correlations larger than 0.02 are statistically significant at the 0.05 level ($p < 0.05$)

Table 3.3. Logistic Regression Results Examining the Effects of *Commodity Range* and *LMIS Practices* on Stock-Outs using Coarsened Exact Matched Sample (Based on *LMIS Practices*)

	Model 2		Model 3		Odds Ratio	
	Urban	**Rural**	**Urban**	**Rural**	**Urban**	**Rural**
DV: Stock-out	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Facility-level Controls						
Secondary Facility	0.49**	-0.11	0.49**	-0.10	1.63	0.90
	(0.24)	(0.09)	(0.24)	(0.09)		
Tertiary Facility	0.91***	-0.60**	0.90***	-0.59**	2.46	0.55
	(0.29)	(0.25)	(0.29)	(0.25)		
Ln (Facility Size)	-0.44***	-0.10*	-0.44***	-0.10*	0.64	0.90
	(0.09)	(0.06)	(0.09)	(0.06)		
Private For-Profit Facility	0.09	0.59***	0.09	0.58***	1.09	1.79
	(0.22)	(0.20)	(0.22)	(0.20)		
Private Non-Profit Facility	-0.21	0.40***	-0.21	0.41***	0.81	1.51
	(0.20)	(0.11)	(0.20)	(0.11)		
Supervision	-0.38*	-0.12	-0.38*	-0.13	0.68	0.88
	(0.22)	(0.36)	(0.22)	(0.36)		
First Expire First Out	-0.28	-0.27**	-0.28	-0.27**	0.76	0.76
	(0.20)	(0.11)	(0.20)	(0.11)		
Protection	-0.08	-0.10**	-0.08	-0.10*	0.92	0.90
	(0.08)	(0.05)	(0.08)	(0.05)		
Client-level Controls						
Client Education	-0.33**	-0.15**	-0.33**	-0.14**	0.72	0.87
	(0.14)	(0.06)	(0.14)	(0.06)		
Client Household Size	-0.09	-0.06*	-0.09	-0.06*	0.91	0.94
	(0.09)	(0.03)	(0.09)	(0.03)		
Client Wealth Index	0.56***	0.17*	0.56***	0.17*	1.75	1.19
	(0.18)	(0.10)	(0.18)	(0.10)		
Commodity Range	0.14***	0.24***	0.14***	0.24***	1.15	1.27
	(0.05)	(0.03)	(0.05)	(0.03)		
LMIS Updating Frequency	-0.46***	0.00	-0.47***	0.05	0.63	1.05
	(0.14)	(0.08)	(0.15)	(0.09)		
Electronic LMIS	0.21	-0.46***	0.17	-0.02	1.19	0.98
	(0.22)	(0.15)	(0.38)	(0.18)		
LMIS Updating Frequency × Electronic LMIS			0.07	-1.01***	1.07	0.36
			(0.43)	(0.31)		
Constant	3.11**	0.98	3.12**	0.83		
	(1.55)	(0.94)	(1.56)	(0.95)		
Country FE	Yes	Yes	Yes	Yes		
Commodity Type FE	Yes	Yes	Yes	Yes		
Commodity Assortment FE	Yes	Yes	Yes	Yes		
Month FE	Yes	Yes	Yes	Yes		
Pseudo R-squared	0.17	0.14	0.17	0.14		
Log Likelihood	-2093	-6252	-2093	-6244		
Observations	5,220	13,918	5,220	13,918		

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Notes:* FE = Fixed Effects. Robust standard errors clustered at the facility level in parentheses.

Next, I examine how the use of electronic LMIS (*Electronic LMIS*) to monitor the inventory of health commodities impacts stock-outs. From Table 3.3 (Model 3: Columns 3 and 5, urban), the use of electronic LMIS does not lead to a significant reduction in the likelihood of health commodity stock-outs at urban facilities. This is true regardless of whether the use of electronic LMIS is implemented as a standalone practice or in conjunction with daily LMIS updating. Thus, for urban facilities, there is no support for H3.3a and H3.4. The results are different for rural health facilities. From Table 3.3 (Model 3: Columns 4 and 6, rural), I observe that the use of electronic LMIS by rural health facilities, when implemented as a standalone practice, does not have a significant impact on commodity stock-outs, i.e., there is no support for H3.3a for rural facilities (and by extension, no support for H3.3b either). Recall from the earlier discussion that daily updating of LMIS records, when implemented as a standalone practice, also does not mitigate the likelihood of stock-outs at rural health facilities. However, when the two LMIS practices are implemented together by rural health facilities, their joint effect (*LMIS Updating Frequency* × *Electronic LMIS*) can significantly reduce the likelihood of stock-outs, i.e., H3.4 is supported for rural health facilities. Particularly, the combination of daily LMIS updating and the use of electronic LMIS can decrease the odds of commodity stock-outs by 64% in rural health facilities (β = -1.01, $p < 0.01$, $e^{-1.01} - 1 = -0.64$).

The results discussed above highlight important differences in the impact of health facilities' LMIS practices on commodity stock-outs across urban and rural facilities. These findings suggest that a one-size-fits-all approach may not be effective at reducing stock-outs in public health supply chains, and highlight the importance of tailoring the LMIS practices to the specific health facility type to achieve maximal impact. This result assumes increased significance especially at a time when the public health system is under constant pressure to meet the growing need for health commodities and services despite being faced with weak to modest funding outlooks. Implementing electronic LMIS and daily updating of LMIS records are both resource intensive and as the public health sector strives to do more with less, it is vitally important to allocate the limited resources in the most effective way possible. The results presented in this section offer valuable and novel insights in this regard by shedding light onto which LMIS practices might be more effective at different types of health facilities.

3.5. Robustness Checks and Additional Analyses

3.5.1. Using a Diagnostic Approach to Examine the Potential for Bias due to Unobserved Factors

As noted earlier, in order to reduce identification concerns in the main model, I matched treatment and control facilities using the CEM technique. To further alleviate concerns pertaining to potential unobserved heterogeneity, I assess the extent to which unobserved factors might be driving the results using a diagnostic approach developed by Altonji et al. (2005) and applied in recent studies (e.g., Assenova and Sorenson 2017, Dey et al. 2016, Starr et al. 2018). Altonji et al. (2005) recommends comparing the estimated coefficients of interest across two models: (i) a saturated model that includes all observed covariates, and (ii) a more restricted model with fewer covariates. Specifically, I calculate a ratio, $\rho = \beta^F/|(\beta^F - \beta^R)|$, where β^F and β^R denote the coefficient estimate for the relationship of interest in the saturated model and a more restricted model, respectively. This ratio essentially measures the extent to which the effects of the unobserved variables would need to be, in comparison to that of observed variables, to explain the results. Altonji et al. (2005) suggest that one should consider an estimate robust to the effects of unobserved factors if $|\rho| > 1$.[17]

Table 3.4. Sensitivity Analysis Results Displaying the Required Strength of Potential Unobserved Variables, Relative to Observed Variables, to Account for the Estimates of *Commodity Range* and *LMIS Practices*

		Before Matching		Coarsened Exact Matching	
	Independent Variable	**Bias** $\lvert(\beta^F - \beta^R)\rvert$	**Ratio** ρ	**Bias** $\lvert(\beta^F - \beta^R)\rvert$	**Ratio** ρ
Urban	*Commodity Range* ($\boldsymbol{\beta_1}$)	0.02	6.32	0.00	> 100
	LMIS Practices ($\boldsymbol{\beta_2}$)	0.18	2.25	0.00	27.25
Rural	*Commodity Range* ($\boldsymbol{\beta_3}$)	0.00	> 100	0.00	> 100
	LMIS Practices ($\boldsymbol{\beta_4}$)	0.07	9.54	0.22	4.56

Notes: In calculating the Altonji et al. (2005) ratio ρ, the saturated model is one that includes the four main independent variables of interest (i.e., commodity range, LMIS updating frequency, Electronic LMIS, and LMIS updating frequency × Electronic LMIS) and all covariates used in the matching process (i.e., facility type, facility size, managing authority, supervision, first expire first out, protection, client education, client household size, client wealth index and country fixed effects.) The unsaturated model is one that drops all covariates used in the matching process.

In calculating the Altonji et al. (2005) ratio, ρ, the saturated model is the full model specification (represented by Model 3 in Table 3.3) and the unsaturated model is one that drops all covariates used in the matching process, while retaining the key independent variables of interest (i.e., *Commodity Range*, *LMIS Updating Frequency*, *Electronic LMIS, and LMIS Updating Frequency* × *Electronic LMIS*). The results of this diagnostic approach are presented in Table 3.4, where I find strong diagnostic evidence that the coefficients of the key relationships of interest are unlikely to be driven by unobserved factors. Specifically, as seen from Table 3.4, the ρ values

[17] In other words, $|\rho| > 1$ would indicate that the selection on unobservables needs to be ρ times stronger than selection on observables to account for the estimated coefficient. However, Altonji et al (2005) argue that this is unlikely to be the case since observable factors are chosen based on theory or past empirical work.

associated with the effects of *Commodity Range* and *LMIS Practices* on stock-outs are higher than the threshold of 1 across both urban and rural facilities in the analysis using the unmatched sample as well as in the main analysis using the matched sample. For instance, looking at the value of ρ in Table 3.4 for urban facilities, the effects of unobserved variables need to be 27.25 times stronger than those of the observed values (and 2.25 times stronger in case of the unmatched sample) to reduce the estimated effects of *LMIS Practices* to zero. Overall, the results shown in Table 3.4 strongly support the notion that unobserved heterogeneity is not likely to bias the results. I provide additional details including algorithmic descriptions of the Altonji et al. (2005) approach in the Appendix.

3.5.2. Addressing Potential Commodity Substitution Effects Within and Between Facilities

Beyond the issue of unobserved heterogeneity discussed above, one could also argue that potential substitution effects across different contraceptive methods *within* a health facility could bias the estimates. That is, when a particular contraceptive method is out-of-stock, clients could potentially switch to other methods, subsequently driving up demand and resulting in stock-outs of other contraceptive methods. While this is a plausible scenario, previous research has shown that people are often reluctant to switch to a different contraceptive method in the event of stock-outs due to various reasons including a lack of awareness of alternative contraceptive methods, concerns related to effectiveness and side-effects, and partner's reluctance to switch (RHSC 2016a). In the instances where they switch, Rosenberg et al. (1995, p. 283) mention that clients switch to "a less reliable contraceptive or no method at all, often leading to unintended pregnancy." This suggests that clients are more likely to switch, if at all, from long-acting (e.g., implants, IUDs) and short-acting (e.g., pills, injectables) contraception to barrier (e.g., male and female condom) and fertility awareness methods (e.g., cycle beads). For example, a qualitative study conducted across Uganda quoted healthcare providers as saying "[clients] come often for family planning and when it is out of stock, we have to convince them to take condoms" (RHSC 2016b, p. 2). In addition to potential substitution *within* health facilities, it is also plausible that the stock-outs of contraceptive methods at a given facility may result in diverting customers to a neighboring facility, resulting in higher levels of demand and increased likelihood of stock-outs for contraceptives at the nearby facility. Therefore, I conduct additional analyses, discussed below, to account for: (i) commodity substitution effects *within* facilities, and (ii) commodity substitution effects *between* facilities.

Commodity Substitution Within Facilities: To control for substitution within facilities, I first omit all stock-out related observations pertaining to barrier (i.e., male and female condom) and fertility awareness contraception (i.e., cycle beads), since these commodities are considered to be most prone to substitution effects when the long-acting and short-acting methods are out of stock (please see the discussion in the previous paragraph). In addition to the above three methods, I also omit observations related to progestin-only contraception (pills and injectables) in order to eliminate any commodity substitution effects that might exist between these commodities and combined contraception.[18] Table 3.5, Columns 1 and 2, present the results of a regression analysis where observations related to the *more* substitution-prone methods of barrier, fertility awareness and progestin-only methods are *excluded* (i.e., the observations of the dependent variable, stock-out, pertaining to the five contraceptive methods deemed more prone to substitution are excluded from the analysis). Therefore, the regression results displayed in Table 3.5, Columns 1 and 2, correspond to the factors that impact the stock-outs of the *less* substitution-prone methods. The results of this analysis are consistent with the main results, ensuring the robustness of the findings to potential substitution effects *within* facilities.[19]

Commodity Substitution Between Facilities: To address the possibility of commodity substitution *between* facilities, I regress the stock-out of a particular method i at a given health facility on *% Neighboring Stock-out*, i.e., the average % stock-out of the same contraceptive method i at neighboring facilities that were surveyed in the last two months. For a given health facility, I consider proximate facilities as "neighbors" if they are located within 30 kms of the facility of interest.[20] The results in Table AP3.2 in the Appendix indicate that clients might be "substituting facilities" for a given contraceptive method. However, more importantly, I find that the direction and significance of the results remain consistent to those of the main model. This demonstrates the robustness of the findings to commodity substitution that could occur *between* health facilities.

