

Yellow Pages: Information, Connections and Firm Performance*

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Abstract

We study the impact of reducing information frictions in rural markets by randomly assigning small and medium enterprises in Tanzania to be listed in a telephone directory. The listed firms expand their communication networks, increase sales, and make greater use of mobile money, with positive spillovers to firms in the same village. Estimated effects are larger and more statistically precise for firms that are more productive at baseline, consistent with consumers seeking out better firms when search costs fall. We find no evidence of negative between-village spillovers on unlisted firms.

Keywords: mobile phones; directories; small and medium enterprises; information frictions; Tanzania.

JEL Codes: O13, Q16, I15

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1. Introduction

The diffusion of mobile phones through low-income countries has been one of the fastest and most comprehensive technological transformations in human history (Comin and Mestieri, 2014). In the last decade, economists have begun to document the implications of this transition. Early studies show that mobile phones facilitated arbitrage in agricultural markets (Jensen, 2007; Aker, 2010). More recent work evaluates mobile-based services that provide curated information to phone users across a variety of sectors (Fafchamps and Minten, 2012; Morten et al., 2012; Jamison et al., 2013; Hall et al., 2014; Aker et al., 2016; Buntaine et al., 2018; Angrist et al., 2020; Grossman et al., 2020; Bergquist et al., 2021; Hasanain et al., 2023), and examines the implications of the changing ICT landscape for economic and political organization (Hjort and Poulsen, 2019; Manacorda and Tesei, 2020; Brunnermeier et al., 2023).

Small and medium-enterprises (SMEs) should, in principle, benefit from this transformation. Prior work has shown that information frictions are substantial for SMEs in both input and output markets (Allen, 2014; Jensen and Miller, 2018; Bergquist et al., 2021; Rudder and Dillon, 2023). Mobile phones can reduce search costs and integrate markets, with potentially large benefits to firms that navigate the transition. Yet most firms in sub-Saharan Africa remain small and unproductive, and serve primarily local markets. One potential factor constraining the impact of mobile phones is the lack of a complementary information service—such as a phonebook or Google search engine—to help phone users search for new contacts. Mobile phones reduce communication costs within *existing* social networks, but they do not necessarily help phone users *expand* their networks.

In this paper we study the importance of this particular information friction—the friction related to finding and contacting new businesses—for firms in Tanzania. Through a randomized controlled trial (RCT), we developed and distributed a telephone directory (“Yellow Pages”) that listed information about SMEs that are relevant to agricultural households (retail, transport, skilled trades, production-related services, and others). The experiment

had two main components. First, we randomized which SMEs were listed in the directory, in order to better understand how publicizing contact information could affect customer contact and business outcomes. Second, we randomized the distribution of the directory to households, to understand how their choices would be impacted by better access to firm information, and how that in turn would impact firm outcomes.¹ We evaluate these experiments using multiple rounds of surveys conducted primarily over one year. Our aims are to test whether the constraint on contact information is binding, and, if so, to examine how and why firm outcomes change when that constraint is relaxed.

Our analysis leads to three main sets of results. First, relative to firms in villages with no treated firms, the firms listed in the directory expand their communication networks, with increases in both calls and text messages with customers. Estimated effects are large in magnitude, ranging from 21-68% of the mean values for untreated firms. These communication-related findings are robust to an exercise in which enumerators manually verified the reported number of business-related calls by checking the respondent’s phone history. We find no advantage to being listed first in a directory subsection, suggesting that directory users took time to read the listing descriptions before choosing whom to contact.

Second, directory firms see increases in the number of sales (by 47%), sales revenue (by 104%), and use of mobile money (by 31%), again relative to firms in villages with no treated firms. The effect on sales revenue is surprisingly large. Although this estimate remains similar across a series of robustness checks, we take a cautious approach and focus our interpretation on the lower bound of the confidence interval (which is 20-221%). We find no treatment effects on employment or stocking purchases, suggesting that firms were not pushed to expand capacity during the study period.

Third, we find evidence of *positive* spillovers to unlisted firms that operate in the same villages as listed firms. Relative to a Pure Control group (firms in villages from which no firms were listed), unlisted firms in villages with treated firms increased SMS traffic (by

¹See Appendix A1 for a discussion of the ethical considerations of this experimental design.

80%), mobile money usage (by 26%), and the number of sales (by 40%). These positive spillovers are consistent with the directory inducing more foot traffic to treated villages, thereby increasing demand to unlisted firms.

After establishing these main results, we turn to mechanisms. There are many ways that relaxing an information constraint for customers could affect firms. We provide evidence on three possible dimensions of adjustment. First, we use the independently randomized distribution of the directories to show that the benefits to firms are similar regardless of whether directories were distributed nearby. This suggests that some directory recipients were induced to search and trade outside of their villages. We also find in household surveys that rates of extra-village search and purchasing are greater for the households randomly selected to receive directories.

If the effects we document are mediated in part by search, that raises the question of whether consumers were able to find better firms. We address this question by testing whether effects are larger for more productive firms. Using baseline data on employment and sales to construct a measure of labor productivity, we show that both the direct and spillover effects of the directory are larger in magnitude and more precise for firms with above median productivity (for most outcomes, we cannot reject null effects on the low productivity firms). This aligns with a key result in [Jensen and Miller \(2018\)](#), who show that when information frictions fall in India, only the higher quality firms benefit.

Finally, we consider whether the widespread drop in search costs led to net increases in economic activity, or simply reallocated business away from unlisted villages and to the treated firms. In two suggestive analyses, we find no evidence of negative between-village spillovers. Three-year survival rates are identical for Treatment, Control, and Pure Control firms. Furthermore, outcomes for Pure Control firms do not vary meaningfully with the number or the share of treated firms in their subdistrict and sector.

Our research makes three contributions. First, we speak to the role of mobile phones in reducing search costs in rural markets. Prior work has found that phones can make rural

markets more efficient (Jensen, 2007; Aker, 2010), and phone-based interventions can in some cases increase input usage and productivity (Fafchamps and Minten, 2012; Nakasone et al., 2013; Aker et al., 2016; Fabregas et al., 2024). Our study differs from most phone-intervention studies in that we seek to facilitate search by providing information that complements phones, rather than use phones as a vehicle for sharing third party information (e.g., prices). In this respect our work connects to a broader literature on the economic consequences of reductions in search costs (Stigler, 1961; Sutton, 1991; Goldfarb and Tucker, 2019; Abebe et al., 2020; Bergquist et al., 2021; Bandiera et al., 2023; Bai, 2024).

We also contribute to the literature on rural market structure and relational contracts. A widespread concern in this literature is the uncompetitiveness of rural markets, due to entry barriers and information asymmetries (Atkin and Donaldson, 2015; Dillon and Dambro, 2017; Bergquist and Dinerstein, 2020). Yet, theoretical and empirical papers on relational contracts highlight the importance of trading with known agents when institutions for contract enforcement are weak, calling into question whether rural households would utilize a directory of mostly unknown firms (Greif, 1993; Banerjee and Duflo, 2000; Baker et al., 2002; Brown et al., 2004; Fafchamps, 2004; Macchiavello and Morjaria, 2015; Casaburi and Reed, 2019; Startz, 2018; Ghani and Reed, 2022; Rudder and Dillon, 2023). We build on a long line of work showing the importance of networks in household choices and outcomes, and show that these networks can expand if information barriers are addressed (Foster and Rosenzweig, 1995; Munshi, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010; Maertens, 2017; Cai et al., 2015; Kondylis et al., 2014; Magruder, 2018; Beaman and Dillon, 2018; BenYishay and Mobarak, 2018; Beaman et al., 2021; Comola and Prina, 2021).

Finally, our paper adds to the growing evidence base documenting reasons for the poor performance of SMEs in low-income countries. Prior work in this area explores the barriers created by entry costs (Ayyagari et al., 2007) and access to finance (Beck and Demirgüç-Kunt, 2006; De Mel et al., 2008, 2012), and highlights the benefits to SMEs from switching technologies (Atkin et al., 2017) and improving management practices (Bloom et al., 2013;

Beaman et al., 2014). A related set of papers emphasizes the importance of information costs to SMEs (Allen, 2014; Aggarwal et al., 2018; Startz, 2018; Jensen and Miller, 2018; Rudder and Dillon, 2023). Our results highlight how reducing one particular information friction—the cost of finding new contacts—can have a meaningful impact on SME performance.

2. Research Setting and Experimental Design

2.1 The Kichabi Directory

In order to understand how information constraints affect the economic outcomes of SMEs, we created and distributed a mobile phone directory in rural Tanzania, called *Kichabi*.² The experiment took place in the Dodoma and Manyara regions, covering approximately 5,000 square miles (see Figure A1). The area is primarily agricultural, with one growing season from January to May. A broad set of formal and informal enterprises provide services to farmers, including input supply shops, pharmacies, transporters, mechanics, and others. These SMEs sell their goods and services directly to farmers in villages, or at weekly markets.

We partnered with the Institute of Rural Development and Planning (IRDP) to conduct a census of all firms in specific sectors across 49 villages.³ The census collected basic data (name, location, sector, phone number(s), areas of specialization) from firms in eight sectors relevant for agriculture: wholesale trade, retail trade, transport, rentals, agricultural processing, agricultural services (e.g., mechanics or hired labor), non-agricultural services (e.g., pharmacies) and financial services. Firms were not incentivized to participate in the census. Out of the 2,100 firms visited, 71% (1,506) agreed to be interviewed and provided their information. The most common reason for refusal was potential exposure to tax authorities. After removing firms with missing information, we have a sample of 1,495 enterprises.

²*Kichabi* is short for *kitabu cha biashara*, or “business book” in Swahili.

³The villages were chosen based upon their size (e.g., having 4,000 or more inhabitants) or their function as the sub-district capital. Each village is comprised of a number of sub-villages, which represent distinct administrative areas. Seven of the villages are separate administrative areas of the two small cities in the study area, Babati and Dodoma, which function like separate villages. For details, see Appendix A2.

Using the information collected through the census, we created the *Kichabi* phone directory. The directory was printed as a folded A4 booklet (Figure 1A). Within the directory, firms were listed alphabetically by village, sub-village, sector, and name (Figure 1B). A description column in the booklet, listing areas of specialization collected in the census, allowed for differentiation between otherwise similar firms.

2.2 Experimental Design

To test the importance of frictions related to contact information, we conducted two separate but related experiments. On the supply side, we randomized which firms were *listed* in the directory; on the demand side, we randomized which households *received* a printed copy of the directory. The experiments were randomized independently. This paper primarily focuses on the firm side of the experiment, although we take advantage of the randomized distribution of directories to study mechanisms behind the observed effects.

For the firm experiment, we first stratified by district, and randomly assigned villages to either be eligible for treatment or not.⁴ In the treated villages, we further stratified by village and sector, and randomly assigned subvillage-sector groups to either Treatment or Control (Figure A2). The firms assigned to Treatment were listed in the directory, whereas Control firms were not.⁵ We thus have treated firms in treated villages (Treated), Control firms in treated villages (Control) and control firms in control villages (Pure Control).

For the distribution experiment, we identified a sample of 99 villages in the study area. Stratifying by ward (subdistrict) and village size, we randomly assigned villages to the distribution treatment (receiving directory booklets) or distribution control. In both sets of villages we held meetings to introduce the directory and explain its potential uses. In the distribution treatment villages, we gave directory booklets to 70 meeting attendees, prior to

⁴Villages in Tanzania are divided into subvillages, each of which has a chairperson that works with the village leaders. There are typically 2-4 subvillages in a village, with a 5-20 minute walk between subvillage centers. Many subvillages have their own commercial centers.

⁵All firms were listed in new directories that we issued at the end of the experiment, to ensure no long-run disadvantage to unlisted firms. See Appendix A1.

the start of the cultivation season. In control villages, we distributed booklets eight months later, after the end of the season (see Appendix A4 for more details). A total of 29 villages were treated in both experiments.

