Nationwide Diffusion of Technology Within Firms' Social Networks*

Deivy Houeix†

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Abstract

I conduct a randomized experiment to study the nationwide technology diffusion of a new digital payment technology in Senegal. By leveraging two novel sources of network data—mobile money transactions and anonymized phone contact directories covering the near universe of the adult population in Senegal—I causally identify three sets of adoption spillovers from taxi firms randomized to receive early access to the technology: intra-industry among taxi firms; inter-industry between taxi drivers and other small businesses; and inter-regional spillovers from the capital city to businesses in other urban centers. I show that spillovers go beyond strategic complementarities, reflecting social learning within firms' social networks, driven by social ties and remote interactions.

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†Department of Economics, MIT

1 Introduction

The idea that firms can grow by building on the technologies of their peers is central to modern theories of economic growth.[1] Although extensive research has predominantly focused on confirming the existence of technological spillovers within specific industries (Griliches, 1957; Nadiri, 1993; Bloom et al., 2013, 2020; Aghion et al., 2019; Myers and Lanahan, 2022), there is still much to explore in disentangling the mechanisms through which technologies are disseminated and adopted across the economy. Understanding the pathways through which technology diffusion takes place is critical for designing interventions that promote technology adoption and bridge technology disparities across firms.

Although some papers have used experiments to tackle the causality issues and the reflection problem faced in studying diffusion, the existing literature is still limited in the breadth of spillovers they can study. Firm networks are typically observed only through formal business relationships like VAT data, which may not accurately reflect the true social networks of firm owners. Firms in developing economies are predominantly small and informal, with social and financial relationships often intertwined (Bernhardt et al., 2019). Observing social network data is thus crucial in such contexts as we might expect diffusion to occur beyond intra-industry boundaries.

I study technology diffusion across firms in an entire economy by combining a randomized control trial of a new technology with the near universe of phone contact directories and mobile money transactions. This unique dataset reveals new patterns of diffusion, including inter-industry and inter-regional spillovers, occurring through social learning.

The intervention randomized access to a digital payment technology for processing customer payments to about 60% of 2,269 taxi businesses and tracked technology diffusion across various industries and regions within these firms' social networks over a seven-month experimental period.[2] The control group remained on a waitlist throughout the experiment, while treated taxi businesses all received the technology, which included a QR hanging card to receive customer payments, a corporate application linked to their personal existing mobile money account, and a training on how to use the product.

To conduct this experiment, I partnered with Senegal's leading mobile money com-

[1] Arrow (1962); Jaffe (1986); Romer (1990); Grossman and Helpman (1991).

[2] Throughout this paper, I refer to taxi owners and taxi drivers in the study as "taxi businesses". In practice, about half of the taxi drivers own their taxis, the rest are drivers working for someone else, and owners not driving their taxi, but employing a driver.

pany, Wave.[3] This partnership was timely, as the company was expanding its digital payment solutions across various business sectors beyond taxis across the country. The collaboration enabled close monitoring of the technology's adoption across all businesses. During the experiment, approximately 200,000 small and medium-sized enterprises (SMEs) in sectors like restaurants, pharmacies, mechanics, and taxis outside the experiment adopted the technology. Prior to this study, cash transactions were ubiquitous in Senegal, making the shift to digital payments a significant step in reducing cash-related transaction costs.

To identify the spillover effects of technology adoption, I analyze comprehensive social network data from encrypted phone contact directories and peer-to-peer transaction data from Senegal's largest mobile money company. Using a novel methodology from a computer science paper (Swamidass et al., 2015), I securely recover people with overlapping phone contacts using cryptosets—a technique that, to my knowledge, has not previously been used in economics. These data cover about 7.2 million individuals, roughly 80% of the adult population and all businesses adopters by the experiment's end, including taxis. Since most firms are sole proprietorships, this data unveils the social networks of these firms. To cross-validate the network data and investigate diffusion mechanisms, I rely on three complementary data sources. First, I conduct a survey with taxi businesses that were initially randomized to receive the digital payment technology. Second, I implement a kinship survey, asking these same businesses to identify the nature of their relationships with a random subset of their transaction recipients. Third, I use GPS tracking from some mobile money transactions to build a panel of location and migration patterns for much of Senegal's population, allowing me to assess how migration and face-to-face influence the spread of the technology. Taken together, these data sources address the measurement challenge noted above.

Two empirical facts motivate this paper. First, firm owners' social networks are sparse and diverse, with people with overlapping phone contacts often located outside their home city, Dakar. These networks include both embedded links (intra-industry) and longer ties (inter-industry), measured by phone contact overlap and validated by surveys.[4] Second, taxi businesses share substantial information within their networks, discussing digital payment technology with 13% of their contacts, hinting at the significant

[3]While the random variation is used to study diffusion, a companion paper (Houeix, 2024) examines the impact of the digital technology on businesses operations, specifically on reducing the costs associated with cash payments and improving transaction traceability to mitigate information asymmetries within firms.

[4]In this paper, I refer to tie length based on the overlap share of phone contacts. Following recent literature (Jahani et al., 2023), "embedded" ties have a high share of mutual contacts, while "long" ties connect individuals with few mutual contacts.

role of social learning.

There are three main findings in this paper: (1) spillovers within firms' networks are large; (2) they occur both intra- and inter-industry, as well as across space; and (3) they are predominantly facilitated through social learning, beyond the strategic complementarities typically observed in the adoption of digital technologies.

First, I identify the causal effects of a firm's technology adoption on other socially connected firms within the same industry, specifically among taxi businesses. I exploit the fact that, for a given taxi business, conditional on the number of taxi businesses from the experimental sample that they have in their network, the random assignment of the technology generates exogenous variation in the number of contacts treated. Using this variation, among the entire phone contact overlap network of taxi businesses, I find that the probability of a taxi business adopting digital payment technology rises by 7.4% for each additional treated taxi connection.

Second, I find that spillovers transcend industry boundaries and geographic areas. I detect significant spillovers between taxi businesses and firms from various industries in Dakar, connected to randomly treated taxis compared to control. On average, inter-industry spillovers amount to about 7.2% in Dakar, meaning that firms are 7.2% more likely to adopt the digital payment technology for each additional treated taxi business they are connected to. Inter-industry spillovers also extend across regions. Individuals living outside Dakar and socially connected to a treated taxi business in Dakar are 10.9% more likely to adopt the technology. These inter-regional spillovers are undetected using my survey data alone, underscoring the critical role of administrative network data to identify spillovers in the entire economy.

I present four pieces of evidence supporting social learning as the primary mechanism driving these spillovers. This contrasts with the role of strategic complementarities in technology diffusion among firms, as emphasized in recent literature (Crouzet et al., 2023; Higgins, 2024). In my context, complementarities could arise when customers expect digital payment options from businesses, incentivizing more firms to adopt the technology. This distinction is critical for shaping policy decisions, such as targeted information campaigns (social learning) versus subsidies for early adopters (strategic complementarities).

First, I leverage survey data to show that substantial intra-industry spillovers occur mostly among networks of self-reported friends and individuals who interact daily or weekly. To rule out confounders, I construct a direct measure of firms' strategic complementarities using transaction-level payment data from all taxi businesses that adopted the technology in Dakar. This allows me to identify if two taxi businesses share customers and assess spillover effects between them, based on whether they are also socially connected or not. My findings indicate limited evidence of adoption spillovers beyond social ties. Socially connected firms that share customers exhibit spillovers approximately three times larger than firms that share customers but lack social ties.

Second, I show that neighborhood-level spillovers among users living near taxi garages primarily occur through social ties. If strategic complementarities are present, proximity to treated taxis in a taxi garage should incentivize nearby non-participating businesses, including other taxis, to adopt digital technologies, even without direct social connections to the adopters. This effect would suggest that geographic proximity to adopters prompts other firms to adopt digital payments due to increased customer demand for digital options, beyond learning from peers. I find that adoption spillovers inter-industry among socially connected firms within the same neighborhood are about thirteen times larger than those without social ties (as measured using the phone contact overlap network). This result is robust across various neighborhood sizes, with spillovers being larger for firms within a 75-meter radius, supporting recent evidence that spillovers can be "very local" (Baum-Snow et al., 2024).

