It Takes Two: Experimental Evidence on the Determinants of Technology Diffusion

Morgan Hardy
Department of Economics
Brown University

Jamie McCasland
Department of Economics
University of British Columbia

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Abstract

Diffusion of skill-based technologies will in general depend on both the willingness of incumbent adopters to teach the skill and the desire of potential adopters to learn it. We report the results of a field experiment that was designed to mimic market interactions among small-scale manufacturing firm owners. Specifically, we develop a new weaving technique and randomly seed both training and technique-specific contracts in a real network of garment making firm owners in Ghana. We collect a rich baseline network map and 8 rounds of network panel data throughout the course of the experiment. The order of contract seeding was randomly determined, without replacement, until enough contracts were filled to exhaust resources. We find that firms that need the technology to complete an order learn it from firms that received training; however, firms that received only training and no order are much less likely to share the technology than those who received both. Our results suggest that competition is an important barrier to technology diffusion in this context.

JEL Classifications: D83, D85, D22, L14, O12, O14, O17, O33

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1 Introduction

Firm productivity in low-income countries is both lower on average than in rich countries, and distributed with a far thicker left tail (Hsieh and Klenow, 2009; Bloom and Reenan, 2007, 2010). One important source of productivity dispersion is the use of inferior technology and managerial practices (Bloom et al., 2013; Syverson, 2011). Much of the literature on firms in developing countries has focused on (sometimes quite successful) interventions targeting capital, labor, and managerial skill constraints (De Mel, McKenzie and Woodruff, 2008; Hardy and McCasland, 2015; Bruhn, Karlan and Schoar, 2013). While technology upgrading can indeed require capital, skilled workers, and managerial aptitude, basic access to information about a new technology is also a necessary condition to adoption. In our context, small-scale garment making in Ghana, within industry peers are the most cited source of information about new technology.

While an influential body of research in development economics has analyzed peer-to-peer technology diffusion and specifically learning about new technology in the context of agriculture,[1] relatively little work has been done on learning in manufacturing and industry in low-income countries. There is reason to believe that peer-to-peer diffusion findings from small-scale agriculture, where farmers tend to produce highly tradable cash crops or subsistence agricultural products for home consumption, may not generalize to other contexts. In particular, most small-scale manufacturing firms in developing countries service exclusively local demand, leading to direct competition between neighboring firms. The potential presence of competitive disincentives to share a new technology highlights a more generic point about this literature, namely that it focuses almost exclusively on the adoption decision of the potential new user. Equally relevant for observed diffusion is the decision of incumbent adopters to actively share the new technology. In our context, we observe network-based technology sharing between directly competing firms in the baseline market[2]. However, we cannot observationally disentangle the true effects of competition on the willingness of incumbent adopters to share a new technology, due to the potential for confounding factors in the structure of the network and the history of market incentives.

In this paper we report the results of a field experiment that randomly varied three things: the

[1] Seminal works include Griliches (1957), Foster and Rosenzweig (1995), Conley and Udry (2010), Munshi (2004), and Bandiera and Rasul (2006).

[2] Competitors were identified using self-reports and a market research survey which linked firms that shared customers.

supply of a new technology, demand for products requiring that technology, and the presence of experimental competition. We study garment making microenterprises in Ghana, and our sample consists of the universe of garment making firm owners in a mid-size district capital. Made-to-order garments are a staple of Ghanaian culture, making up the majority of clothing worn to weddings, funerals, church, mosque, and holiday events, as well as a sizable share of professional and casual everyday wear. It is typical for new garment styles to become popular periodically and for garment makers to learn these new styles in order to attract and retain customers[3]. We collaborate with a designer in Accra to design our own style innovation, which we call Sharawakil[4]. The technique involves the use of the motor from a commonly available toy car as a weaving tool to produce a specific pattern in multi-colored thick thread that can be added to augment any garment. The technique is very difficult to figure out without being shown. However, once shown how to construct the weaving tool from the toy car and the correct way of folding the twisted thread so it releases with the correct pattern, it is extremely easy to execute.

We implement a cross-cut randomization in which 15% of the firm owners in our sample were invited to participate in a skills training in this new technique. The second randomization, stratified by the first, was implemented several weeks later, and involved a randomly timed rollout of randomly sized garment orders, known by firm owners to be without replacement, featuring Sharawakil. The random timing is the key to the experimental competition portion of our design, as groups of firms were invited to complete orders in waves. The use of experimental waves allowed us to manage on-the-spot the pool of resources available for making garment orders. It also introduced experimental competition, as unfilled orders would imply an extension of the program into later waves. Firm owners who were not at the training had the opportunity to refuse the order on the grounds of not being able to produce the design, or the option to take the order and find a way to learn the design in the time necessary to complete the order. Firm owners who attended the training were thus a natural resource.

Throughout the paper, we consider four treatment groups: training only, demand only, both, and neither. The demand only and neither groups enter the market as potential consumers of the technology, with the demand only group having a randomly higher benefit to learning. The training

[3] In our market research survey, conducted on over 1,600 randomly selected district residents, availability (or lack) of desired styles is the number one reason for choosing (or leaving) specific garment makers.

[4] A mix of the designer's name, Osman Mutawakil, and "Shara", a Hausa word for "twisted."

only and both groups enter the market as potential providers of the technology. Competition with the entire sample over our experimental demand (a potential future order) was relevant for the training only group, but not for the both group (having been given an order without replacement).

Data collection included a detailed baseline survey, which captured the full network map within the sample along several dimensions, including the sharing of technology, physical capital, workers, advice, and cash. The follow-up data includes 8 rounds of information on network activity, as well as firm-level outcomes. The invitation to training and the training itself happened between rounds 1 and 2, while the demand randomization, order offers, and collections happened between rounds 7 and 8. All firm owner level specifications use the panel of network activity, with round and firm fixed effects. Dyadic regressions use all possible dyad pairs in our sample of 417 firm owners.

We document two primary findings. First, demand for the product increases learning for potential consumers of our technology. Demand only firms, those that were not invited to the training but were offered an order, are much more likely to report learning the skill than neither firms. Second, competition over experimental demand decreases teaching of our new technology for potential providers. Training only firms, those that were invited to the training but were not offered an order, are much less likely to report teaching the skill than firms that were both invited to the training and offered an order. We interpret this main finding as evidence that experimental competition inhibits the willingness of potential suppliers of a new technology to share that technology.

We conduct a series of robustness checks to test the interpretation that our main empirical findings are driven by experimental competition. We find that trained firms with an order are not more likely than trained firms without an order to report an ability to produce Sharawakil. This result, together with the simplicity of the new technique once shown, makes learning by doing an unlikely explanation for our results. We also find that sharing is not higher only at the time of production, but increases upon receiving an order and stays higher even after the order has been completed. This makes it unlikely that our results are driven by teaching being easier during production. Lastly, we find that the incidence of sharing increases discretely upon receiving an order of any size and does not significantly increase with order size. We interpret this last robustness check as evidence against both learning by doing and teaching while doing, as well as evidence against a taste for equity or fairness. Instead, it implies that experimental competition (the removal of eligibility for future orders), is the main driver of our primary results.

In our next set of empirical findings, we explore the importance of existing firm owners' technology diffusion networks. While our network data is rich in different types of within industry relationships, we focus in the paper on firm dyads in which technology has been shared in the past. If either member of the dyad taught a skill to the other in the year preceding the baseline survey, they are "baseline technology sharing contacts". The vast majority of our firm owners have at least one baseline technology sharing contact within the sample, and the majority have more than one. Overall, diffusion of the new technology is more likely within these already existing social networks. We present evidence of spillovers both from baseline contacts with orders (increasing teaching) and firms with training (increasing learning). However, training spillover effects are only experienced by those firm owners' with a trained baseline contact not in competition over future orders (who received both training and an order contract).

While transactions between (pre-experimental) connected peers are more likely, social networks in our study are surprisingly dynamic. We find that the experiment generated new network relationships. In particular, demand only firm owners are much more likely to report learning a skill from a contact from whom they never learned a skill during any prior round of observation, including the entire year prior to our baseline. On the other side of the market, both training and demand firm owners report on average nearly one new contact to whom they taught the skill.

We develop a simple model to formalize our interpretation. Technology diffusion is conceptualized as a market for technology, in which both potential teachers and potential learners face costs and benefits of participating in a diffusion transaction. These costs and benefits depend both on static pairwise characteristics (e.g. distance, gender, ethnicity), and on technology-specific costs and benefits to learning or teaching. These technology-specific incentives, as well as the actual seeding of technology within the industry, can be systematically related to static characteristics, confounding their effects in conventionally observed network data. Our experiment exogenously seeded a new technology, and exogenously varied the costs and benefits of teaching and learning, allowing us to disentangle these underlying determinants of diffusion. The model is useful for exploring the external validity of our experimental results within our own context, in addition to thinking about future work that considers the incentives of both parties in peer-to-peer technology diffusion in other contexts.

Our paper contributes to a small but growing literature on network-based technology diffusion in manufacturing in low-income countries. In a pair of papers that randomized network links, Fafchamps and Quinn (2013, 2015) find that new firm-to-firm connections led to limited diffusion of managerial practices, in contrast to cross-sectional evidence from Ethiopia and Sudan that suggests business practices of network-linked firms are actually negatively correlated (Fafchamps and Soderbom, 2013). Atkin et al. (2014) find little network-based diffusion in the context of Pakistani soccer-ball producers, and instead focus on organizational barriers to technology adoption that relate to principal-agent issues between firm owners and their workers. Other influential explorations of low levels of technological upgrading in manufacturing include Parente and Prescott (1994), who model differences in barriers to technology adoption across countries, Bloom et al. (2013) who find an unwillingness among firm owners to delegate managerial tasks, and Tybout (2000) and Atkin, Khandelwal and Osman (2014) who consider the productivity enhancing benefits of trade. Our paper also relates to work by Bandiera, Bankerey and Rasul (2005) and others on field experiments within and across firms, which is nicely surveyed in Bandiera, Bankerey and Rasul (2000).

In studying small firm growth, we relate to the recent experimental literature that considers interventions aimed at growing both employment and profitability in small firms. For example, De Mel, McKenzie and Woodruff (2008) and Fafchamps et al. (2013) find high rates of return to capital in microenterprises; Hardy and McCasland (2015) find evidence that small firms face large search costs in hiring; and Bruhn, Karlan and Schoar (2013) study the impacts of business training.

The networks literature includes several papers that highlight the potential importance of business networks for businesses and job seekers, though ours focuses more specifically on their role in technology adoption (Greif, 1993; Casella and Rauch, 2002; Barr, 2000, 1998; Patnam, 2011; McMillan and Woodruff, 1999; Munshi, 2011; Beaman and Magruder, 2012). Immorlica, Lucier and Sadler (2014) develop a model particularly relevant to our context, in the sense that they consider incentives to withhold information that coexist with incentives to share information. Banerjee et al. (2012) have experimental variation in rival information about participation in an experimental game, and find evidence of withheld information. Finally, our findings relate to the literature on endogenous network formation (Udry and Conley, 2004).

The paper proceeds as follows: In Section 2, we describe the experimental design. In Section 3, we discuss the data and estimation. Section 4 discusses the results. Section 5 present robustness checks on our main finding. Section 6 focuses on interpretation of our results. Section 7 concludes.