3.5.3. Balancing the Advantages and Disadvantages of Offering a Wider Commodity Range

As discussed earlier in Section 3.1, the advantage of offering a wider range of commodities through the public health supply chain is the ability to meet the needs and preferences of clients more

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[18] Progestin-only contraception contains the progestin hormone and does not contain any amount of estrogen. This is in contrast to combined contraception which contains some amount of both hormones (i.e., progestin and estrogen combined). In general, it is believed that progestin-only contraception is associated with fewer side-effects. For instance, progestin-only methods are recommended for clients who might be breastfeeding, are older than 35 and smoke, or those who have poorly controlled high blood pressure (see https://www.mayoclinic.org/healthy-lifestyle/birth-control/in-depth/art-20044807). These clients are unlikely to switch to a combined contraception in the event of progestin-only stock-outs. On the other hand, the users of combined contraception (i.e., progestin and estrogen) might switch to a method that contains progestin only.

[19] For comparison, I also present the estimated coefficients for the subgroup of contraceptive methods that are *more* substitution-prone in Table 3.5, Columns 3 and 4, and find qualitatively consistent results.

[20] The results remain consistent if I use alternative ranges (i.e., 20 km).

closely. On the other hand, the disadvantage, as I show in this study, is that increasing the commodity range can increase the complexity of inventory management in the public health supply chain and contribute to a higher likelihood of stock-outs. To find a balance between the advantage and disadvantage of offering a wider commodity range, I conduct additional analyses that offer insights into how the optimal commodity range might vary based on a health facility's location (urban vs. rural) as well as its LMIS practices.

To aid this analysis, I develop a model to estimate the impact of commodity range on the likelihood of stock-outs. Specifically, I consider a piecewise linear model that allows the marginal rate of increase in stock-outs to vary across the following commodity range intervals: (i) between 4 to 6 contraceptive methods, (ii) between 6 and 8 contraceptive methods, and (iii) between 8 and 10 contraceptive methods. This regression utilizes the same set of covariates as the ones in the main model including commodity assortment fixed effects. Controlling for commodity assortment fixed effects (*Commodity Assortment FE*) in the regression model would ensure that the estimates of the commodity range are not driven by the potential heterogeneity in the types and combinations of methods offered by facilities. I present the results obtained using this estimation model in Figure 3.3.

In Figure 3.3, I display the estimated values of stock-outs across the subgroups of urban vs. rural facilities. For each type of facility, I present the results separately for facilities with less mature vs. more mature LMIS practices, given the significant role played by LMIS practices in determining the likelihood of stock-outs. As a reminder, less mature LMIS refers to the case where facilities are neither engaged in daily LMIS updating nor the use of electronic LMIS, while more mature LMIS represents the case where health facilities are engaged in at least one of those practices. The results reported in Figure 3.3 indicate that in general, an increase in the range of commodities offered leads to an increase in the likelihood of stock-outs. However, the effect of commodity range varies significantly based on a health facility's location (urban vs. rural) as well as the LMIS practices. This has different implications for determining the appropriate commodity range for urban vs. rural facilities as discussed below.

Urban Facilities: For urban facilities with less mature LMIS practices, I see from Figure 3.3 that offering 8 contraceptive methods is better than offering less than 8 methods since the benefit in terms of offering more choices comes without the downside of the increased likelihood of stock-outs. However, the likelihood of stock-outs increases sharply as commodity range increases beyond 8 (roughly 20% increase in stock-outs as commodity range increases from 8 to 10). At high commodity ranges (8 and beyond), the additional value of offering one more contraceptive method (in terms of increasing contraceptive use) is likely to be outweighed by the negative impact of an increase in the likelihood of stock-outs. Given these trade-offs, the appropriate commodity range is likely to be around 8 methods for urban facilities with less mature LMIS practices. The results are slightly different for urban facilities with more mature LMIS practices. In that setting, offering 7 to 8 commodities is better than offering 6 contraceptive methods. However, whether to increase commodity range from 4 to 6 would require a careful consideration of the trade-off between increasing contraceptive use by offering more methods vs. the negative effects of a higher stock-out rate on contraceptive usage. A similar consideration would also apply for such facilities when determining whether or not to increase the commodity range beyond 8. Tools such as the "reducing stock-outs impact calculator"[21] can be useful in conducting a what-if analysis regarding how changes in the likelihood of stock-outs translate into changes in the contraceptive prevalence rate (i.e., the percentage of women or their partners who are currently using a contraceptive method). However, this tool does not take into account the potential impact of the range of commodities offered by a health facility on the likelihood of stock-outs and a result, it may not be possible to make direct inferences from this tool regarding how increasing/decreasing the commodity range would impact the contraceptive prevalence rate. This study serves to bridge this gap by demonstrating the link between commodity range and the likelihood of stock-outs, which in turn could be a valuable input to the "reducing stock-outs impact calculator" to understand the subsequent impact on contraceptive prevalence..

Rural Facilities: Looking at rural facilities with less mature LMIS practices, the increase in the likelihood of stock-outs is gradual for commodity ranges less than 8 but the increase is sharp beyond that. Hence, accounting for heterogeneity in the mix of contraceptive methods offered, the appropriate commodity range is likely to be between 6 to 8 for such facilities. For rural facilities with more mature LMIS practices, the considerations to determine an appropriate commodity range are similar to the one discussed earlier for urban facilities with more mature LMIS practices. In addition to these setting-specific insights, a higher level observation from Figure 3.3 is that for any given level of commodity range, the likelihood of stock-outs is lower for facilities with more mature LMIS practices compared to those with less mature LMIS practices. Hence, for any given level of stock-out risk that the relevant decision-makers in developing countries might deem "acceptable," facilities with more mature LMIS practices would be able to offer a wider range of contraceptive methods relative to their less mature LMIS counterparts.

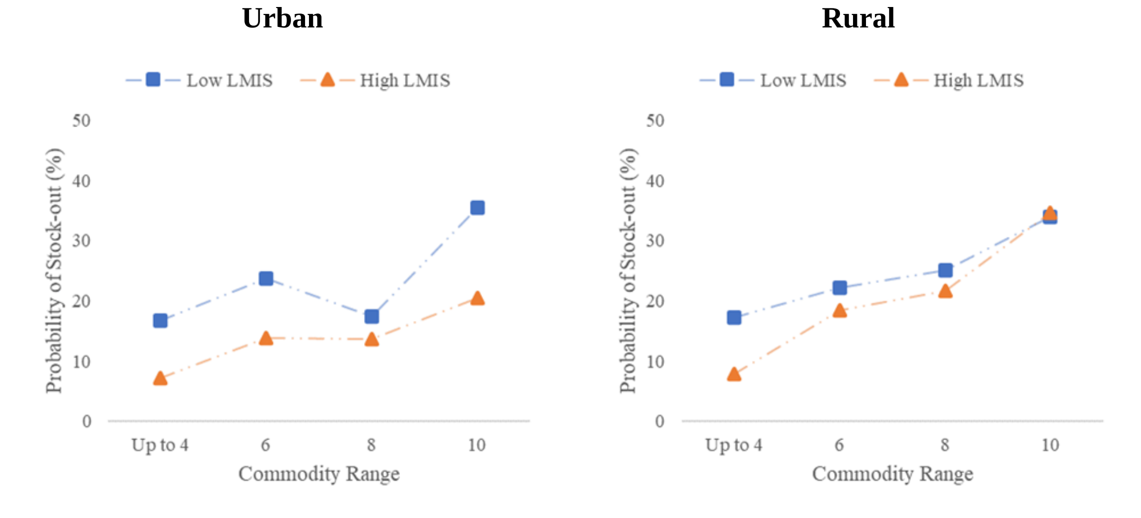
[21] https://www.rhsupplies.org/activities-resources/tools/reducing-stockouts-impact-calculator/

Table 3.5. Logistic Regression Results for *Less* vs. *More* Substitution-Prone Contraceptive Methods using Coarsened Exact Matched Sample (Based on *LMIS practices*)

	Model 1: Less Substitution Prone Methods		**Model 2: More Substitution Prone Methods**	
	Urban	**Rural**	**Urban**	**Rural**
DV: Stock-out	**(1)**	**(2)**	**(3)**	**(4)**
Facility-level Controls				
Secondary Facility	0.63**	-0.22*	0.28	0.00
	(0.32)	(0.12)	(0.30)	(0.11)
Tertiary Facility	1.04***	-0.44	0.66*	-0.82**
	(0.38)	(0.34)	(0.39)	(0.33)
Ln (Facility Size)	-0.41***	-0.16**	-0.40***	-0.01
	(0.12)	(0.07)	(0.12)	(0.07)
Private For-Profit Facility	0.19	0.79***	0.09	0.47**
	(0.28)	(0.30)	(0.26)	(0.21)
Private Non-Profit Facility	-0.10	0.58***	-0.30	0.26*
	(0.27)	(0.16)	(0.27)	(0.13)
Supervision	-0.05	-0.28	-0.58**	0.00
	(0.29)	(0.32)	(0.28)	(0.47)
First Expire First Out	-0.27	-0.05	-0.20	-0.34***
	(0.24)	(0.15)	(0.24)	(0.12)
Protection	-0.10	-0.07	-0.08	-0.09*
	(0.11)	(0.07)	(0.10)	(0.06)
Client-level Controls				
Client Education	-0.38**	-0.15*	-0.25	-0.16**
	(0.17)	(0.08)	(0.17)	(0.07)
Client Household Size	-0.14	-0.10*	-0.03	-0.02
	(0.10)	(0.05)	(0.12)	(0.04)
Client Wealth Index	0.42*	0.16	0.61***	0.20
	(0.23)	(0.14)	(0.21)	(0.12)
Commodity Range	0.17***	0.30***	0.16***	0.16***
	(0.06)	(0.03)	(0.06)	(0.03)
LMIS Updating Frequency	-0.59***	0.07	-0.40**	0.06
	(0.17)	(0.13)	(0.19)	(0.10)
Electronic LMIS	0.20	0.28	-0.14	-0.55**
	(0.37)	(0.24)	(0.55)	(0.22)
LMIS Updating Frequency ×	0.04	-1.85***	0.21	-0.10
Electronic LMIS	(0.44)	(0.46)	(0.60)	(0.37)
Constant	1.40	-0.50	2.31	0.42
	(1.34)	(1.14)	(1.79)	(1.06)
Country FE	Yes	Yes	Yes	Yes
Commodity Type FE	Yes	Yes	Yes	Yes
Commodity Assortment FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.19	0.13	0.18	0.16
Log Likelihood	-1003	-2942	-1082	-3144
Observations	2,576	6,112	2,674	7,631

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Notes:* FE = Fixed Effects. Robust standard errors clustered at the facility level in parentheses.

Figure 3.3. Impact of Commodity Range on Stock-Outs Based on a Health Facility's Geographic Location and LMIS Practices



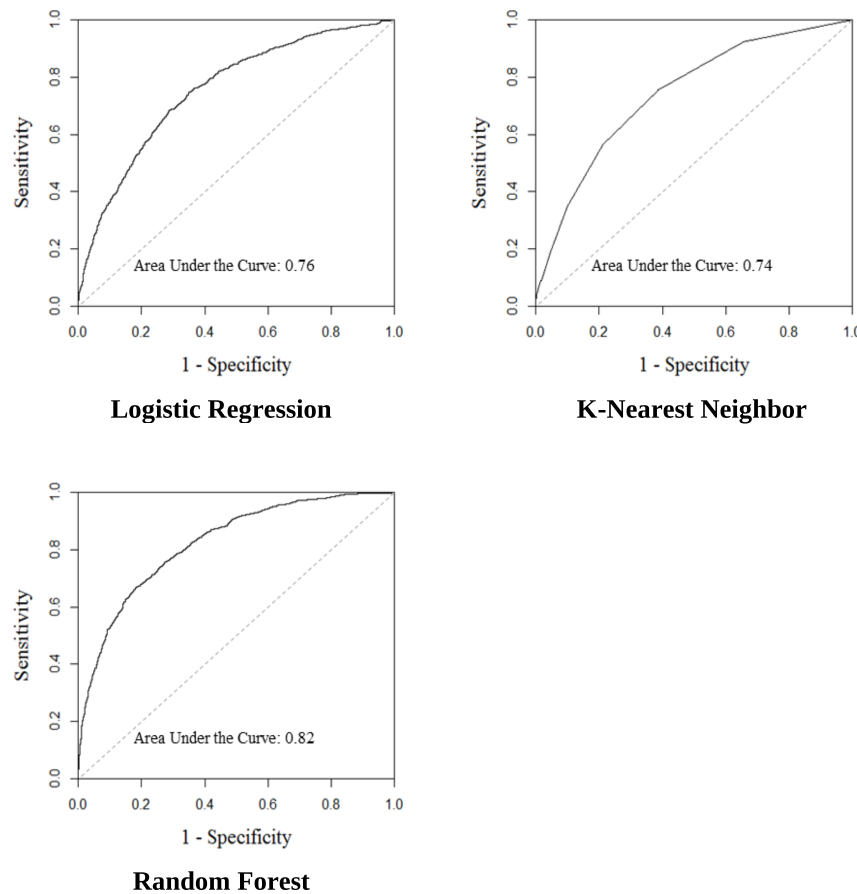
Notes: Due to the relatively small sample size of facilities offering less than four contraceptive methods, these facilities were aggregated into one group.