2.3 Data

Our analysis is based primarily on surveys that we conducted with a random subset of study firms before and after the intervention. Among the 1,495 firms in the census, we randomly selected 440 for five rounds of data collection: a baseline in-person survey (beginning in September 2014); a midline in-person survey (beginning in March 2015); two phone surveys that were short and focused on business-related communications (May-July 2015); and an endline in-person survey (beginning in September 2015). In 2017 we conducted a brief follow-up survey with all firms, to measure any long-term differences in survival across treatment groups (see Figure A3 for a study timeline). The baseline occurred prior to treatment; all other surveys took place after.

The baseline, midline, and endline surveys covered a range of topics including communication, customer contact, mobile money, sales transactions, revenues, and employment. Attrition for in-person surveys was low, ranging from 2% to 15%, depending upon the survey round. There was no differential attrition between the Treatment, Control, and Pure control groups. We use these data to estimate the impact of being listed in the directory on firms' communication and business outcomes.

Appendix Table A1 provides summary statistics from the baseline enterprise survey. Firm characteristics are generally balanced between the Treat, Control and Pure Control groups. Out of 27 variables tested, there are three that are statistically different across groups at 90% confidence (only one at 95%), which is consistent with random chance. In Appendix Table A2 we show that our results are unchanged if we control for the variables that exhibit slight baseline imbalance.

2.4 Empirical Strategy

To estimate the impact of being listed in the directory on firm-level outcomes, we use analysis of covariance (ANCOVA) regressions of the following form:

$$Y_{ivdt} = \beta_0 + \beta_1 Treat_{ivd} + \beta_2 Control_{ivd} + \beta_3 Y_{ivd0} + \lambda_t + \psi_d + \epsilon_{ivdt} \quad (1)$$

where Y_{ivdt} is the value of the outcome for firm i , in village v , district d , and survey round t ; $Treat_{ivd}$ is a binary variable equal to 1 if the firm is listed in the directory; $Control_{ivd}$ is a binary variable equal to 1 if the firm is unlisted, but located in a village with some listed firms; λ_t are survey round fixed effects; ψ_d are fixed effects for districts, which are the randomization strata; and ϵ_{ivdt} is the error term. The excluded category is the Pure Control group, consisting of firms located in villages where no firms were listed. The coefficient $\hat{\beta}_1$ estimates the impact of the directory listing on treated firms, which we refer to as the intent-to-treat effect (ITT) following [Baird et al. \(2018\)](#). The coefficient $\hat{\beta}_2$ estimates the within-village spillover effect on unlisted firms. In extensions to the main analysis, we estimate models in which we include controls for variables unbalanced at baseline, restrict attention to the 80% of respondents that allowed enumerators to verify phone activity, estimate heterogeneous effects using interactions, or estimate the total effect of the treatment using the variable $AnyTreat_{ivd} = \max\{Treat_{ivd}, Control_{ivd}\}$. Because there are 49 villages (treatment clusters) across the three groups, and 7 Pure Control villages, inference in all regressions is based on p -values calculated with the wild cluster bootstrap (WCB) of ([Cameron et al., 2008](#)).

We focus our analysis on four communication-related outcomes (total business calls, incoming business calls, total business text messages, and incoming business text messages), and six economic outcomes (using mobile money, employing any workers, number of workers, number of sales, sales revenue, and number of stocking purchases). Full definitions of these variables are provided in [Appendix A3](#).

3. Results

3.1 Direct and Spillover Effects of Directory Listings

Direct Effects on Communication. Columns 1-3 of Table 1 present our estimates of the direct effects of directory listings on firm-level communication outcomes. Compared to Pure Control firms, being listed in the directory significantly increases a firm’s total number of business calls and text messages (Panel A, column 1). The impacts are large in magnitude, with effects ranging from 21-68% of the Pure Control mean.

Although communication outcomes were self-reported, enumerators verified the number of calls by asking the respondent if they could look through the phone history together. Approximately 4 out of 5 respondents allowed the enumerator to check the phone. In Panel B of Table 1 we show that results are larger in magnitude and more precisely estimated when we focus on firms that allowed verification. Taken together, these results suggest that being listed in the directory made it easier for customers to communicate with firms.

Direct Effects on Business Outcomes. The increase in business communication led to changes in other business-related outcomes (Table 2). Compared to the Pure Control, firms listed in the directory made 4.9 more sales in the previous two operating days (46% increase), and saw a 137,936 TSH increase in sales revenue (104% increase; Panel A, column 1). These sales effects are surprisingly large. They are not driven by outliers: the outcome variables are winsorized, and in quantile regressions we see that there are statistically significant impacts on revenue in the middle of the distribution (Appendix Figure A4, Panel A). Nor are these effects the result of differences in survey timing. Firms in all three groups were interviewed in the same survey effort, and results are unchanged if we include the survey date as an additional control (Appendix Table A3). Perhaps the most important takeaway is that the bootstrap confidence interval for sales revenues is 25,987 – 294,203, or 20 – 221% of the Pure Control mean. Even a revenue increase of 20%, at the lower end of that interval, would

still be of economic importance.

We find no effects of the directory listing on the extensive or intensive margin of employment, and no effect on stocking purchases. These null results suggest that the increases in sales did not push firms to increase capacity, at least over the study period. The sales-related impacts were also associated with an increase in mobile money usage: firms listed in the directory were 16 percentage points (28%) more likely to use mobile money than Pure Control firms. All of these findings are similar for the verified firms (Table 2, Panel B).

Within-Village Spillovers on Communication. Our experimental design allows us to test for spillover effects to control firms in villages where some firms were listed. The direction of this spillover is ambiguous: if listed firms take business from unlisted firms, unlisted firms would see fewer customers and sales. On the other hand, if the directory crowded in business to treated areas or prompted new investment by reducing search costs, unlisted firms might benefit from the additional foot traffic.

The communication-related results in Table 1 (Column 4, Panel A) are more consistent with the latter story. None of the coefficients are negative and statistically significant; most are positive and large in magnitude. Estimated impacts on text messages are statistically significant and similar in magnitude to the effects on listed firms.⁶ These spillover results are largely unchanged, though less precise, when we restrict attention to the 80% of firms that allowed verification (Panel B).

Within-Village Spillovers on Business Outcomes. We also find positive spillover effects on business outcomes for Control firms. These spillover effects are similar in magnitude and significance to the direct effects on listed firms. Relative to Pure Control, Control firms are more likely to use mobile money, make more sales, and have higher sales revenues (Table

⁶Finding a communication spillover on text messages but not calls is not surprising, based on anecdotes from the study site. New customers did not have access to the phone numbers of Control firms until they met in person, while doing business in treated villages. Ongoing communication with someone met recently is more likely to occur via text.

2, Panel A).⁷ The sales results are slightly smaller in magnitude and less precise when we restrict attention to the verified firms (Panel B). Quantile regressions show that there are statistically significant spillover effects on sales revenue in the middle of the distribution, as there were for the listed firms (Appendix Figure A4, panel B). As with the direct effects, the confidence interval for spillover effects on revenue ranges from the modest to the very large, and we think it is safest to focus on the lower end of the estimated interval.

Total Effect on Communication and Business Outcomes. Following (Baird et al., 2018), we also estimate the total effect of the treatment on communication and business-related outcomes. This effect is identified by replacing the Treatment and Control dummies in equation (1) with an “Any Treat” dummy variable, which is equal to 1 for members of both the Treatment and the Control groups. The estimated total effects are presented in Appendix Table A4. The total effects closely match those presented in Tables 1 and 2, with positive and significant effects on phone calls, texts, mobile money usage, number of sales, and sales revenue.

3.2 Mechanisms

We have shown that the telephone directory led to substantial increases in customer contact, mobile money usage, and sales for listed firms, and to positive spillovers on unlisted firms in the same villages. Next we explore the mechanisms behind these effects. Specifically, we analyze household use of the directory, study heterogeneity in impacts, and try to understand whether the positive effects we document came at the expense of firms in untreated villages.

Household Use of the Directory. When we distributed the directory, we selected distribution villages at random from across the study area (see Section 2.2). In follow-up surveys conducted with 831 households roughly 7-8 months after directories were distributed, we find that just under 30% of the directory recipients reported calling at least one listed firm.

⁷In general, we do not observe statistically significant differences between Treated and Control firms.

A large majority of recipients reported sharing or lending the directory to others. In our analysis of household data we find effects that align with those on the firm side: households that received the directory spent more on phone credit, made greater use of mobile money, and increased investment on their farms (see Appendix A4). We find it reassuring that data collected from households corroborates the information reported by firms.

We also test whether effects are larger for firms that are listed first in their directory subsections, relative to those listed later (firms were listed in alphabetical order). We find no significant differences by listing order (Appendix Table A5). We take this as evidence that households took the time to read the firm descriptions and choose whom to call.

Heterogeneity By Firm Type. The average treatment effects reported above may disguise heterogeneity in how firms benefit from the listing. We first examine heterogeneity by sector, where the most natural division is between retail and non-retail firms.⁸ These estimated effects are reported in Panels C of Tables 1 and 2. The overall pattern is that both direct and spillover effects are larger in magnitude for retail firms. Effects on calls, texts, and sales revenue are statistically significant for retail firms, but not for non-retail firms. Because the non-retail effects are imprecise, we cannot reject the equality of effects across sectors. Nevertheless, these findings suggest that the directory was more impactful for firms selling goods rather than services.

Perhaps more interesting is the possibility that the directory allowed consumers to search more broadly and switch their business to more productive firms. While we do not have data to estimate total firm productivity at baseline, we can calculate a measure of labor productivity (revenue per worker) using baseline data on employment and sales. In Table 4 we observe that the statistically significant effects of the directory are almost entirely concentrated among firms with above median baseline labor productivity. This finding is consistent with the directory lowering search costs, allowing customers to find more productive firms.

⁸We define the retail group to include any firm that primarily sells goods (including wholesalers), while the non-retail group includes transporters, processors, financial services, veterinarians, skilled tradespeople, and others.

This result aligns with [Jensen and Miller \(2018\)](#), who find that when information frictions fall in Kerala boat markets, benefits accrue only to the higher quality boat builders.

Heterogeneous Effects from Directory Distribution in a Firm’s Village. In randomizing where directories were distributed, we created exogenous variation in whether directories were received by households in the same villages as listed firms. This makes it possible to test whether treatment effects on firms depend on whether nearby households received copies of the directory. We might expect this interaction to be negative, if demand were fixed and access to the directory allows households to shop outside their local neighborhood.⁹ However, the interaction could be positive if the reduction in search costs led to a net increase in investment and expenditure by recipient households. Hence, the net effects of local distribution on firms are ambiguous *ex ante*.

Table 3 reports heterogeneous effects by whether directories were distributed in the firm’s village. We find no meaningful differences in magnitudes, no clear pattern of larger point estimates for one group, and no statistically significant differences. While this pattern admits multiple interpretations, the average firm in our setting does not appear to be made worse off when the local customer base experiences a reduction in search costs. This finding also suggests that the directory induced more inter-village exchange. If it had not, then positive effects to listed firms would be concentrated in the villages where distribution occurred.

Business-Stealing, or Economic Growth? Given the evidence of positive within-village spillovers, a key question is whether there were spillovers between treated and untreated villages. While the study was not designed *ex ante* to test for between-village spillovers, two pieces of evidence suggest that Pure Control firms were not negatively affected by the directory. The first comes from a follow-up phone survey that we conducted in 2017, three years after our initial contact with study firms, to assess whether firms were still reachable.

⁹The key idea here is that the randomized distribution operates like a separate experiment, one in which treatment makes it easier for previously captive consumers to find firms outside their village.

The response rate was highest for Pure Control firms, and of those that we reached, 95.8% were still operating (compared to 94.8% and 95.7% for the Treat and Control groups). The implication is that there were no between-village effects on firm survival more than two years after the launch of the directory.