2 Experimental Design

2.1 Industry Background

Small-scale garment making firms are ubiquitous and prolific in Ghana, as in many other parts of Africa and the developing world. The vast majority of their production is bespoke garments for the local market. In many parts of Africa, traditional African wear is worn at weddings, funerals, and special events, "African wear Fridays" are common in government offices and banks, and more modern cuts in African prints are popular with stylish middle class consumers. Ready-to-wear production, school uniform contracts, and contracted production for export occur, but are a relatively small part of the market (due both to consumer tastes and the fact that uniform sizing is poorly standardized)[5]. Market research by the largest producer of African print fabrics in West Africa predicts growth in consumer spending on bespoke garments, despite local and imported ready-to-wear alternatives (KPMG, 2014). In our own market research survey of nearly 1,600 people in our study district, respondents averaged consumption of 3.5 bespoke garments in the last year. At average garment prices and 2014 average exchange rates, this amounts to about 2% of GDP.

Production technology in these firms typically consists of a mix of hand or foot-crank sewing machines that do not require electricity, and electrically powered embroidery, overlock, and sewing machines. 40% of our sample has an electrically powered machine of some kind, while the remainder exclusively use human-powered machines. Demographically, a large majority of small-scale garment making firm owners are women (both in Ghana and around Africa), though male-owned firms make up about 20% of our sample and tend to be both bigger and more profitable. 40% of our sample (cut about evenly between those with and without electric equipment) employ at least one apprentice or other paid worker. Competition in the local market is fierce, and is driven not only by price, but also by fashion style differentiation, including ability to produce the latest trends. Nearly 60% of the respondents in our market research survey cited style/on-trend fashion skills as a primary determinant in choosing a garment maker. Within-industry network relationships in this context are utilized for skill acquisition, to learn about NGO and government opportunities targeting garment

[5] Industrial textile production for export in Ghana has declined sharply in the post-independence period, and more recently due to major electricity shortages. 5,000 people were employed in factory-style garment making jobs in Ghana in 2000, down from 25,000 in 1975 (Quartey, 2006).

makers, to discuss business, and to adapt to highly variable product demand.

In our study district, as in many parts of Ghana, garment makers voluntarily organize themselves into trade associations. The largest is the local chapter of the national Ghana National Tailors and Dressmakers Association (GNTDA). These associations charge small membership fees and offer a range of services, among them access to a network of relatively more powerful and larger garment making firm owners, and organized skill trainings in new fashion designs and production technologies.

2.2 Sample Recruitment

We study the garment making industry in Hohoe town and its outlying suburbs, with a total population of 73,641 in 2010. Hohoe town is the capital of Hohoe District, a middle income district by Ghanaian standards, in the Volta Region near the border with Togo. The dominant ethnic group is Ewe, a community that straddles the Ghana-Togo border from the coast up to the Northern reaches of the Volta Region[6].

The sample we aim to study is the universe of garment making firm owners in Hohoe town and its outlying suburbs. Sample recruitment took place in February of 2014, and included a census of all garment making firm owners in all of Hohoe District. The recruitment strategy began with existing lists of firms procured from trade association leadership, and continued via snowball sampling from there. The final phase of the census included geographic canvassing, in which surveyors covered all roads and alleys in the district searching for commercial storefronts and inquiring with locals in commercial areas after garment making firm owners. The census turned up 1,024 active garment making firm owners in the district, with 12% co-owning with one or more other firm owner(s). The unit of measurement throughout is the firm owner, as co-owned firms tend to be able to easily divide income, variable expense, and profit streams, and share primarily physical space and physical capital.

In Hohoe town and surroundings, the February 2014 census identified 445 garment making firm owners. Of these 445, 417 were still operating a business in Hohoe town or a surrounding suburb at the time of the experiment, 95 of whom are men and 322 of whom are women. Table 1 shows the

[6]Hohoe is also home to small minority ethnic groups, primarily members of various Muslim communities in Northern Ghana, and Twi and Ga people from the Accra area. Ethnic tension in Ghana is relatively minimal, though political parties are divided along ethnic lines.

summary statistics for the Hohoe town and surroundings sample which we use for the majority of this paper. Our sample is 75% Ewe, the dominant ethnicity in Ghana's Volta Region. Firms employ an average of 1 worker, but the distribution is skewed with a maximum of 15 workers and the median number of workers at 0. Owners have an average of 9 years of school, equivalent to a junior high school education, while some have no formal schooling and some have tertiary degrees. The average monthly profits at baseline are 138 Ghana Cedis (GHC), which is equal to approximately 60 USD at the time of the survey. Figure 1 shows the distribution of baseline technology sharing degree. If we consider all possibly dyadic relationships, we find in our baseline that the average probability of a skill sharing relationship is .7%. Firm owners report interactions over many dimensions outside of just technology sharing, including working for one another, borrowing each others' equipment, outsourcing subsections of certain orders to one another, discussing prices, exchanging of gifts or loans, discussing business practices, complaining about the continual "lights out" crisis in Ghana or even discussing personal matters. The average probability of any interaction, including something as simple as "shared greetings" is 3.7%.

2.3 Study Design

In this paper we report on a cross-cut randomized controlled trial that randomly seeded both invitation to a specific garment design skills training, and demand for that garment design via direct purchase from the project, without replacement. Stratified by gender, 15% of the 445 firms from the census sample in Hohoe District and its suburbs were randomly invited to participate in a skills training to learn a new garment design. Over the course of the next few weeks, 29 firm owners were confirmed to have left the sample (by leaving the industry or leaving the district permanently), and these firms were thus dropped from the subsequent demand randomization.

The remaining 417 firm owners were randomly assigned both an order size of one, four or ten shirts, as well as "wave," with wave 1 being rolled out first, wave 2 second, and onwards. After each wave, based on compliance and remaining project resources, it would be decided if more orders would be distributed. Of the 417 firm owners remaining in the product demand randomization, 80% were ultimately offered a contract to produce one or more garments featuring the new design over two waves, with nearly half of all firms selected to be offered a contract to produce one garment, equivalent to the median weekly sales in the sample, about 20% selected to be offered contracts to produce four garments, equivalent to the 90th percentile of weekly sales in the sample, and 10% randomized to receive contract offers of 10 garments featuring the design, equivalent to the 99th percentile of weekly sales in the sample. All larger orders were offered during wave 1, with wave 2 containing only orders of size one.

Order contract offers specified a fixed price of 35 GHC for each shirt or other garment featuring the new design. The price was chosen to reflect a generous price for intricately designed garments. The median prices for a standard (unembellished) slit and kabbah (traditional Ghanaian skirt and top for women) and standard (unembellished) man's shirt are 20 GHC, and 12 GHC respectively, in our baseline survey. However, more intricate designs bring these prices up to as much as 40 GHC. As is typical for this market, we gave a 10GHC deposit for each garment. For orders larger than one garment, we asked for a sample garment and verified the accuracy of the new design before submitting the full deposit.

Figures 2 and 3 show the distribution of network level treatments, with the number of trained contacts in Figure 2 and the total number of shirt orders offered to baseline contacts in Figure 3. Because those who receive training invitations and orders are random, network level treatments are also random, conditional on baseline degree.

2.4 New Technology

The new design is called Sharawakil, and was commissioned for the project from a somewhat well-known designer in Accra. It involves a technique of twisting thread using a deconstructed common children's toy car, easily found in local markets for around 5GHC at the time of the experiment. Figure 4 depicts the use of the tool in spinning the thread to create Sharawakil. After spinning, the thread is folded using a particular technique before it is released and collapses into the final product, shown in Figure 5. The colorful result can and has been applied to garments in many creative ways, an example of which is shown in Figure 6.

This design was created for the sole purpose of this experiment, and has some important features for the purpose of our study: (1) It is very difficult to figure out without being shown how to spin, wrap and release the thread to achieve the correct pattern. (2) Once someone has shown you the technique, it is very easy. Everyone who attended the one-day training had mastered the technique before leaving. (3) It is unisex and versatile in its use and thus should be equally valuable to all kinds of firm owners. (4) It requires no electricity and minimal capital investment and thus it should be equally accessible to all kinds of firm owners. (5) The algorithmic nature of the technique and the results allows for a clear assessment of the quality of the Sharawakil itself, while the freedom in application allows for variation in innovation, allowing us to observe both through analysis of the orders completed.

3 Data and Estimation

3.1 Data

What we refer to in the paper as the baseline network, is the listing of all network relationships and network activity among garment making firm owners in our sample, collected in late 2014. The baseline survey targeted the full Hohoe District sample, but we restrict our analysis of baseline network relationships to the 417 firms in our final sample. Data include demographic information, cognitive testing, profits, assets, labor, management, prices and production breakdown of the most commonly sold products. Also included are general questions about possible substitutes for missing institutions, taxes and reasons for self-employment, which we took to validate the relevance of networks to the functioning of most of the businesses in our sample.

The network section of the instrument in the baseline survey was designed to create a full within-industry, within-district network map. While firm owners were not prompted to confirm or deny acquaintance with each of the more than 1,000 other firm owners, the self-reported contact section was designed to capture as many relevant contacts as possible. Firm owners were asked whom they know in the district by category (former employer, former employee or apprentice, trade association co-member, neighbor, close friend in the business, etc.). Once all contacts were revealed, network activity over the last year between contacts was collected along the following dimensions: gift and loan giving, skill sharing, labor sharing, equipment sharing, customer referrals, mentorship, and outsourcing. Additionally, these instruments included questions about relative size, experience, work quality, competition, altruism and trust between the respondent and each network member.

The remainder of the data was collected as weekly follow-up surveys. The first of these took place in March 2015 before the training randomization. The next six took place in the weeks following the training. And the final survey, which includes two weeks of data, took place in June

2015, after the product demand randomization and purchases. Each weekly survey includes sales and expenses, hours worked by the owner and any other employees, weekly physical outputs in terms of number of garments, and network activity in the preceding week, which mirrors that collected in the baseline survey. This 9 week panel survey forms the basis of much of our analysis.

In addition to the firm owner level data, we conducted nearly 1,600 customer market research surveys over the course of the study, which attempted to create an additional diversion network mapping competition between firms. Random individuals were approached in public places in Hohoe and its surroundings, systematically near each of the shops in our sample. Each respondent was asked how frequently he or she buys bespoke garments or uses the services of garment making businesses, how much he or she has spent on these services recently, and which businesses he or she frequents, in rank order. In addition, we collected some information on what draws customers to one garment maker or another, or away from their current favored garment maker.

Lastly, a trained garment maker among our staff evaluated the quality of all completed orders along three dimensions: (1) quality of the Sharawakil itself, (2) quality of the garment less the Sharawakil, and (3) overall estimated cash value of the garment. For firms who were in the 4 garment and 10 garment random treatment groups, we evaluated the single sample garment separately from the remaining 3 or 9 garments, to measure increases or decreases in quality over time.

The order quality data are not utilized in this version of the paper. However, they are mentioned here in order to provide the full picture of resources available in any future analysis on this subject.

3.2 Estimation of Direct Effects

We have four main outcome variables of interest: (1) learning the new technology from another garment maker, (2) teaching the new technology to other garment makers, (3) learning the new technology from a new technology sharing contact (4) teaching the new technology to a new technology sharing contact[7]. Our main specification stacks all rounds of the firm-owner level panel, as follows:

[7] An earlier version of this project was registered with the American Economics Association (AEA) Randomized Controlled Trial Registry, complete with a Pre-Analysis Plan (PAP). The PAP was intended to coalesce ideas on the direction of analysis, and limit both the risks and perception of data mining or specification search. The earlier version of the study design did not include random demand for the product, which was inspired partway through implementation both by lower than expected demand and skill-sharing in the original design and field-based insights into what motivates sharing in our context. Consequently, the specifications in this version of the paper do not match those laid out in the PAP. The main hypotheses, however, remain relevant.

$$Y_{it} = \alpha + \beta T_{it} + \eta_t + \varphi_i + \epsilon_{it} \tag{1}$$

where Y_{it} is the outcome of interest, T_{it} is the vector of treatment groups of interest (training only or demand only or both), η_t are round fixed effects, φ_i are firm fixed effects (which control for randomization strata), and ϵ_{it} is an error term. With the pure control group omitted, the coefficients in β are the Intent-to-Treat effects of being assigned each particular treatment group, relative to the control, and are identified from both within round, and within firm variation. Standard errors are clustered at the firm level.