Third, inter-regional spillovers from taxi businesses in Dakar highlight the role of social learning in technology diffusion across space, occurring mostly through remote interactions. This spatial diffusion challenges the notion dating back to Marshall (1920) that knowledge spillovers primarily occur within local clusters. Using location and migration data from all firm owners, I distinguish between face-to-face and remote diffusion (e.g., social media, texts, calls). I find that while temporary migration for at least a month to and from Dakar is common, it does not significantly explain the identified spatial diffusion. Spillovers are more pronounced among business owners who do not migrate. Additionally, among users living in the most populated cities in Senegal, knowing a treated taxi who migrated to their city does not increase their likelihood of adoption any further than knowing a non-migrant treated taxi business. Lastly, I do not observe higher spillovers among business owners from other urban centers who temporarily migrated to Dakar and could have interacted with taxi businesses.

Fourth, network structure significantly influences diffusion, especially across industries and locations: long social ties connecting firms with fewer mutual contacts drive technology diffusion. Strategic complementarities suggest that the particular length or strength of a network link should not matter beyond customer links with other firms, but my findings contradict this. Using phone contact overlap networks, I find that tie characteristics are crucial, with inter-industry and inter-regional spillovers occurring through long ties. This underscores the role of longer ties in information dissemination, a well-documented theme in sociology (Granovetter, 1973; Aral, 2016).[5] Rather than creating a long tie experimentally, I here examine how spillover effects manifest along existing connections. I cross-validate the importance of tie length with survey data to show that social learning inter-industry occurs within networks marked by self-reported casual interactions.

Overall, the results suggest that variations in social networks, as observed in this context, may explain the large heterogeneity in firm technology adoption rates (Syverson, 2011). Since small businesses are crucial to the output of low and middle-income countries (LMICs), these findings suggest that targeted policies for specific firm owners could enhance technology adoption and support private sector development.

A key gap in the literature on technology diffusion arises from the lack of comprehensive social *and* business network data: existing studies rely on household surveys or administrative data with limited geographic scope or exogenous variation, potentially missing broader diffusion patterns. This study aims to bridge that gap by combining network datasets across an entire economy with randomized technology access. Specifically, it makes three key contributions to the development and trade literatures.

First, this study contributes to the extensive research on technology adoption and social learning, traditionally focused on particular agricultural technologies among small rural communities, as reviewed in Suri and Udry (2024). These technologies are costly and have varying returns, resulting in mixed diffusion evidence. I shift the focus to firms in urban areas and address survey measurement limitations by leveraging administrative network data sources, enabling to reveal new pathways of diffusion.

Second, this study advances the literature on the micro-foundations of knowledge spillovers among firms by providing evidence of inter-industry and inter-regional spillovers through social ties, in contrast to the predominant focus on intra-industry contexts,[6] typically in local clusters (Moretti, 2021; Baum-Snow et al., 2024), and with face-to-face interactions (Cai and Szeidl, 2017; Atkin et al., 2024). While recent research delineates diffusion channels, such as joining multinational supply chains (Alfaro-Ureña et al., 2022) and age composition (Crouzet et al., 2024), many unknowns remain in explaining technology diffusion due to lack of data on social networks of firm owners. This study addresses

[5]The literature has sometimes equated weak ties and long ties (Gee et al., 2017; Rajkumar et al., 2022), treating the share of mutual contacts as a measure of tie strength, where long ties are considered "weak". Here, I follow recent research by Jahani et al. (2023), which emphasizes that long ties may not be weak ties. The importance of long ties in my study supports treating tie strength and tie length as distinct dimensions.

[6]Notable exceptions include Faber and Gaubert (2019) documenting local inter-industry spillovers from tourism to manufacturing, and foundational studies by Glaeser et al. (1992); Duranton and Puga (2001) on spillovers in cities.

some of these gaps in a context of extensive technology proliferation and is among the first to causally measure the role of remote interactions in fostering technology diffusion.

Third, this research relates to the growing literature on the network effects of technology adoption, often focused on households (Björkegren, 2018; Fafchamps et al., 2023) and recently on electronic payment systems (Alvarez et al., 2023; Crouzet et al., 2023; Higgins, 2024). Specifically, Crouzet et al. (2023); Higgins (2024) are closely related as they examine firms' adoption, emphasizing strategic complementarities in response to large policy shocks using geographical variations. In contrast, I observe firms' social networks and employ a more localized randomized intervention to highlight that social learning, in addition to strategic complementarities, significantly drives diffusion among firms across the economy.

The rest of the paper proceeds as follows: Section 2 describes the setting, research design, and data. Section 3 presents empirical patterns in firms' social networks. Section 4 provides causal estimates of technology adoption spillovers. Section 5 examines mechanisms that drive technology diffusion within firms' networks. Section 6 concludes.

2 Context, Experimental Design, and Data

2.1 The Technology

The Digital Payment Technology This research leverages a new digital payments technology that I developed with Wave, the largest mobile money company in Senegal. Wave is Francophone Africa's first unicorn and one of seven in all of Africa, with operations spanning six countries. The focal technology in this study is a peer-to-business (P2B) payment system designed to facilitate secure (irreversible transactions) and convenient (QR code scanning) digital payments from consumers to taxi drivers. The adoption of the technology is one-sided; transactions are conducted using customers' personal mobile money accounts, which are already established and widely used in the country, to the business mobile wallets of taxi drivers. In collaboration with the leading mobile money company in Senegal, I designed QR codes to be installed in taxis, enabling passengers to securely pay via mobile money at a 1% fee for drivers (see Figure 2).[7] This digital payment

[7] I deliberately do not discuss the 1% fee barrier. The technology is popular, with over two million unique Senegalese users making business payments during the experiment, though cash remains dominant. All drivers who adopted the technology were aware of the fee, and the primary focus of this study is adoption, not subsequent usage. Additionally, for all drivers in this experiment, the fee was waived for the first CFA 50,000 (approximately USD 83) collected digitally.

technology differs from personal mobile money transfers in two key ways: (i) *irrevocability*—passengers cannot reverse the transactions after the ride, which is possible with a simple phone call for personal mobile money transfers—and (ii) *convenience*—payment is made by scanning a QR code instead of entering the driver's phone number into a mobile money account. The technology was offered to both taxi owners and drivers, and I elicited willingness-to-pay at the baseline (incentivized) and endline (non-incentivized) for the entire experimental sample. Note that while the technology was tailored for taxi businesses, different versions of the QR code (e.g., a blue sticker) and the same corporate application were also available to various business sectors, including restaurants, pharmacies, street vendors, mechanics, etc.—see a subset of business adopters in Figure A7.

To randomize access to this technology, I collaborated with Senegal's largest mobile money company in early 2022 to launch this digital payment technology within the taxi industry. This partnership emerged as the company was leading the business payment market in expanding its digital payment services to various business sectors beyond taxis.[8] The collaboration enabled me to monitor the diffusion of this technology across different businesses, capitalizing on the substantial expansion that followed during the experiment in 2022 (see Figure 1). Within a year, nearly 200,000 businesses in Senegal had adopted the digital payment technology. As shown in the figure, no taxis had adopted the technology at the start of the experiment, and only a small number of businesses outside the taxi industry had done so (about 13,000). As with many digital technologies (Jack and Suri, 2014; Suri, 2017), the adoption rate increased rapidly, following an S-shaped curve. Adoption began to plateau as the experiment neared its conclusion. By early 2024, data show that approximately 17,000 taxis and 220,000 other businesses had adopted the technology, suggesting that by the end of the experiment in October 2022, about 75-80% of the potential business population had adopted the technology. The technology adoption was not only located in Dakar, the capital city, where the experiment took place, but also across many cities in Senegal (see Figure A8). This paper leverages this widespread technology diffusion to study the mechanisms driving its adoption within industries, across different industries, and across geographic regions.

Technological Benefits The economic impact of the technology on businesses is the focus of a separate paper (Houeix, 2024): from the point of view of this paper, the key takeaway is that this technology is beneficial for businesses. To summarize, the adoption of digital payment technology significantly reduced various costs associated with using

[8]The company has one main competitor, less popular but that started digitizing payments around the same time. Some businesses adopted both technologies to satisfy more customers.

cash transactions for drivers. Passengers usually negotiate fares at the beginning of a ride and predominantly paid in cash before the technology is introduced. While peer-to-peer (P2P) mobile money payments were available, they were rarely used due to revocability concerns related to transaction reversibility. The technology decreased the time spent searching for small change and the incidence of change-related issues, such as mistakes in giving change. In addition, the technology improved several non-monetary outcomes, including better account management, reduced anxiety about theft, and fewer incidents of digital robbery. Overall, taxi businesses expressed substantial willingness to pay for this technology. See Houeix (2024) for more details.