The second piece of evidence comes from testing whether outcomes for Pure Control firms vary with the intensity of treatment in their same ward and sector. The listing randomization created quasi-experimental variation in the share of between-village competitors that could potentially steal business from Pure Control firms. In Appendix Table A7 we report estimated coefficients from regressing outcomes for the Pure Control firms on the number or share of their competitors (defined as firms in the same ward and sector). The main takeaway is that we find no evidence of negative or positive between-village spillovers, as none of the estimated coefficients are statistically significant. An important caveat is that because the sample sizes are not as large as in the main analysis, these null effects are not especially precise.¹⁰

If the increases in customer contact and sales that we document did not come at the expense of Pure Control firms, where did they come from? One possibility is that, as a result of the decrease in search costs, the expected value of harvests may have increased for directory recipients (e.g., from anticipating better sales outcomes via easily searching for buyers), which in turn could lead to net increases in investment and expenditure. In the household survey data we see that relative to non-recipients, directory recipients increased farm investment, engaged in more search outside their village, used their phones more for search, and received weakly higher prices for the crops that they sold (Appendix Table A6).¹¹ Our research team is currently engaged in a large-scale follow-up experiment to better understand how receiving a directory with firm contact information affects household

¹⁰For most outcomes the point estimates are very small in magnitude, but the bootstrap confidence intervals include effects of the same order of magnitude as the treatment effects on listed firms.

¹¹We have not emphasized the treatment effects on households in the main analysis, because although the directory distribution was randomized and all households were interviewed in the same month, treatment and control households were recruited 6-8 months apart.

investment and choices.

4. Conclusion

The results of our field experiment highlight the importance of information frictions for small and medium enterprises in rural Tanzania. In an economy recently transformed by mobile phones, we find that the dissemination of contact information facilitates communication between firms and customers, and improves business outcomes of listed firms. There is evidence of heterogeneity, as positive impacts are concentrated among more productive firms and firms in the retail sector. We do not find evidence of negative spillovers, either to unlisted firms in the same villages as listed firms, or to nearby villages where no firms were listed.

More broadly, these findings highlight the importance of the information frictions still facing many SMEs in developing economies, and the potential for low-cost interventions to reduce those frictions. The spread of mobile phones has dramatically reduced the cost of communication within existing social networks. But without a complementary information service to facilitate new connections, those networks may be slow to evolve, and may not reach their full productive potential.

References

- Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey Wooldridge, “When Should You Adjust Standard Errors for Clustering?,” Technical Report, National Bureau of Economic Research 2017.
- Abebe, Girum, Stefano Caria, Marcel Fafchamps, Paolo Falco, Simon Franklin, and Simon Quinn, “Anonymity or distance,” *Job Search and Labour Market Exclusion in a Growing African City*, 2020.
- Aggarwal, Shilpa, Brian Giera, Dahyeon Jeong, Jonathan Robinson, and Alan Spearot, “Market access, trade costs, and technology adoption: evidence from Northern Tanzania,” Technical Report, National Bureau of Economic Research 2018.
- Aker, Jenny C, “Information from markets near and far: Mobile phones and agricultural markets in Niger,” *American Economic Journal: Applied Economics*, 2010, 2 (3), 46–59.
- , Ishita Ghosh, and Jenna Burrell, “The promise (and pitfalls) of ICT for agriculture initiatives,” *Agricultural Economics*, 2016, 47 (S1), 35–48.
- Allen, Treb, “Information frictions in trade,” *Econometrica*, 2014, 82 (6), 2041–2083.
- Angrist, Noam, Peter Bergman, and Moitshepi Matsheng, “School’s out: Experimental evidence on limiting learning loss using “low-tech” in a pandemic,” Technical Report, National Bureau of Economic Research 2020.
- Atkin, David and Dave Donaldson, “Who’s getting globalized? The size and implications of intra-national trade costs,” Technical Report, National Bureau of Economic Research 2015.
- , Azam Chaudhry, Shamyla Chaudry, Amit K Khandelwal, and Eric Verhoogen, “Organizational barriers to technology adoption: Evidence from soccer-ball producers in Pakistan,” *The Quarterly Journal of Economics*, 2017, 132 (3), 1101–1164.
- Ayyagari, Meghana, Thorsten Beck, and Asli Demirguc-Kunt, “Small and medium enterprises across the globe,” *Small Business Economics*, 2007, 29 (4), 415–434.
- Bai, Jie, “Melons as lemons: Asymmetric information, consumer learning and seller reputation,” *Review of Economic Studies*, 2024.
- Baird, Sarah, J. Aislinn Bohren, Craig McIntosh, and Berk Özler, “Optimal Design of Experiments in the Presence of Interference,” *The Review of Economics and Statistics*, December 2018, 100 (5), 844–860.
- Baker, George, Robert Gibbons, and Kevin J Murphy, “Relational Contracts and the Theory of the Firm,” *The Quarterly Journal of Economics*, 2002, 117 (1), 39–84.
- Bandiera, Oriana and Imran Rasul, “Social networks and technology adoption in northern Mozambique,” *The Economic Journal*, 2006, 116 (514), 869–902.

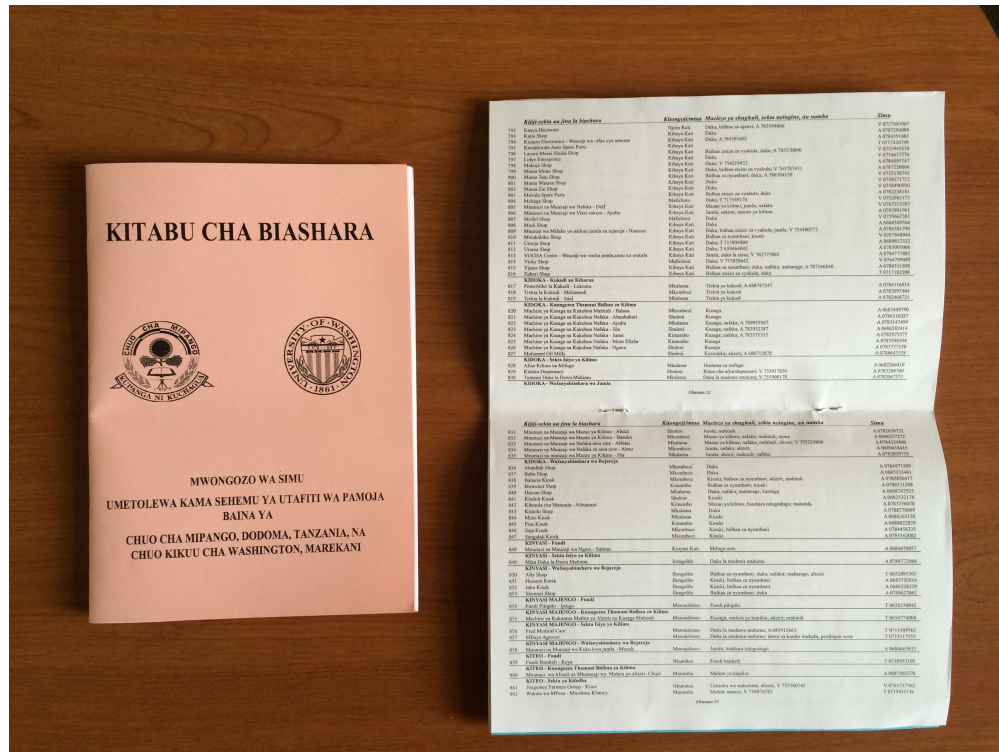
- , **Vittorio Bassi, Robin Burgess, Imran Rasul, Munshi Sulaiman, and Anna Vitali**, “The search for good jobs: evidence from a six-year field experiment in Uganda,” Technical Report, National Bureau of Economic Research 2023.
- Banerjee, Abhijit V and Esther Dufo**, “Reputation effects and the limits of contracting: A study of the Indian software industry,” *The Quarterly Journal of Economics*, 2000, *115* (3), 989–1017.
- Beaman, Lori and Andrew Dillon**, “Diffusion of agricultural information within social networks: Evidence on gender inequalities from Mali,” *Journal of Development Economics*, 2018, *133*, 147–161.
- , **Ariel BenYishay, Jeremy Magruder, and Ahmed Mushfiq Mobarak**, “Can network theory-based targeting increase technology adoption?,” *American Economic Review*, 2021, *111* (6), 1918–43.
- , **Jeremy Magruder, and Jonathan Robinson**, “Minding small change among small firms in Kenya,” *Journal of Development Economics*, 2014, *108*, 69–86.
- Beck, Thorsten and Asli Demirguc-Kunt**, “Small and medium-size enterprises: Access to finance as a growth constraint,” *Journal of Banking & Finance*, 2006, *30* (11), 2931–2943.
- BenYishay, Ariel and A Mushfiq Mobarak**, “Social learning and incentives for experimentation and communication,” *The Review of Economic Studies*, 2018, *86* (3), 976–1009.
- Bergquist, Lauren Falcao and Michael Dinerstein**, “Competition and entry in agricultural markets: Experimental evidence from Kenya,” *American Economic Review*, 2020, *110* (12), 3705–47.
- , **Craig McIntosh, and Meredith Startz**, *Search cost, intermediation, and trade: Experimental evidence from Ugandan agricultural markets*, eScholarship, University of California, 2021.
- Bloom, Nicholas, Benn Eifert, Aprajit Mahajan, David McKenzie, and John Roberts**, “Does management matter? Evidence from India,” *The Quarterly Journal of Economics*, 2013, *128* (1), 1–51.
- Brown, Martin, Armin Falk, and Ernst Fehr**, “Relational contracts and the nature of market interactions,” *Econometrica*, 2004, *72* (3), 747–780.
- Brunnermeier, Markus Konrad, Nicola Limodio, and Lorenzo Spadavecchia**, *Mobile Money, Interoperability and Financial Inclusion*, Centre for Economic Policy Research, 2023.
- Buntaine, Mark T, Ryan Jablonski, Daniel L Nielson, and Paula M Pickering**, “SMS texts on corruption help Ugandan voters hold elected councillors accountable at the polls,” *Proceedings of the National Academy of Sciences*, 2018, *115* (26), 6668–6673.

- Cai, Jing, Alain De Janvry, and Elisabeth Sadoulet**, “Social networks and the decision to insure,” *American Economic Journal: Applied Economics*, 2015, 7 (2), 81–108.
- Cameron, A Colin, Jonah B Gelbach, and Douglas L Miller**, “Bootstrap-based improvements for inference with clustered errors,” *The Review of Economics and Statistics*, 2008, 90 (3), 414–427.
- Casaburi, Lorenzo and Tristan Reed**, “Interlinked transactions and competition: Experimental evidence from cocoa markets,” 2019.
- Comin, Diego and Marti Mestieri**, “Technology diffusion: Measurement, causes, and consequences,” in “Handbook of economic growth,” Vol. 2, Elsevier, 2014, pp. 565–622.
- Comola, Margherita and Silvia Prina**, “Treatment effect accounting for network changes,” *Review of Economics and Statistics*, 2021, 103 (3), 597–604.
- Conley, Timothy G and Christopher R Udry**, “Learning about a new technology: Pineapple in Ghana,” *American economic review*, 2010, 100 (1), 35–69.
- Dillon, Brian and Chelsey Dambro**, “How competitive are crop markets in Sub-Saharan Africa?,” *American Journal of Agricultural Economics*, 2017, 99 (5), 1344–1361.
- Fabregas, R, M Kremer, M Lowes, R On, and G Zane**, “Digital information provision and behavior change: Lessons from six experiments in East Africa,” Technical Report, National Bureau of Economic Research 2024.
- Fafchamps, Marcel**, “Market institutions in sub-Saharan Africa,” 2004.
- **and Bart Minten**, “Impact of SMS-based agricultural information on Indian farmers,” *The World Bank Economic Review*, 2012, 26 (3), 383–414.
- Foster, Andrew D and Mark R Rosenzweig**, “Learning by doing and learning from others: Human capital and technical change in agriculture,” *Journal of political Economy*, 1995, 103 (6), 1176–1209.
- Ghani, Tarek and Tristan Reed**, “Relationships on the rocks: Contract evolution in a market for ice,” *American Economic Journal: Microeconomics*, 2022, 14 (1), 330–365.
- Goldfarb, Avi and Catherine Tucker**, “Digital economics,” *Journal of economic literature*, 2019, 57 (1), 3–43.
- Greif, Avner**, “Contract enforceability and economic institutions in early trade: The Maghribi traders’ coalition,” *The American economic review*, 1993, pp. 525–548.
- Grossman, Guy, Macartan Humphreys, and Gabriella Sacramone-Lutz**, “Information technology and political engagement: Mixed evidence from Uganda,” *The Journal of Politics*, 2020, 82 (4), 1321–1336.