3.3 Estimation of Spillovers

In the spillovers section of the paper, we estimate:

$$Y_{it} = \alpha + \beta NT_{it} + \omega T_{it} + \eta_t + \varphi_i + \epsilon_{it} \tag{2}$$

where NT_{it} is the vector of baseline technology network treatment (at least one contact invited to training only, at least one contact selected for an order only, at least one contact invited to/selected for both). The firm fixed effects control for the baseline degree, making the number of baseline contacts trained random, and allowing for causal identification of β, which in this case can be interpreted as the marginal effect of having at least one baseline network contact in a given treatment group. Standard errors are clustered at the firm level.

3.4 Dyadic Level Analysis

In our dyadic specifications that utilize the full network panel, we estimate:

$$Y_{ijt} = \alpha + \beta_1 DT_{it} + \eta_t + \psi_i + \epsilon_{it} \tag{3}$$

where Y_{ijt} is a binary variable, equal to one when diffusion of the new technology has occurred from firm i to firm j in round t. DT_{it} is the vector of dyadic level treatment groups (i invited to train and selected to receive an order and j selected to receive an order only, i is in control and j invited to train only, etc...) with the pure control dyadic set (both i and j receive neither) omitted. ψ_i is the pair specific fixed effect, controlling for all constant characteristics of firm i and j's relation. The vector β here can be be interpreted as the Intent-to-Treat effects of a particular i and j treatment combination on technology diffusion from i to j.

4 Findings

4.1 Balance

Tables 1 shows balance along major observables across the four treatment groups. With the exception of a slightly higher probability of being Ewe for the training only group, a slightly lower age for the training only group, and slightly fewer years of schooling for the training and order group, all observables appear balanced. Firm fixed effects are included in all specifications, which should control for any imbalanced constant unobservables.

4.2 Intervention Compliance

For the training treatment, compliance is defined as actually receiving training in the new style, either through attending one of the trainings offered in the district or from a mop-up training held shortly after the main training. For the order treatment, compliance is defined as actually receiving an order for a garment utilizing the new technology. Not every firm owner was able to attend the training, nor were they reachable to receive an order offer during the scope of the project. The largest reason for non-compliance on both accounts was short term travel out of the district.

Figures 7 and 8 show treatment compliance for training and orders, respectively. Over 90% of those randomly selected for training invitations or order receipt were in compliance, with travel being the main reason for failure to attend or receive an order. No firm owner not randomly selected to receive training or an order did so. This is very high compliance and means that reduced form regressions may be considered very similar to treatment on the treated effects.

4.3 Direct Treatment Effects on Order Completion and Learning

Figure 9 shows the effect of a random training invitation on order completion for the 298 firm owners who received an order. Those invited to the training are 17.8% more likely to complete an order, if offered. However, those who were not invited are still 67.9% likely to complete an order, if offered.

Figure 10 shows the treatment effects on learning for all 417 firm owners. Over 90% of those invited to the training report being able to use the technology. Those firm owners not invited to train have a 43.5% chance of reporting the ability to use the technology if randomly selected to receive an order and a 16% chance if not.

4.4 Treatment Effects on Technology Diffusion

Figure 11 plots the likelihood of teaching or learning a technology across all 8 rounds of data collection during the experiment. Orders were placed during the period covered in round 8. Firm owners are 20.5% more likely to share or learn a technology in round 8 than in the 7 previous rounds.

Figure 12 plots the probability of learning the new technology from another garment maker by treatment status. Firm owners selected to receive an order but not training have a 38.5% probability of learning the new technology from another garment maker, while those without an order are less than 0.5% likely to learn the new technology from another garment maker.

Figure 13 plots the probability of teaching the new technology to another garment maker by treatment status. Firm owners selected to receive both an order and training are 54.2% likely to teach the new technology to another garment maker, while those without an order are only 2.1% likely to teach.

Because the orders were all placed during the final round, the above figures are more illustrative than experimentally informative. In order to truly estimate the treatment effects on technology diffusion, it is important to control for round fixed effects. Table 2 shows the reduced form treatment effects on learning and teaching, controlling for firm and round fixed effects.

Firm owners not invited to the training, but randomly selected to receive an order are 26.3% more likely to learn the technology from another firm owner than a firm owner who received neither.

Those firm owners randomly selected for a training invitation, but not to receive an order are no more likely to teach the technology to another firm owner than a firm owner who was not invited to train and/or received nothing. Firm owners randomly selected for both training and an order are 44.1% more likely to teach the technology to another firm owner.

4.5 Network Treatment Effects on Technology Diffusion

Table 3 shows the reduced form network treatment effects on learning and teaching from and to other firm owners. Firm owners with at least one baseline technology sharing contact randomly selected to receive both training and an order are 14.5% more likely to learn the new technology from another garment maker. Baseline contacts randomly selected for only an order or training do not increase the likelihood of learning. Firm owners with at least one baseline technology sharing contact selected to receive an order but not invited to the training are 9.9% more likely to teach another firm owner the new technology.

4.6 Treatment Effects on Network Formation

Figure 14 plots the likelihood of reporting teaching or learning a technology form a new contact across all 8 rounds of data collection. A contact is new as of a certain round if neither firm owner reported teaching or learning a technology from the other in any round prior to that round. Orders were placed during the period covered in round 8. Firm owners are 13.4% more likely to report teaching or sharing a technology with a new contact in round 8 than in the 7 previous rounds.

Table 4 shows the reduced form treatment effects on new network formation, controlling for firm and round fixed effects. Firm owners not invited to the training, but randomly selected to receive an order are 27.1% more likely to learn the technology from a new technology sharing contact than a firm owner who received neither. Firm owners randomly selected for both training and an order are 86.5% more likely to teach the technology to a new network sharing contact than those who received neither.

4.7 Dyadic Analysis

The findings in Tables 2, 3 and 4, at the firm level, are the result of dynamics actually observed at the dyadic level. We present them first, because they are much easier to understand and interpret than the more complicated dyadic regression table. However, we have included Table 6 to illustrate the results of all three tabes and how they fit into the overall story of what has happened in this experiment.

Table 6 shows that technology diffusion is mainly occurring from those who received training to those who received only an order. Additionally, those who received only an order act as vessels for technology diffusion to those who also received only an order. The majority of technology diffusion happens between those firm owners who were contacts already at baseline, from those who received both training and an order to those who did not receive training, even if they did not receive an order (perhaps in anticipation of a potential order). Also note that those who received only training appear likely to teach the technology to those in need if they are a baseline sharing contact, even though this finding is not quite significant. However, we also see that diffusion still occurs even between those dyads not already contacts at baseline.

5 Robustness

The previous section clearly shows that technology is diffusing most between those who received orders (from those trained to those not trained). We interpret these findings as evidence of a negative effect of competition on the willingness of incumbent adopters to share the new technology. Because orders were given without replacement, those who had already received their order were no longer competing over potential future orders. Those who had not yet received an order were in direct competition with potential learners, as each completed order lowered the potential teacher's chance of an eventual order offer (the likelihood that we would reach their experimental wave before exhausting all resources for garment orders). Therefore, receiving an order increases sharing because the loss of market share is no longer adding to the cost of sharing.

In this section, we exploit both the random size (1, 4, or 10 garments) of orders and random timing of ultimately offered orders (over 2 waves) to empirically test this interpretation. If competition is the main driver of our findings, we would expect to see the significant increase in sharing occur between no orders and any order, rather than with each additional order. Additionally, we would expect to see less diffusion from wave 2 firm owners to wave 1 firm owners, as compared to any other wave combination. From Tables 7 and 8, we see that sharing increases discretely between no order and 1 order, but not between orders of size 1 and larger orders, consistent with the story that those who are no longer competing over orders have a lower cost of sharing not effected by order size. We also see that those with earlier orders share more than those with later orders, consistent with the story that those who have already received an order cannot receive another and are no longer competing, and thus have a lower cost of sharing even after their own order has been completed.

These empirical findings, in conjunction with the intended framing of the experiment, suggests that competition may be an important barrier to technology diffusion in this context. In the remainder of this section, we outline and empirically explore some potential alternative theories for this decrease in cost. Although it is difficult to perfectly pin down the driving channel for the reduction in the cost of sharing, competition is most likely the strongest, taking together all the evidence available.

First, we consider "learning by doing". Learning by doing would imply that those who went to the training did not actually feel confident in the skill until they got their own order and practiced. This explanation for the increase in sharing is unlikely. To see this, look at Figure 10, which depicts the likelihood of reporting the ability to produce the design for a customer based on the different treatment arms. Those who went to the training but did not receive an order are no less likely to report confidence in their ability to produce the design than those selected to receive both. This is inconsistent with a learning by doing story.

A second possibility to consider is "teaching while doing." The cost of teaching may be lower when one is already doing the skill that must be demonstrated. If teaching while doing is the dominant channel for the reduction in the cost of sharing, we should see that those who randomly received larger orders are more likely to share relative to those who randomly received an order size of 1. Additionally, we should see that diffusion is occurring more between dyads that received orders during the same random time period. We see neither.

Table 6 shows the reduced form treatment effects by order size of both learning and sharing. Although those who were not invited to training are more likely to share with larger order sizes (perhaps this is consistent with learning by doing for these firm owners), those invited to the training are not significantly more likely to share if selected for a larger order. These regressions only include those selected to receive an order in Wave 1 or none at all, because the larger order sizes were only given during Wave 1 and including Wave 2 may confound the timing effect with the order size effect.

Table 7 shows potential teacher and learner treatment effects on sharing at the dyadic level. Column 1 shows only those dyads for which i and j were both selected to receive an order in Wave 1, or neither were selected to receive an order. Column 2 shows those dyads for whom, if selected to receive an order, the potential teacher was selected for Wave 1 while the potential learner was selected for Wave 2. Column 3 shows those dyads for whom, if selected to receive an order, the potential teacher was selected for Wave 2, while the potential learner was selected for Wave 1. Column 4 shows only those dyads for whom both were selected to receive an order in Wave 2. These regressions only include dyads in which owners were selected to receive an order size of 1 or none at all to remove the potential for confiding the timing effect with the order size effect explained above. From table 7, it is clear that the sharing is occurring from Wave 1 teachers to both Wave 1 and Wave 2 learners, or from Wave 2 teachers to Wave 2 learners only. This is not consistent with teaching while doing, in which Wave 1 teachers should not be equally helpful to Wave 2 learners.

A final possible alternative explanation for our findings we consider here is fairness. Receiving fewer orders than another garment maker may cause a reduction in sharing out of a sense of fairness. If this is the case, receiving an order will increase sharing out of that same sense of fairness. If fairness is based on relative order size, it would be expected that firm owners would not be less likely to share with firm owners who received larger orders than they did. This behavior should be observed between those with order size 0 and higher orders as well as for those who received a positive order size and those with a higher order size. Thus, if fairness is a driving channel through which sharing is increased with an order, it should be that those with order size 10 share more than those with smaller orders. Table 7 shows this not to be true.