3.6. Post Hoc Analysis

The main analysis in this study, along with the multiple robustness checks, were aimed at developing explanatory models to rigorously evaluate the association between the independent variables of interest (commodity range and LMIS practices) and contraceptive stock-outs. In this section, I build upon these analyses and insights by assessing the predictive accuracy of the main model. The goal is to understand whether the same set of control and independent variables can also be used to predict the likelihood of stock-outs with reasonable accuracy. Toward this end, I use a logistic regression model as the main classification approach in order to predict the likelihood of contraceptive stock-outs. First, I randomly split the sample into training/test data-sets based on an 80/20 percent ratio. Next, I use the randomly selected observations in the 80-percent training group to develop a predictive model based on the variables used in the specifications thus far.[22] I then use the predictive model developed from the training group as the basis for predicting stock-outs in the 20-percent test group.

[22] These variables are: facility-related controls (facility type, facility size, managing authority, supervision, first expire first out, protection), client-related controls (client education, household size, wealth index), commodity-related controls (commodity type, commodity assortment fixed effects), time fixed effects, administrative-level controls (i.e., country/ region/district fixed effects, geographic location), commodity range, LMIS updating frequency and electronic LMIS.

Figure 3.4. Receiver Operating Characteristics (ROC) Curves for the Predictive Models



In order to evaluate the predictive accuracy of the model, I utilize an approach frequently used in the predictive modeling literature known as the receiver operating characteristics (ROC) curve. The ROC curve can capture the values associated with two types of prediction errors for all possible classification thresholds: (i) the true positive rate, also known as *sensitivity* which equals the number of *correctly* predicted facility-method stock-outs divided by the actual number of stock-outs in the sample; and (ii) false positive rate which is equivalent to *one minus specificity* and is measured as the number of *incorrectly* predicted stock-outs divided by the actual number of facility-method observations that were not out-of-stock. The overall prediction accuracy of a classifier can be represented by the area under the ROC curve (see James et al. 2013) — this is a metric that assumes values between 0 and 1, where larger numbers indicate better prediction accuracies. As seen in Figure 3.4, the area under the curve in the predictive model was found to be approximately 76%. In essence, my model can predict the likelihood of stock-outs correctly 76% of the time. The above *out-of-sample* prediction accuracy is consistent with those reported in the extant literature including the studies by Padmanabhan et al. (2006) and Wang et al. (2013) who utilize decision tree-based classifiers, and a recent study by Guajardo (2019) that utilizes a combination of predictive modeling methods. More importantly, the advantage of my predictive model lies in its parsimony, in that a simple logistic regression model achieves a prediction accuracy of 76%. Finally, to further evaluate the confidence in the predictive power of the variables, I use two alternative, well-known predictive modeling methods, namely the "k-nearest-neighbors" (a non-parametric method) and "random forest" (an ensemble method) classifiers. The prediction accuracy of these methods are 74% and 82%, respectively.

3.7. Conclusion

3.7.1. Contributions and Implications for Public Health Supply Chains

In developing countries, significant resource constraints faced by the public health sector hamper the effective and efficient delivery of health commodities, leading to supply chain failures such as "stock-outs." While the prevalence of stock-outs in this context is widely acknowledged, there exist few studies that rigorously explore the underlying factors that drive the stock-outs of health commodities. This study contributes to filling this gap in the extant literature by exploring the drivers of stock-outs through the lens of the "logistics cycle" framework (see Figure 3.1) that is widely adopted by organizations involved in managing public health supply chains in developing countries. Specifically, I focus on the relationship between two key elements of the logistics cycle framework, i.e., *product selection* and *LMIS* practices within the public health supply chain, and health commodity stock-outs. In addition, I also investigate how the above-mentioned relationships are moderated by a health facility's location defined as urban vs. rural. I test the hypotheses of this chapter through rigorous empirical analysis that utilizes field data collected from health facilities across five developing countries: Bangladesh, Haiti, Malawi, Senegal, and Tanzania. The field data correspond to contraceptive availability at health facilities, a class of health commodities that are commonly distributed through public health supply chains in developing countries.

The results of the empirical analysis demonstrate that offering a broader range of health commodities, notwithstanding its benefits in terms of providing more choices to clients, can negatively impact their availability in public health supply chains. Furthermore, I find that the negative impact of increasing the range of commodities offered is more severe for rural health facilities, relative to their urban counterparts. Next, the analysis uncovers interesting insights regarding how a facility's LMIS practices impact the likelihood of stock-outs. Specifically, I find that daily updating of the LMIS records is an important step towards reducing health commodity stock-outs at both urban and rural facilities. However, in rural facilities, daily updating does not lead to a reduction in stock-outs when implemented as a standalone practice; such a practice needs to be implemented in conjunction with electronic LMIS to realize the potential benefits. The results of this study have several actionable implications for the different stakeholders involved in managing public health supply chains including national governments, donors, and policy-makers.

First, policy decisions such as expanding the range of commodities offered through public health supply chains should be reconciled with the operational implications of those decisions. While expanding the range of commodities is beneficial from the standpoint of offering more choices to clients, it also comes with the downside risk of a higher likelihood of stock-outs, with the negative impact being more severe for facilities located in rural areas. I offer two recommendations to balance the trade-offs associated with expanding the commodity range offered in public health supply chains:

(i) The findings suggest that the appropriate commodity range that balances the above-discussed trade-offs varies based on a health facility's location and LMIS practices. I find that the appropriate range for facilities with less mature LMIS practices is around 8 contraceptive methods in case of urban locations and between 6 to 8 methods for rural locations. For facilities with more mature LMIS practices, determining an appropriate commodity range is more nuanced, as highlighted in Section 3.5.3. By offering the appropriate range of contraceptive methods, facilities would provide clients with a reasonable breadth of methods so that they are likely to be able to access a contraceptive method of their choice, while keeping stock-outs at a relatively low level.

(ii) The finding that the negative impact of commodity range is more severe for rural facilities could be driven by the logistical and human resource challenges faced by these facilities (Schöpperle and Woodburn 2013, USAID 2017). Hence, national governments and other organizations involved in managing public health supply chains need to focus on addressing these limitations to ensure that efforts to expand the commodity offerings do not have an adverse impact on commodity availability. Particular attention needs to be paid towards creating better incentives to recruit and retain staff personnel and mobilizing funds to improve training at rural health facilities (Waako et al. 2009). Beyond addressing the human resource limitations, public health managers should also explore creative approaches to overcome the logistical challenges faced by health facilities located in rural areas. One such example is the use of drones as an emergency delivery method for blood samples and essential medicines in Rwanda. These drones supplement the traditional transportation methods to improve the reliability and timeliness of replenishments from upstream facilities and ultimately, reduce stock-outs of essential health commodities (Rosen 2017).

Second, the study findings have implications for funding allocation in resource-constrained settings that are typical of most public health supply chains. Specifically, the results highlight the need to tailor the funding allocation decisions based on the geographic location of the health facilities. For example, urban facilities are likely to see a significant reduction in stock-outs with the implementation of daily LMIS updating but pairing it with the use of electronic LMIS brings no additional benefits. Hence, funding allocations to urban health facilities should be directed towards increasing the frequency with which the LMIS records are updated. In case of rural facilities, daily LMIS updating reduces stock-outs, but only when used in conjunction with electronic LMIS. Taken together, these findings suggest that resources dedicated toward transitioning facilities from paper-based to electronic LMIS would be best utilized if allocated to rural health facilities.

Finally, the research findings have implications for managing the health supply chains of a broader class of commodities beyond contraceptives. Lai et al. (2008) discuss a framework to classify commodities offered through public health supply chains into different categories based on two key attributes: inventory holding cost and demand predictability. Contraceptives have low inventory holding costs and exhibit relatively stable demand patterns compared to other commodities such as antimalarial medications that have highly unpredictable and seasonal demand (see Yadav et al. 2014). I expect the study findings to be generalizable to commodities that share similar attributes to those of contraceptives — examples include antibiotics (USAID 2010) and iron and vitamin supplements (Yadav et al. 2014).

3.7.2. Limitations and Future Research Directions

Like any study, this study is not without limitations. These limitations serve as avenues for future research. One potential concern with this study is the dependent variable, which is "stock-outs on the day the facilities are surveyed." A question that may arise is whether stock-outs, as measured on the day the survey was administered, are representative of the overall stock-out situation prevalent at health facilities. This point is valid when a particular health facility is considered in isolation or if a small number of facilities are surveyed. My study sample consists of 24,730 facility-method observations spanning 3995 facilities, and the facilities were included in the survey based on random sampling. In addition, the survey timings for the facilities included in the sample (in terms of the month in which the survey was conducted) are spread throughout the year with no discernible patterns. I believe that the large sample size, combined with random sampling and the broad range of survey dates (controlled for by including *Month FE*), alleviate the concerns related to using "stock-outs on the day of survey" as a dependent variable. Future research could benefit from using alternative measures of stock-outs (e.g., health commodity availability over a period of time) to test the robustness of the results.

As noted in Section 2.7.2, some of the independent variables of interest are also subject to limitations. For instance, the SPA survey only captures whether or not the LMIS records are updated on a daily basis. Similarly, the use of electronic LMIS is captured as a binary variable that does not account for the specifics of LMIS data or how they are utilized to make inventory management decisions at health facilities. Future studies would benefit from the availability of more granular data on the above-mentioned factors. In addition, I execute the empirical analyses using a particular type of health commodity, namely contraceptives, which are commonly distributed through public health supply chains in developing countries and exhibit characteristics that are representative of a broad range of health commodities. Future work could focus on replicating the results of this study for other types of health commodities and countries not included in the sample. Notwithstanding the above limitations, this study provides novel, empirically-grounded insights into the factors impacting stock-outs in public health supply chains. The subsequent chapter investigates how frontline healthcare providers can help mitigate the likelihood of health commodity stock-outs in developing countries.

Chapter 4:
Mitigating Stock-outs through Healthcare Provider Training

4.1. Introduction

As noted in Chapters 2 and 3, the effective distribution of health products from upstream warehouses to the last-mile relies on the effective flow of accurate inventory data from health facilities to the warehouses (e.g., information regarding quantities of supplies received/issued, see Kraiselburd and Yadav 2013, Yadav 2015). In developing countries, managing and collecting inventory data at health facilities is oftentimes assigned to frontline healthcare providers (e.g. midwives, nurses), who are primarily responsible for the provision of clinical services and lack sufficient training on inventory management (Lee and Tang 2017, McCoy and Lee 2014). Given the lack of adequate training, healthcare providers often collect inventory data using ad-hoc protocols that are inconsistent with the standard operating procedures, deteriorating the quality of inventory data. For example, surveys conducted across developing countries have found significant deviations from the standard operating procedures, including considerable discrepancies between recorded stock counts and the actual number of supplies observed in the storage area (Bock et al. 2011, JSI 2016). The potential inaccuracies in the inventory data could hamper the visibility of the consumption patterns, leading to imperfect resupply orders and increasing the risk of health commodity shortages in the last-mile.

Toward combating the challenges faced by healthcare providers in managing inventories, one public health supply chain initiative has advocated for a transition from paper-based to electronic inventory management. The transition to an electronic system can mitigate the risk of human error by automating inventory-related calculations (e.g., balance on-hand, see Section 3.2.2.2 for more details; USAID 2012). However, such technological interventions are capital intensive and might require the availability of certain infrastructural components within health facilities (e.g., electricity, internet connectivity) which might not always be available. Further, as highlighted by USAID (2012, p. 5), "if there are data quality issues at one level of the supply chain, automation will not improve the data quality without appropriate efforts in quality assurance, management, supervision, and data collection training." These challenges might explain why investments in technology-based interventions in the context of healthcare delivery in developing countries have yielded mixed results. For instance, Lemaire (2011) reported that more than 60% of technology-based health initiatives in Uganda "did not scale up after the pilot phase" in 2008-2009. Similarly, in 2009, there were over 30 technological health initiatives in India that failed to advance beyond the pilot phase (Lemaire 2011).

An alternative public health supply chain initiative has focused instead on the provision of inventory management trainings to frontline healthcare providers (Henry et al. 2017, JSI 2016). On the one hand, the trainings have the potential to increase the accuracy of data at health facilities by improving the inventory management skills of healthcare providers and establishing recording procedures that are consistent with the national guidelines. On the other hand, several factors might impede the effectiveness of such interventions in developing countries. First, healthcare providers are primarily responsible for providing clinical services, making inventory and logistics management a “secondary priority” (SIAPS 2014). Second, developing countries are often faced with a shortage of healthcare providers (McCoy and Lee 2014), further deprioritizing the inventory management responsibilities that are delegated to these providers. Despite these trade-offs, little empirical evidence exists as to whether these initiatives can have a meaningful impact on the inventory management practices of healthcare providers and more importantly, the availability of health commodities in the last-mile. In this study, I raise and investigate the following research questions: *(i) Does an improvement in the inventory management skills of healthcare providers, through formal training programs, lead to a meaningful and sustained reduction in health commodity stock-outs at health facilities in developing countries? (ii) What factors moderate the relationship between training programs and health commodity stock-outs?*

Toward addressing these research questions, I rely on a public health supply chain intervention in Indonesia which focused on improving the skills of healthcare providers in managing inventories through the provision of *initial* and *refresher* trainings (i.e., using classroom-based training, paper-based and video-based job aids). Using the staggered expansion of the intervention, I evaluate the effect of training programs on health commodity stock-outs by applying a difference-in-differences (DID) estimation. The results show that the provision of *initial trainings* leads to an average reduction of 5 percentage points in the likelihood of stock-outs, although the benefits vary considerably across different types of health facilities. I find that health facilities with higher levels of inventory data inaccuracies prior to initial trainings experience reductions of up to 20 percentage points in the likelihood of stock-outs. Further, the results indicate that the provision of *refresher trainings* leads to reductions of 6 percentage points in the likelihood of stock-outs, after controlling for the effect of initial trainings in the regression models. Interestingly, I find that these benefits are primarily realized by health facilities with lower magnitude of learning after initial trainings. Hence, the findings show that the adoption and assimilation of training materials by health facilities follows a learning curve. I complement the main analyses with a number of robustness checks including the application of the synthetic control method (Abadie et al. 2010) to ensure that diverging trends between treated and control units are not driving the estimates. I supplement the synthetic control method with placebo tests to evaluate the robustness of the findings to an alternative inferential technique. The results have actionable implications for stakeholders managing public health supply chains in developing countries.