- Hall, Charles S, Edward Fottrell, Sophia Wilkinson, and Peter Byass**, “Assessing the impact of mHealth interventions in low-and middle-income countries—what has been shown to work?,” *Global health action*, 2014, 7 (1), 25606.
- Hasanain, Syed Ali, Muhammad Yasir Khan, and Arman Rezaee**, “No bulls: Experimental evidence on the impact of veterinarian ratings in Pakistan,” *Journal of Development Economics*, 2023, 161, 102999.
- Hjort, Jonas and Jonas Poulsen**, “The arrival of fast internet and employment in Africa,” *American Economic Review*, 2019, 109 (3), 1032–1079.
- Jamison, Julian C, Dean Karlan, and Pia Raffler**, “Mixed method evaluation of a passive mHealth sexual information texting service in Uganda,” Technical Report, National Bureau of Economic Research 2013.
- Jensen, Robert**, “The digital divide: Information (technology), market performance, and welfare in the South Indian fisheries sector,” *The Quarterly Journal of Economics*, 2007, 122 (3), 879–924.
- **and Nolan H Miller**, “Market Integration, Demand, and the Growth of Firms: Evidence from a Natural Experiment in India,” *American Economic Review*, 2018, 108 (12), 3583–3625.
- Kondylis, Florence, Valerie Mueller, and Siyao Zhu**, *Seeing is believing? Evidence from an extension network experiment*, The World Bank, 2014.
- Macchiavello, Rocco and Ameet Morjaria**, “The value of relationships: evidence from a supply shock to Kenyan rose exports,” *American Economic Review*, 2015, 105 (9), 2911–45.
- Maertens, Annemie**, “Who cares what others think (or do)? Social learning and social pressures in cotton farming in India,” *American Journal of Agricultural Economics*, 2017, 99 (4), 988–1007.
- Magruder, Jeremy R**, “An assessment of experimental evidence on agricultural technology adoption in developing countries,” *Annual Review of Resource Economics*, 2018, 10, 299–316.
- Manacorda, Marco and Andrea Tesei**, “Liberation technology: Mobile phones and political mobilization in Africa,” *Econometrica*, 2020, 88 (2), 533–567.
- McKenzie, David**, “Beyond baseline and follow-up: The case for more T in experiments,” *Journal of Development Economics*, 2012, 99 (2), 210–221.
- Mel, Suresh De, David McKenzie, and Christopher Woodruff**, “Returns to capital in microenterprises: evidence from a field experiment,” *The quarterly journal of Economics*, 2008, 123 (4), 1329–1372.

- , —, and —, “One-time transfers of cash or capital have long-lasting effects on microenterprises in Sri Lanka,” *Science*, 2012, *335* (6071), 962–966.
- Morten, Melanie, Dean S Karlan, and Jonathan Zinman**, “A personal touch: Text messaging for loan repayment,” Technical Report 2012.
- Munshi, Kaivan**, “Social learning in a heterogeneous population: technology diffusion in the Indian Green Revolution,” *Journal of development Economics*, 2004, *73* (1), 185–213.
- Nakasone, Eduardo et al.**, “The role of price information in agricultural markets: Experimental evidence from rural Peru,” in “Annual Meeting of the Agricultural and Applied Economics Association, August” 2013, pp. 4–6.
- Rudder, Jessica and Brian Dillon**, “Search Costs and Relational Contracting: The Impact of a Digital Phonebook on Small Business Supply Chains,” 2023.
- Startz, Meredith**, “The value of face-to-face: Search and contracting problems in Nigerian trade,” *Available at SSRN 3096685*, 2018.
- Stigler, George J.**, “The Economics of Information,” *Journal of Political Economy*, 1961, *69* (3), 213–225.
- Sutton, John**, *Sunk costs and market structure: Price competition, advertising, and the evolution of concentration*, MIT press, 1991.

Figure 1: The *Kichabi* Directory



(a) The directory booklet

<i>Kijiji-sekta au jina la biashara</i>	<i>Kitongoji/mtaa</i>	<i>Maelezo ya shughuli, sekta nyingine, au namba nyingine</i>	<i>Namba ya simu</i>
Kavindi Supplier	Msikitini	Jumla; mazao ya kilimu	A 789032035
Mnunuzi na Muuzaji wa mihogo - Hija	Msikitini	Jumla; mazao ya biashara; mahindi	V 757517853
Subira Group - Wauzaji wa miche ya miti na asali	Msikitini	A 787158359	A 787456754
<i>MNENIA - Wafanyabiashara wa Rejareja</i>			
A Shop	Msikitini	Duka	T 652625962
Genge la Mariam	Msikitini	Biashara ndogodogo	T 714319223
Genge la Shangazi	Msikitini	Biashara ndogodogo	A 684319959
Kidisa Bustani	Msikitini	Sokoni	A 682264585
Maguo Shop	Msikitini	Duka; nafaka; A 783288699	T 717205419
Muuzaji wa Mbogamboga - Vudu	Msikitini	Biashara ndogodogo; viuongo; matunda	A 782776215
Salum Shop	Msikitini	Duka	A 787011534
Yusuf Spare Shop	Msikitini	Duka; T 719996930	T 715634797
<i>MONDO - Fundi</i>			
Fundi Cherehani - Jera	Araa Kati	Fundi cherehani	A 788610072
Fundi Cherehani - Mama Mchungaji	Araa Kati	Fundi cherehani; A 681323267	A 685698421
Fundi Cherehani - Mama Zahara	Araa Kati	Fundi cherehani; T 659921925	A 785521659

(b) Example directory entries

Notes: Panel A shows the front cover with the Swahili title “Kitabu Cha Biashara” (“business book”) alongside a page from the directory. Panel B shows a snapshot from the printed directory. The columns from left to right are the enterprise name, sub-village or neighborhood, description field that allows for differentiation and the listing of additional phone numbers, and the primary phone number with a letter code (A/T/V) to indicate the mobile network. The entries shown are a subset of those from the villages Mnenia and Mondo. The first three rows are wholesalers from Mnenia (carried over from the previous directory page). The middle group of entries are retailers in Mnenia, differentiated by the description field: *Sokoni* is “at the market,” *matunda* indicates a specialty in selling fruit, *Biashara ndogodogo* is a “small business,” likely a kiosk. The Mondo entries shown are all *Fundi*, skilled tradespeople, in subvillage Araa Kati. All three are tailors (*Fundi cherehani*).

Table 1: Communication-related effects of being listed in the directory

	——Direct effect——			——Spillover——				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Treat	<i>p</i> clust.	<i>p</i> WCB	Control	<i>p</i> clust.	<i>p</i> WCB	N	PC mean
A. All firms								
Total business calls	2.93**	0.01	0.03	1.67	0.34	0.36	1560	13.67
Incoming business calls	1.76	0.14	0.20	0.75	0.63	0.63	1558	11.57
Total business texts	1.15**	0.02	0.04	1.35**	0.02	0.03	825	1.69
Incoming business texts	0.53*	0.05	0.10	0.65*	0.03	0.07	807	1.00
B. Phone history verified								
Total business calls	3.94***	0.00	0.01	1.27	0.35	0.36	1225	13.19
Incoming business calls	2.64*	0.01	0.05	0.63	0.61	0.57	1223	11.04
Total business texts	1.38**	0.00	0.03	1.02**	0.02	0.04	648	1.73
Incoming business texts	0.65*	0.01	0.07	0.50	0.06	0.11	640	1.02
C. By sector (marginal effects)								
<u>Retail</u>								
Total business calls	4.16*	0.01	0.08	1.67	0.45	0.51		
Incoming business calls	2.90	0.03	0.11	1.01	0.57	0.60		
Total business texts	1.42*	0.02	0.09	2.00**	0.01	0.04		
Incoming business texts	0.65	0.07	0.17	0.87	0.03	0.10		
<u>Non-retail</u>								
Total business calls	1.72	0.29	0.23	1.62	0.45	0.40	1560	13.67
Incoming business calls	0.66	0.68	0.68	0.47	0.82	0.74	1558	11.57
Total business texts	0.96	0.20	0.21	0.77	0.33	0.36	825	1.69
Incoming business texts	0.46	0.22	0.22	0.49	0.26	0.25	807	1.00

Notes: All regressions include fixed effects for survey round, randomization strata, and the baseline value of the dependent variable. Sample size varies across regressions because (i) phone call outcomes were measured four times post-treatment, while other outcomes were measured only twice post-treatment, and (ii) rates of non-response or "I don't know" varied across questions. Total business calls is the sum of incoming and outgoing business calls, as well as missed calls (which are used as a way to request a call back from the business). Panel B is based on the 80% of the sample that allowed enumerators to confirm calls by looking through the phone history together. Panel C marginal effects are based on a single set of regressions with interactions for the retail sector. In Panel C, daggers based on the wild cluster bootstrap indicate whether estimated effects are significantly different between retail and non-retail firms: † † †: significant at 1%; ††: significant at 5%; †: significant at 10%. *p*-values in columns 2 and 5 are based on standard errors clustered at the village level. *p*-values in columns 3 and 6 are based on the wild cluster bootstrap of [Cameron et al. \(2008\)](#), where the cluster is the village (49 total clusters). Significance stars based on WCB *p*-values. ***: significant at 1%; **: significant at 5%; *: significant at 10%.

Table 2: Business effects of being listed in the directory

Dependent variable	—Direct effect—			—Spillover—			(7) N	(8) PC mean
	(1) Treat	(2) <i>p</i> clust.	(3) <i>p</i> WCB	(4) Control	(5) <i>p</i> clust.	(6) <i>p</i> WCB		
A. All firms								
Use mobile money (=1)	0.16**	0.00	0.04	0.15**	0.01	0.04	641	0.57
Firm has employees (=1)	-0.00	0.99	0.98	-0.01	0.93	0.95	642	0.37
Number of employees	-0.31	0.21	0.36	-0.21	0.45	0.56	642	1.27
Number of sales, last week	4.94**	0.00	0.04	4.26*	0.06	0.09	523	10.61
Sales revenues (TSH)	137936**	0.01	0.03	177293**	0.02	0.03	580	132998
Number of business purchases	1.27	0.28	0.40	0.83	0.44	0.49	641	1.21
B. Phone history verified								
Use mobile money (=1)	0.18**	0.00	0.03	0.14**	0.01	0.05	520	0.58
Firm has employees (=1)	0.03	0.69	0.78	-0.01	0.88	0.91	521	0.35
Number of employees	-0.18	0.44	0.49	-0.27	0.33	0.42	521	1.08
Number of sales, last week	4.33**	0.01	0.04	2.51	0.34	0.37	421	10.66
Sales revenues (TSH)	147993**	0.01	0.01	155377	0.07	0.13	474	130736
Number of business purchases	1.58	0.30	0.42	1.16	0.40	0.36	520	1.27
C. By sector (marginal effects)								
<u>Retail</u>								
Use mobile money (=1)	0.24	0.00	0.14	0.23	0.01	0.14		
Firm has employees (=1)	0.07	0.37	0.45	0.08	0.40	0.48		
Number of employees	0.10	0.82	0.84	0.29	0.52	0.57		
Number of sales, last week	9.79	0.01	0.12	10.39	0.02	0.12		
Sales revenues (TSH)	204440**,†	0.00	0.02	245712**	0.00	0.04		
Number of business purchases	1.36	0.10	0.15	0.81	0.17	0.14		
<u>Non-retail</u>								
Use mobile money (=1)	0.10	0.20	0.21	0.09	0.32	0.33	641	0.57
Firm has employees (=1)	-0.01	0.89	0.90	-0.05	0.52	0.60	642	0.37
Number of employees	-0.45	0.33	0.50	-0.51	0.31	0.58	642	1.27
Number of sales, last week	-0.85	0.76	0.78	-2.38	0.54	0.56	523	10.61
Sales revenues (TSH)	64910	0.24	0.30	105491	0.20	0.22	580	132998
Number of business purchases	0.90	0.53	0.58	0.66	0.64	0.65	641	1.21

Notes: All regressions include fixed effects for survey round, randomization strata, and the baseline value of the dependent variable. Sample size varies across regressions because rates of non-response or "I don't know" varied across questions. Panel B is based on the 80% of the sample that allowed enumerators to confirm calls by looking through the phone history together. Panel C marginal effects are based on a single set of regressions with interactions for the retail sector. In Panel C, daggers indicate whether estimated effects are significantly different between retail and non-retail firms: †††: significant at 1%; ††: significant at 5%; †: significant at 10%. *p*-values in columns 2 and 5 are based on standard errors clustered at the village level. *p*-values in columns 3 and 6 are based on the wild cluster bootstrap of Cameron et al. (2008), where the cluster is the village (49 total clusters). Significance stars based on WCB *p*-values. ***: significant at 1%; **: significant at 5%; *: significant at 10%.