6 Interpretation

In this section, we provide an intuitive interpretation of the field experiment and empirical findings presented in this paper. We conceptualize technology diffusion as occurring (or not occurring) as a transaction in a market for technology. The potential learner is modeled as the potential consumer of a technology and the potential sharer is modeled as the potential supplier of the technology. For trade to occur (technology to diffuse), it must be the case the the potential consumer's reservation price is less than or equal to that of the potential supplier's reservation price. Reservation prices are determined by the consumer's net benefit from learning and the supplier's net benefit of teaching, which are driven both by constant pair-wise characteristics and dynamic market factors.

The learner's benefit and costs are teacher and technology specific. These could be anything, but are most likely related to the profit increases expected from adopting the new technology and the time and effort it takes to find and/or learn from a particular teacher. The teacher's cost is also technology and learner specific, and may include the time or effort it takes to teach a particular learner, as well as any forfeit of market share in the case where the learner is in competition with the teacher over demand for the technology. The price paid to the supplier by the consumer could be anything from real currency, to some other favor or exchange, to a general sense of reciprocity. We abstract from the specifics of the exchange however, as it is the relative value of that price to both the potential consumer and potential supplier that matters for whether technology diffusion will occur.

This framework leaves us with two main lessons. First, the learner's benefit alone will not guarantee technology diffusion. The existence of technology diffusion requires at least one incumbent adopter and one potential adopter to BOTH net benefit from the exchange of that knowledge. Conditional on the existence of such a pair, the particular pattern of technology diffusion will be between specific pairs of incumbents and potential learners for whom the joint net benefit is highest. Second, the mere observation of a technology sharing relationship does not tell us much about its underlying determinants. Recall that the costs and benefits of diffusion between a particular learner and teacher are related both to constant pair-wise characteristics and technology specific factors. Therefore, the resulting diffusion patterns confound the effects of many possible underlying determinants related both to constant pair-wise costs and benefits of diffusion and dynamic technology-specific market factors.

We interpret our field experiment as randomly varying the benefit to the learner (through the placing of orders) as well as the cost to the teacher (through he removal of potential for future orders). This model predicts that potential learners with an order will be more likely to learn and that potential teachers with an order (and thus no potential for future orders) will be more likely to teach. These predictions are consistent with the findings of this paper. Additionally, random variation in the initial adopters of a technology allows us to disentangle these dynamic market incentives from other factors, illuminating forces that may be at play outside of our experimental context.

6.1 Model Set-up

Let N be the set of members of a population. In this case, let us say this population is the set of all firm owners in some particular industry. Let the time-specific $A_t \subset N$ be the incumbent adopters of technology a at time t. Let X be the set vectors of pair-wise characteristic, $\forall(i,j) : i \in N$ and $j \in N$. For example, these vectors may include (i,j) specific distance, relative business size or education level, indicators for matching gender or ethnicity, and any other mostly constant observables or unobservables. For each time, t, $i \notin A_t$ and $j \in A_t$, let i's net benefit of learning be $B_{a,i,j,t} - L_{a,i,j,t} - S_{a,i,j,t}$. Let j's net benefit of teaching be $S_{a,i,j,t} - T_{a,i,j,t}$.

$B_{a,i,j,t} \sim \mathcal{U}(0, 2B_{a,x_{ij}})$ is the benefit to i from learning a from j at time t. $B_{a,i,j,t}$ could be anything, but is most likely related to the profit increases expected from adopting the new technology. The expected value of this benefit varies by the specific elements of $x_{i,j}$, for example an indicator for "speaking the same language", which may effect the expected quality of any technology transfer. The expected benefit also varies by the specific a, with some technologies being particularly useful and others quite useless on average within the the industry.

$L_{a,i,j,t} \sim \mathcal{U}(0, 2L_{a,x_{ij}})$ is the cost incurred by i in learning a from j at time t. The expected value of $L_{a,i,j,t}$ also varies by $x_{i,j}$ and a. Perhaps some particular i has a higher expected cost of learning from j for any technology, due to a large distance between i and j, or perhaps some a may be easier to learn on average than some other technologies.

$T_{a,i,j,t} \sim \mathcal{U}(0, 2T_{a,x_{ij}})$ is the cost incurred by j in teaching a to i at time t. $T_{a,i,j,t}$ may include the time it takes to teach, as well as any forfeit of market share in the case where the learner is in competition with the teacher over demand for the technology. $T_{a,i,j,t}$ has an expected value conditioned both on x and a. It may be that teaching any technology to some i is always expected to be more costly, because of some constant element in $x_{i,j}$. for example, closer firms may compete more over local demand. Additionally, teaching certain technologies may be more costly than others. For example, if some technology is labor enhancing (some method reducing the chance of injury) rather than demand shifting (a new product), this technology may be less costly to share on average within the industry.

$S_{a,i,j,t}$ is the surplus transfer made from i to j for learning a at time t. The particulars of $S_{a,i,j,t}$ could be anything from real currency, to some other favor or broad sense of reciprocity. We abstract from the specifics of the exchange however, as it is the relative value of that transfer to both the potential consumer and potential supplier that matters for whether technology diffusion will occur.

Let $G_{a,t}$ be the graph representing all $i \in N$ and $j \in N$: i learned a from j in t. Note that the typical networks dataset asks respondents about interactions concerning the set of all technologies, Λ over a particular time period, T. Let $G_{\Lambda,T}$ be the set of $(i,j) \in N : (i,j) \in G_{a,t}, \forall t \in T, a \in \Lambda$.

6.2 Conditions for Technology Diffusion

Theorem 1 (It Takes Two):

$G_{a,t} \neq O \iff \exists (i,j) : B_{a,i,j,t} - L_{a,i,j,t} - T_{a,i,j,t} \geq 0$

Proof:

If so, then $\exists (i,j) : B_{a,i,j,t} - L_{a,i,j,t} \geq T_{a,i,j,t}$

$\Rightarrow \exists S_{a,i,j,t} : B_{a,i,j,t} - L_{a,i,j,t} \geq S_{a,i,j,t} \geq TC_{a,i,j,t}$

$\Rightarrow B_{a,i,j,t} - L_{a,i,j,t} - S_{a,i,j,t} \geq 0$ and $S_{a,i,j,t} - TC_{a,i,j,t} \geq 0$

If not, then $\forall (i,j), B_{a,i,j,t} - L_{a,i,j,t} < T_{a,i,j,t} \Rightarrow$

$\nexists S_{a,i,j,t} : S_{a,i,j,t} - T_{a,i,j,t} \geq 0$ and $B_{a,i,j,t} - L_{a,i,j,t} - S_{a,i,j,t} \geq 0$

Intuitively, what this theorem states is that the overall surplus from the transfer of technology a from j to i at time t must be positive. Otherwise, there is no surplus transfer that would make the transaction worthwhile for both parties involved. In the case of peer-to-peer technology diffusion, it must be the case that both parties net benefit.

Theorem 2 (Path of Least Resistance):

$g_{ij} \in G_{a,t} = 1 \iff B_{a,i,j,t} - L_{a,i,j,t} - T_{a,i,j,t} \geq 0$

and $B_{a,i,j,t} - L_{a,i,j,t} - T_{a,i,j,t} \geq B_{a,i,k,t} - L_{a,i,k,t} - T_{a,i,k,t}, \forall k$

Proof:

If so, then $B_{a,i,j,t} - L_{a,i,j,t} - T_{a,i,j,t} \geq B_{a,i,k,t} - L_{a,i,k,t} - T_{a,i,k,t}, \forall k$

$\Rightarrow (B_{a,i,j,t} - L_{a,i,j,t}) - (B_{a,i,k,t} - L_{a,i,k,t}) \geq T_{a,i,j,t} - T_{a,i,k,t}, \forall k$

$\Rightarrow \forall S_{a,i,k,t} : S_{a,i,k,t} - T_{a,i,k,t} \geq 0,$

$\exists S_{a,i,j,t} : S_{a,i,j,t} - T_{a,i,j,t} \geq 0 \cap B_{a,i,j,t} - L_{a,i,j,t} - S_{a,i,j,t} \geq B_{a,i,k,t} - L_{a,i,k,t} - S_{a,i,k,t}$

If not, then $\exists(i,k) : B_{a,i,j,t} - L_{a,i,j,t} - T_{a,i,j,t} < B_{a,i,k,t} - L_{a,i,k,t} - T_{a,i,k,t}$

$\Rightarrow (B_{a,i,j,t} - L_{a,i,j,t}) - (B_{a,i,k,t} - L_{a,i,k,t}) < T_{a,i,j,t} - T_{a,i,k,t}$

$\Rightarrow \exists S_{a,i,k,t} : S_{a,i,k,t} - T_{a,i,k,t} \geq 0 \cap B_{a,i,j,t} - L_{a,i,j,t} - S_{a,i,j,t} < B_{a,i,k,t} - L_{a,i,k,t} - S_{a,i,k,t}$

Intuitively, what this theorem states it that, conditional on the overall surplus from the transfer of technology a being positive for at least one j, i pair at time t, the exact j from whom i will choose to learn will be the one for whom the overall surplus is highest. Otherwise, some other k teacher can offer to teach i for a lower surplus transfer and still benefit from the exchange.

Taken together, Theorems 1 and 2 imply that $G_{\Lambda,T}$ will be determined (with some noise) by both constant industry factors, X, as well as dynamic market factors, Λ, during T.

6.3 Experimental Predictions

In our experiment, we create a new technology a and essentially randomize N into 4 distinct subsets:

- β_{cs} receives training only
- β_{oc} receives an order only
- β_{os} receives both training and an order
- β_{cc} receives neither

We conceptualize β_{cs} and β_{os} as $\subset A_t$ and β_{oc} and β_{cc} as $\subset A_t^c$, where A_t^c is the compliment of A_t. For some $i \in A_t^c$, receiving an order involving a increases $B_{a,i,j,t}$ by $\beta_1, \forall j$. For some $j \in A_t$, receiving an order involving a lowers $T_{a,i,j,t}$ by $\beta_2, \forall i$. Let $P_{a,i,j,t}$ be the probability that $g_{ij} \neq 0 \in G_{a,t}$.