The remainder of this study is structured as follows. In Section 4.2, I review the relevant literature and highlight the key contributions of the study. Section 4.3 proposes the study hypotheses. In Section 4.4, I specify the econometric techniques, and describe the data and variables used in the study. Section 4.5 presents the results of the empirical analysis. In section 4.6, I delineate the study's theoretical and practical contributions and highlight avenues for future research.

4.2. Literature Review

This study makes contributions to two main streams of literature. The first stream is related to managing operations in not-for-profit and public health settings (e.g., Cavallaro et al. 2016, Gallien et al. 2017, Kazaz et al. 2016, Natarajan and Swaminathan 2014, Tougher et al. 2012, Vledder et al. 2019). For a detailed review of the studies in this literature, I refer the reader to Section 2.2.1.

The second stream is on healthcare delivery in resource-constrained settings (Babigumira et al. 2017, Ngo et al. 2017, Rowe et al. 2012, 2018, Trap et al. 2018, Zurovac et al. 2011). In this literature, studies have evaluated the impact of interventions to improve the performance of healthcare providers in resource-constrained settings. While the majority of studies have investigated the performance of healthcare providers with respect to *clinical* outcomes (e.g., percentage of patients diagnosed/treated appropriately, see Section 2.2.2 for more details, Rowe et al. 2018), a smaller body of literature has focused on the healthcare providers' *inventory management* outcomes. For example, Chalker et al. (2005) explore the effect of regulation enforcement on the dispensing practices of healthcare providers in Vietnam and Thailand. They find that the announcement of regulations led to a reduction in the dispensing of illegal steroids. Trap et al. (2018) evaluate the impact of a supervisory training intervention on the medicine management practices of health facilities in Uganda. They show that the intervention can improve the stock management of health commodities, although they do not directly study its impact on health commodity shortages. Babigumira et al. (2017) report mixed benefits of the effect of inventory management training programs on access to health commodities in Malawi. However, they do not measure "access" at the health facility-level, but rather at the household level.

This study fills important gaps in this body of literature. First, in contrast to the majority of studies in this stream that have evaluated the clinical outcomes of healthcare providers in developing countries, I focus on an alternative performance outcome that deals with the management of health commodities. Second, prior studies have fallen short of measuring health commodity shortages longitudinally and at the health facility-level, both of which are critical to the establishment of precise estimates that form the basis for informed health policy-making. In contrast, I measure health commodity stock-outs at the facility-level and use novel data from close to 19,000 health facilities over the duration of January 2015-December 2019. Finally, this study explores the interplay between initial and refresher trainings and the moderating conditions under which the benefits provided by these training programs could vary. To the best of my knowledge, these relationships have not been investigated in the extant literature.

4.3. Hypotheses Development

4.3.1. Impact of Initial Training

Health facilities are the "originating point" for collecting inventory data in developing country health supply chains (e.g., quantities of supplies received from upstream, quantities issued to clients, and the available stock on-hand; see USAID 2011c). These data are subsequently transmitted to upstream supply locations, forming the foundation for replenishment decisions. As mentioned in Section 4.1, one major challenge faced by public health supply chains in developing countries is that the delegation of inventory management to frontline healthcare providers (e.g., nurses, midwives) often takes place with limited "formal policy guidance" and "without the necessary support through systematic training and supervision" (Wiedenmayer et al. 2015). For instance, Wiedenmayer et al. (2015) reported that health commodity management was conducted by "non-pharmaceutically trained cadres" in more than 95% of the sampled health facilities in Tanzania. Given the lack of sufficient training, healthcare providers often collect inventory data using ad-hoc protocols, increasing the risk of errors in the collected data that would be used in the replenishment process, and consequently driving up the risk of commodity shortages.

Toward mitigating these challenges, one public health supply chain initiative in developing countries has focused on the provision of inventory management trainings to healthcare providers (see Babigumira et al. 2017, JSI 2016). The trainings are typically provided to healthcare workers in multiple rounds involving initial trainings, followed by refresher trainings. During the initial trainings, healthcare providers are trained on various tasks pertaining to the effective inventory management of health commodities, consistent with the national standard operating procedures (e.g., correctly using stock cards to track the receipt/issuance of health commodities, conducting a physical count of inventories; see MOH Malawi 2003, MOH Philippines 2015, WHO 2006). Therefore, the initial trainings have the potential to improve the skills of healthcare providers in managing inventories, increasing the quality of data recorded on stock cards and transmitted to upstream locations in the form of inventory reports. This could subsequently lead to resupply orders that are more consistent with the actual needs of a health facility, reducing the likelihood of health commodity shortages. However, I postulate that the potential benefits provided by initial trainings are not likely to be uniform across different types of health facilities. Particularly, health facilities with higher levels of inventory record inaccuracies prior to initial trainings are more likely to be deviating from the national standard operating procedures. I posit that these facilities are likely to gain higher benefits from the initial trainings. Given this discussion, I hypothesize the following:

HYPOTHESIS 4.1 (H4.1):

a) *Public health supply chains experience a decrease in the likelihood of stock-outs in the post-initial training period of healthcare providers, compared to the pre-initial training period.*

b) *The decrease in the likelihood of stock-outs is greater at health facilities with higher levels of inventory data inaccuracies in the pre-initial training period.*

4.3.2. Impact of Refresher Training

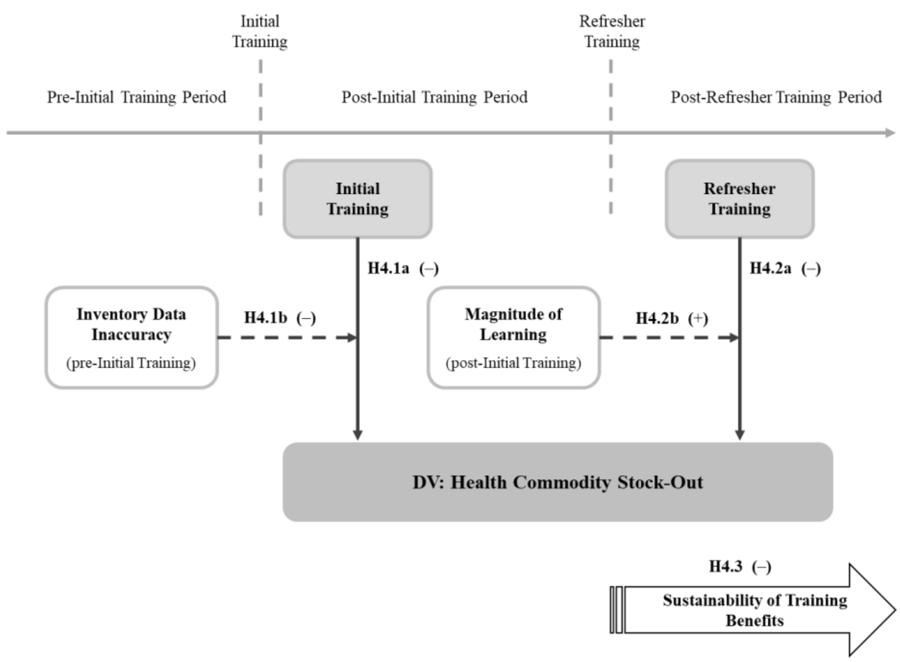
As noted in the previous section, the initial training of healthcare providers on inventory management is commonly followed by refresher trainings that serve two key purposes. First, refresher trainings can compensate for the potential loss of skills that might occur subsequent to the provision of initial trainings, by refocusing the attention of healthcare providers toward adherence to the newly established inventory management routines (Anand et al. 2012, Bailey 1989). For instance, WHO (2015, p. 35) argues that "if regular refresher training is not available, acquired skills and knowledge are quickly lost." Second, refresher trainings can help identify potential implementation gaps after the provision of initial trainings and facilitate troubleshooting (Dhanorkar et al. 2018, MacDuffie 1997). Taken together, refresher trainings contribute to the effective acquisition and long-term retention of inventory management guidelines by healthcare providers (Mendoza et al. 2013). Hence, I expect refresher trainings to have a positive impact on the inventory management practices of healthcare providers and help alleviate the likelihood of health commodity stock-outs. Similar to the previous hypothesis, I argue that the potential benefits provided by refresher trainings are likely to vary across different types of health facilities, specifically, depending on the extent to which healthcare workers can internalize the learning materials after the provision of initial trainings. Hence, I argue that facilities with a higher magnitude of learning after the initial trainings are likely to gain lower benefits from the refresher trainings, compared to those with a lower magnitude of learning. I summarize this discussion in the following hypothesis.

HYPOTHESIS 4.2 (H4.2):

a) *Public health supply chains experience a decrease in the likelihood of stock-outs in the post-refresher training period of healthcare providers, compared to the post-initial training period.*

b) *The decrease in the likelihood of stock-outs is smaller at health facilities with higher magnitudes of learning in the post-initial training period.*

Figure 4.1. An Integrated View of the Study Hypotheses



4.3.3. Sustainability of Training Benefits over Time

The hypotheses thus far have focused on evaluating the *overall* effect of initial and refresher trainings on the likelihood of health commodity stock-outs. A follow-up question with significant policy implications is whether or not the potential benefits provided by the training programs are likely to be *sustained* over time. The inventory management tasks completed by healthcare providers are procedural in nature, involving both mental and physical tasks, and requiring adherence to pre-defined sequences of steps (e.g., to calculate the amount of ending balance; see Bailey 1989, Staats and Gino 2012). Bailey (1989) finds that in the case of procedural tasks, the labor skills gained by frontline workers through training programs are likely to depreciate with long operational breaks in the completion of tasks (e.g., due to strikes). In context of this study, healthcare workers are involved in the dispensing and recording of health commodity transactions on a frequent basis, hence, making the depreciation of skills over time less likely. Therefore, for the average health facility, I expect that the benefits of refresher trainings in reducing the likelihood of stock-outs would be sustained over time (Figure 4.1 provides an integrated view of the hypotheses proposed in this study):

> HYPOTHESIS 4.3 (H4.3): *The decrease in the likelihood of stock-outs due to refresher trainings is sustained over time in the post-refresher training period.*

4.4. Empirical Analysis

4.4.1. Study Context and Econometric Techniques

I empirically test the hypotheses of this chapter using the context of a public health intervention in Indonesia named MyChoice Project that was funded by the Bill & Melinda Gates Foundation. The supply chain component of MyChoice Project was implemented through a joint collaboration between John Snow Research & Training Institute, Inc. (JSI), Johns Hopkins University Center for Communication Programs (CCP), and the Indonesian National Population & Family Planning Board (BKKBN). The supply chain intervention involves the provision of inventory management trainings to healthcare providers through the following mediums: classroom training, paper-based job aids, and video tutorials (see Figure 4.2). This approach is consistent with how similar interventions have been implemented across other developing countries (see Babigumira et al. 2017, Trap et al. 2018). The inventory management protocols emphasized throughout the trainings include the usage of stock cards for recording product receipt/issuance, preparation of inventory reports to be shared with upstream warehouses, and conducting a physical count of inventories. Starting in 2016, the intervention was expanded to health facilities across 11 districts of Indonesia in a staggered manner, followed by expansions to 16 additional districts in 2018 (see Figure 4.3).

Difference-in-Differences (DID) Estimation (H4.1 and H4.2). I argue that the expansion of the supply chain intervention is not likely to be endogenous to health facilities for two main reasons. First, the decision to receive the intervention was not made by health facilities themselves, but rather by JSI and BKKBN. In other words, health facilities cannot self-select into the supply chain intervention. Second, within the treated districts, the intervention was expanded to *all* health facilities (i.e., regardless of a facility's characteristics and operational outcomes). I exploit this staggered expansion across districts and time to identify the effect of the supply chain intervention on health commodity stock-outs using a generalized DID specification (Angrist and Pischke 2008).