Adoption Cost The primary cost of adopting this technology is time. Business owners must find a "merchant opener," an agent located throughout the city, to obtain the technology at no monetary cost. To adopt the technology, a business must meet the following requirements: possess an official identification document, a personal mobile money account, and a smartphone.[9] This technology is especially suited for studying technology adoption since, like many digital technologies, its adoption costs are non-monetary (mostly time and minimal paperwork), thereby eliminating concerns about liquidity and credit constraints that could impede adoption for some businesses.

2.2 Taxi Industry in Senegal

The primary firms involved in this project, from which diffusion occurs, are private taxi businesses operating in Dakar, Senegal. Taxis are ubiquitous in Dakar, employing about 4-6% of the urban male population, with about 21,000 active taxis in 2019 (CETUD).[10] The sector is predominantly informal and includes two key stakeholders: the taxi business owners and the drivers. In this industry, the owner is the legal entity that owns the car and the majority of the experimental sample consists of single taxi owners who drive their own taxis. In this study, I have grouped all drivers and owners together under the term "taxi businesses," each considered as a business entity.

The taxi sector provides a compelling context to examine technology diffusion for at least three reasons. First, the technological benefits discussed in the previous section

[9]Smartphone adoption in urban Senegal is relatively high, with the vast majority of taxi businesses in this experiment possessing one. This high rate of smartphone adoption is also observed in other African countries, as documented in Figure A1, about 51% across Sub-Saharan Africa, including rural areas.

[10]This figure from the CETUD is notably high for a city of 3 million people, with 53% under 19 years old. Since the CETUD data include only formally licensed taxis, this share is likely a lower bound and excludes other transportation-related industries like minibuses. For comparison, New York City, with 8 million residents, has 13,000 licensed taxis.

make it an attractive technology for businesses, especially in sectors where the transaction costs associated with cash transactions are particularly high, such as taxis. Second, the mobile nature of the taxi sector involves frequent interactions with multiple individuals daily. On average, a taxi driver meets about 14 customers a day, and 90% of drivers report engaging in conversation with customers at least half of the time, with 50% doing so most of the time. Additionally, a typical taxi driver reports interacting and regularly spending time with about 15 other taxi drivers. The social aspect of the job suggests a potentially high level of information sharing. In Section 3, I further explore how this translates into network data and why this social component is not unique to the taxi industry, but is prevalent among small business owners more generally. Third, the taxi industry is a significant source of employment for the urban male population (4-6%).

The population under study predominantly consists of urban poor (according to the PPI Index developed by Innovations for Poverty Action), typically male workers aged 30-50. The taxi industry is often a family enterprise, with family members involved in about 50% of the cases. The vast majority of taxi drivers and owners have not completed primary education (68%) and about half of the drivers were unable to save any money over the past three months (see Table B1).

2.3 Experimental Design

The experiment was structured through several stages:

Listing Survey. Initially, owners and drivers were identified and invited to participate in the study to adopt a newly developed digital technology. This listing exercise was conducted from March to May 2022 (see the GPS locations of the listing survey in Figure A3). Drivers were recruited at garages, car wash stations, meeting points, and on the streets of Dakar (e.g., during traffic jams). Owners who were not drivers were recruited primarily by obtaining their contact information from the drivers during the listing survey. About 3,600 eligible owners and drivers were listed.[11]

Baseline Survey. I contacted 3026 owners and drivers in twelve batches to be surveyed in three locations in Dakar. The baseline survey was conducted following the listing survey, from March to June 2022. Both owners and drivers participated in the survey sep-

[11] I collected their basic characteristics to stratify the randomization. Non-eligible taxis include drivers that stated not having a smartphone during the listing $\approx 15\%$: the technology requires drivers to have an Android smartphone to install the business app, drivers unreachable after several attempts $\approx 10\%$, owners with more than four taxis $\approx 1\%$.

arately at designated locations. The attrition rate from invitation to actual participation in the experiment was about 25%.[12] The treatment arms assigned to respondents were revealed at the end of the baseline survey to rule out concerns of differential attrition or selection patterns across groups at this initial stage. I also show the non-significant differential attrition rates by treatment arm at the top row of Table B1.

This randomized experiment aimed to (1) measure the impact of the technology on small businesses using the taxi industry as a case study and (2) track and quantify technology diffusion within the networks of treated and control taxi businesses. The first set of results is summarized in Section 2.1. The experimental design is shown in Figure A2.

The unit of randomization was the taxi business owner. Most businesses involved here were single owned and had no employees. The treatment group drivers were provided with a QR code hanging card for their cars to facilitate direct payment from customers, training on how to use the product, and a corporate application account on their smartphones. Owners who did not drive were also informed about the technology. The control group was not provided with detailed explanations nor access to the technology during the 7-9 months of the experiment. The control group was provided with the technology only at the end of the experiment, in October-December 2022. I did not explicitly encourage taxi businesses to share information or knowledge about the technology with others. By the end of the experiment, awareness of the technology had become widespread in Senegal. Here, I focus on understanding social learning beyond basic awareness, particularly how businesses acquire knowledge about the technology's specific features, its benefits for adopters, and the steps required for adoption.

Randomization was executed on a computer across twelve batches, using the listing data, with the control group constituting approximately 40% of the sample. The batches were designed for logistical reasons, to limit the time between the listing and the baseline surveys, thereby minimizing the respondents' attrition. To ensure compliance with research protocols and that all participating businesses received accurate and consistent information about the technology, I followed best survey practices by conducting follow-up phone back-checks on the listing data. More than seventy survey staff were involved in this process itself, which included listing drivers, verifying their data, forming their pairs, calling both owners and drivers to specified locations in Dakar, and conducting the

[12]Some drivers came to get surveyed—about one quarter of this attrition—but were, in fact, not eligible to receive the product; namely they did not have an Android smartphone, a driver's license, or an ID card. Also, about 130 owners, mostly not driving their taxi, did not want to come to the designated locations, so a short phone survey was administered to them, revealing their treatment at the end, with the app training was conducted over the phone if they were treated. The later owners are not included in this analysis.

baseline survey in person.[13]

Table B1 displays the randomization balance of the effective baseline sample for all taxi businesses (both owners and drivers). There is no significant imbalance across key individual and network characteristics between treated and control taxi businesses

2.4 Data Sources

2.4.1 Two Novel Sources of Network Data

To define social links, I rely on two complementary large datasets: (1) phone contact network data from most mobile money users in Senegal, covering about 80% of the entire adult population, as most adults in Senegal are mobile money users from the partner provider at baseline; and (2) transaction network data from the universe of mobile money transactions that occurred on this provider's platform. These datasets are sourced from the leading mobile money provider in Senegal, which covered about 7.2 million individuals by the end of the experiment in December 2022.

Phone Contact Network Upon their first log-in, users are prompted to agree to share their contact list with the mobile money company. Upon agreement, the phone contacts of each mobile money user in Senegal are systematically collected and encrypted by the company. It uses this data to facilitate mobile money transfers among its users' phone contacts. Over 95% of users consented to share their contact information, providing an almost complete mapping of the phone contact network for the majority of the country's inhabitants. This data was accessed only in February 2024, post-experiment. I conduct robustness checks to ensure the technology does not affect the number or nature of phone contacts. There are no significant differences in the average number of phone contacts between treated and control drivers, in the growth of phone contacts (February to April 2024), or in the share of recovered social contacts located in Dakar and in urban areas, as shown in Panel C of Table B1. Additionally, the phone contact overlap share analysis described below, which leverages the entire country's network, is designed to be less sensitive to potential changes in phone contacts. This is because the definition of a connection used extends beyond simply being in a user's phone contact directory.

The anonymized encrypted data contain each user's phone contacts, with each mobile number mapped to a number between 0 and 65,535 (i.e., a 16-bit value) called a hash.

[13] The randomization was stratified based on several dimensions, particularly useful to study the impact of the technology on businesses. In particular, the baseline variables used were: digital usage of the drivers, business type (owners driving or not), number of taxis (dummy variable indicating whether they have one or multiple taxis), length of the relationship, and risk aversion.