Table 3: Heterogeneity by whether directories distributed in same village

Dependent variable	—Direct effect—			—Spillover—			(7) N	(8) PC mean
	(1) Treat	(2) <i>p</i> clust.	(3) <i>p</i> WCB	(4) Control	(5) <i>p</i> clust.	(6) <i>p</i> WCB		
A. Areas where directory was distributed (marginal effects)								
Total business calls	2.64*	0.06	0.07	3.03	0.14	0.17		
Incoming business calls	1.53	0.24	0.27	1.87	0.31	0.34		
Total business texts	1.36**	0.01	0.04	1.35**	0.04	0.03		
Incoming business texts	0.65*	0.04	0.08	0.68*	0.07	0.09		
Use mobile money (=1)	0.18**	0.00	0.04	0.17**	0.01	0.02		
Firm has employees (=1)	-0.02	0.81	0.87	0.02	0.75	0.69		
Number of employees	-0.36	0.14	0.31	-0.19	0.50	0.58		
Number of sales, last week	5.71*	0.01	0.05	3.75	0.18	0.20		
Sales revenues (TSH)	135077**	0.02	0.04	200400*	0.06	0.08		
Number of business purchases	1.02	0.31	0.32	0.76	0.44	0.48		
B. Areas where directory was <i>not</i> distributed (marginal effects)								
Total business calls	3.68*	0.03	0.07	-0.47	0.80	0.84	1560	13.67
Incoming business calls	2.41	0.12	0.17	-1.01	0.52	0.59	1558	11.57
Total business texts	0.73	0.19	0.20	1.37**	0.01	0.02	825	1.69
Incoming business texts	0.30	0.35	0.34	0.63*	0.05	0.08	807	1.00
Use mobile money (=1)	0.14**	0.01	0.04	0.11	0.14	0.16	641	0.57
Firm has employees (=1)	0.03	0.62	0.67	-0.05	0.59	0.66	642	0.37
Number of employees	-0.21	0.44	0.48	-0.24	0.45	0.51	642	1.27
Number of sales, last week	3.27	0.29	0.33	5.05*	0.08	0.08	523	10.61
Sales revenues (TSH)	149404*	0.04	0.10	146141	0.05	0.13	580	132998
Number of business purchases	1.76	0.24	0.43	0.93	0.43	0.45	641	1.21

Notes: All regressions include fixed effects for survey round, randomization strata, and the baseline value of the dependent variable. Sample size varies across regressions because (i) phone call outcomes were measured four times post-treatment, while other outcomes were measured only twice post-treatment, and (ii) rates of non-response or "I don't know" varied across questions. Total business calls is the sum of incoming and outgoing business calls, as well as missed calls (which are used as a way to request a call back from the business). Marginal effects are based on a single set of regressions with interactions for whether the village was randomly assigned to the household treatment (distribution of directories to households). Daggers indicate whether estimated effects are significantly different between distribution village and non-distribution village firms: † † †: significant at 1%; ††: significant at 5%; †: significant at 10%. *p*-values in columns 2 and 5 are based on standard errors clustered at the village level. *p*-values in columns 3 and 6 are based on the wild cluster bootstrap of [Cameron et al. \(2008\)](#), where the cluster is the village (49 total clusters). ***: significant at 1%; **: significant at 5%; *: significant at 10%.

Table 4: Heterogeneity by baseline labor productivity

Dependent variable	——Direct effect——			——Spillover——			(7) N	(8) PC mean
	(1) Treat	(2) <i>p</i> clust.	(3) <i>p</i> WCB	(4) Control	(5) <i>p</i> clust.	(6) <i>p</i> WCB		
A. Above median labor productivity at baseline (marginal effects)								
Total business calls	4.18*	0.01	0.05	3.38	0.11	0.15		
Incoming business calls	2.43	0.13	0.17	1.78	0.35	0.41		
Total business texts	1.96**,†	0.00	0.04	2.47***	0.00	0.00		
Incoming business texts	0.85*	0.01	0.06	1.20**	0.00	0.02		
Use mobile money (=1)	0.28**	0.00	0.04	0.30**	0.00	0.03		
Firm has employees (=1)	-0.02	0.89	0.93	-0.06	0.62	0.64		
Number of employees	0.23	0.45	0.48	0.43	0.22	0.28		
Number of sales, last week	10.30**,†	0.00	0.04	10.60*	0.03	0.07		
Sales revenues (TSH)	164966*	0.04	0.06	305917**	0.00	0.01		
Number of business purchases	1.68	0.28	0.37	1.19	0.36	0.32		
B. Below median labor productivity at baseline (marginal effects)								
Total business calls	2.61	0.16	0.20	1.65	0.48	0.44	1440	13.36
Incoming business calls	2.00	0.19	0.26	1.14	0.56	0.51	1438	11.39
Total business texts	0.60	0.30	0.25	1.13	0.18	0.19	758	1.45
Incoming business texts	0.48	0.15	0.16	0.69	0.10	0.14	742	0.85
Use mobile money (=1)	0.09	0.32	0.29	0.05	0.63	0.59	579	0.52
Firm has employees (=1)	0.01	0.96	0.96	0.03	0.81	0.80	580	0.37
Number of employees	-0.42	0.21	0.36	-0.34	0.31	0.48	580	0.89
Number of sales, last week	-1.08	0.74	0.75	-1.09	0.79	0.79	471	9.27
Sales revenues (TSH)	131023*	0.01	0.08	71209	0.26	0.28	525	120743
Number of business purchases	1.90	0.13	0.10	1.68	0.20	0.10	579	0.97

Notes: All regressions include fixed effects for survey round, randomization strata, and the baseline value of the dependent variable. Sample size varies across regressions because (i) phone call outcomes were measured four times post-treatment, while other outcomes were measured only twice post-treatment, and (ii) rates of non-response or "I don't know" varied across questions. Total business calls is the sum of incoming and outgoing business calls, as well as missed calls (which are used as a way to request a call back from the business). Marginal effects are based on a single set of regressions with interactions for whether the firms was above median labor productivity at baseline, where labor productivity is defined as sales revenue divided by the number of workers. Daggers indicate whether estimated effects are significantly different between above median and below median productivity firms: † † †: significant at 1%; ††: significant at 5%; †: significant at 10%. *p*-values in columns 2 and 5 are based on standard errors clustered at the village level. *p*-values in columns 3 and 6 are based on the wild cluster bootstrap of [Cameron et al. \(2008\)](#), where the cluster is the village (49 total clusters). ***: significant at 1%; **: significant at 5%; *: significant at 10%.

Appendices – For Online Publication Only

A1. Ethical Considerations

Throughout the study we were worried about the possibility of negative spillovers, if benefits to enterprises listed in the directory came at the expense of their unlisted competitors. It was not *ex ante* obvious that such spillovers would occur, or that the directory would have effects. Recipients had to trust the directory, and use it sufficiently to influence enterprise outcomes, neither of which was assured. Nonetheless, we took numerous steps to mitigate any potential negative spillovers.

First, we created a pure control group to allow us to measure within-village spillovers. Second, we made the treatment group substantially larger than the control group, sacrificing some statistical power in order to minimize the number of potentially disadvantaged firms. Third, we broke the experiment after one year, and distributed thousands of complete directories that listed every enterprise. We did not attempt to remove the experimental directories from the study communities, as that would have been logistically infeasible. However, we distributed approximately twice as many complete directories as experimental directories.

This study was reviewed and approved by the Institutional Review Board of the University of Washington, application number 47445-EC. This study was also reviewed and approved by the director of research and the rector (equivalent to president) of the Institute of Rural Development Planning (IRDP) in Tanzania, our partner organization. At the time of this project, IRDP had standing permission to review and approve social science research in Tanzania.

A2. Study Area and Enterprise Census

Figure A1 shows the study area, with the census towns and villages marked. Dodoma, in the southwest corner, is the capital of Tanzania and the largest city in the study. Other large towns include Kondoa, in the northwest; Kibaya, in the northeast; and Babati. Most study villages are located in the roughly 5,000 square mile area that is covered by the markers indicating census towns and villages. This is a region of semi-arid plains, with some lightly forested areas. There is one rainy season, from January to May. Planting takes place from December to early February, and harvest is from May to July. Maize and sunflower are the primary crops, and many households plant additional crops such as beans, cassava, or potatoes.

A3. Definitions of Outcome Variables

The definitions of the outcome variables in our analysis are as follows. We winsorize the 1% tails of all continuous variables.

Total business calls: The sum of the number of business calls received, number of business calls made, and number of missed calls, during the previous two operating days. Missed calls in this context are used as a way to request a call-back from a business. The recall period for these variables was one week during the baseline survey, but was shortened to reduce measurement error (see the discussion in McKenzie (2012) regarding the robustness of ANCOVA estimation to changes in the variable definition between baseline and follow-up).

Incoming business calls: The number of incoming business-related calls during the previous two operating days.

Total business texts: The sum of the number of business text messages received and the number of business text messages sent, during the previous two operating days.

Incoming business texts: The number of incoming business-related calls during the previous two operating days.

Uses mobile money: A binary variable that takes a value of 1 if the enterprise sent or received payments via mobile money during the previous month, and 0 otherwise.

Employs any workers: A binary variable that takes a value of 1 if the enterprise employs any workers other than the owner, and 0 otherwise.

Number of workers: The sum of the number of non-family permanent (full-time) employees, non-family temporary (part-time) employees, and the number of family members that work at the business (with or without being paid), excluding the owner.

Number of sales: The number of sales transactions completed in the previous two operating days.

Sales revenue: The total value in Tanzania shillings of sales made in the previous two operating days.

Number of business purchases: The total number of purchase transactions completed in the previous two operating days.

A4. Directory Recipient Experiment

A4.1 Design

To choose villages for directory distribution, we stratified by ward and village size and randomly selected one village from each of the 47 stratum.¹² The 47 distribution villages were the treatment villages for the household/recipient RCT. In each treatment village we held a

¹²We did not distribute directories in the two cities, because we targeted farmers in rural areas.

community meeting in Dec. 2014 - Jan. 2015, advertised in advance as relevant to farming and promoted by community leaders. During the meeting we introduced the directory and answered questions. We then gave a directory to 70 randomly selected attendants, for a total of 3,290 experimental directories.¹³

To create a recipient control group, we held an identical set of meetings in July–August 2015, in 34 villages randomly selected from the same strata used to choose treatment villages. The staggered recruitment ensured that the treatment villages received the directory prior to the 2015 cultivation season, while the control villages received it afterwards.¹⁴ Treatment and control households were interviewed at the same time, at the end of the harvest period (approximately 8 months after the distribution of directories).