Prediction 1: ($\uparrow$ Benefit of Learning $\uparrow$ Learning)

$P_{a,i,j,t} > P_{a,c,j,t}, \forall j \in A, i \in \beta_{oc}, c \in \beta_{cc}$

Proof:

Because the assignment of $i \in \beta_{oc}, c \in \beta_{cc}$ is random, their expected distributions no longer depend on X, but differ only in the mean shift of B_a by β_1. Therefore:

$P_{a,i,j,t} > P_{a,c,j,t} \iff$

$P(B_{a,i,j,t} - L_{a,i,j,t} - T_{a,i,j,t} \geq 0) > P(B_{a,c,j,t} - L_{a,c,j,t} - T_{a,c,j,t} \geq 0) \iff$

$B_a - L_a - T_a + \beta_1 > B_a - L_a - T_a \iff$

$\beta_1 \geq 0$

Prediction 2: ($\downarrow$ Cost of Teaching $\uparrow$ Teaching)

$P_{a,i,j,t} > P_{a,i,k,t}, \forall i \notin A, j \in \beta_{os}, k \in \beta_{cs}$

Proof:

Because the assignment of $j \in \beta_{os}, k \in \beta_{cs}$ is random, their expected distributions no longer depend on X, but differ only in the mean shift of T_a by β_2. Therefore:

$P_{a,i,j,t} > P_{a,i,k,t} \iff$

$P(B_{a,i,j,t} - L_{a,i,j,t} - T_{a,i,j,t} \geq B_{a,i,k,t} - L_{a,i,k,t} - T_{a,i,k,t})$

$> P(B_{a,i,k,t} - L_{a,i,k,t} - T_{a,i,k,t} \geq B_{a,i,j,t} - L_{a,i,j,t} - T_{a,i,j,t}) \iff$

$B_a - L_a - (T_a - \beta_2) > B_a - L_a - T_a \iff$

$\beta_2 \geq 0$

Prediction 3: (The Network has Memory)

$P_{a,i,j,t} > P_{a,c,k,t}, \forall (i,j) : g_{ij} \neq 0 \in G_{\Lambda,t-1}, (c,k) : g_{ck} = 0 \in G_{\Lambda,t-1}$

Proof:

Because the assignment of N to A and A^c is random, membership to either set should be orthogonal to X. Thus, if a randomly chosen $(i,j) \in G_{\Lambda,t-1}, (c,k) \notin G_{\Lambda,t-1}$, then knowing nothing else about these pairs, it can be expected that:

$B_{a,x_{i,j}} - L_{a,x_{i,j}} - T_{a,x_{i,j}} \geq B_{a,x_{c,k}} - L_{a,x_{c,k}} - T_{a,x_{c,k}} \iff$

$P(B_{a,i,j,t} - L_{a,i,j,t} - T_{a,i,j,t} \geq B_{a,c,k,t} - L_{a,c,k,t} - T_{a,c,k,t})$

$> P(B_{a,c,k,t} - L_{a,c,k,t} - T_{a,c,k,t} \geq B_{a,i,j,t} - L_{a,i,j,t} - T_{a,i,j,t}) \iff$

$P_{a,i,j,t} > P_{a,c,k,t}$

Taken together, these three predictions suggest that the diffusion of our new technology should occur mostly from $j \in \beta_{os}$ and mostly to $i \in \beta_{oc}$. They suggest that this diffusion is more likely to occur if $i, j : g_{ij} \neq 0 \in G_{\Lambda,t-1}$, but that $g_{ij} \neq 0 \in G_{\Lambda,t-1}$ is not necessary for diffusion to occur between i and j.

6.4 Unpacking Observed Diffusion

Taking together our model and experiment, we can begin to think about unpacking the determinants of baseline diffusion. The experiment has shown the importance of demand and competition in driving (or inhibiting) diffusion. Table 8 shows the relationship between various potential dyadic characteristics in X and both baseline diffusion and the diffusion of our new technology. Because the seeding of our new technology was random, we are able to both observe the effects of various characteristics on sharing decoupled from real world patterns of technology seeding and, by comparing column 2 with column 1, we can say something about those real world patterns.

The only dyadic characteristic associated with higher sharing of the new technology is distance. Being within 500 feet of one another is associated with both higher baseline technology diffusion and higher sharing of our new technology. Specifically, baseline sharing and the sharing of our new technology are higher by about 4 times the average.

Competition has a positive relationship with baseline diffusion. Specifically, being listed as competitors by our market research survey is associated with a 1.9% increase in the likelihood of sharing, or an increase of 3 times the average. However, baseline competition has little to no relationship with the diffusion of Sharawakil. Similarly, management practices has a positive and significant relationship to sharing at baseline, but loses significance for sharing of Sharawakil.

We see significant, but lower, relationships between gender, ethnicity, business size and baseline sharing that remain relatively constant with sharing of Sharawakil. This suggests that the observed relationship between diffusion and these dyadic characteristics is due to more static market frictions or preferences than the result of systematically related market based incentives.

7 Conclusion

Increases in firm productivity are the backbone of economic growth. Understanding how and when technology upgrading occurs is thus a central challenge for academics and policymakers interested in combating poverty. As a conceivably scalable alternative to direct intervention, network-based technology diffusion presents both an opportunity and a puzzle. Why do we observe some peer-to-peer technology diffusion within industry networks, but not full access to new technologies across the board? What market incentives and barriers drive the observed pattern?

In this paper, we report the results of a field experiment designed to study technology sharing in the context of garment makers in Ghana. We designed a new weaving technology and randomly varied direct training (direct access to the technology), benefits of adoption (demand for garments featuring the technology), and the existence of competition over potential future orders in a real network of garment making firm owners. We find that the majority of this new technology's diffusion occurs from those with direct training who are not in competition over future orders to those without direct training with a higher benefit of adoption. Those with direct training who remained in competition over future orders were no more likely to share than those without direct training.

We interpret our findings as evidence that competition is an important barrier to technology diffusion in the context of small-scale manufacturing in low-income countries. We develop a model designed to frame our understanding of the findings as the result of internal market incentives to both learn and share, with diffusion being the final result of a learner's overall benefit being higher than a teacher's overall cost. Taken together, the findings and the model suggest that productivity-increasing technologies may fail to diffuse, in part because the incentives of incumbent adopters may not encourage active sharing.

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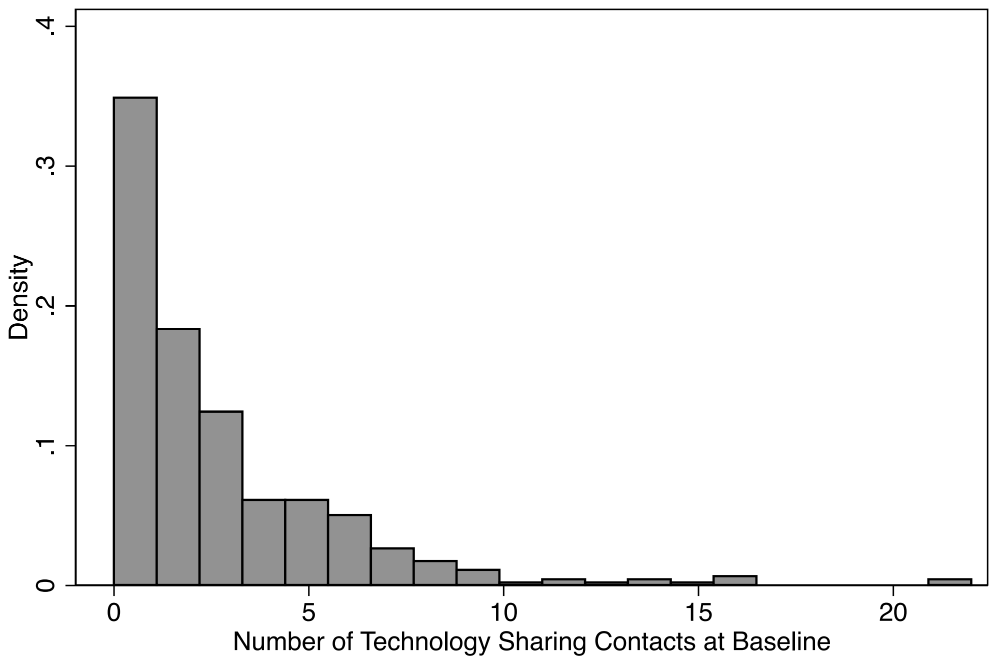
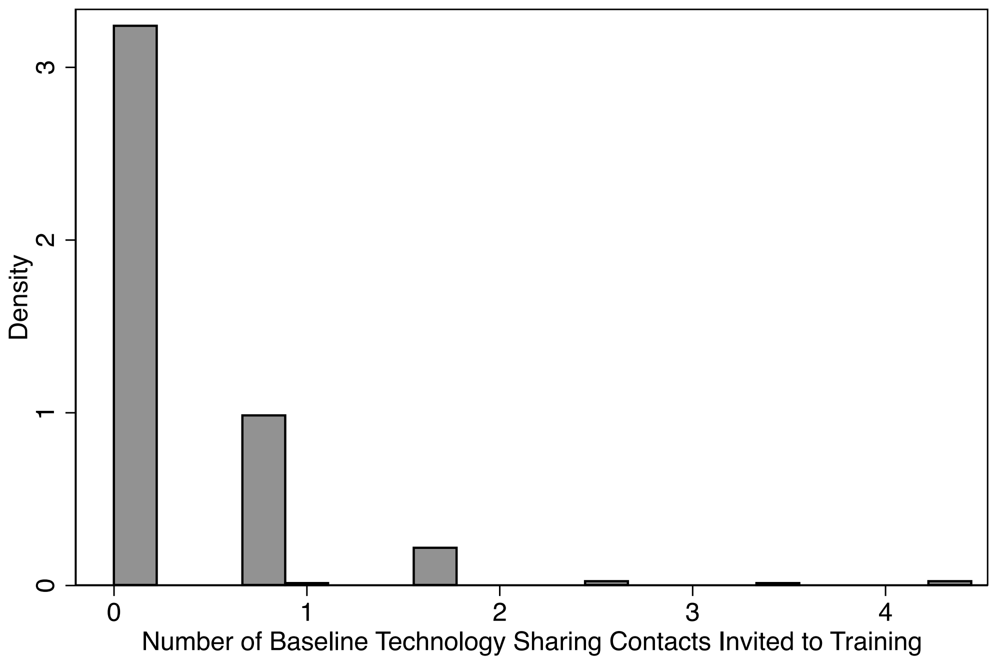
Figure 1: **Baseline Degree**



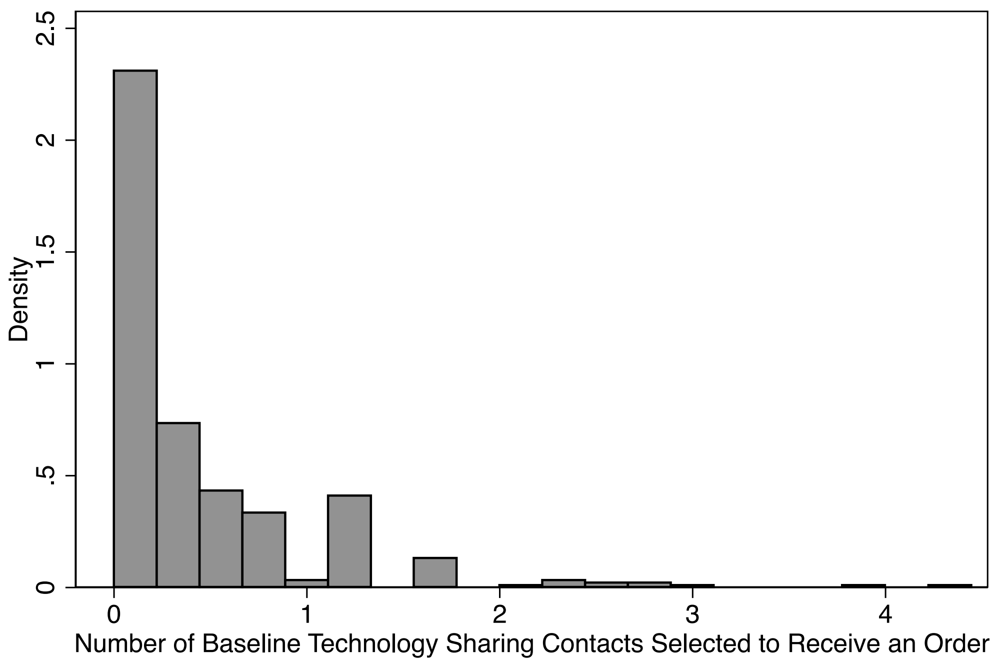
Note: A firm owner is another firm owner's technology sharing contact at baseline if either reports teaching/learning a business related technique or skill to/from the other in the year prior to the baseline.

Figure 2: **Network Training Treatment**



Note: A firm owner is another firm owner's technology sharing contact at baseline if either reports teaching/learning a business related technique or skill to/from the other in the year prior to the baseline.