Consistent with prior literature applying DID models in the context of staggered expansions (e.g., Dhanorkar 2019, Greenwood and Agarwal 2016), I use the following empirical specification to test for H4.1 and H4.2:

$$\begin{aligned}
Ln\left[\frac{Pr\left(Stock - \ Out_{ijdt} = 1 \mid X_{ijdt}\right)}{1 - Pr\left(Stock - \ Out_{ijdt} = 1 \mid X_{ijdt}\right)}\right] \\
&= \beta_0 + \lambda . X_{CL} + \alpha . District\ FE_d + \gamma . Time\ FE_t \\
&+ \beta_1 . Initial\ Training_{dt} + \beta_2 . Inventory\ Data\ Innacuracy_{i,\ \textit{Pre-Initial Training}} \\
&+ \beta_3 . Initial\ Training_{dt} \times Inventory\ Data\ Innacuracy_{i,\ \textit{Pre-Initial Training}} \\
&+ \beta_4 . Refresher\ Training_{dt} + \beta_5 . Magnitude\ of\ Learning_{i,\ \textit{Post-Initial Training}} \\
&+ \beta_6 . Refresher\ Training_{dt} \times Magnitude\ of\ Learning_{i,\ \textit{Post-Initial Training}} \\
&+ \varepsilon_{ijdt}
\end{aligned} \tag{1}$$

The above specification is based on a logistic regression model since I measure health commodity stock-outs in a binary manner (see Section 4.4.2 for more detail). In Equation 4.1, ε_{ijdt} is the error term associated with the estimated outcome for health commodity type *i* at health facility *j* located in district *d* at time *t*. *District* FE_d is a vector of *District Fixed Effects* controlling for time-invariant differences across districts. *Time* FE_t is a vector of *Year Fixed Effects* and *Month Fixed Effects* controlling for changes in the dependent variable over time and across seasons. In addition, I control for *Province Time Trends,* allowing for province-level unobservables to follow diverging trends over time. The inclusion of *District Fixed Effects* and *Province Time Trends* would absorb the effects of potential supply chain improvements that took place at the upstream-level throughout the duration of the intervention. I incorporate additional control variables in the vector of X_{CL} (see Section 4.4.2 for details). *Initial* $Training_{dt}$ is the binary indicator for the presence of initial trainings — taking the value of 1 after initial trainings are rolled-out to a certain district, and 0 otherwise. Similarly, *Refresher* $Training_{dt}$ is the binary indicator for the presence of refresher trainings — taking the value of 1 after refresher trainings are rolled-out to a certain district, and 0 otherwise.

The coefficients β_1 and β_4 are the DID estimates for the effects of the initial and refresher trainings on health commodity stock-outs, respectively. To investigate the moderating effects of *Inventory Data Inaccuracy* and *Magnitude of Learning*, I utilize triple-difference estimations, where the coefficients β_3 and β_6 are the triple-difference estimates for the moderating effects of the above variables on *Initial* $Training_{dt}$ and *Refresher* $Training_{dt}$, respectively. To account for the possibility of correlated standard errors, I use robust standard errors clustered at the health facility level in all specifications. I supplement these estimations with matching techniques (i.e., propensity score matching and coarsened exact matching) to evaluate the DID diverging trends assumption.

Synthetic Control Method (H4.3). The DID estimations explained earlier capture the *overall* effect of initial and refresher trainings on the likelihood of health commodity stock-out (i.e., H4.1 and H4.2). To investigate whether the potential benefits provided by refresher trainings are *sustained* over time (i.e., H4.3), I trace the trajectories of health commodity stock-outs over the duration of the study timeframe (see Banker et al. 2001) using the *synthetic control method* (Abadie et al. 2010). The synthetic control method reduces discretion in selecting an appropriate counterfactual by creating a weighted average of untreated units that are almost identical to the treated units in terms of their outcome trajectories. In essence, the synthetic control method extends the conventional DID design by allowing the impact of unobserved heterogeneity on the outcome to vary over time. Abadie et al. (2015, p. 498) 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.” Hence, any discrepancy in the outcome variable of treated and control units after the intervention is “interpreted as produced by the intervention” (Abadie et al. 2015, p. 498). This approach is a powerful remedy for evaluating the impact of public health interventions “when randomization is impractical” (Bouttell et al. 2018) and has been previously used in such contexts (Kreif et al. 2016, Ryan et al. 2016). Hence, the synthetic control method not only allows us to trace the trajectories of stock-outs over time and test for H4.3, but it also provides an alternative approach to evaluate the feasibility of the parallels trends assumption.

Since the implementation of the synthetic control method requires the construction of a single treatment period, I divide the intervention’s staggered expansion into four separate treatment periods as follows: (i) before/after 3rd quarter 2016; (ii) before/after 1st quarter 2017; and (iii) before/after 3rd quarter 2018. Within each of the above categories, I construct the treatment variable in a mutually exclusive manner: taking the value of 1 after the initial training is rolled-out to the specific districts that were treated during each of the above periods (e.g., 3rd quarter 2016) and dropping all observations pertaining to the districts that were treated at a different time period (e.g., 1st quarter 2017, and 3rd quarter 2018). For districts that are never treated, the treatment variable takes the value of 0.

4.4.2. Data and Variables

In order to execute the empirical analysis, I rely on novel field data collected through the Indonesian Logistics Management Information System (LMIS) database. As noted in Sections 2.3.2 and 3.2.2, in developing countries, the LMIS is a platform used to transmit the inventory data collected by health facilities to upstream warehouses (e.g., amount issued/received, beginning/ending balance). The study sample contains data from 18,911 unique health facilities across Indonesia over the period of January 2015 through December 2019. I have more than 2 million facility-method-month observations in the above duration.

Figure 4.2. Provision of (a) Classroom Training and (b) Video-based Job Aids to Healthcare Providers in Developing Countries (Source: John Snow Inc.)

(a)

(b)

Video Tutorial on management of family planning commodities for Health facility workers in Indonesia

Dependent variable. The dependent variable of interest in this study is the *Stock-Out* of contraceptive methods, which form an integral part of public health supply chains in developing countries (see Section 2.4.2 for more details on the rationale for choosing contraceptive methods to execute the empirical analysis). I capture *Stock-Out* as a binary variable indicating whether or not the ending balance of a particular contraceptive method was recorded as zero in a given month

— taking the value of 1 when ending balance is zero, and 0 otherwise. My approach in capturing *Stock-Out* is consistent with that of USAID (2018). I drop observations pertaining to the contraceptive methods that were not offered by health facilities (i.e., "never available," see MSPA 2014). This includes health commodities for which both the ending balance and the issued quantity were recorded as zero for the past twelve consecutive months.[23]

Moderating variables. I create a proxy to capture *Inventory Data Inaccuracy* by calculating the magnitude of discrepancy between a health facility's reported beginning balance for a given month and its ending balance in the previous month. My approach in measuring inventory data inaccuracy is consistent with the prior literature on managing inventories in public health supply chains (see Tiye and Gudeta 2018). I specify *Inventory Data Inaccuracy* as follows:

$$Inventory\ Data\ Inaccuracy_{i,\ \textit{Pre-Initial Training}} = \frac{Beginning\ Balance_{ijt,\ \textit{Pre-Initial Training}} - Ending\ Balance_{ijt-1,\ \textit{Pre-Initial Training}}}{Ending\ Balance_{ijt-1,\ \textit{Pre-Initial Training}}} \tag{4.2}$$

Where i, j and t denote health commodity i offered by health facility j at time t. I average *Inventory Data Inaccuracy* at the health facility-level.[24] Further, I calculate the marginal reductions in the likelihood of *Inventory Data Inaccuracy* as a function of initial training to serve as a proxy for a health facility's magnitude of learning. I calculate the marginal effects using a logistic regression model, where *Inventory Data Inaccuracy* is measured as a binary variable, taking the value of 1 in the case of any inaccuracies, and 0 otherwise. Hence, I specify the *Magnitude of Learning* as follows:

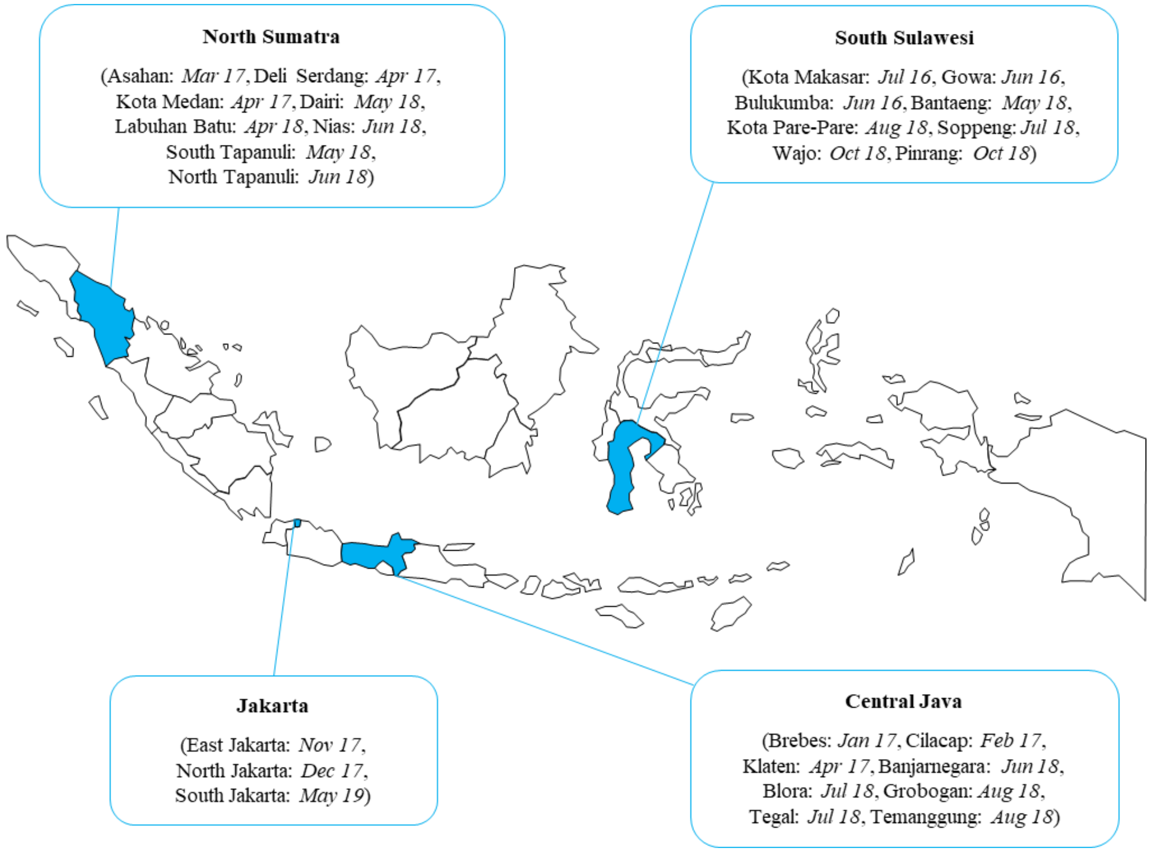
$$\begin{aligned} Magnitude\ of\ Learning_{\ i,\ \textit{Post-Initial Training}} &= Marginal\ Effect\left[\, Pr(Inventory\ Data\ Inaccuracy_{ijdt}) \mid \beta_0 + \lambda . X_{CL} \right. \\ &\quad \left. + \alpha . District_d + \gamma . Time_t + \beta_7 . Initial\ Training_{dt} + \varepsilon_{ijdt} \,\right] \end{aligned} \tag{4.3}$$

In the above specification, the marginal effects are calculated as negative values, representing reductions in the likelihood of inaccuracies as a function of initial trainings. Next, I take the absolute values of the marginal effects and average at the health facility-level. Hence, an increase in the marginal effect corresponds to a higher magnitude of learning, and vice versa.

[23] The results remain fully consistent if I only drop observations when the ending balance and issued quantity are recorded as zero for the past six consecutive months.

[24] I add 1 to the value of $Ending\ Balance_{ijt-1}$ to prevent values of 0 in the denominator.

Figure 4.3. Staggered Roll-out of Initial Training Across Provinces (Districts) of Indonesia; Shaded Areas Represent the Presence of Treatment



Notes. Not all districts within a treated province received the intervention. The italicized dates correspond to the timing when the intervention was fully expanded across all health facilities in a district.

Control variables. I control for several commodity-level and facility-level factors that might influence the availability of health commodities. Particularly, I control for *Commodity Type Fixed Effects* capturing the specific types of contraceptive supplies offered by a health facility: condoms, implants, injectables, intrauterine devices (IUDs) and oral pills. In addition, I control for *Commodity Range Fixed Effects* by including dummy variables that capture the total number of contraceptive methods offered by a facility (ranging from a minimum of 1 to a maximum of 5 methods). At the facility-level, I control for the quantities of supplies received from upstream (*Quantity Received*) and the amount issued to clients (*Quantity Issued*). I log-transformed these two variables in order to reduce their skewness, after adding the value of 1.

4.5. Results

4.5.1. Difference-in-Differences Results (H4.1 and H4.2)

Table 4.1 displays the summary statistics for the main variables and Table 4.2 shows the estimation results for the impact of the intervention on health commodity stock-outs. The results in Table 4.2

indicate that the provision of *initial trainings* lead to statistically significant reductions in the likelihood of stock-outs at health facilities (Column 5: β = -0.39, p < 0.01), providing support for H4.1a. This effect is equivalent to an average of 5 percentage-point reductions in the probability of stock-outs. However, I find that the effect of initial trainings on the likelihood of stock-outs varies based on a health facility's inventory data inaccuracy prior to the provision of these trainings (Column 5: β = -0.10, p < 0.01). This provides support for H4.1b. Specifically, I find that health facilities with higher levels of inventory data inaccuracies experience additional reductions of up to 16 percentage points in stock-outs, compared to those with lower levels of inaccuracies.