These hashed values encode the data and prevent the recovery of actual phone numbers, ensuring that it is not possible to determine whether two people have each other as contacts. However, by comparing hashed values, one can estimate an upper bound of the *overlap share* of contacts between pairs of users. This methodology is borrowed from a computer science paper by Swamidass et al. (2015), and has, to my knowledge, not been previously used in economics.[14] For each pair, I compute a proxy for their social *tie length* based on the estimated overlap share of phone contacts, using a similar formula to the one used in other contexts like LinkedIn (Rajkumar et al., 2022).

The following summary statistic is computed:

$$OverlapShare_{ij} = \frac{OverlapCount}{Min\{NumberContacts_i, NumberContacts_j\}}$$

The distribution of the overlap share for pairs connected to the drivers is skewed to the left (see Figure A6). The average user in the country has about 481 contacts, with the median at 313. The 99.5^{th} percentile of the full distribution for $OverlapShare_{ij}$ among any pair of users is 10%, so I use 10% as the cutoff to define a social link between two users (i.e., at least 10% overlap in phone contacts). I demonstrate the robustness of the key results using several other cutoff values. The treatment effect along different "overlap shares" is discussed in detail in the mechanism section.[15]

The use of the overlap share of connections is based on the idea that individuals are likely to share social connections with those who have a sufficient number of mutual contacts, as established in the literature (e.g., Ureña-Carrion et al. (2020)). To validate this approach in my setting, I cross-referenced the phone contact network overlap share with survey data collected from all experimental participants. This survey data focused on a random subset of their mobile money recipients and senders, as detailed in the following Section 2.4.2. Table B2 reports summary statistics of the overlap share for different types of relationships to validate the accuracy of the overlap measures. I find that higher overlap shares correlate with stronger social "links" between two users. For example, a taxi business owner (all males) and their wife share on average 24% of contacts, while a taxi business shares on average 9% of contacts with a friend (upper bounds). However,

[14]The methodology is based on the idea that the overlap in cryptosets conveys valuable information: 65,535 is sufficiently large such that two complete strangers are typically uncorrelated (see Figure A6), while even a small percentage of overlap is sufficiently unlikely to occur between strangers (see Table B2). While a few other economics papers, such as Ederer et al. (2024), have used hashes to recover IP addresses, I am not aware of any papers that use Swamidass et al. (2015)'s approach to capture social network overlap between cryptosets.

[15]In this context, people often have multiple phone numbers and sometimes multiple mobile money accounts. To construct the phone contact overlap network, I assume one mobile money account per person. The adoption outcome requires an ID card, and 98% of merchants have one account.

the relatively large standard errors also indicate the presence of "long ties"—significant connections with a limited number of mutual contacts. For instance, these could be close friends of taxi businesses living outside of Dakar.

Transaction Network To complement the social link definition discussed above, and to explore mechanisms driving the effect, I also examine the universe of mobile money transactions occurring through the same platform. The mobile money company partner for this project began operations in Senegal in 2017, initially focusing on peer-to-peer (p2p) transfers, i.e., personal transactions between mobile money users. As previously described, the company only expanded to digitize business payments in 2022, and the technology randomized in this study is the corporate mobile money p2b (peer-to-business) technology. The p2p activity from 2017 enables me to directly observe personal transfers among all users pre-experiment, thereby providing an additional measure of a social link based on whether two individuals transacted directly.

This transaction network is less exhaustive: on average, at baseline, a typical user sent or received money from 27 other users, compared to having 481 phone contacts. However, the transaction network contains another layer of information regarding financial transfers: on average a typical user sent or received 59 transactions pre-experiment (with many users adopting the personal mobile money account in the year before the experiment), equating to CFA 1.4M (USD 2400) in total per user. The average transfer size was CFA 18,000 (USD 30). This transaction network allows various analyses, particularly leveraging interaction intensity, such as the frequency or count of transactions between a taxi business and their network.

2.4.2 Survey Data

To complement the network data, I collected two types of survey data. First, I gathered extensive baseline characteristics of the experimental taxi businesses. Second, from September to December 2023, I collected detailed relationship data among this sample with two primary goals in mind.

The first goal was to cross-validate the administrative network data and map these relationships more precisely for a random subset of sixteen links identified in the transaction network. To avoid potential privacy concerns and misinterpretations about the study's objectives, I used the transaction network of mobile money recipients and senders instead of the overlapping phone contact network data, which was encrypted. Half of these sixteen links were randomly selected from the pre-experiment transaction network, while the other half were randomly extracted from transactions that occurred during or after the experiment. Specifically, I asked all respondents about each of the randomly extracted links to (1) define the nature of the relationship (e.g., family, close friends, homeowner), and (2) identify the main professional activity of the link.

The second goal was to uncover evidence supporting or refuting the social learning mechanism. For each link, I inquired (3) how frequently they had conversations in the past three months, (4) whether they shared important advice or information with this person, and (5) whether they would borrow money from this person. The wording of the questionnaire followed that used in Banerjee et al. (2013). Finally, I explicitly asked whether they discussed or recommended the technology to each randomly selected link. Summary statistics on the nature of the social links are detailed in Section 3.

2.4.3 Location and Migration Data

This study utilizes granular geolocation data collected throughout the duration of the experiment. Notably, I leverage the fact that mobile money transactions involve withdrawals and deposits to convert cash to mobile money and vice versa, actions that every user performs regularly. These transactions thus enable the tagging of the GPS locations using the coordinates of the mobile money agents handling the deposits or withdrawals. These agents are widespread across all cities in Senegal and are also present in most rural villages of the country (see Figure A4). This feature allowed me to construct a panel dataset of the location patterns of each user over time. This data facilitate the measurement of precise seasonal migration of all mobile money users in Senegal over the course of the experiment, a phenomenon rarely observed at that scale in such developing settings.[16]

The location data serves two primary purposes for this study. First, by enabling the identification of monthly locations for each user, it allows the measurement of spillover effects across spaces based on the subset of people who had been to or lived in that specific area during the time of the experiment. Second, by accurately measuring temporary or seasonal migration, it allows for a robust analysis of whether this widespread phenomenon serves as a channel for spatial diffusion.[17]

2.4.4 Technology Adoption Data

The main outcome variable in this study is whether a given inhabitant of Senegal adopted the digital payment technology over the course of the experiment. To measure adoption,

[16] In compiling this panel data, I assume the user did not move in months with no recorded withdrawals or deposits. For each user, the panel data starts from the time of their first withdrawal/deposit.

[17] As a demonstration of the robustness of this constructed data, significant population movements can be observed in the city of Touba during the month of the pilgrimage, as illustrated in Figure A5.

I analyze the adoption decisions of mobile money users using administrative data provided by the leading mobile money company. Specifically, I observe the exact date of adoption, the subsequent digital transactions, the GPS location of the business at the time of registration, and the industry as self-reported to the registration agent. Throughout this analysis, the adoption of other businesses is measured from the first day of the baseline survey (March 28, 2022) to the first day of the endline survey (October 5, 2022), at which point the control group began to receive treatment.

3 Empirical Patterns in Firms' Networks

I begin by documenting two key patterns in the networks of small firms, using the comprehensive network data. These patterns motivate the investigation of technology diffusion within firms' social networks.

Stylized Fact 1 **- Firms' networks not only are local and intra-industry, but also expand across industries and regions.** In Table B3, I present summary statistics extracted from the phone contact network. On average, the taxi businesses in the experiment have 587 phone contacts. While I cannot retrieve the exact phone contacts due to the encryption process, I can determine the number of contacts for each user and utilize the overlap share of contacts to demonstrate the geographical reach of the network. The data reveals that the taxi businesses' network extends significantly beyond Dakar, where the experiment took place. Notably, over half of their phone contacts reside outside the capital city, as indicated in the third row. Most of these contacts are located in urban areas across the country, as shown in the second row.