Figure 3: **Network Order Treatment**



Note: A firm owner is another firm owner's technology sharing contact at baseline if either reports teaching/learning a business related technique or skill to/from the other in the year prior to the baseline.

Figure 4: **Design Sample 1**

Figure 5: **Design Sample 2**

Figure 6: **Design Sample 3**

Figure 7: **Training Treatment Compliance**

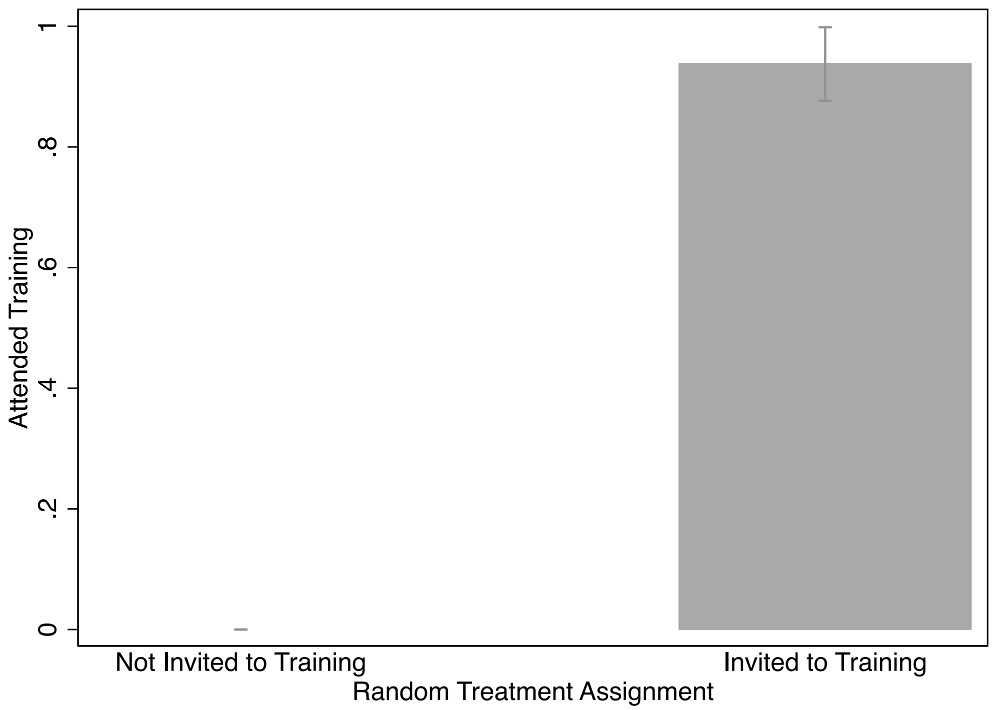


Figure 8: **Order Treatment Compliance**

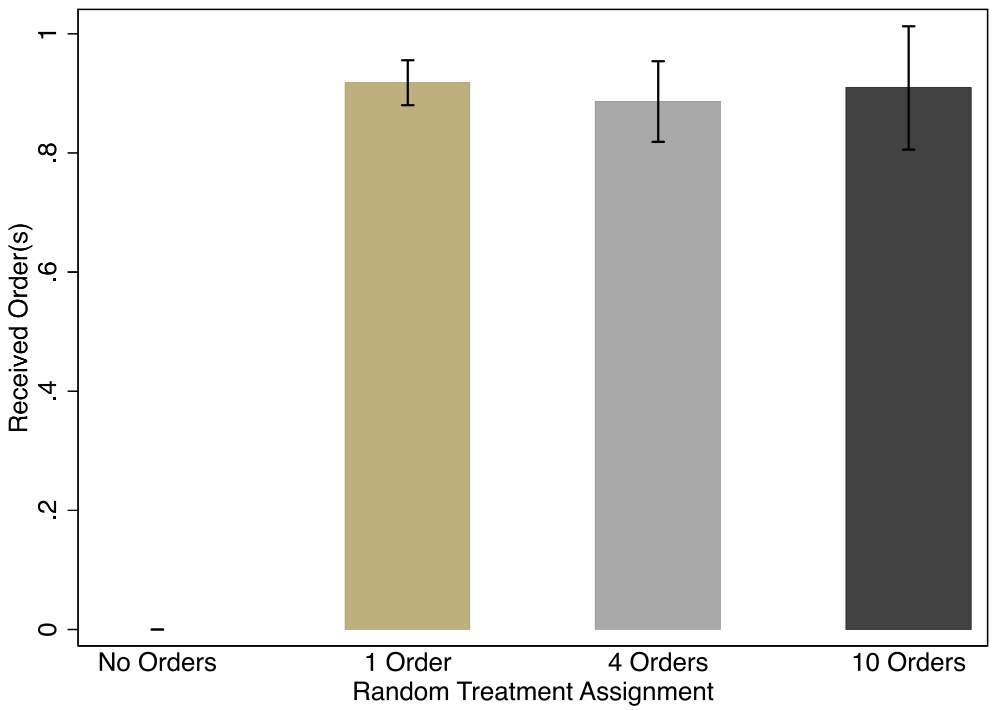


Figure 9: **Order Completion Conditional on Order Request**

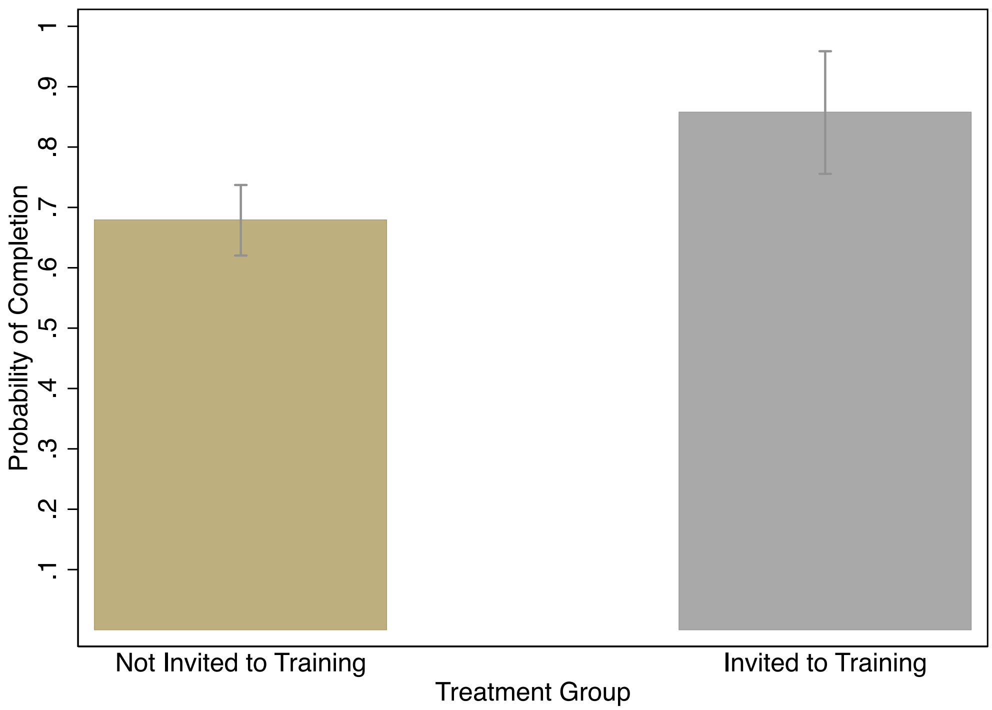
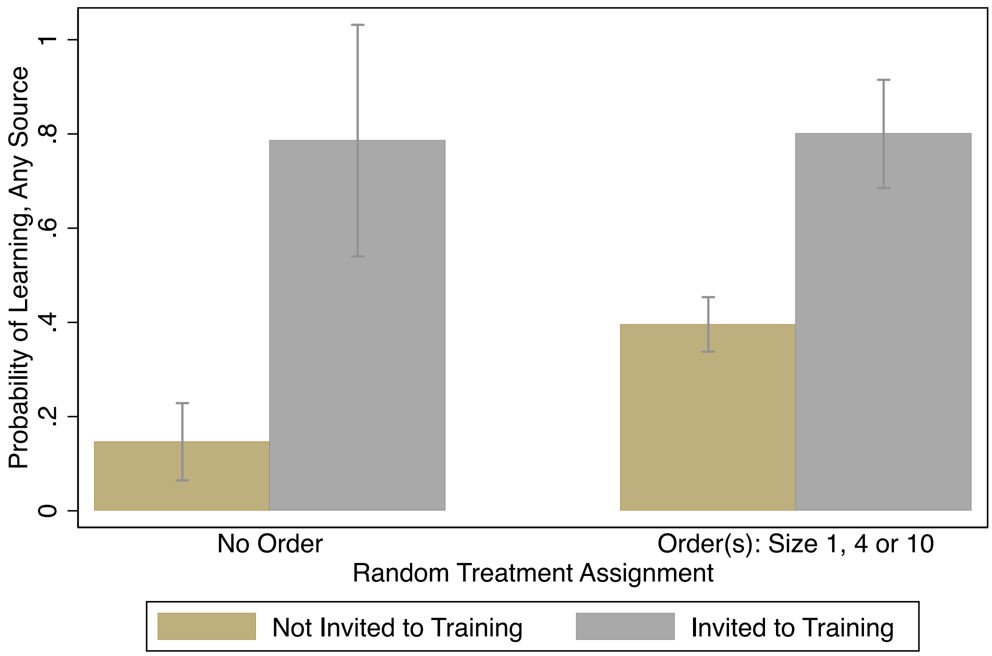


Figure 10: **Treatment Effects on Overall Learning**



Note: A firm owner is considered to have learned the technology if they've ever reported learning or being able to produce it in any round of data collection, regardless of the learning source.