Having discussed the impact of initial trainings, I now turn my attention to the effect of refresher trainings on the likelihood of health commodity stock-outs. The results in Table 4.2 indicate that the provision of *refresher trainings* leads to statistically significant reductions in the likelihood of stock-outs (Column 5: β = -0.47, p < 0.01), lending support to H4.2a. This effect is equivalent to an average of 6 percentage-point reductions in the probability of health commodity stock-outs. Interestingly, I observe that these benefits are primarily experienced by health facilities with lower magnitudes of learning (Column 5: β = 0.07, p < 0.01), i.e., those that gained the least from the provision of initial trainings. These facilities can gain up to 7% additional reductions in stock-outs as a result of refresher trainings, compared to those with higher magnitudes of learning. This result provides empirical support for H4.2b. Taken together, the findings provide compelling evidence in support of the benefits of training programs in public health supply chains.

The results presented in Table 4.2 are robust to the inclusion of province-level time trends (Column 5), allowing for treatment and control units to follow different trends over time. This approach serves as a check on the DID identification assumption of parallel-trends (Angrist and Pischke 2008, Besley and Burgess 2004). I further evaluate the sensitivity of the results to the DID parallel trends assumption by applying two different matching techniques, namely propensity score matching and coarsened exact matching. The results of matching techniques presented in Table AP4.1 in the Appendix are consistent with those of the main models, therefore ensuring their robustness.

4.5.2. Synthetic Control Method Results (H4.3)

The results of the synthetic control method presented in Figure 4.4 show that the synthetic control and treated units follow nearly identical trajectories prior to the expansion of the intervention across all four scenarios. I observe that the trajectories of stock-outs between the two units begin to diverge subsequent to the provision of initial trainings.

Table 4.1. Summary Statistics and Pairwise Correlations

	Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	*Stock-Out*	1.00						
2	*Initial Training*	-0.05*	1.00					
3	*Refresher Training*	-0.03*	0.64*	1.00				
4	*Inventory Data Inaccuracy$_{Pre\text{-}Initial\ Training}$*	0.04*	-0.02*	-0.02*	1.00			
5	*Magnitude of Learning $_{Post\text{-}Initial\ Training}$*	-0.05*	0.90*	0.54*	0.00*	1.00		
6	*Ln (Quantity Issued)*	-0.18*	0.01*	0.01*	0.07*	-0.01*	1.00	
7	*Ln (Quantity Received)*	-0.05*	-0.02*	-0.01*	0.01*	0.02*	0.54*	1.00
	Mean	0.23	0.05	0.02	0.38	0.00	1.97	1.09
	Std. Dev.	0.42	0.22	0.14	0.82	0.01	2.00	2.04
	Min	0.00	0.00	0.00	0.00	-0.06	0.00	0.00
	Max	1.00	1.00	1.00	8.81	0.00	12.61	14.51

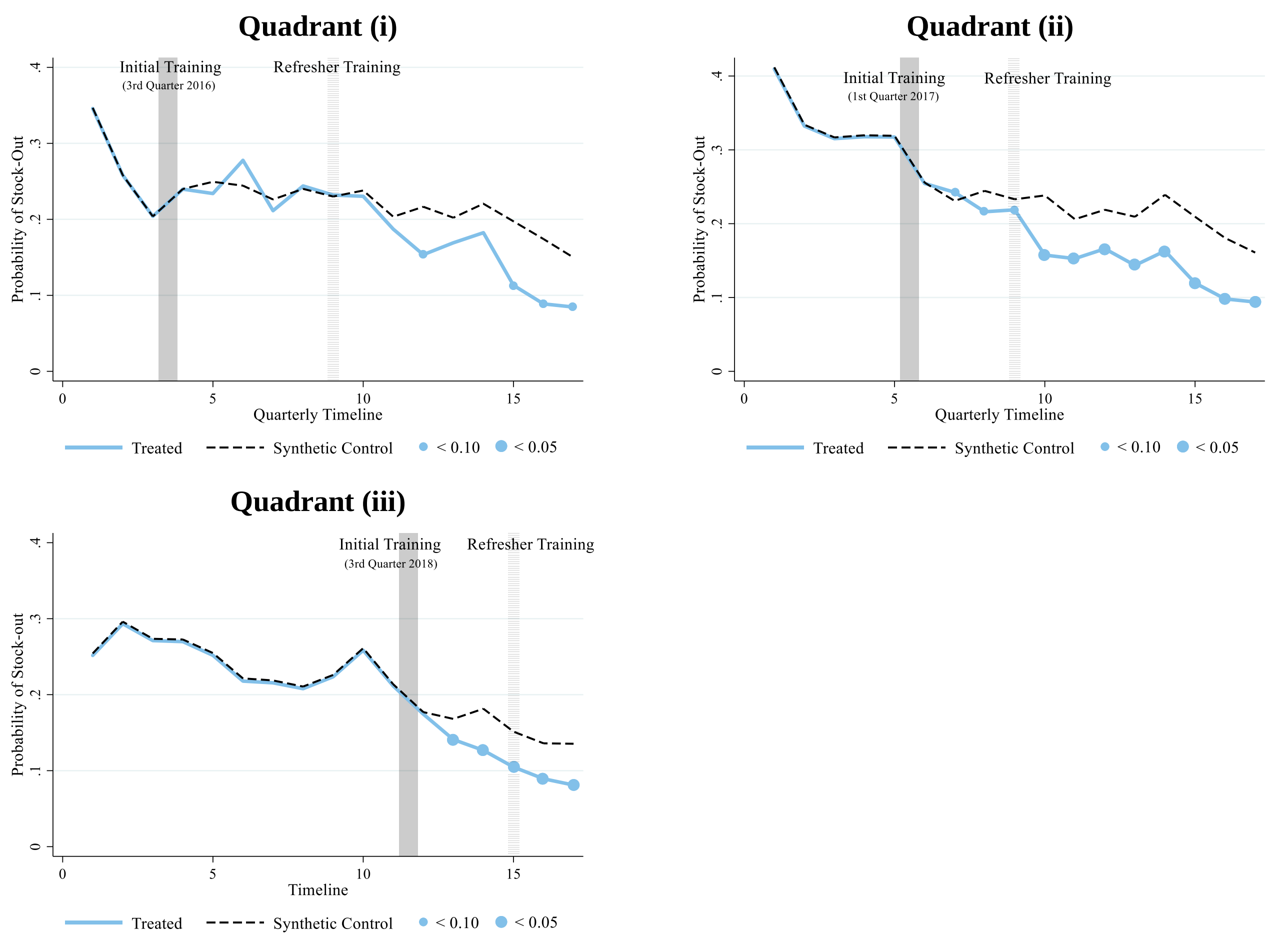
* $p < 0.05$

Table 4.2. Difference-in-Differences Estimation Results: Effect of *Initial Training* and *Refresher Training* on Stock-Outs

DV: Stock-Out	Model 1 (1)	Model 2 (2)	Model 3 (3)	Model 4 (4)	Full Model (5)	
Initial Training	-0.59*** (0.04)	-0.60*** (0.04)			-0.39*** (0.08)	H4.1a
Inventory Data Inaccuracy$_{Pre\text{-}Initial\ Training}$		0.08*** (0.01)			0.08*** (0.01)	
Initial Training × Inventory Data Inaccuracy$_{Pre\text{-}Initial\ Training}$		-0.10*** (0.03)			-0.10*** (0.03)	H4.1b
Refresher Training			-0.52*** (0.05)	-0.61*** (0.08)	-0.47*** (0.08)	H4.2a
Magnitude of Learning $_{Post\text{-}Initial\ Training}$				-0.11*** (0.01)	-0.03 (0.02)	
Refresher Training × Magnitude of Learning $_{Post\text{-}Initial\ Training}$				0.10*** (0.02)	0.07*** (0.02)	H4.2b
Ln (Quantity Issued)	-0.34*** (0.00)	-0.35*** (0.00)	-0.34*** (0.00)	-0.34*** (0.00)	-0.35*** (0.00)	
Ln (Quantity Received)	-0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	
Commodity Type Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Commodity Range Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Province Time Trends	—	—	—	—	Yes	
Constant	1.51*** (0.21)	1.44*** (0.21)	1.53*** (0.21)	1.48*** (0.21)	1.07*** (0.22)	
Pseudo R-squared	0.17	0.17	0.17	0.17	0.18	
Log Likelihood	-1006000	-1005000	-1007000	-1006000	-1002000	
Observations	2,297,602	2,297,602	2,297,602	2,297,602	2,297,602	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Notes:* Robust standard errors clustered at the facility level in parentheses. The variables *Inventory Data Inaccuracy* and *Magnitude of Learning* were standardized.

Figure 4.4. Synthetic Control Method Results: Effect of Intervention on Health Commodity Stock-Outs



Notes. The *p*-value is defined as the proportion of placebo units that have an estimated effect size at least as large as that of the treated unit.

Table 4.3. Synthetic Control Method Results: Changes in the Probability of Stock-Outs at Treated Units Subsequent to Initial Trainings

	Changes in the Probability of Stock-Outs at Treated Units, Relative to Placebo Units (%)		
Quarters Elapsed Since Refresher Training	**Quadrant (i)**	**Quadrant (ii)**	**Quadrant (iii)**
T+1	-6.30*	-8.10**	-4.67**
T+2	-3.30	-5.34**	-5.43**
T+3	-3.81	-5.28**	
T+4	-8.41*	-6.59**	
T+5	-8.52*	-7.60**	
T+6	-6.51*	-8.97**	
T+7		-8.25**	
T+8		-6.70**	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Notes*. The p-value is defined as the proportion of placebo units that have an estimated effect size at least as large as that of the treated unit.

Performing Placebo Tests. I perform placebo tests in order to ascertain whether the reductions in the likelihood stock-outs observed in Figure 4.4 are statistically significant (Abadie et al. 2010). This involves iteratively reassigning the treatment status to untreated units (i.e. placebo unit) and recording the trajectories of stock-outs for these units. Next, I draw inferences by comparing the magnitude of the estimated coefficients across the treated and placebo units. The essential idea behind this type of inference is as follows. If I observe that the placebo units lead to many effect sizes that are as large as the main effects, then I can conclude that the estimated effects could have been produced by chance. Using this placebo-based inferential approach (Galiani and Quistorff 2017), I calculate the statistical significance of the post-intervention changes in stock-outs for all quarterly periods (see Table 4.3, and the blue circles in Figure 4.4). The results of the synthetic control method indicate that the benefits of interventions in reducing the likelihood of stock-outs are likely to be sustained up to 8 quarters following the provision of refresher trainings (Quadrant (ii), Table 4.3), hence lending support to H4.3

4.6. Conclusion

4.6.1. Contributions and Implications for Public Health Supply Chains

Public health supply chains in developing countries are faced with the shortages of pharmacy professionals with sufficient training in the supply chain management of health commodities. As a result, managing inventories of health supplies is commonly delegated to frontline healthcare providers (e.g., nurses, midwives) who are primarily responsible for the provision of clinical services and lack sufficient training on inventory management. Given the lack of adequate training, healthcare providers frequently deviate from the national standard operating procedures on inventory management, leading to the increased inaccuracies in the inventory records that form the foundation for the replenishment decisions. This could subsequently amplify the risk of a mismatch between supply and demand and contribute to health commodity stock-outs. Towards combating these challenges, one public health supply chain initiative in developing countries has focused on improving the skills of frontline healthcare providers in managing inventories through training programs (i.e., using classroom-based training, paper-based job aids, and video tutorials). In reviewing the extant literature, however, I find little by way of rigorous and systematic empirical research on whether the implementation of such initiatives can improve the inventory management practices of healthcare providers and subsequently alleviate the risk of stock-outs. Further, prior studies in the operations management domain have primarily focused on the operational drives of stock-outs at the macro-level (e.g., Gallien et al. 2017, Kazaz et al. 2016, Natarajan and Swaminathan 2014), and little attention has been paid to the role played by frontline healthcare providers at the health facility-level. Using the staggered expansion of a supply chain intervention in Indonesia, this study is aimed at filling these gaps in the literature.

Beyond theoretical contributions, the findings have significant implications for various stakeholders (e.g., donors, governments) managing public health supply chains in developing countries. The DID estimation results show that the provision of initial trainings to healthcare providers reduces the likelihood of stock-outs by an average of 5 percentage points. However, I find that initial trainings bring about additional reductions of up to 16 percentage-point in the likelihood of stock-outs for health facilities with higher levels of inventory data inaccuracies, when compared to those with lower inaccuracies. Further, the empirical findings indicate that the provision of refresher trainings to healthcare providers decreases the likelihood of stock-outs by an average of 6 percentage points, although the majority of these benefits are gained by health facilities with lower magnitudes of learning after initial trainings. Given the capital-intensive nature of training programs and the tight resource constraints faced by the public health sector in developing countries, the results have actionable implications for the effective allocation of resources in public health supply chains. Particularly, the findings show that policy-makers should prioritize the provision of initial trainings to health facilities with the highest levels of inventory data inaccuracies. The findings also demonstrate that policy-makers should prioritize the provision of refresher trainings to health facilities with lower magnitudes of learning following the provision of initial trainings. Importantly, the findings from synthetic control method indicate that the benefits provided by refresher trainings are likely to be sustained over time.