As a descriptive exercise, I identify business links within the phone contact network of the taxi businesses. To achieve this, I leverage data on all business adopters of digital payments by April 2023 and their registered industry. I find that, on average, each business is connected to about 48 other business owners (where a social connection is defined by a computed phone contact overlap share of at least 10%). This represents a non-trivial share of their phone contacts. Like most business sectors, taxi businesses' connections span various industries, as demonstrated in the Industry Network Matrix Table B4. Notably, the taxi industry tends to be more concentrated within its own sector, which might downward bias the spillover effects observed across different industries compared to other sectors. This extensive network spread is a critical feature of the data, which not only allows me to track technology diffusion across both space and industry, but also reflects the broader characteristics of firm networks in this low-income context.

Stylized Fact 2 - Substantial information sharing among social networks. Small taxi businesses not only share information and advice among themselves but also with firms beyond the taxi industry. As described earlier, I extracted a random subset of about sixteen mobile money recipients and senders from the experimental participants and surveyed each subject about the nature of their relationships with these individuals. As shown in Table B5, taxi businesses are familiar with 58% of the extracted contacts, the majority being family or friends. Notably, many of these family and friends also own businesses, often outside the taxi industry, providing additional support that many social connections are with other business owners. Among the people they know, businesses communicate frequently, interacting daily or weekly with 68% of them. Taxi businesses share important advice and information with about 74% of the people they know, particularly other businesses and taxi drivers.[18] More specifically, they reported having discussed or recommended the digital payment technology to 13% of the people they know. This underscores the high level of information sharing and potential for social learning within business networks, motivating the exploration of social learning as a key mechanism for technology diffusion.

4 Technology Adoption Spillovers in Firm's Networks

4.1 Estimating Adoption Spillovers

Preferred Specification To analyze technology adoption spillovers within firms' networks, I construct the social network of each experimental taxi business relying on the two network data sources described above: phone contact and transaction networks. The primary analysis uses the phone contact network, employing a minimum cutoff of 10% overlap share, representing the 99.5^{th} percentile of overlap shares, with robustness on this cutoff value that follows. I examine all potential connections, leveraging pre-experiment transaction data spanning November 2017 to February 2022 and phone contact data from February 2024.[19] For anyone in the country, the identification strategy exploits the exogenous variation in the number of treated contacts, conditional on the total number of RCT-sample contacts. The main specification used to estimate the technology adoption

[18] The exact survey question asked was "More generally, do you provide important information/advice to [Name]?" in the spirit of Banerjee et al. (2013).

[19] To address potential endogeneity concerns, robustness tests confirmed that the technology did not influence the number of phone contacts or their growth, as the data was accessed post-experiment (see the discussion in Section 2.4.1).

spillovers is expressed as follows:

$$Adoption_i = \alpha + \beta_1 TreatedContacts_i + \beta_2 TreatedControlContacts_i + \epsilon_i \tag{1}$$

The outcome variable, $Adoption_i$, is a binary indicator of whether user i adopted the digital payment technology at any time during the experiment (from March 28, 2022, to the beginning of the endline survey on October 5, 2022). $TreatedContacts_i$ denotes the number of treated connections user i has in their network, $TreatedControlContacts_i$ is the number of experimental connections (both treated and control) of user i, and ϵ_i is the error term. Figure 3 illustrates the experimental strategy.

The adoption outcome is drawn from the administrative data among all mobile money users connected to at least one taxi business in the experiment, excluding the experimental drivers themselves. Following Athey et al. (2018), I restrict my sample to *focal units*, i.e., I exclude all the drivers part of the experiment themselves, whether or not they received the treatment, because the focus of this paper is on the spillover effects, not the direct treatment effect of the technology.[20]

This analysis differentiates between two types of adoption spillovers: (1) *intra-industry*: an individual connected to a taxi in the experiment, who adopted the digital payment technology as a taxi, and (2) *inter-industry*: an individual connected to a taxi in experiment, who adopted as a non-taxi business owner. The latter adoption is assessed both in Dakar, where the experiment was conducted, and across space, when individuals adopted the technology as a non-taxi business owner and were located outside of Dakar upon adoption. The company only launched the digital payment technology for taxi businesses in Dakar and one nearby city during the experiment. Therefore, the main analysis focuses on diffusion across industries and regions, not within the taxi industry across different regions. Industry and location are self-declared upon registration, with the GPS location of each business recorded.

The preferred specification assumes some linearity in the treatment effect and is chosen for interpretation purposes. This specification abstracts from any higher-order spillovers (e.g., second-order spillovers). Specifically, β_1 can be interpreted as the *causal* effect of knowing an additional (randomly) treated taxi business on an individual's adoption, conditional on the number of taxi businesses in the experiment known in total (treated and control). The main object of interest is the percent change in the likelihood of

[20]The majority of taxi businesses received the treatment as expected, but some taxi drivers who were randomized ended up being ineligible, mostly because they self-declared having a smartphone during the listing, but showed up not having one. That happened before knowing they knew their treatment status, and hence is uncorrelated with treatment status. These individuals are excluded from the analysis.

adoption above the adoption rate in the pure control group, i.e., β_1 divided by the control mean, the adoption rate among users who do not know any treated drivers.

This specification resembles the linear-in-means model à la Manski (1993); Brock and Durlauf (2001), and is used in recent empirical work, e.g., Cai et al. (2015); Duflo et al. (2023). Additionally, I propose an alternative specification, considering the *share* of treated taxis known rather than the *number*. This variation allows for a different interpretation: assessing the causal effect of an increase in the proportion of treated taxi drivers within a user's network. I analyze the latter separately for clarity.

Inference Inference in this study can represent a challenge due to network dependence. Unlike most papers that examine spillovers within social networks (e.g., Cai et al. (2015); Oster and Thornton (2012)) and assume partial interference, i.e., potential for spillovers within a cluster (like a village) but not across clusters, my analysis faces challenges due to the inability to easily partition the social network into a set of plausibly independent clusters. The considerable overlap in the network data is characteristic of many social networks, where interconnections often remain unobserved. This overlap is noteworthy but introduces complications due to network interference, as the data cannot be assumed to be independent and identically distributed across users. The error term ϵ_i may exhibit network dependence.

To address this issue, I draw on recent advancements in statistical methods for network data. I first clean the network measures to remove uninformative and noisy interference. This involves several cleaning steps to compute the overlap share measure.[21] Then, I derive network-adjusted standard errors following Leung (2020), which developed a method to construct variance estimators that are robust to both heteroskedasticity and network dependencies. This approach uses the entire dependency network graph to compute robust standard errors and allows for network correlation effects between observations. Furthermore, I conduct a randomization inference test using the Score Test Statistics, as discussed in Athey et al. (2018), applying a one-sided test under the sharp null hypothesis of no positive spillovers. Inference with network interference remains an active and evolving area of research: Athey et al. (2018) showed that, in simulations where the null hypothesis of no spillovers is false, exact p-values are typically high, and both the choice of the test statistic and of the focal units "matter a great deal". Thus, I report all three statistics for the main specifications: the heteroskedasticity-robust stan-

[21]The cleaning steps for overlap share are: (i) removing individuals with fewer than 10 phone contacts, (ii) excluding pairs with an overlap share over 95%, as this often indicates the same person, and (iii) removing the top 2% of drivers with unusually high numbers of contacts. Results remain qualitatively robust to these cleaning steps, albeit with less power.

dard errors, the network robust standard errors à la Leung (2020), and the randomization inference p-value. By doing so, this paper aims to contribute to the ongoing refinement of empirical strategies in this field. Besides the main specifications, I default to display heteroskedasticity-robust standard errors unless specified otherwise.[22]

4.2 Causal Evidence of Technology Adoption Spillovers

Table 1 presents the spillover effects, detailing the effect of an additional treated contact on the likelihood of adoption both locally and across space, using the specified model in Equation 1. In Column 1 of Table 1, I observe substantial and significant positive *intra-industry spillovers* within the taxi industry in Dakar. Conditional on the number of RCT-taxi businesses known, knowing an additional treated taxi business increases the likelihood of a given user to adopt the technology as a taxi by 7.4% by the end of the experiment (an increase of 0.030 percentage points (pp) above a control mean of about 0.40%, i.e., 0.40% of the first-order network of taxi businesses adopted the technology as a taxi). The coefficient on the number of connections is smaller and negative—holding the number of treated taxis fixed, the more (control) taxis known in the experiment, the less likely to adopt the technology. This finding emphasizes that peer effects might not be linear. Using the preferred definition (at least 10% overlap), each user is connected to approximately 22.8 taxi businesses in the experiment, conditional on knowing at least one. The first-order network sample includes about 974,145 users, with around 19,906 businesses adopting the technology, including 3,946 taxis. This 10% cutoff serves as a reasonable proxy for the likelihood being in an individual's network, as detailed in Section 2.4.1 and Table B2. Robustness checks on the definition of a network link show that the spillover effects are consistent across several definitions of network links (see Tables B7 and B8 for 12% and 8% overlap share cutoffs, respectively). I also run the same specification considering the first-order baseline transaction network connections only, containing 8,770 business adopters in total, including 2,762 taxis, and the spillover effects are also large and significant intra-industry (16.5%), see Table B6. All in all, I find that the magnitude of the spillover effect varies depending on the connection cutoff and the type of network, ranging from 4 to 17%. This variation leads me to further explore this heterogeneity in the mechanisms section 5.4, in particular the role of tie length in influencing technology diffusion.