A4.2 Household Survey

To choose a sample of directory recipients for surveying, we randomly selected 36 treatment and 34 control villages (stratifying on ward and village size), and then randomly selected 12 out of the 70 directory recipients in each village to survey. Recipient surveys were conducted in July–August 2015. Surveys in control and treatment villages within a stratum were conducted at the same time. We successfully interviewed 831 out of 840 selected respondents (423 treatment, 408 control).

In addition to basic descriptive variables, the survey focused on primary outcomes related to using a mobile phone for search and contacting enterprises, and secondary outcomes related to input use, production, crop sales, and household enterprises. Households characteristics are similar across treatment and control, with the exceptions of slight imbalance on gender and years in the village. Importantly for a directory intervention, literacy rates are

¹³In the few cases where the meeting was attended by fewer than 70 people, we asked subvillage representatives to deliver the remaining booklets to other community members.

¹⁴We recruited treatment and control households at different times for two reasons. The first was a binding budget constraint. The second is that we worried about attrition / frustration in the control group if we held village meetings to introduce the directory at the start of the season, but did not deliver the directories until almost a year later. Our decision to break the experiment after one season and distribute a complete version of the directory created an opportunity for us to enroll control households in a manner identical to how we enrolled treatment households.

high among recipients: 92 percent of respondents can read Swahili. Among the households where the head cannot read Swahili, there are only 16 households in which no one can read Swahili. These literacy rates are similar to those from nationally representative surveys of Tanzanian households.

A4.3 Estimating Effects on Households

Impacts on outcomes for directory recipients are estimated using the recipient survey data and the following OLS specification:

$$Outcome_{js} = \delta_0 + \delta_1 Treatment_v + \phi_s + \epsilon_{js} \quad (2)$$

where $Outcome_{js}$ is the value of the outcome for household j in stratum s ; ϕ_s is a set of strata dummy variables; and ϵ_{js} is a statistical error term. Because non-compliance is a possibility, the estimate of $\hat{\delta}_1$ from specification (2) is the intent-to-treat (ITT) effect of the directory for the population of rural households who would attend a community meeting to learn about an information service for farming households.

We estimate (2) for two types of household outcomes. The first are communication outcomes related to phones or other linkages outside the village. The second category includes agricultural choices, agricultural outcomes, and outcomes related to non-farm enterprises, all of which may be affected by the realized or expected change in search and communication costs facilitated by the *Kichabi*. We report standard errors clustered at the level of treatment assignment (Abadie et al., 2017).

A4.4 Results for Directory Recipients

General Communication Outcomes. Over the study period, 27% of recipients reported contacting one or more enterprises in the directory. The average number of calls to directory enterprises, among the callers, was 1.65. Almost three quarters of recipients reported sharing

the directory with members of their household, and 43% reported sharing it with at least one person outside the household.

Estimated effects of receiving a directory on communication behaviors are reported in Panel A of Table A6. There is no extensive margin effect on the likelihood of making at least one call, because there is almost no variation—96% of control respondents made a phone call during the last two weeks. However, treated recipients spent 848 TSH (21%) more on phone credit over the previous two weeks, indicating that they made more calls (phone users were on pay-as-you-go plans during the study period, so spending on phone credit is a proxy for making calls).

Treatment led to a 9 percentage point (15%) increase in the likelihood of sending an SMS message, an increase of 51 stored phone contacts (37%), a 6 percentage point (18%) increase in the likelihood of receiving a mobile money transfer, an 11 percentage point (33%) increase in the probability of sending mobile money, a 5 percentage point (20%) increase in the likelihood of ordering goods for delivery from outside the village, and a 7 percentage point (40%) increase in the likelihood of using the phone to coordinate the delivery of goods ordered from outside. There are no impacts on the probability of receiving calls or SMS messages. Overall, the breadth and variety of positive, significant effects suggests substantial pent-up demand for information and communication beyond current networks.

Crop-related Search Outcomes. Panel B of Table A6 reports the effects of receiving a directory on search and communication related to crop production. Most of the variables in this panel were only collected for maize and sunflower, the dominant local crops. The first row indicates that directory recipients were 11 percentage points (37%) more likely to use their phone for crop-related activities; the outcome in this regression is an index equal to 1 if the farmer used the phone for any crop activity. Subsequent rows show effects on specific crop-related activities. Recipients were significantly more likely to use their phones to search for inputs (10 percentage points; 76% more likely), acquire those inputs (9 p.p.;

53%), coordinate with buyers (5 p.p.; 105%), seek agricultural advice (4 p.p.; 44%), and search for output prices, conditional on conducting any output price search (11 p.p.; 67%). These effects remain statistically significant after corrections for multiple hypothesis testing.

We find no effects on the intensity or location of search for inputs. This is not surprising given that most inputs are sourced in the village. While there was no effect on the likelihood of searching output prices overall, treated households were 14 percentage points (28%) more likely to search crop prices outside their villages (conditional on searching). This is a key pathway through which the directory could increase the prices farmers receive for their output.

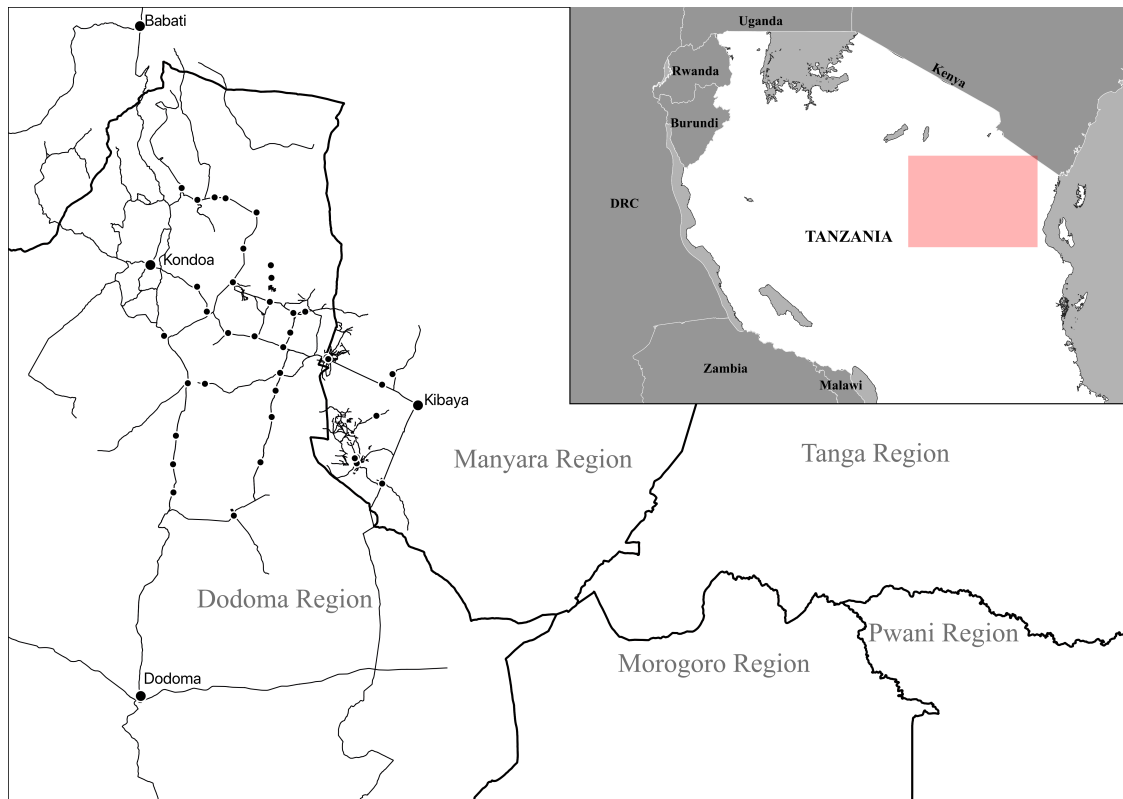
Effects on Crop Inputs, Outputs, and Prices. Panel C of Table A6 reports ITT effects on crop inputs, outputs, prices, and values. We find no significant effects on using tractors or animals, or purchasing seeds. There is little room for increased usage in some of these inputs: 91% of control households used tractors or plow animals, and 92% purchased seeds. On the extensive margin, treated households were 4 percentage points (26%) more likely to rent land, and 12 percentage points (24%) more likely to hire pre-harvest labor. Treated households spent less than control households on land rental (-25%), possibly because the marginal rentals induced by treatment occurred during the replanting period when demand and prices were lower than usual.

The study area was hit by a severe drought during the planting period, which continued through the growing season. Yields were low across the region. We find a positive but imprecise effect on maize yields among those who had completed their harvest. However, treated households were seven percentage points (27%) less likely to report a maize crop failure, 6 percentage points (114%) more likely to report that their maize harvest is ongoing, and 4 percentage points (55%) more likely to hire harvest labor, which is a proxy for output. It seems that we may have found a more precise, positive effect on maize yields had we conducted the survey after all harvesting was complete. Estimated effects on sunflower

point in the same directions as those for maize, but are statistically imprecise.

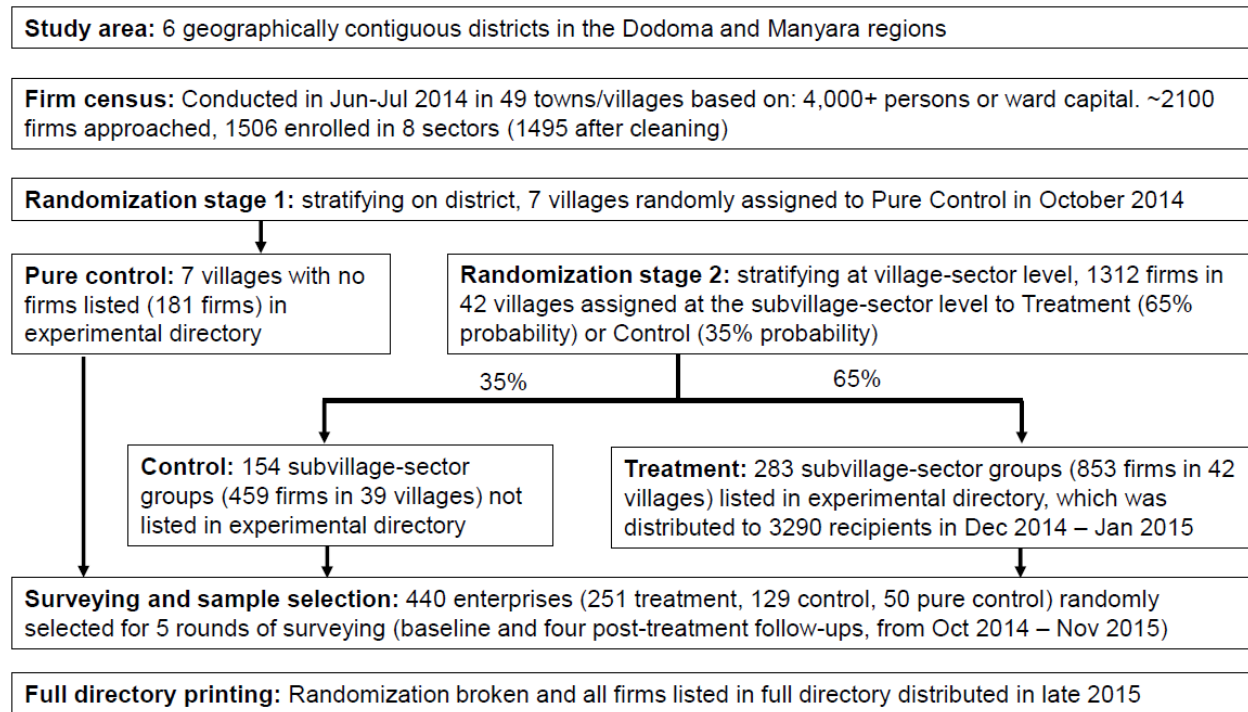
To analyze effects on the prices received, we pool maize and sunflower sales and regress the log price received on controls for crop-by-unit fixed effects and strata fixed effects. Receipt of the directory had a positive but marginally imprecise effect on the price received for crops. The point estimate indicates 7% higher prices for treated recipients, with a p -value of 0.102. This finding is based on an unexpectedly small number of sales. Because of the drought and generally low production volumes, only 271 sales resulted from 1,427 plantings of maize and sunflower. We expected 3-4 times as many sales based on other agricultural survey data from Tanzania. Hence, while we do find substantial impacts on searching prices by phone and searching prices outside the village, we do not know whether in a more typical year the impact on prices would have been more precise.