The effects of initial and refresher trainings on reducing the likelihood of stock-outs are not only statistically significant, but also practically meaningful with respect to their consequent impact on the overall health outcomes. In order to provide a quantifiable read on the impact of the intervention on health outcomes, I rely on "Reducing Stock-outs Impact Calculator" developed by the Reproductive Health Supplies Coalition (RHSC 2020). The tool is based on estimates from prior research that evaluate the elasticity in the number of contraceptive users as a function of the range of contraceptive methods offered on the shelf. Assuming that the partial stock-out of a method equates to the partial removal of that method from the shelf, the tool quantifies how changes in stock-outs would translate into health outcomes based on estimates from past research. Using the "Reducing Stock-outs Impact Calculator" and the marginal effects from the DID regressions, I find that the reductions in stock-out owing to the intervention can increase the number of contraceptive users across the treated districts by approximately 200,000 people (BPS 2010).[25] This increase in the number of users could potentially translate into 60,000 fewer unintended pregnancies, 30,000 fewer induced abortions, and 1,000 fewer maternal/infant deaths annually.[26] The findings assume greater significance especially considering that multiple supply chain initiatives in developing countries have been designed to deliver change at the macro-level including at the level of manufacturers (Kazaz et al. 2016, Tougher et al. 2012), donors (Gallien et al. 2017, Natarajan and Swaminathan 2014, Taylor and Xiao 2014), and national/regional warehouses (Vledder et al. 2019). At the last-mile level, the interventions designed to deliver change have primarily directed investments toward the adoption of technologies by healthcare providers (e.g. mobile phone text messaging and electronic inventory management, see Githinji et al. 2013, USAID 2012). Hence, the results highlight significant opportunities to reduce the likelihood of stock-outs by allocating resources to training programs at the healthcare provider-level.

Finally, the implications from the results are likely to be generalizable to other health commodities that have similar characteristics to those of contraceptives. This includes health commodities with relatively low demand unpredictability such as vitamin supplements and antibiotics (Lai et al. 2008). In contrast, I expect that the benefits of the interventions would be lower for health products for which demand is seasonal and highly unpredictable (e.g., antimalarials). The underlying intuition behind this is as follows. In many developing countries, the replenishment process for health commodities is based on a minimum-maximum system, which relies on past consumption data to predict the demand for future periods. However, for products with highly unpredictable and seasonal demand, prior consumption data is likely to be a poor predictor of future demand, even in the case when healthcare providers are sufficiently trained on managing inventories. Hence, for products with higher levels of demand unpredictability, policy-makers should prioritize alternative approaches (e.g., increasing the levels of safety stocks, see USAID 2011a) before they allocate resources to inventory management training programs.

4.6.2. Limitations and Future Research Directions

This study has some limitations that serve as avenues for future research. First, the measure of stock-out used in this study is based on whether the ending balance of a health commodity in a given month was recorded as zero. While this approach to measuring stock-outs is well-accepted

[25] These districts represent about 3% of the total population of women in their reproductive age (i.e., between 15 and 49 years old) in Indonesia.

[26] These estimates are likely to be conservative given that my measure of population is relatively old and based on 2010 Indonesian census data.

in the literature (see USAID 2018), it does not capture the total number of days a health product was out of stock within a period. Despite this limitation, all of the estimated coefficients remain unbiased, as potential measurement error in the dependent variable would only inflate the standard errors (Wooldridge 2010), therefore, making the estimates conservative. Future research could replicate the findings using alternative measures of stock-outs (e.g., on the day of survey visit). Second, I execute the empirical analysis using the context of supply chains for the distribution of contraceptive methods across Indonesia. Prospective studies can corroborate the findings by focusing on alternative geographical and supply chain contexts. Despite these limitations, my research findings highlight significant opportunities to reduce the likelihood of stock-outs in public health supply chains by providing training at the healthcare provider-level.

Chapter 5: Conclusion

5.1. Key Theoretical Contributions

Supply chains are the backbone of a health system and well-functioning public health supply chains that ensure availability of health commodities, when and where they are needed, are critical to advancing health outcomes in developing countries. However, in many developing countries, significant resource constraints hamper the effective and efficient delivery of health commodities to health facilities in the last-mile, leading to supply chain failures such as “stock-outs.” While the prevalence of stock-outs in developing countries is well-acknowledged, there exist little by way of systematic and rigorous empirical research on the underlying factors that drive such stock-outs at the last-mile level. This dissertation is aimed primarily at filling this void in the literature. I summarize the key theoretical contributions of the dissertation below:

(a) In Chapter 2, I empirically evaluate the effect of distribution model (i.e., pull vs. push) on health commodity stock-outs, a relationship that has not been rigorously tested in the extant literature. In addition to testing the magnitude of the main effect, I also identify previously unexplored facility characteristics that moderate the above relationship.

(b) In Chapter 3, I investigate how a health facility’s product selection (i.e., the range of health commodities offered) and LMIS practices (i.e., LMIS updating frequency, and electronic LMIS) impact the likelihood of health commodity stock-outs. To the best of my knowledge, the inter-relationship between product selection, LMIS practices and public health supply chain performance has not been explored in the extant literature.

(c) In Chapter 4, I use empirical methods to explore how the provision of inventory management trainings to frontline healthcare providers can help alleviate the likelihood of stock-outs, a relationship that has not been rigorously tested in the extant literature. Importantly, I investigate facility-specific characteristics that can moderate the relationship between training programs and health commodity stock-outs.

In sum, this dissertation is the first systematic attempt in the literature to conduct a rigorous empirical evaluation of the factors driving the stock-outs of health commodities in public health supply chains in developing countries.

5.2. Key Practical Implications for Public Health Supply Chains in Developing Countries

Beyond theoretical contributions, the findings from this dissertation have actionable implications for various stakeholders managing public health supply chains to improve the availability of health commodities in developing countries. Below, I summarize the key practical implications of my dissertation:

(a) The findings from Chapter 2 have actionable implications for the implementation of push interventions in developing countries which require the allocation of significant resources toward start-up investments, operating costs, and ongoing supervision. Given that developing countries often face significant resource constraints, the results highlight the need for policy-makers to prioritize the transition of facilities with less mature LMIS practices and less developed logistics infrastructure to push distribution. This involves the allocation of limited resources to transition facilities with the least data management capabilities, limited supply chain visibility and constrained transportation capacity. In contrast, I find no statistically significant benefits of a transition to push distribution for health facilities with superior data management capabilities, stronger supply chain visibility and adequate transportation capacity (i.e., more mature LMIS and more developed logistics infrastructure).

(b) The finding from Chapter 3 that the negative impact of commodity range is more severe for rural facilities is driven by the logistical and human resource challenges faced by these facilities (McCoy and Lee 2014, USAID 2017). Toward combating the human resource challenges, particular attention needs to be paid to create better incentives for the recruitment and retainment of staff personnel and mobilizing funds to improve training at rural health facilities (Waako et al. 2009). Beyond addressing the human resource limitations, public health managers should also explore creative approaches to overcome the logistical challenges faced by health facilities located in rural areas. One such initiative involves the utilization of delivery trucks to deliver health commodities from upstream warehouses to the last-mile in Senegal (see Chapter 2 for more detail). Another example is the use of drones as an emergency delivery method for blood samples and essential medicines in Rwanda. Both approaches have the potential to improve the reliability and timeliness of replenishments from upstream facilities and ultimately, reduce the stock-outs of health commodities (Rosen 2017).

(c) The results from Chapter 3 highlight the need to tailor funding allocation decision-making to the geographic location of health facilities (i.e., urban vs. rural). Particularly, urban facilities are likely to see a significant reduction in stock-outs with the implementation of daily LMIS updating but pairing it with the use of electronic LMIS brings no additional benefits. Hence, funding allocations to urban health facilities should be directed towards increasing the frequency with which the LMIS records are updated. In case of rural facilities, daily LMIS updating reduces stock-outs, but only when used in conjunction with electronic LMIS. Taken together, these findings suggest that resources dedicated toward transitioning facilities from paper-based to electronic LMIS would be best utilized if allocated to rural health facilities.

(d) The results from Chapter 4 highlight significant opportunities to reduce the likelihood of stock-outs by allocating resources toward the provision of inventory management trainings to frontline healthcare providers. The findings indicate that in the case of initial trainings, policy-makers should prioritize health facilities with the highest levels of inventory data inaccuracies prior to the provision of trainings. Further, I find that resources dedicated toward refresher trainings are best utilized if directed toward health facilities with lower magnitudes of learning subsequent to the provision of initial trainings. These results assume greater significance especially when considering that multiple public health supply chain interventions in developing countries have been designed to deliver change at the macro-level (e.g., manufacturer-level, donor-level), in contrast to the healthcare provider-level.

(e) Finally, the dissertation findings have implications for managing the health supply chains of a broader class of commodities beyond contraceptives. Lai et al. (2008) discuss a framework to classify commodities offered through public health supply chains into different categories based on two key attributes: inventory holding cost and demand predictability. Contraceptives have low inventory holding costs and exhibit relatively stable demand patterns compared to other commodities such as antimalarial medications that have highly unpredictable and seasonal demand (see Yadav et al. 2014). I expect the findings to be generalizable to commodities that share similar attributes to those of contraceptives — examples include antibiotics (USAID 2010), and iron and vitamin supplements (Yadav et al. 2014).

In closing, I highlight avenues to expand the scope of this dissertation. First, the literature on public health supply chains in developing countries would benefit from more rigorous empirical research on the impact evaluation of operational interventions. This is critical considering that the direction and size of effects for many operational interventions in this context are not well-known. To this end, one empirical challenge facing the researchers might be related to the availability of large-scale, granular, and reliable data, which has historically been scarce within the public health supply chain context in developing countries. However, this trend has begun to change in recent years with the growing recognition of the need for data-driven decision-making within the public health sector and the advent of innovative technologies (e.g., smart mobile devices) that facilitate the collection of reliable, nationally representative data. Second, future research could expand the scope of this dissertation by conducting a rigorous empirical evaluation of the impact of stock-outs on health outcomes. While there is a considerable volume of anecdotal and qualitative insights that attest to the negative effect of stock-outs on health outcomes, the literature would significantly benefit from research evaluating the relevant effect sizes for various health outcomes. I hope that the potential availability of reliable data, together with the consequential nature of the studied phenomenon, will serve as the motivation for scholars to further advance this line of inquiry.

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Appendix

Table AP2.1. Difference-in-Differences Estimation Results Using Coarsened Exact Matching: Effects of Push Distribution on Health Commodity Stock-Outs

DV: Stock-Out	All (H2.1)	LMIS Only (H2.2)		Logistics Infrastructure Only (H2.3)		LMIS and Logistics Infrastructure (H2.4)	
		More Mature	Less Mature	More Developed	Less Developed	More Mature and More Developed	Less Mature and Less Developed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Push	-2.48***	-1.58	-2.76**	-0.28	-4.76***	0.58	-17.73***
	(0.70)	(1.08)	(1.23)	(0.81)	(1.00)	(1.05)	(2.11)
Primary Facility	-0.55	-0.79*	-0.25	-0.43	-1.55*	-0.22	0.00
	(0.37)	(0.41)	(0.57)	(0.33)	(0.84)	(0.39)	0.00
Piped Water	-0.48	-0.77	-0.32	0.33	-1.68**	0.77	0.85
	(0.57)	(0.65)	(1.26)	(0.64)	(0.67)	(0.64)	(1.60)
External Supervision	-1.09	-0.75	0.00	-0.71	-1.09	-0.66	0.00
	(0.69)	(0.69)	0.00	(1.06)	(1.32)	(1.05)	0.00
Management Meetings	-0.71	-0.73	-10.99***	0.00	-1.74*	0.00	0.00
	(0.56)	(0.68)	(1.24)	0.00	(1.01)	0.00	0.00
Commodity Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Commodity Range FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.27	0.83	-3.42	10.68***	5.74**	9.45***	2.21
	(1.43)	(1.78)	(2.96)	(1.81)	(2.41)	(1.73)	(1.82)
Pseudo R-Squared	0.29	0.30	0.46	0.34	0.40	0.37	0.65
Log Likelihood	-774	-608	-110	-349	-332	-296	-47
Observations	4,002	3,054	816	2,028	1,882	1,623	358

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$. *Notes*: All models are estimated using a logistic regression specification. FE = Fixed Effects. Robust standard errors clustered at the facility level in parentheses.

Table AP3.1. Logistic Regression Results Examining the Effects of *Commodity Range* and *LMIS Practices* on Stock-Outs using Coarsened Exact Matched Sample (Based on *Commodity Range*)

DV: Stock-out	Urban (1)	Rural (2)
Facility-level Controls		
Secondary Facility	0.18	-0.09
	(0.21)	(0.10)
Tertiary Facility	0.52**	-0.21
	(0.27)	(0.25)
Ln (Facility Size)	-0.33***	-0.08
	(0.09)	(0.06)
Private For-Profit Facility	0.22	0.73***
	(0.20)	(0.19)
Private Non-Profit Facility	-0.23	0.20
	(0.20)	(0.14)
Supervision	-0.10	-0.43
	(0.24)	(0.26)
First Expire First Out	-0.13	-0.42***
	(0.22)	(0.12)
Protection	-0.13	-0.07
	(0.11)	(0.06)
Client-level Controls		
Client Education	-0.17	-0.21***
	(0.13)	(0.06)
Client Household Size	0.01	-0.07**
	(0.07)	(0.04)
Client Wealth Index	0.40**	0.21*
	(0.17)	(0.11)
Commodity Range	0.15***	0.23***
	(0.04)	(0.03)
LMIS Updating Frequency	-0.31**	-0.03
	(0.14)	(0.09)
Electronic LMIS	0.31	-0.06
	(0.31)	(0.19)
LMIS Updating Frequency × Electronic LMIS	-0.39	-1.09***
	(0.37)	(0.34)
Constant	1.43	2.01***
	(1.53)	(0.74)
Country FE	Yes	Yes
Commodity Type FE	Yes	Yes
Commodity Assortment FE	Yes	Yes
Month FE	Yes	Yes
Pseudo R-squared	0.15	0.14
Log Likelihood	-2481	-6619
Observations	6,001	14,300

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Notes:* FE = Fixed Effects. Robust standard errors clustered at the facility level in parentheses. Facilities offering a range above (below) the median range of commodities were considered as treated (untreated).