Second, I evaluate *inter-industry spillovers* in Column 2 of Table 1 on the same sample of

[22]In replicating Cai et al. (2015), Leung (2020) derives slightly lower network standard errors in their setting. In my setting, Leung (2020)'s standard errors appear to be slightly higher.

individuals knowing at least one taxi business in the experiment. The hypothesis tested is whether information sharing through social networks of firm owners could facilitate diffusion beyond a business owner's own industry. The findings support this hypothesis: on average, conditional on the number of RCT-taxi businesses known, knowing an additional treated business significantly increases the likelihood of adopting the technology as a business owner (non-taxi) in Dakar by 7.2%. This effect is consistently significant and positive across different definitions of network links (see Tables B7 and B8 for 12% and 8% overlap share, respectively).

Finally, I investigate the presence of *spillovers across-space*, i.e., between taxi businesses in the experiment and non-taxi businesses located outside of the capital city, Dakar. In Column 3 of Table 1, I find that for users in the first-order network of experimental taxi businesses, knowing an additional treated taxi business significantly increases the likelihood of adoption from a different city than Dakar by 10.9%.[23] Because the control mean of adoption outside Dakar is lower than inside Dakar, fewer firms are affected by the inter-regional spillovers compared to within Dakar, but the effects are large and significant. More specifically, Figure A10 documents positive spillovers from Dakar to most major cities in Senegal, focusing exclusively on residents present in each city during the experiment, as identified in the geolocation data. The spillover effects of treated connections consistently is positive for most cities although not always statistically significant at the 95% level. The spillover effect across space ranges from about 5% to 75% increase in adoption likelihood caused by an additional treated connection, depending on the city. The inter-regional spillovers are not detected using only the transaction network, possibly due to the limited number of links in that specific network, as shown in Table B6.

5 The Role of Social Learning in Technology Diffusion

This section aims to distinguish between two main mechanisms driving adoption spillovers: social learning and strategic complementarities. These have been challenging to disentangle in the literature. While social learning primarily involves knowledge spillovers and interactions within a firm owner's network, strategic complementarities do not require information sharing. Instead, a firm's decision to adopt new technology is positively influenced by its widespread adoption among other firms, increasing perceived benefits. In this context, strategic complementarities would manifest through customers, as the technology studied is a digital business payment app facilitating business

[23]Since the digital payment technology specific to taxi businesses (QR hanging card) was primarily launched in Dakar, I am not equipped to measure spillovers within the taxi industry across areas.

payments from customers, rather than between businesses. To make digital payments, customers use their existing mobile money apps but need to adjust their practices, like scanning businesses' QR codes. Thus, in the presence of strategic complementarities, firms may be more inclined to adopt digital payments if they observe an increasing customer preference for business payments as more firms adopt the technology. This dynamic differs from other two-sided market interactions for mobile money, where both parties must adopt the technology, as seen in studies like Higgins (2024) and Alvarez et al. (2023). Instead, this Senegalese setting more closely aligns with the firm-to-consumer-to-firm complementarities discussed in Crouzet et al. (2023) in India.

I present four pieces of evidence that the primary mechanism behind the identified technology adoption spillovers intra- and inter-industry is social learning and information sharing.

5.1 Intra-Industry Spillovers Through Friends

This section provides evidence of intra-industry spillovers using two main data sources. First, I leverage survey responses from taxi businesses to demonstrate that spillovers occur through friendships within the industry. Second, I construct a measure of strategic complementarities based on whether two taxi businesses share customers in the payment data. I then analyze the spillovers for these businesses, whether they are social connections or not, to directly distinguish social learning from strategic complementarities.

Survey Insights on the Role of Kinship in Technology Adoption I pinpoint the importance of firm owners' social networks using survey data. Specifically, I analyze which types of relationships are pivotal for technology diffusion. I extracted a random set of 16 transaction recipients and senders for each taxi business involved in the experiment, as detailed in Section 2.4.2. I make the important assumption that the nature of the relationship between existing ties was not affected by the technology itself, as this survey data was collected after the experiment. This survey data allows me to obtain precise information on network links and subsequently run spillover regressions for various definitions of a link within these sub-networks.

The intra-industry spillover effects within each of these sub-networks are documented in Table 2. Within the taxi industry, spillover effects are substantial and significant among close ties: friends and those with whom the taxi businesses frequently communicate with. The spillover effect is smaller and non-significant among casual interactions, i.e., those individuals from whom drivers have received or sent money but could not clearly define or remember their relationship. This finding supports the notion that social interactions via friends enhance diffusion among taxi businesses.

Customer Overlap Across Taxi Businesses I examine whether spillover effects are present when two taxi businesses, which do not socially know each other or interact, share customers in common. The primary hypothesis is that taxi businesses sharing the same customers with taxis in the experiment should be more sensitive to their adoption in the presence of strategic complementarities, beyond their social ties. For this analysis, I leverage customer data on all taxi payments from January 2022 to August 2023, to all taxi businesses in Dakar that adopted digital payments. During this period, each taxi business serviced 110 customers on average, with some businesses serving up to 1,585 unique customers who paid digitally. About 19% have regular customers, which already suggests a somewhat limited potential for strategic complementarities (see Table B10. This suggests that, in this context, taxis are unlikely to share customers or coordinate with one another when arranging pickups. More formally, I explore the spillover effect through the customer network of taxi businesses that share at least one or several customers with the taxis in the experiment—in essence, examining spillover effects in the second-order network of experimental taxi businesses, linked via customers.

The following specification is used to differentiate social learning from strategic complementarities:

$$\begin{aligned} Adoption_i = \alpha + \beta_1 \#TreatedSocial_i + \beta_2 \#TreatedNonSocial_i \\ + \beta_3 \#TreatedControlSocial_i + \beta_4 \#TreatedControlNonSocial_i + \epsilon_i \end{aligned} \tag{2}$$

The variable $Adoption_i$ represents adoption by the end of the experiment. The sample consists of taxi businesses outside the experiment that are connected to at least one taxi within the experiment through shared customers. These businesses adopted digital payments by August 2023, roughly a year after the experiment, when most taxi businesses in Dakar had adopted the technology, including the control group. This customer data provides a comprehensive view of all possible customer overlaps and thus a measure of strategic complementarities. $\#TreatedSocial_i$ and $\#TreatedNonSocial_i$ indicate whether the business that shares customers with the treated taxi businesses is also a social connection or not. $\#TreatedControlSocial_i$ is the same intuition, but including all RCT-taxi businesses (treated and control). A social connection is defined arbitrarily by a 8% overlap share of phone contacts in order to include most social ties, including longer ties. The goal is to separate between pure strategic complementarities through customer demand vs. from someone they also know. Results are similar using other overall cutoffs, such as 6 or 10%.

In Table 3, the analysis reveals that the spillover effects are large between the taxis connected via customers and occur through social ties, rather than through businesses with shared customers but no social links. I considered taxis that shared at least two "customers" from January 2022 to August 2023. The two columns define a "customer" in two different ways: the first column defines a link through "frequent customers," those who transacted at least three times with the same taxis, while the second column considers all customers, including irregular ones. Among the taxis that partly shared the same customers, the effect of knowing an additional treated taxi business in their social contacts is about 3-4 times larger than the effect of knowing an additional treated not in their social contacts (11 vs. 3 pp intra-industry, and this holds for both definitions of a customer). Conditional on the number of RCT-taxi businesses known, a taxi business is 16.8% more likely to adopt if an additional social link with whom they share customers adopts the technology. Between non-social links, the spillover effect goes down to 5.3% (F-stat = 4.99). This is not driven by a higher average number of customers shared with social links: non-social links have about the same number of shared customers (about 3, as shown at the bottom of Table 3). Note that the baseline mean adoption by the end of the experiment is particularly high in this sample, because the measure of customer overlap itself utilizes business adopters during and after the experiment, up to August 2023, so most of these businesses adopted during the time of the experiment, not after.