Figure A1: Map of Study Area



Notes: Inset map shows Tanzania with the enlarged area highlighted. In the enlargement, markers indicate the locations of towns and villages that contain enterprises listed in the directory, with the four larger cities labeled.

Figure A2: Design of Firm Randomization



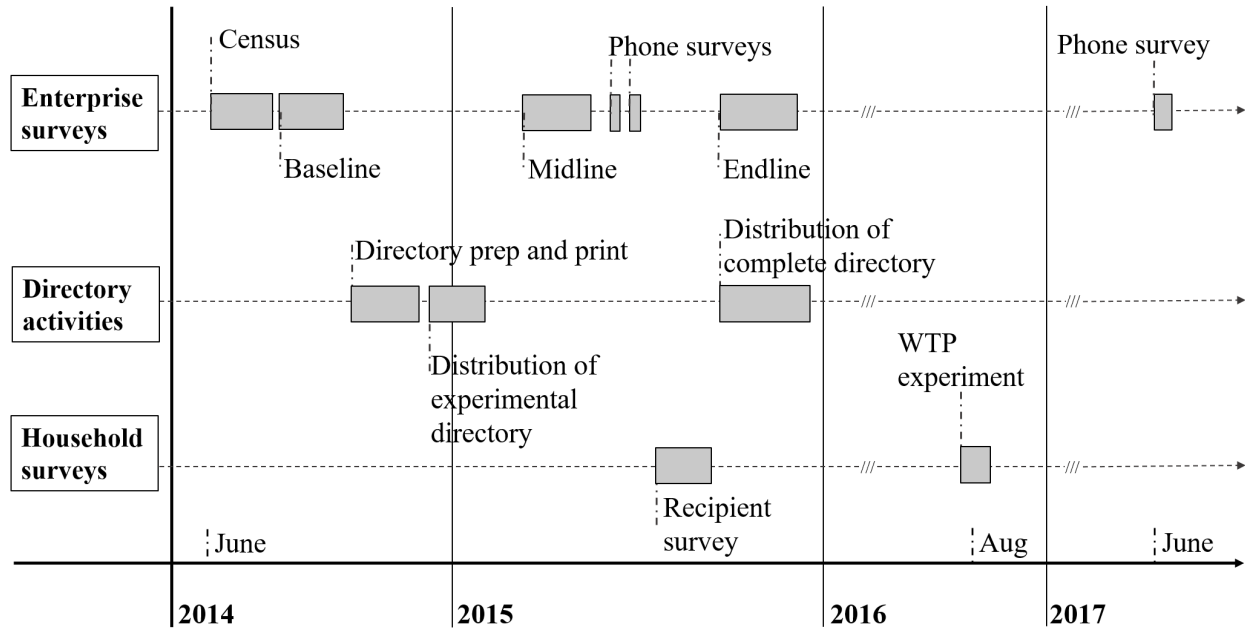
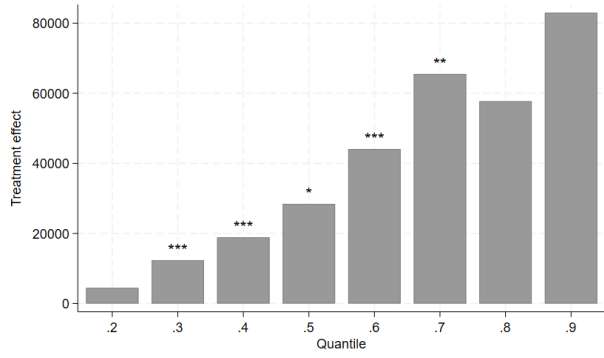
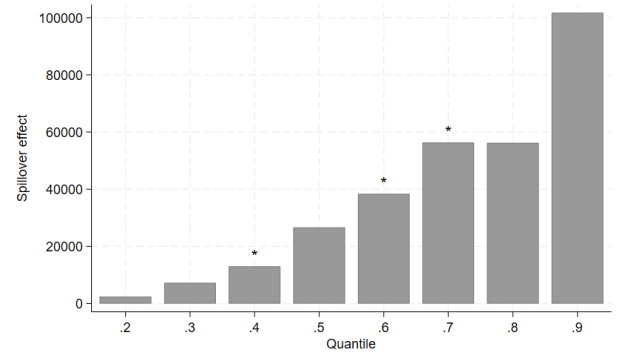


Figure A3: Timeline of the *Kichabi* Telephone Directory Experiment

Notes: This figure shows a timeline for the primary *Kichabi* activities. The agricultural cultivation season runs from roughly January to May. Planting can occur as early as December, and continue through February. Harvest typically occurs in May–July.



A. Direct effects on listed firms



B. Within-village spillover effects

Figure A4: A. Direct and Spillover Quantile Treatment Effects

Notes: Vertical bars indicate the magnitudes of estimated treatment effects from quantile regressions. The dependent variable is sales revenue over the previous two operating days in Tanzania shillings (the USD exchange rate was roughly 2000 TSH per dollar at the time of data collection). Significance stars based on robust standard errors. ***: significant at 1%; **: significant at 5%; *: significant at 10%.

Table A1: Summary Statistics and Treatment Balance

	Treatment (1)	Control (2)	Pure Control (3)	N (4)	<i>p</i> -value (5)
Interviewee is male (=1)	0.83	0.83	0.88	440	0.18
Interviewee age	38.16	38.10	39.66	440	0.17
Interviewee is owner (=1)	0.91	0.87	0.86	440	0.79
Single owner, is male (=1)	0.80	0.76	0.88	440	0.02**
Mobile business (=1)	0.15	0.17	0.12	440	0.61
Business based at home (=1)	0.22	0.22	0.14	440	0.82
Electricity access (=1)	0.74	0.76	0.80	440	0.85
Days open per week	6.28	6.17	6.12	438	0.26
Family workers in last week (=1)	0.34	0.31	0.24	440	0.31
Num. family workers	0.53	0.50	0.44	440	0.69
Permanent workers in last week (=1)	0.18	0.21	0.28	440	0.63
Num. permanent workers	0.35	0.38	0.56	440	0.57
Temporary workers in last week (=1)	0.18	0.22	0.30	440	0.07*
Num. temporary workers	0.58	0.71	0.88	439	0.45
Number of sales, last week	20.48	16.83	16.77	401	0.23
Made sales on credit, last week (=1)	0.41	0.41	0.42	440	0.88
Number of business purchases, last week	1.13	2.96	3.89	426	0.10
Sales revenue, last two days	1.7e+05	2.5e+05	3.8e+05	422	0.58
Number of contacts in phone	179.35	190.09	187.83	410	0.58
Business calls received, last week	6.37	5.86	10.35	384	0.09*
Business calls made, last week	6.33	6.48	10.95	380	0.24
Business texts received, last week	1.85	1.87	3.35	338	0.43
Business texts sent, last week	1.71	1.85	4.03	326	0.58
Phone accesses internet (=1)	0.18	0.21	0.14	440	0.64
Use internet for business (=1)	0.09	0.10	0.08	440	0.73
Mobile money incoming, last week (=1)	0.34	0.45	0.36	440	0.57
Mobile money outgoing, last week (=1)	0.29	0.35	0.42	440	0.65

Notes: Columns (1)-(3) are subsample means. Column (5) reports the *p*-values on a joint test of significance of Treatment and Control dummy variables in regressions of each variable on a those dummy variables and district-sector fixed effects. Standard errors clustered at the level of treatment assignment (village, 49 clusters), adjusted using the bias reduced linearization estimator of (?). This approach to inference is conservative, in that it can in some cases over-reject at an expected rate greater than that of the wild cluster bootstrap. For the four communication outcomes in the lowest section of Panel A with the lowest response rates, almost all of the non-responses are coded as “Not applicable (NA).” The “NA” response rates are similar for across treatment groups, and the implications for balance are the same if we recode “NA” as 0.

Table A2: Robustness: controlling for two variables that exhibit baseline imbalance

Dependent variable	—Direct effect—			—Spillover—			(7) N	(8) PC mean
	(1) Treat	(2) <i>p</i> clust.	(3) <i>p</i> WCB	(4) Control	(5) <i>p</i> clust.	(6) <i>p</i> WCB		
Total business calls	3.60**	0.01	0.03	2.19	0.25	0.30	1495	13.35
Incoming business calls	2.31	0.08	0.18	1.11	0.52	0.55	1493	11.34
Total business texts	1.35**	0.01	0.04	1.66**	0.01	0.02	790	1.57
Incoming business texts	0.66*	0.03	0.08	0.84**	0.02	0.04	772	0.92
Use mobile money (=1)	0.19**	0.00	0.04	0.17**	0.01	0.04	608	0.56
Firm has employees (=1)	0.02	0.81	0.81	0.02	0.83	0.80	609	0.37
Number of employees	-0.02	0.93	0.93	0.13	0.59	0.58	609	0.97
Number of sales, last week	4.46*	0.02	0.06	3.41	0.17	0.18	496	10.71
Sales revenues (TSH)	203705**	0.00	0.02	233522**	0.01	0.02	550	128465
Number of business purchases	1.90	0.13	0.16	1.42	0.21	0.25	608	0.87

Notes: All regressions include fixed effects for survey round, randomization strata, the baseline value of the dependent variable, and the three variables exhibiting some baseline imbalance at 90% confidence (number of temporary workers, whether the owner is male conditional on there being a single owner, and number of incoming business calls). Sample size varies across regressions because (i) phone call outcomes were measured four times post-treatment, while other outcomes were measured only twice post-treatment, and (ii) rates of non-response or "I don't know" varied across questions. Total business calls is the sum of incoming and outgoing business calls, as well as missed calls (which are used as a way to request a call back from the business). *p*-values in columns 2 and 5 are based on standard errors clustered at the village level. *p*-values in columns 3 and 6 are based on the wild cluster bootstrap of [Cameron et al. \(2008\)](#), where the cluster is the village (49 total clusters). Significance stars based on WCB *p*-values. ***: significant at 1%; **: significant at 5%; *: significant at 10%.

Table A3: Robustness: Controlling for Survey Date

Dependent variable	—Direct effect—			—Spillover—			(7) N	(8) PC mean
	(1) Treat	(2) <i>p</i> clust.	(3) <i>p</i> WCB	(4) Control	(5) <i>p</i> clust.	(6) <i>p</i> WCB		
Total business calls	2.78**	0.02	0.03	1.47	0.41	0.42	1560	13.67
Incoming business calls	1.68	0.17	0.22	0.64	0.69	0.67	1558	11.57
Total business texts	1.12*	0.02	0.05	1.29**	0.02	0.04	825	1.69
Incoming business texts	0.51	0.06	0.10	0.61*	0.05	0.09	807	1.00
Use mobile money (=1)	0.17**	0.00	0.04	0.15**	0.01	0.04	641	0.57
Firm has employees (=1)	-0.00	0.95	0.98	-0.01	0.88	0.92	642	0.37
Number of employees	-0.32	0.19	0.35	-0.23	0.42	0.55	642	1.27
Number of sales, last week	4.44**	0.00	0.04	3.71	0.08	0.12	523	10.61
Sales revenues (TSH)	135056**	0.01	0.03	173196**	0.02	0.04	580	132998
Number of business purchases	1.28	0.29	0.40	0.84	0.44	0.51	641	1.21

Notes: All regressions include fixed effects for survey round, randomization strata, the baseline value of the dependent variable, and the date of the survey. Sample size varies across regressions because (i) phone call outcomes were measured four times post-treatment, while other outcomes were measured only twice post-treatment, and (ii) rates of non-response or "I don't know" varied across questions. Total business calls is the sum of incoming and outgoing business calls, as well as missed calls (which are used as a way to request a call back from the business). *p*-values in columns 2 and 5 are based on standard errors clustered at the village level. *p*-values in columns 3 and 6 are based on the wild cluster bootstrap of [Cameron et al. \(2008\)](#), where the cluster is the village (49 total clusters). Significance stars based on WCB *p*-values. ***: significant at 1%; **: significant at 5%; *: significant at 10%.