Table AP3.2. Logistic Regression Results Regressing "Stock-outs at a Focal Facility" on "Average Stock-out at Neighboring Facilities" using Coarsened Exact Matched Sample

	Model 1		**Model 2**	
	Urban	**Rural**	**Urban**	**Rural**
DV: Stock-out	**(1)**	**(2)**	**(3)**	**(4)**
Facility-level Controls				
Secondary Facility	0.38	-0.09	0.39	-0.08
	(0.35)	(0.11)	(0.35)	(0.12)
Tertiary Facility	0.69*	-0.74**	0.69*	-0.61*
	(0.40)	(0.32)	(0.40)	(0.32)
Ln (Facility Size)	-0.37***	-0.11	-0.37***	-0.12
	(0.12)	(0.07)	(0.12)	(0.07)
Private For-Profit Facility	-0.08	0.81***	-0.05	0.82***
	(0.31)	(0.25)	(0.31)	(0.25)
Private Non-Profit Facility	0.02	0.54***	0.04	0.52***
	(0.34)	(0.15)	(0.34)	(0.16)
Supervision	-0.52*	-0.45	-0.54*	-0.44
	(0.31)	(0.55)	(0.32)	(0.57)
First Expire First Out	-0.42*	-0.36**	-0.43*	-0.38***
	(0.24)	(0.14)	(0.24)	(0.14)
Protection	-0.18	-0.12*	-0.19*	-0.12*
	(0.11)	(0.07)	(0.11)	(0.07)
Client-level Controls				
Client Education	-0.72	-0.33	-0.61	-0.31
	(0.95)	(0.41)	(0.93)	(0.40)
Client Household Size	-0.09	-0.06	-0.06	-0.02
	(0.11)	(0.05)	(0.11)	(0.05)
Client Wealth Index	0.38	0.12	0.34	0.13
	(0.30)	(0.14)	(0.31)	(0.13)
Additional Controls				
Neighboring Stock-out			0.98***	1.30***
			(0.28)	(0.13)
Neighboring Public Facilities			-0.16	-0.41**
			(0.43)	(0.20)
Commodity Range	0.14**	0.24***	0.13**	0.21***
	(0.06)	(0.03)	(0.06)	(0.03)
LMIS Updating Frequency	-0.50**	0.00	-0.49**	0.02
	(0.20)	(0.10)	(0.20)	(0.10)
Electronic LMIS	-0.24	-0.24	-0.20	-0.26
	(0.55)	(0.21)	(0.56)	(0.21)
LMIS Updating Frequency ×	0.80	-0.71*	0.72	-0.66*
Electronic LMIS	(0.68)	(0.38)	(0.69)	(0.38)
Constant	3.88*	0.98	3.67*	0.21
	(2.14)	(1.19)	(2.11)	(1.23)
Country FE	Yes	Yes	Yes	Yes
Commodity Type FE	Yes	Yes	Yes	Yes
Commodity Assortment FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.20	0.15	0.21	0.16
Log Likelihood	-1168	-4315	-1158	-4249
Observations	2,880	9,874	2,880	9,874

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Notes:* FE = Fixed Effects. Robust standard errors clustered at the facility level in parentheses. LMIS practices of health facilities were matched using the following covariates: facility type, facility size, managing authority, supervision, first expire first out, protection, client education, client household size, client wealth index and country fixed effects. The cut-off points for categorizing the continuous variables in the coarsened exact matching process are based on the median values. Facilities utilizing at least one of the LMIS practices — i.e., frequent LMIS updating or electronic LMIS — were considered as treated.

Table AP3.3. Logistic Regression Results Controlling for Region and District Fixed Effects using Coarsened Exact Matched Sample

	Region Fixed Effects		District Fixed Effects	
	Urban	**Rural**	**Urban**	**Rural**
DV: Stock-out	**(1)**	**(2)**	**(3)**	**(4)**
Facility-level Controls				
Secondary Facility	0.25	-0.06	0.33*	-0.05
	(0.18)	(0.08)	(0.20)	(0.09)
Tertiary Facility	0.56**	-0.22	0.81***	-0.17
	(0.25)	(0.24)	(0.28)	(0.27)
Ln (Facility Size)	-0.33***	-0.17***	-0.35***	-0.17***
	(0.07)	(0.05)	(0.08)	(0.06)
Private For-Profit Facility	0.39**	0.38**	0.45**	0.59***
	(0.19)	(0.17)	(0.23)	(0.19)
Private Non-Profit Facility	-0.05	0.30***	-0.01	0.26**
	(0.17)	(0.10)	(0.20)	(0.12)
Supervision	-0.25	-0.22	-0.37	-0.10
	(0.23)	(0.33)	(0.23)	(0.29)
First Expire First Out	-0.10	-0.37***	-0.06	-0.29***
	(0.17)	(0.10)	(0.21)	(0.11)
Protection	-0.02	-0.12**	-0.09	-0.14***
	(0.07)	(0.05)	(0.08)	(0.05)
Client-level Controls				
Client Education	-0.03	-0.19**	0.54	-0.09
	(0.21)	(0.08)	(0.55)	(0.13)
Client Household Size	0.29*	-0.06	-0.07	-0.06
	(0.15)	(0.05)	(0.37)	(0.08)
Client Wealth Index	0.27	0.09	-1.33	-0.05
	(0.28)	(0.14)	(0.85)	(0.22)
Commodity Range	0.17***	0.23***	0.14***	0.22***
	(0.04)	(0.02)	(0.05)	(0.02)
LMIS Updating Frequency	-0.45***	0.01	-0.49***	0.05
	(0.13)	(0.08)	(0.16)	(0.08)
Electronic LMIS	0.32	0.04	0.79	-0.21
	(0.35)	(0.18)	(0.52)	(0.19)
LMIS Updating Frequency ×	-0.20	-1.01***	-0.49	-0.72**
Electronic LMIS	(0.41)	(0.32)	(0.57)	(0.33)
Constant	2.50	1.94**	1.47	1.74
	(1.93)	(0.96)	(3.67)	(1.18)
Region FE	Yes	Yes	—	—
District FE	—	—	Yes	Yes
Commodity Type FE	Yes	Yes	Yes	Yes
Commodity Assortment FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.19	0.15	0.21	0.19
Log Likelihood	-2582	-6975	-2312	-6539
Observations	6,426	15,469	5,556	14,761

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Notes:* FE = Fixed Effects. Robust standard errors clustered at the facility level in parentheses. Client-level variables were averaged based on the distance of clients to health facilities (within 30km range).

Description of Diagnostic Approach by Altonji et al. (2005)

Here, I briefly discuss the underpinnings of the diagnostic approach developed by Altonji et al. (2005). The essential idea behind this diagnostic approach is that "selection on unobservables is the same as selection on observables." In other words, Altonji et al. postulate that the part of a dependent variable (e.g., likelihood of stock-outs) that is related to the observable control variables has the *same* relationship with the independent variable of interest as the part related to the unobservables. Consider the following regression model:

$$DV = \beta IV + W'\Gamma = \beta IV + X'\gamma + \epsilon \qquad \text{(AP3.1)}$$

where *DV* is the dependent variable, *IV* is the independent variable, and W is the full set of observed and unobserved control variables that impact the dependent variable. Vector X contains the observable components of W, ϵ is such that $Cov(\epsilon, X) = 0$, and γ captures both the direct effect of *X* on the dependent variable and the relationship between X and the unobserved part of W. Next, consider the linear projection of the independent variable onto $X'\gamma$ and ϵ:

$$IV = \varphi_0 + \varphi_{obs}X'\gamma + \varphi_{unobs}\epsilon \qquad \text{(AP3.2)}$$

where Altonji et al. argue that γ is identified when $\varphi_{obs} = \varphi_{unobs}$. In other words, the condition for identification is that selection on observables equals selection on unobservables. They show that the above condition is equivalent to the following:

$$\frac{E(\epsilon|IV = 1) - E(\epsilon|IV = 0)}{Var(\epsilon)} = \frac{E(X'\gamma|IV = 1) - E(X'\gamma|IV = 0)}{Var(X'\gamma)} \qquad \text{(AP3.3)}$$

Next, let $X'\alpha$ and $\widetilde{IV}$ be the predicted values and residuals from regressing *IV* on *X* as follows: $IV = X'\alpha + \widetilde{IV}$. Then, Equation AP3.1 can be written as:

$$DV = \beta\widetilde{IV} + X'(\gamma + \beta\alpha) + \epsilon \qquad \text{(AP3.4)}$$

Therefore, the estimated $\tilde{\beta}$ can be represented as follows:

$$plim\,\tilde{\beta} = \beta + \frac{Cov(\widetilde{IV}, \epsilon)}{Var(\widetilde{IV})} = \beta + \frac{Var(IV)}{Var(\widetilde{IV})} * [E(\epsilon|IV = 1) - E(\epsilon|IV = 0)] \qquad \text{(AP3.5)}$$

In order to estimate the magnitude of selection on unobservables in Equation AP3.5, i.e., $E(\epsilon|IV = 1) - E(\epsilon|IV = 0)$, I rely on an estimate of selection on observables from Equation AP3.3, i.e., $E(X'\gamma|IV = 1) - E(X'\gamma|IV = 0)$. Therefore, I can rewrite Equation AP3.5 as follows:

$$plim\,\tilde{\beta} = \beta + \frac{Var(IV)}{Var(\widetilde{IV})} * \frac{Var(\epsilon)}{Var(X'\gamma)} [E(X'\gamma|IV = 1) - E(X'\gamma|IV = 0)] \qquad \text{(AP3.6)}$$

Under the null hypothesis of no effect of the *IV*, the expression to the right hand side of β in Equation AP3.6 represents the degree of bias. This bias is equivalent to the difference between the estimates of β under the following conditions: (i) an unsaturated estimate of β where observables are excluded from the models (i.e., reduced model), and (ii) a saturated estimate of β where observables are incorporated into the models (i.e., full model). Altonji et al. develop a normalized ratio of bias, $\rho = \beta^F/|(\beta^F - \beta^R)|$, where the numerator is the saturated estimate of β and the denominator is the degree of bias described above. They argue that the estimates with a ratio above the value of 1 are robust to the effect of unobservable factors. I summarize the bias levels and Altonji ratios in Table 3.4, where I find that the ratios are above the threshold of 1 across all the estimates. For instance, the ratio of 27.25 pertaining to the coarsened exact matching coefficient of LMIS Practices at urban facilities indicates that the "normalized shift" in the distribution of the unobservables would need to be approximately 27 times as large as the shift in observables to fully account for the estimate, which is highly unlikely. Therefore, I conclude that the estimates are robust to the effect of unobserved variables.

Table AP4.1. Difference-in-Differences Estimation Results: Effect of *Initial Training* and *Refresher Training* on Health Commodity Stock-Outs using Propensity Score Matching and Coarsened Exact Matching

	Propensity Score Matching	**Coarsened Exact Matching**
DV: Stock-Out	**(1)**	**(2)**
Initial Training	-0.52***	-0.49***
	(0.09)	(0.08)
Inventory Data Inaccuracy$_{\textit{Pre-Initial Training}}$	0.16***	0.14***
	(0.01)	(0.01)
Initial Training × *Inventory Data Inaccuracy*$_{\textit{Pre-Initial Training}}$	-0.17***	-0.16***
	(0.03)	(0.03)
Refresher Training	-0.56***	-0.50***
	(0.09)	(0.09)
Magnitude of Learning $_{\textit{Post-Initial Training}}$	-0.01	-0.01
	(0.02)	(0.02)
Refresher Training × *Magnitude of Learning* $_{\textit{Post-Initial Training}}$	0.10***	0.07***
	(0.02)	(0.02)
Ln (Quantity Issued)	-0.43***	-0.42***
	(0.01)	(0.00)
Ln (Quantity Received)	-0.06***	-0.08***
	(0.01)	(0.01)
Constant	0.73**	1.12***
	(0.31)	(0.21)
Commodity Type FE	Yes	Yes
Commodity Range FE	Yes	Yes
Year FE	Yes	Yes
Month FE	Yes	Yes
District FE	Yes	Yes
Province Time Trends	Yes	Yes
Pseudo R-squared	0.18	0.17
Log Likelihood	-144700	-886810
Observations	1,837,661	2,155,557

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. *Notes:* Robust standard errors clustered at the facility level in parentheses. The propensity score matching process was based on the nearest neighbors estimator, where a caliper of 0.20 was used. The cut-off points for categorizing the continuous variables in the coarsened exact matching process are based on the Sturges automatic rule.