This finding suggests that strategic complementarities are not the only driver behind technology adoption. While adoption spillovers among taxi drivers who share customers are relatively large, they are stronger through friends and social connections. This supports the idea that social learning is the primary mechanism driving diffusion within firms' social networks. Although strategic complementarities may also exist, they do not appear to play the most significant role in the network dynamics observed in this study. Next, I explore the possibility of strategic complementarities within neighborhoods to examine their importance beyond firm customer networks.

5.2 Neighborhood-Level Spillovers Through Social Ties

This section evaluates potential strategic complementarities that could arise outside of direct social and customer networks, specifically within local neighborhoods. Using data from taxi garages, I analyze whether proximity to taxis that participated in the digital payment experiment—and were randomly treated—incentivizes nearby non-participating businesses, including other taxis, to adopt digital payments, even without direct social connections to the adopters. Strategic complementarities posit that geographic proximity to adopters would prompt other firms to adopt digital payments in response to increased customer demand for digital options, independent of direct social connections.

Given that taxi businesses are predominantly mobile and not stationary, analyzing local spillovers within a confined area is challenging for most of the sample. However, a significant proportion of taxi drivers (15%) operate from taxi garages where they await customers. Typically, garages are informal locations in high foot traffic urban areas like supermarkets, hotels, and large restaurants, where taxi drivers may queue for customers. The experiment included an extensive listing of taxi businesses across Dakar, and I collected detailed data on most taxi garage locations in the city, as depicted in Figure A9. This setup allows me to exploit variations in the share of treated taxis at each garage. Although this share itself was not randomized, I can still use the variation across garages to assess the impact on nearby businesses and other taxi drivers but not involved in the experiment.

I use a similar specification as in the previous section (Equation 2), but restrict it to individuals residing within a 75-meter radius of each taxi garage's centroid. Here, I link individuals living in the neighborhood rather than taxi businesses sharing the same customers. Individuals' locations were derived from geolocation data, identifying someone as living near a taxi garage if one of the top two most visited mobile agents was within the garage's radius. The 75-meter radius follows the one used in the Canadian context in Baum-Snow et al. (2024), with robustness in the Appendix.

The analysis measures spillover effects among individuals residing near taxi garages hosting at least one experimental taxi business, considering both social and non-social ties (defined as at least 8% overlap like before). The primary hypothesis is that local customers who frequent these garages might become familiar with digital payments and prefer to use them at other businesses in the area. Randomly treating more taxis within these garages could increase the likelihood that nearby firms will adopt digital payment technologies due to increased customer demand. Following Crépon et al. (2013), I cluster the standard errors at the garage level, assuming partial interference (independence across garage clusters).

In Table 4, I present the results for adoption outcomes both intra- and inter-industry in Columns 1 and 2, respectively. In Column 1, I find insignificant and small intra-industry spillover effects at the neighborhood level within a 75-m radius among social connections (around 3%). In Column 2, inter-industry spillovers are significant and positive, with the treatment effect of knowing an additional treated taxi in the social circle being 7.10

compared to 0.54 for non-social links, thirteen times larger. Specifically, knowing an additional treated taxi business, conditional on the number of RCT-taxi businesses known in the garage, increases the likelihood of adoption by 213% for a non-taxi business owner, and by 24% if the neighbor is not socially linked to the adopter, a difference that is large and significant (F-stat = 7.46). These conclusions hold considering other radii of 100-m and 200-m, with consistently much larger effects among social connections—see Tables B11 and B12. Local spillovers tend to fade away with increasing distance. The negative coefficient of spillover effects among taxis (intra-industry) for non-social ties at the 75-meter radius, although suggestive given the high standard error, is consistent with results presented later in Section 5.4, where adoption was slightly negatively affected among taxis with longer ties. This suggests that business competition might be occurring at the very local level.

Overall, these results based on this granular neighborhood data indicate that very local spillovers may occur, but they appear to be mostly driven by social learning or information sharing among social ties rather than strategic complementarities.

5.3 Inter-Regional Spillovers Through Remote Interactions

This section focuses on spillovers across regions and delineate mechanisms through which technology diffusion operates nationwide. Specifically, it examines the determinants of social learning, since strategic complementarities across different areas are less likely to occur. Leveraging extensive network and migration data of most inhabitants in Senegal, I distinguish between two types of social diffusion across space: *face-to-face interactions* among migrating business owners, and *remote knowledge spillovers*, such as those occurring through social media, text, or calls. This analysis capitalizes on the prevalent temporary migration patterns observed in many LMICs. I first outline empirical evidence on the temporary migration of business owners, and subsequently analyze the differential treatment effects on firms connected to migrating taxis versus those connected to non-migrant taxis.

Temporary Migration Temporary migration emerges as a significant and widespread phenomenon in Senegal. GPS tracking of transaction data reveals that 34% of all mobile money users migrated out of their primary city or location for at least a month in 2022. Among business owners residing in Dakar, identified as technology adopters by the end of 2023, 26% migrated outside of Dakar during 2022, and the pattern is similar for 28% of taxi businesses involved in the experiment. Typically, this temporary migration lasted about one month on average, spanning various locations.

Evaluating the Migration Channel The extensive movements of business owners located in Dakar to other urban centers presents a potential avenue for exploring how this movement might catalyze diffusion across different spaces. I further probe the significance of the migration channel in facilitating diffusion across space using the following specification.

$$\begin{aligned} AdoptionInCityX_i = \alpha &+ \beta_1 MigrantTreatedContacts_i + \beta_2 NonMigrantTreatedContacts_i \\ &+ \beta_3 MigrantTreatedControlContacts_i \\ &+ \beta_4 NonMigrantTreatedControlContacts_i + \epsilon_i \end{aligned} \tag{3}$$

With $AdoptionInCityX_i$ whether an individual adopted the technology in that specific city; $MigrantTreatedContacts_i$ indicate the number of treated taxi businesses, connected to that individual, who migrated to that city versus $NonMigrantTreatedContacts_i$ the number of treated taxi businesses that did not migrate to that city. A connection is defined with the 10% overlap share. The regression model predicts adoption in a given city based on the direct connections to treated migrants and non-migrants, while controlling for the total number of connections.

Although about a third of drivers migrated away from Dakar during the experiment, I show in Table 5 that temporary migration of business owners to secondary cities is not the main driver of technology diffusion across space. For four major cities in Senegal, I compare the spillover effects from the migrant taxi businesses vs. the non-migrant taxi as in Equation 3.[24] For example, in Touba, Column 2, the spillover effect from connections to treated non-migrant taxis is approximately 13%, but it is insignificant and negative for connections to migrant taxis. This pattern is consistent across all major secondary cities of Senegal—spillover effects are consistently similar or more pronounced for non-migrants—and indicates that remote knowledge diffusion, rather than physical migration, is likely the more significant driver of geographical spillovers in this context.

Additionally, I show in Table 6 that temporary migration in the reverse direction does not drive technology diffusion across space either. One hypothesis is that business owners from secondary cities might temporarily visit Dakar, learn from treated businesses, and subsequently disseminate that knowledge upon returning home. Over the time of the experiment, approximately 12% of all business owners (adopters) in Senegal located

[24] I select these cities so that each has enough businesses connected to experimental taxi businesses that migrated: they each host at least ten business adopters linked to migrant (experimental) taxi businesses.

outside Dakar visited the capital city, as detected using the GPS tracking of mobile money agents. I assess the spillover effects among all individuals who visited Dakar compared to those who did not. The findings do not support the hypothesis that such migration to Dakar facilitates diffusion across space: the spillover effects are statistically insignificant and if anything negative among businesses that visited Dakar compared to those that stayed outside the capital (about 5%), which emphasizes the important role of remote diffusion.