Figure 11: **Technology Diffusion By Round**

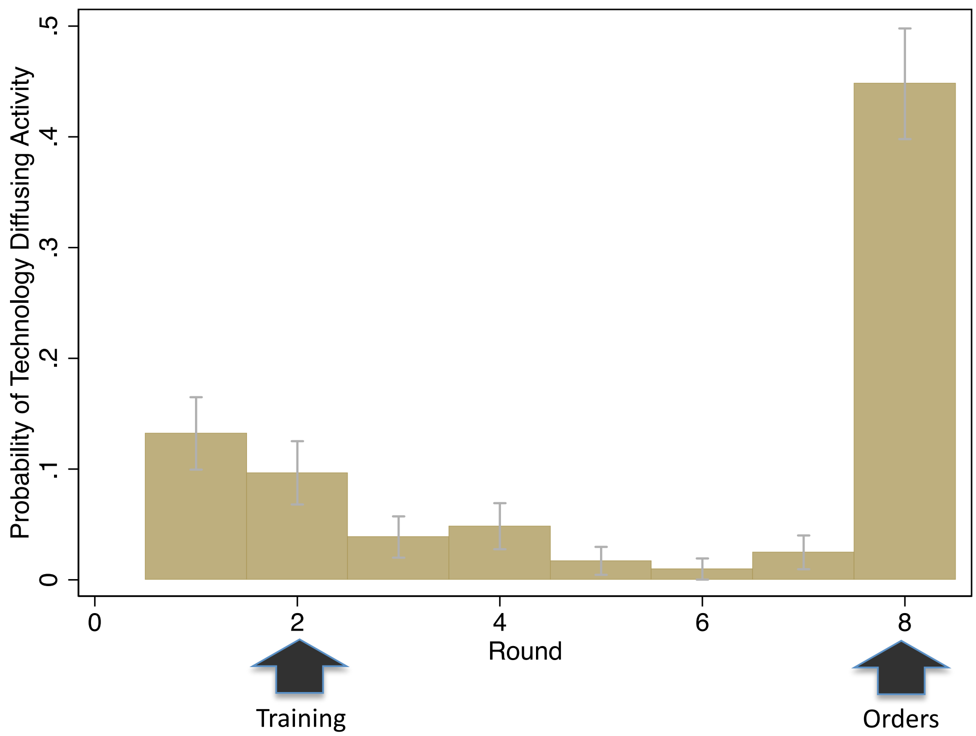
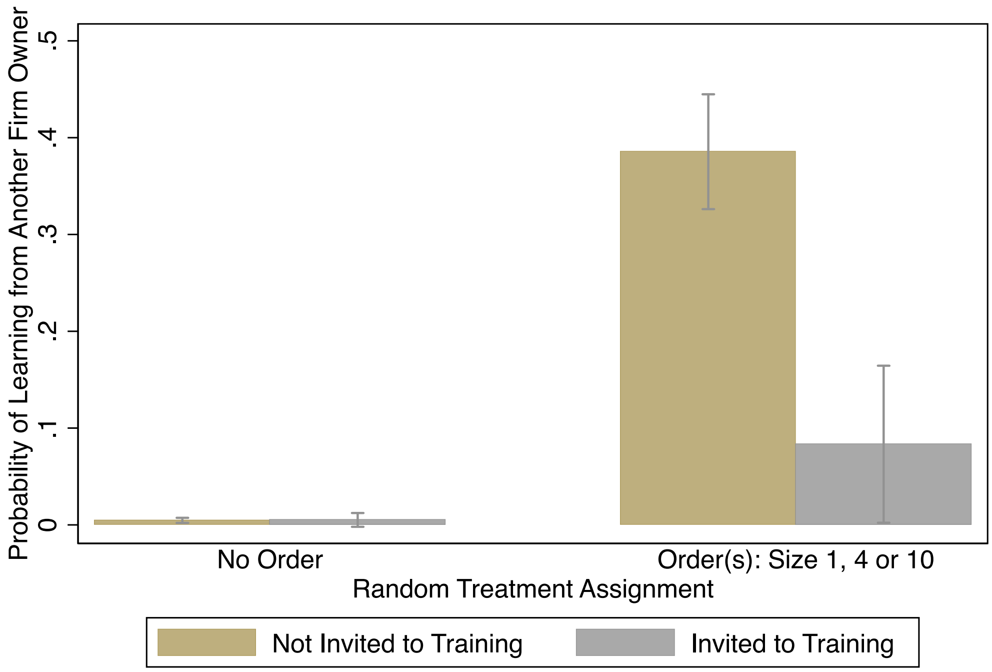
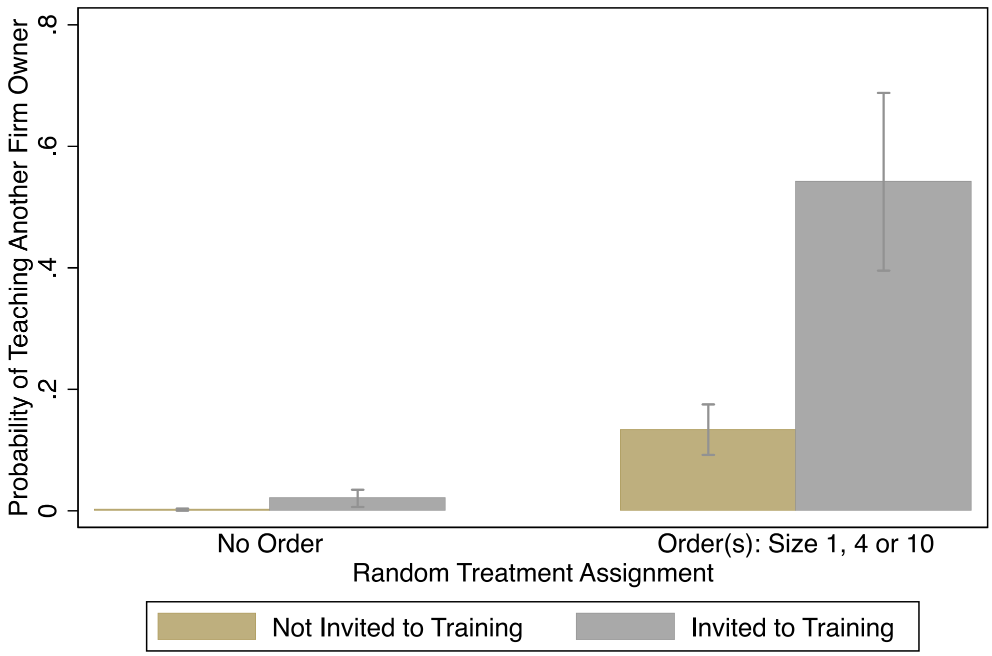


Figure 12: **Treatment Effects on Learning**



Note: Includes 8 rounds. Training occurred in round 2. Orders occurred in round 8. Learning is 1 if either the firm owner or any other respondent reports that firm owner learning during that round.

Figure 13: **Treatment Effects on Teaching**



Note: Includes 8 rounds. Training occurred in round 2. Orders occurred in round 8. Teaching is 1 if either the firm owner or any other respondent reports that firm owner teaching during that round.

Figure 14: **New (Not in Previous Rounds) Contacts By Round**

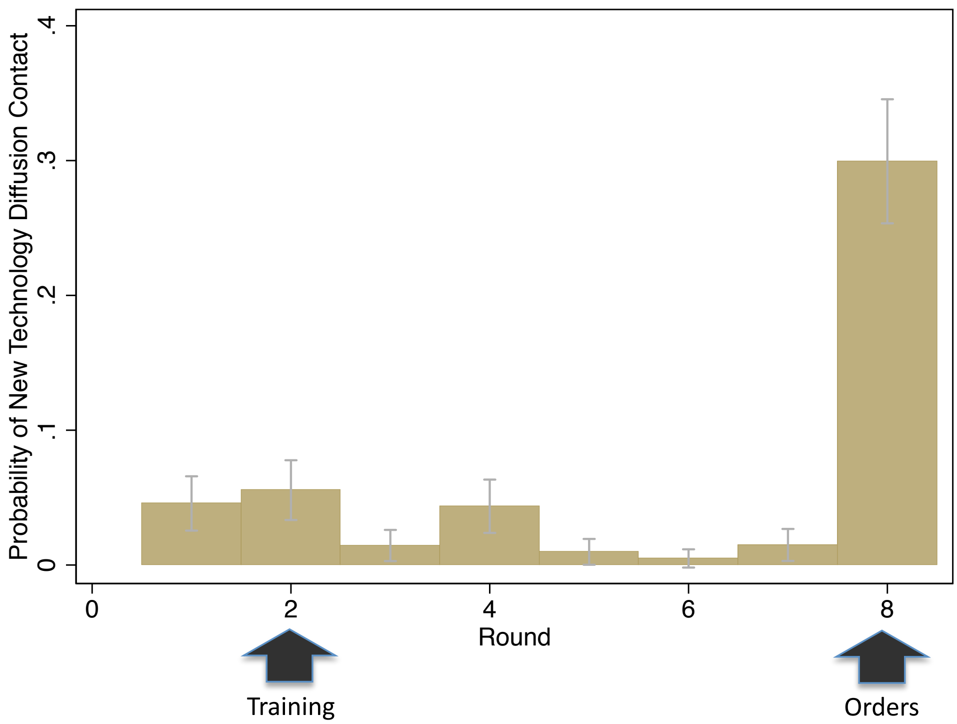


Table 1: **Summary Statistics and Covariate Balance.** Columns labeled mean give the mean value for all firms in our sample, firms randomized to receive no order-no training (cc), firms randomized to receive training but no order offer (cs), firms randomized to receive order offers but no training (oc), and firms randomized to receive both an order offer and training (cs), in that order. Columns 4-5, 7-8, and 10-11 show the difference between the mean in the control group and the three treatment groups, with the corresponding p-value on the test of equality.

	All Firms	cc	cs	cc-cs			cc-oc		os	cc-os	
	mean	*mean*	*mean*	*diff*	*p-val*	*mean*	*diff*	*p-val*	*mean*	*diff*	*p-val*
Male	0.23	0.23	0.21	0.01	0.92	0.23	0.00	0.99	0.24	-0.01	0.86
Ewe ethnicity	0.76	0.83	0.86	-0.03	0.78	0.73	0.10	0.09*	0.78	0.05	0.52
Years schooling	8.85	8.69	8.21	0.47	0.51	8.83	-0.14	0.66	9.38	-0.69	0.06*
Ravens score (of 12)	5.63	5.45	6.21	-0.76	0.28	5.58	-0.13	0.71	6.00	-0.55	0.22
Owner age	35.53	33.74	35.14	-1.40	0.61	36.07	-2.33	0.07*	35.28	-1.54	0.33
Within industry/sample degree	15.56	14.37	15.00	-0.63	0.84	15.75	-1.38	0.35	16.46	-2.09	0.36
Firm size (including owner)	1.99	1.93	2.29	-0.36	0.42	1.99	-0.06	0.78	2.00	-0.07	0.82
Has any worker(s) besides owner	0.47	0.44	0.57	-0.13	0.37	0.50	-0.06	0.38	0.36	0.08	0.38
Revenues (GHC)	197	195	178	17	0.83	196	-2	0.96	206	-11	0.82
Profits (GHC)	138	144	123	21	0.72	136	8	0.68	145	-0	0.99
Assets excl land/building (GHC)	1214	1187	1057	130	0.79	1256	-69	0.76	1069	118	0.67
Management practices (of 4)	2.32	2.21	2.21	-0.00	0.99	2.38	-0.16	0.20	2.18	0.03	0.85
Firm age	9.49	9.06	9.00	0.06	0.98	9.66	-0.60	0.59	9.38	-0.32	0.83
Trade association member	0.22	0.19	0.14	0.04	0.69	0.23	-0.05	0.41	0.22	-0.03	0.65
Registered w/any govt agency	0.17	0.19	0.00	0.19	0.08*	0.17	0.02	0.68	0.18	0.01	0.93
Number of Firms	417	75	14			278			50		
F Stat of Joint Sig					0.77			0.19			0.31

Table 2: **Reduced Form Treatment Effects on Technology Diffusion**

	(1) Learned Technology from Another Garment Maker	(2) Taught Technology to Another Garment Maker
Randomly Selected to Receive:		
Order Only	0.263***	0.0255
	(0.0526)	(0.0453)
Training Only	0.00657	0.0122
	(0.00866)	(0.00810)
Order and Training	-0.0436	0.441***
	(0.0301)	(0.0731)
Average Across All Rounds	0.0365	0.0227
Observations	3,263	3,263
R-squared	0.407	0.349
Firm FE	YES	YES
Round FE	YES	YES

Notes: This table reports reduced form effects of being randomly invited to a training in and/or selected to recieve an order for a new technology on the sharing of that technology between firm owners over the 8 rounds of data collection. The training was held in the period covered by the second round. The orders occurred during the period covered by the final round. Orders were given out on a randomized rolling basis until all resources had been exhausted. Once a firm owner recieved an order, they could not recieve another. If a firm owner had not yet recieved an order, they were eligable to recieve one if enough of the existing orders were not met by their peers. A firm owner is considered to be a teacher or learner if either firm owner reports an interaction in a given round. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: **Reduced Form Network Treatment Effects on Technology Diffusion**