Table A4: Effects of Any Treatment Exposure (Direct or Spillover)

Dependent variable	(1) Any Exposure	(2) p clust.	(3) p WCB	(4) N	(5) PC mean
Total business calls	2.58*	0.04	0.06	1560	13.67
Incoming business calls	1.48	0.23	0.30	1558	11.57
Total business texts	1.21**	0.01	0.04	825	1.69
Incoming business texts	0.57*	0.04	0.09	807	1.00
Use mobile money (=1)	0.16**	0.00	0.04	641	0.57
Firm has employees (=1)	-0.00	0.97	0.99	642	0.37
Number of employees	-0.28	0.28	0.41	642	1.27
Number of sales, last week	4.73**	0.00	0.03	523	10.61
Sales revenues (TSH)	150300**	0.01	0.04	580	132998
Number of business purchases	1.14	0.32	0.42	641	1.21

Notes: All regressions include fixed effects for survey round, randomization strata, and the baseline value of the dependent variable. Sample size varies across regressions because (i) phone call outcomes were measured four times post-treatment, while other outcomes were measured only twice post-treatment, and (ii) rates of non-response or "I don't know" varied across questions. Total business calls is the sum of incoming and outgoing business calls, as well as missed calls (which are used as a way to request a call back from the business). p -values in columns 2 and 5 are based on standard errors clustered at the village level. p -values in columns 3 and 6 are based on the wild cluster bootstrap of [Cameron et al. \(2008\)](#), where the cluster is the village (49 total clusters). Significance stars based on WCB p -values. ***: significant at 1%; **: significant at 5%; *: significant at 10%.

Table A5: Heterogeneity by whether firm is listed first in its directory subsection

Dependent variable	Direct effects						Spillover			(10) N	(11) PC mean
	(1) Treat, not first	(2) <i>p</i> clust.	(3) <i>p</i> WCB	(4) Treat, first	(5) <i>p</i> clust.	(6) <i>p</i> WCB	(7) Control	(8) <i>p</i> clust.	(9) <i>p</i> WCB		
Total business calls	3.77**	0.00	0.02	1.03	0.43	0.40	1.54	0.38	0.38	1560	13.67
Incoming business calls	2.37	0.05	0.11	0.35	0.78	0.72	0.65	0.68	0.67	1558	11.57
Total business texts	1.32**	0.01	0.03	0.74	0.22	0.20	1.32**	0.02	0.04	825	1.69
Incoming business texts	0.61*	0.03	0.07	0.32	0.37	0.34	0.63*	0.04	0.07	807	1.00
Use mobile money (=1)	0.17**	0.00	0.03	0.13*	0.05	0.07	0.14**	0.01	0.04	641	0.57
Firm has employees (=1)	-0.05	0.48	0.60	0.11	0.15	0.22	-0.00	0.97	0.99	642	0.37
Number of employees	-0.44	0.09	0.27	0.01	0.96	0.98	-0.20	0.49	0.58	642	1.27
Number of sales, last week	5.64**	0.00	0.02	3.28	0.21	0.23	4.20*	0.06	0.09	523	10.61
Sales revenues (TSH)	134079**	0.00	0.02	148533*	0.06	0.09	177987**	0.02	0.03	580	132998
Number of business purchases	1.36	0.27	0.39	1.03	0.35	0.36	0.82	0.44	0.50	641	1.21

Notes: All regressions include fixed effects for survey round, randomization strata, and the baseline value of the dependent variable. Sample size varies across regressions because (i) phone call outcomes were measured four times post-treatment, while other outcomes were measured only twice post-treatment, and (ii) rates of non-response or "I don't know" varied across questions. Total business calls is the sum of incoming and outgoing business calls, as well as missed calls (which are used as a way to request a call back from the business). *p*-values in columns 2 and 5 are based on standard errors clustered at the village level. *p*-values in columns 3 and 6 are based on the wild cluster bootstrap of [Cameron et al. \(2008\)](#), where the cluster is the village (49 total clusters). Significance stars based on WCB *p*-values. ***: significant at 1%; **: significant at 5%; *: significant at 10%.

Table A6: Intent-to-Treat Effects for Recipient Households

Dependent variable	Coeff. (1)	s.e. (2)	p-val (3)	q-val (4)	N (5)	Control mean (6)	% change (7)
Panel A. General Communication and Extra-village Linkages (last two weeks, unless noted)							
Outgoing communication							
Made calls (=1)	-0.02	0.02	0.264	0.264	738	0.96	-1.9
Sent SMS (=1)	0.09**	0.03	0.015	0.029	738	0.60	14.5
Spending on phone credit (TSH)	848*	429	0.052	0.070	786	4142	20.5
Number of contacts in phone, as of interview	50.87***	12.31	0.000	0.000	683	137.56	37.0
Incoming communication							
Received calls (=1)	-0.01	0.02	0.571	0.571	738	0.97	-0.9
Received SMS (=1)	0.03	0.04	0.424	0.571	738	0.76	4.6
Mobile money							
Sent mobile money (=1)	0.11***	0.03	0.002	0.005	738	0.32	32.9
Received mobile money (=1)	0.06*	0.04	0.079	0.079	738	0.36	17.6
Ordering deliveries, recent agricultural season							
Ordered any goods from outside village (=1)	0.05*	0.03	0.081	0.081	831	0.26	20.0
Used phone to order goods (=1)	0.07**	0.03	0.028	0.055	831	0.18	40.4
Panel B. Crop-related Search and Communication (most recent agricultural season)							
Phone use index							
Any phone use for crops (=1)	0.11***	0.04	0.0031	0.0031	831	0.31	37.3
Components of phone use index							
Used phone to seek general ag advice (=1)	0.04*	0.03	0.0951	0.0951	797	0.10	44.0
Used phone to coordinate with buyer (=1)	0.05***	0.02	0.0077	0.0093	677	0.05	104.5
Searched for inputs, phone (=1)	0.10***	0.03	0.0003	0.0020	776	0.13	75.5
Used phone for input acquisition (=1)	0.09***	0.03	0.0023	0.0068	776	0.18	52.5
Used phone to coordinate transport (=1)	0.01***	0.01	0.0077	0.0093	677	0.00	391.1
Used phone, output price search, if searched (=1)	0.11***	0.04	0.0077	0.0093	616	0.17	66.5
Input search							
Actively searched for inputs (=1)	0.03	0.02	0.2816	0.5632	776	0.84	3.2
Searched for inputs, outside village (=1)	-0.00	0.03	0.9290	0.9290	776	0.22	-1.3
Searched for inputs, within village (=1)	0.04	0.03	0.1763	0.5632	776	0.79	4.9
Sourced inputs from outside village (=1)	0.02	0.05	0.6462	0.8616	776	0.45	5.3
Output price search							
Any output price search (=1)	0.04	0.04	0.2744	0.2744	776	0.74	6.0
Searched outside village, if any search (=1)	0.14***	0.04	0.0021	0.0042	616	0.50	27.7

Table A6 (continued)

Dependent variable	Coeff. (1)	s.e. (2)	<i>p</i> -val (3)	<i>q</i> -val (4)	N (5)	Control mean (6)	% change (7)
Panel C. Crop Inputs, Outputs, and Prices (most recent agricultural season)							
Non-labor inputs, extensive margin							
Borrowed or rented land (=1)	0.04*	0.02	0.0667	0.3335	776	0.16	25.7
Tractors or plow animals (=1)	0.03	0.03	0.2762	0.6904	776	0.91	3.4
Purchased seeds (=1)	-0.00	0.02	0.8367	0.8367	776	0.92	-0.5
Non-labor input costs							
Land rental, total cost (TSH)	-9146**	4500	0.0460	0.1379	776	37044	-24.7
Tractor/plow rental, total cost (TSH)	-11759	21617	0.5882	0.5882	776	249013	-4.7
Seed purchases, total cost (TSH)	-2127	2076	0.3091	0.4636	776	13780	-15.4
Hired labor, extensive margin							
Hired pre-harvest labor (=1)	0.12***	0.03	0.0008	0.0017	776	0.49	24.0
Hired harvest labor (=1)	0.04*	0.02	0.0613	0.0613	776	0.08	54.6
Hired labor costs							
Pre-harvest labor, total cost (TSH)	5942	16568	0.7210	0.7663	774	115495	5.1
Harvest labor, total cost (TSH)	-954	3197	0.7663	0.7663	775	12730	-7.5
Maize output							
Maize harvest ongoing (=1)	0.06**	0.03	0.0156	0.0400	743	0.06	113.8
Maize crop failure (=1)	-0.07**	0.03	0.0267	0.0400	743	0.27	-26.9
Maize yield, if harvest complete (kg)	3.56	9.40	0.7062	0.7062	489	46.96	7.6
Sunflower output							
Sunflower harvest ongoing (=1)	0.02	0.02	0.2641	0.3962	684	0.05	51.5
Sunflower crop failure (=1)	-0.04	0.03	0.1510	0.3962	684	0.12	-31.4
Sunflower yield, if harvest complete (kg)	5.85	11.13	0.6010	0.6010	568	76.81	7.6
Crop sales price							
Log of crop sales price (TSH)	0.07	0.04	0.1017	0.1017	271	10.22	7.3

Notes: Authors' estimates from a single round of post-treatment survey data. All regressions include strata fixed effects and controls for two time invariant variables that exhibited some imbalance (gender and number of years in village). *p*-values are based on the reported standard errors, which are clustered at the level of treatment assignment. There are 36 treatment clusters and 34 control clusters. *q*-values are *p*-values corrected for multiple hypothesis testing within categories, where categories are indicated by boldface headings. ***: significant at 1%; **: significant at 5%; *: significant at 10%.

Table A7: Between-village spillover analysis for Pure Control firms

Dependent variable	(1) Treatment	(2) <i>p</i> robust	(3) <i>p</i> WCB	(4) N
A. Treatment variable = number of competitors treated				
Total business calls	-0.09	0.11	0.12	180
Incoming business calls	-0.06	0.22	0.14	178
Total business texts	-0.00	0.96	0.73	95
Incoming business texts	0.01	0.57	0.86	92
Use mobile money (=1)	-0.01	0.16	0.29	75
Firm has employees (=1)	-0.02	0.02	0.28	75
Number of employees	-0.05	0.04	0.14	75
Number of sales, last week	0.47	0.12	0.14	56
Sales revenues (TSH)	-1707	0.20	0.18	65
Number of business purchases	0.02	0.40	0.16	75
B. Treatment variable = share of competitors treated				
Total business calls	-3.26	0.46	0.64	180
Incoming business calls	-4.70	0.24	0.21	178
Total business texts	1.52	0.22	0.83	95
Incoming business texts	0.48	0.51	0.79	92
Use mobile money (=1)	0.01	0.98	0.93	75
Firm has employees (=1)	0.12	0.51	0.92	75
Number of employees	2.22	0.12	0.92	75
Number of sales, last week	0.18	0.98	0.99	56
Sales revenues (TSH)	-52970	0.60	0.66	65
Number of business purchases	1.33	0.49	0.13	75

Notes: All regressions include fixed effects for survey round and randomization strata. The competitors for each firm are defined as those in the same ward-sector; wards are the administrative category below district, typically consisting of 2-4 villages. Total business calls is the sum of incoming and outgoing business calls, as well as missed calls (which are used as a way to request a call back from the business). *p*-values in column 2 are based on heteroskedasticity-robust standard errors, *p*-values in column 3 are based on the wild cluster bootstrap of [Cameron et al. \(2008\)](#), where the cluster is the village (7 clusters). Significance stars based on WCB *p*-values. ***: significant at 1%; **: significant at 5%; *: significant at 10%.