	(1) Learned Technology from Another Garment Maker	(2) Taught Technology to Another Garment Maker
At Least One Baseline Contact Randomly Selected to Receive:		
Order Only	0.0203	0.0994***
	(0.0529)	(0.0377)
Training Only	-0.00401	-0.0112*
	(0.0153)	(0.00640)
Order and Training	0.145**	0.00385
	(0.0605)	(0.0440)
Firm Owner Randomly Selected to Receive:		
Order Only	0.261***	0.0292
	(0.0512)	(0.0446)
Training Only	0.00651	0.0106
	(0.00916)	(0.00786)
Order and Training	-0.0162	0.448***
	(0.0583)	(0.0859)
Average Across All Rounds	0.0365	0.0227
Observations	3,263	3,263
R-squared	0.419	0.358
Firm FE	YES	YES
Round FE	YES	YES

Notes: This table reports reduced form effects of a firm owners' technology sharing contact being randomly invited to a training in and/or selected to recieve an order for a new technology on the sharing of that technology between firm owners over the 8 rounds of data collection. Another firm owner is a technology sharing contact if either owner reported sharing technology during the year prior to the start of the study. The training was held in the period covered by the second round. The orders occurred during the period covered by the final round. Orders were given out on a randomized rolling basis until all resources had been exhausted. Once a firm owner recieved an order, they could not recieve another. If a firm owner had not yet recieved an order, they were eligable to recieve one if enough of the existing orders were not met by their peers. A firm owner is considered to be a teacher or learner if either firm owner reports an interaction in a given round. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: **Reduced Treatment Effects on Network Formation**

	(1)	(2)
	Learned a Technology from a New Contact	Taught a Technology to a New Contact
Randomly Selected to Receive:		
Order Only	0.271***	0.0421
	(0.0453)	(0.0635)
Training Only	0.0116	-0.000879
	(0.0219)	(0.0276)
Order and Training	0.0504	0.865***
	(0.0679)	(0.272)
Average Across All Rounds	0.0429	0.0429
Observations	3,263	3,263
R-squared	0.283	0.269
Firm FE	YES	YES
Round FE	YES	YES

Notes: This table reports reduced form effects of being randomly invited to a training in and/or selected to recieve an order for a new technology on the formation of new network connections between firm owners over the 8 rounds of data collection. A network connection is "new", if teaching/learning to/from that contact has never been mentioned in a previous round by either the firm owner or that contact. The training was held in the period covered by the second round. The orders occurred during the period covered by the final round. Orders were given out on a randomized rolling basis until all resources had been exhausted. Once a firm owner recieved an order, they could not recieve another. If a firm owner had not yet recieved an order, they were eligable to recieve one if enough of the existing orders were not met by their peers. A firm owner is considered to be a teacher or learner if either firm owner reports an interaction in a given round. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: **Reduced Form Dyadic Treatment Effects on Technology Diffusion**

	(1)	(2)	(3)
Dyads Included in Regression:	All	Not Technology Sharing Contacts at Baseline	Technology Sharing Contacts at Baseline
	New Technology Diffused	New Technology Diffused	New Technology Diffused
Teacher RandomlySelected to Receive Order and Training			
Reciever Randomly Selected to Receive:			
Order and Training	0.00036	0.00036	-0.00010
	(0.00039)	(0.00039)	(0.00016)
Order Only	0.00447***	0.00337***	0.16219***
	(0.00064)	(0.00056)	(0.04215)
Training Only	0.00010	0.00011	-0.00013
	(0.00011)	(0.00011)	(0.00015)
Neither	0.00135*	-0.00001*	0.13597**
	(0.00075)	(0.00001)	(0.06925)
Teacher RandomlySelected to Receive Order Only			
Reciever Randomly Selected to Receive:			
Order and Training	0.00023	0.00016	0.01074
	(0.00015)	(0.00012)	(0.01160)
Order Only	0.00060***	0.00041***	0.02367***
	(0.00010)	(0.00008)	(0.00694)
Training Only	0.00030	0.00030	0.00087
	(0.00032)	(0.00032)	(0.00109)
Neither	0.00032**	0.00019	0.01660
	(0.00015)	(0.00012)	(0.01244)
Teacher RandomlySelected to Receive Training Only			
Reciever Randomly Selected to Receive:			
Order and Training	0.00010	0.00011	-0.00013
	(0.00011)	(0.00011)	(0.00015)
Order Only	0.00142**	0.00087	0.10586
	(0.00071)	(0.00055)	(0.08043)
Training Only	0.00012	0.00012	-0.00023
	(0.00013)	(0.00013)	(0.00016)
Neither	-0.00001	-0.00002*	0.00306
	(0.00002)	(0.00001)	(0.00216)
Teacher RandomlySelected to Receive Neither			
Reciever Randomly Selected to Receive:			
Order and Training	0.00000	-0.00000	0.00088
	(0.00001)	(0.00000)	(0.00109)
Order Only	0.00026*	0.00026*	0.00006
	(0.00014)	(0.00014)	(0.00005)
Training Only	0.00001	-0.00000	0.00095
	(0.00001)	(0.00000)	(0.00125)
Average Probability of New Technology Diffusion	0.0001	0.0001	0.0043
Average Probability of Any Technology Diffusion	0.0002	0.0001	0.0106
Observations	1,328,400	1,319,102	9,298
R-squared	0.136	0.131	0.210
Pair FE	YES	YES	YES
Round FE	YES	YES	YES

Notes: This table reports reduced form dyadic treatment effects, depicting the effects of potential teachers and/or potential learners being randomly invited to a training in and/or selected to recieve an order for a new technology on diadic level technology diffusion over the 8 rounds of data collection. Column 1 shows the basic effects of each dyadic treatment status on the full sample. Columns 2 includes only dyads that are not technology sharing contacts at baseline, while column 3 includes only the opposit. The training was held in the period covered by the second round. The orders occurred during the period covered by the final round. Orders were given out on a randomized rolling basis until all resources had been exhausted. Once a firm owner recieved an order, they could not recieve another. If a firm owner had not yet recieved an order, they were eligable to recieve one if enough of the existing orders were not met by their peers. Technology diffused between a potential teacher and learner in a given round, if either respondent reported teaching or learning in that round. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: **Reduced Form (Order Size) Effects on Technology Diffusion**

	(1) Learned Technology from Another Garment Maker	(2) Taught Technology to Another Garment Maker
Randomly Selected to Receive:		
Order Only, Any	0.325***	-0.00570
	(0.0767)	(0.0556)
Order Only, Size 4	0.00309	0.0806
	(0.0904)	(0.0629)
Order Only, Size 10	-0.113	0.269**
	(0.117)	(0.107)
Training Only	0.00587	0.0133
	(0.0114)	(0.0110)
Order and Training, Any	-0.0393	0.344**
	(0.0905)	(0.154)
Order and Training, Size 4	-0.0277	0.165
	(0.0951)	(0.213)
Order and Training, Size 10	0.0897	0.227
	(0.182)	(0.255)
Average Across All Rounds	0.0379	0.025
Observations	2,324	2,324
R-squared	0.436	0.373
Firm FE	YES	YES
Round FE	YES	YES

Notes: This table reports reduced form effects of being randomly invited to a training in and/or selected to recieve an order for a random number of garments utilizing a new technology on the sharing of that technology between firm owners over the 8 rounds of data collection. The training was held in the period covered by the second round. The orders occurred during the period covered by the final round. Orders were given out on a randomized rolling basis until all resources had been exhausted. Once a firm owner recieved an order, they could not recieve another. If a firm owner had not yet recieved an order, they were eligable to recieve one if enough of the existing orders were not met by their peers. Orders were given out over two waves. Wave 1 contained orders of size 1,4 and 10. Wave 2 contained orders only of size 1. Therefore, to remove any timing effect, these regression include only firm owners selected to receive an order in Wave 1 or never recieved an order. A firm owner is considered to be a teacher or learner if either firm owner reports an interaction in a given round. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: **Reduced Form Dyadic Treatment Effects on Technology Diffusion, Order Timing**

Dyads Included in Regression: **Teacher Wave, Learner Wave**	(1) Wave 1, Wave 1	(2) Wave 1, Wave 2	(3) Wave 2, Wave 1	(4) Wave 2, Wave 2
	New Technology Diffused	New Technology Diffused	New Technology Diffused	New Technology Diffused
Teacher RandomlySelected to Receive:				
Order and Training	0.00228*	0.00258**	0.00168	0.00203**
	(0.00126)	(0.00125)	(0.00102)	(0.00099)
Order Only	0.00028	-0.00001	-0.00020	-0.00005
	(0.00050)	(0.00033)	(0.00036)	(0.00028)
Training Only	0.00026**	0.00006	0.00013*	0.00001
	(0.00011)	(0.00005)	(0.00007)	(0.00003)
Learner Randomly Selected to Receive:				
Order and Training	-0.00038	-0.00045	0.00018	0.00016
	(0.00043)	(0.00040)	(0.00055)	(0.00042)
Order Only	0.00053	0.00022	0.00032	0.00043
	(0.00059)	(0.00049)	(0.00032)	(0.00031)
Training Only	-0.00001	0.00001	-0.00002	0.00002
	(0.00005)	(0.00004)	(0.00001)	(0.00003)
Average Diffusion of New Technology	0.0001	0.0001	0.0000	0.0001
Average Diffusion of Any Technology	0.0002	0.0001	0.0001	0.0001
Observations	177,834	221,248	221,248	270,730
R-squared	0.141	0.126	0.126	0.144
Pair FE	YES	YES	YES	YES
Round FE	YES	YES	YES	YES

Notes: This table reports reduced form dyadic treatment effects, depicting the importance of order timing in the effects of potential teachers and/or potential learners being randomly invited to a training in and/or selected to recieve an order for a new technology on diadic level technology diffusion over the 8 rounds of data collection. The training was held in the period covered by the second round. The orders occurred during the period covered by the final round. Orders were given out on a randomized rolling basis until all resources had been exhausted. Once a firm owner recieved an order, they could not recieve another. If a firm owner had not yet recieved an order, they were eligable to recieve one if enough of the existing orders were not met by their peers. Orders were given out over two waves. Wave 1 contained orders of size 1,4 and 10. Wave 2 contained orders only of size 1. Therefore, to remove any size effect, these regression include only dyads in which owners were selected to receive an order of size 1 or not selected for an order at all. Technology diffused between a potential teacher and learner in a given round, if either respondent reported teaching or learning in that round. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Tables 8**: Experimental and External Determinants of Technology Diffusion**

	(1) Any Technology Diffusion in the Year Prior to Experiment	(2) Sharawakil Diffusion During Experiment
Dyadic Characteristics		
Competitors (Market Research Survey)	0.01916***	0.00081
	(0.00513)	(0.00169)
Neighbors (< 500')	0.02366***	0.00309***
	(0.00098)	(0.00041)
Same Gender	0.00430***	0.00035***
	(0.00039)	(0.00013)
Same Ethnicity	0.00202***	0.00033**
	(0.00039)	(0.00015)
Same Size (Either No Workers or Workers)	0.00127***	0.00027**
	(0.00035)	(0.00013)
Matching Management Practices (>2/5)	0.00102**	0.00020
	(0.00050)	(0.00016)
Average Diffusion	0.0062	0.0008
Observations	139,886	139,886
R-squared	0.015	0.002

Notes: This table reports correlations between baseline dyadic level characteristics and all technology sharing at baseline, in Column 1, and sharing of our newly developed technology during the orders round, in Column 2. Because the seeding of training in and demand for the new technology were random, any persistent relationship between a dyadic charcteristic and sharing in Column 2 exists as a result of something unrelated to the supply and demand of technology. Standard errors are bootstrapped.