Speed of Technology Adoption I examine the speed of technology diffusion to understand how quickly the spillover effects manifest across the country. I show that diffusion across regions unfolds more slowly, with larger impacts after 6-7 months into the experiment. In Figure 4, I use the exact dates of adoption to plot dynamic technology adoption over time, both intra- and inter-industry. I compare the cumulative residualized rate of adoption of digital payments—after removing variations stemming from the number of connections—between users connected only to control taxi businesses (and no treatment), and users connected to at least one treated business. I observe that inter-regional spillover effects primarily occur mid- and towards the end of the experiment, from 3 to 7 months, peaking in October 2022—see Figure 4(c). Panels (a) and (b) show that intra- and inter-industry spillovers in Dakar are qualitatively similar and consistent over time. This trend highlights that technology diffusion was particularly rapid, occurring just a few months after implementation, but adoption spillovers required more time to propagate across regions.

Taken together, the results show that although temporary migration is common and measurable, it is not the primary driver of diffusion across geographic boundaries in this context. Instead, remote knowledge spillovers, facilitated by the recent increase in smartphone ownership and social media engagement, emerge as a significant channel for spatial diffusion. Anecdotal evidence from multiple sources in the field indicates that taxi drivers shared images and videos of their digital payment QR codes on social media platforms like WhatsApp, Facebook, and Instagram, to showcase the modernization of their business. This social media activity may be one factor that contributed to remote spillovers through remote ties. This observation aligns with contemporary research in various contexts, showing that social learning extends beyond direct face-to-face interactions to also encompass remote exchanges, such as via Twitter in Alatas et al. (2024).

5.4 Social Propagation Through Embedded and Long Ties

In this final part, I leverage the granularity of the network data to measure the treatment effect among both embedded and long ties connecting firms with many and fewer mutual phone contacts, respectively. Strategic complementarities suggest that the particular length or strength of a network link should not matter beyond customer links with other firms, but my findings indicate that tie length between two firm owners influences technology diffusion.

Ties are defined in two ways: (1) by the overlap share of phone contacts (*contact network*), and (2) by the intensity of interactions, i.e., the number of mobile money transfers (*transaction network*).

I employ the following specifications for both definitions of ties:

$$\begin{aligned} Adoption_i = \alpha &+ \sum_{ties} \beta^1_{ties} TreatedContacts_{ties} \\ &+ \sum_{ties} \beta^2_{ties} TreatedControlContacts_{ties} + \epsilon_i \end{aligned} \tag{4}$$

where $Adoption_i$ indicates whether user i adopted the digital payment technology at any point during the experiment. $TreatedContacts_{ties}$ and $TreatedControlContacts_{ties}$ represent the number of treated and total experimental connections, respectively, within different "ties" characteristics, e.g., ties with phone contact overlap share between 7 and 9%. I conduct a joint regression to compare treatment effects across the tie length. The goal is to quantify the spillover effects across different social links, i.e., how more likely a user is to adopt the technology when an additional link of length X in their network is randomly treated, conditional on the number of connections. The coefficient β^1_{ties} represents the treatment effect and is directly displayed on the figure.

The results in Figures 5 and 6, for phone contact network and transaction network, respectively, can be interpreted as follows. The first bin defines a network link as having a 5-7% overlap in phone contacts between an individual and an RCT-taxi business. An individual's likelihood of adopting the technology increases by β^1_{ties} percentage points for each additional treated taxi business known with this level of overlap (5-7% overlap), conditional on the number of such connections. The control mean of adoption, displayed in parentheses on the x-axis below the label, represents the adoption rate among users connected only to control subjects, with no treated contacts, for each tie length separately.

Different patterns emerge depending on the industry of the adopters. Intra-industry, I show that more embedded and stronger social links result in higher spillover effects—see Figures 5(a) and 6(a). This greater treatment effect is observed using both contact and transaction networks. Among longer social ties in Figure 5(a), the effect is small but significantly estimated and negative. This suggests that treated taxis might withhold information from known competitors with longer social ties more than control taxis do. Taxi businesses seem to share knowledge with embedded connections to help them benefit from the technology, but not to others if it might negatively impact their own business, such as when customers prefer businesses with digital payment options.[25]

To further investigate the information withholding effect, I regressed the *share* of treated known on adoption intra-industry. The goal is to examine local market effects when a large share of known competitors adopts the technology. The share of treated taxis known, defined using the 10% overlap share cutoff, is non-significant, but if anything negative—see Table B9. Figure A11 shows that this negative effect is more concentrated among longer ties, although quite small overall, and disappears among more embedded social ties. These findings indicate that embedded ties play a key role in the diffusion of technology within the same industry, but this role is diminished among longer ties, potentially due to information withholding.

Inter-industry, a different pattern emerges, both locally and across space. Contrary to the intra-industry results, longer ties matter as much as embedded ties among firms in different industries. One hypothesis is that there are limited concerns about information withholding across industries, and long ties are particularly useful for obtaining novel information about technology used in a different industry, especially when the contact is outside the business city. In Figures 5(b) and (c), I show that inter-industry spillover effects are consistent across social network ties in Dakar and across regions, indicating similar magnitudes for connections with varying degrees of overlap. This pattern persists when considering interaction intensity (Figure 6(b)): inter-industry spillovers in Dakar are significant and somewhat larger for longer links. However, spillover effects are not detected across regions in the transaction network, possibly due to the limited number of links in that network. This highlights the importance of phone contact network data for this analysis.

On the other hand, I use survey data to cross-validate the findings on long ties. In Table 7, I show that inter-industry spillover effects in Dakar are generally positive in most sub-networks, but are significantly detected (and larger in this survey data) only for potentially longer ties. Specifically, there is a significant treatment effect for casual interactions and a large, though non-significant, effect for former or regular clients of the taxi. This pattern supports the narrative of the importance of longer ties in inter-

[25]These negative spillover effects among longer ties do not hold when using the transaction network, possibly because the transaction network is less exhaustive or already captures a minimal level of closeness.

industry spillovers, aligning with recent literature in higher-income contexts showing the importance of serendipity (e.g., Atkin et al. (2024)). However, the survey data itself is insufficient for detecting spillovers across geographical areas within these sub-networks, as indicated by the highly insignificant and inconclusive results in Table B13. The limited survey sample size within sub-networks, about 4000-5000 links at most, restricts the ability to detect most spillovers. This limitation highlights the critical role of administrative network data in analyzing diffusion patterns, beyond survey evidence.

Together, these results illustrate that social tie length plays a key role in enhancing technology diffusion: embedded links are especially key *within industries* to enhance diffusion and mitigate information withholding concerns, while diffusion beyond a business's own industry seems to also operate through long ties, connecting firms with fewer mutual contacts. This finding highlights the importance of network structure and could have implications for targeting the right nodes based on policy objectives and the type of technology deployed.

6 Conclusion

This paper presents a randomized controlled trial (RCT) that varies access to technology and leverages its expansion in an economy to study technology diffusion within firms' networks. The combination of random variation, comprehensive network data, and detailed surveys enables causal inferences and insights into spillover effects across an entire economy.

I identify three types of adoption spillovers: intra-industry among taxi firms, inter-industry between taxi drivers and small businesses, and inter-regional from the capital city to other urban centers. Given the significant contribution of small businesses to the output in low- and middle-income countries, these results suggest potential policy interventions targeting specific firm owners to boost technology adoption. How to effectively target and leverage firms' networks to enhance diffusion remains an intriguing question for future work.

I provide four pieces of evidence that social learning and knowledge spillovers are occurring in this context, beyond the strategic complementarities in adoption observed with digital technologies. First, adoption spillovers occur through friends with the taxi industry. Spillovers through firms sharing the same customers are limited beyond social ties, validated by survey data. Second, neighborhood-level spillovers are significantly larger among social connections. Third, there is substantial diffusion across space, occurring primarily through remote interactions. Fourth, both embedded and long social ties influence diffusion, with long ties playing a key role across industries and regions. Within industries, embedded social ties with a treated firm lead to higher spillover effects, mitigating information withholding concerns.

Overall, these findings demonstrate that social learning within firms' networks is a crucial driver of technology diffusion, facilitated by information flows and remote interactions. In this context, I believe three features of this study—random assignment of technology access, exhaustive network data, and nationwide diffusion of a technology—contribute to the literature that studies technology adoption and knowledge spillovers in developing contexts.

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Main Figures and Tables

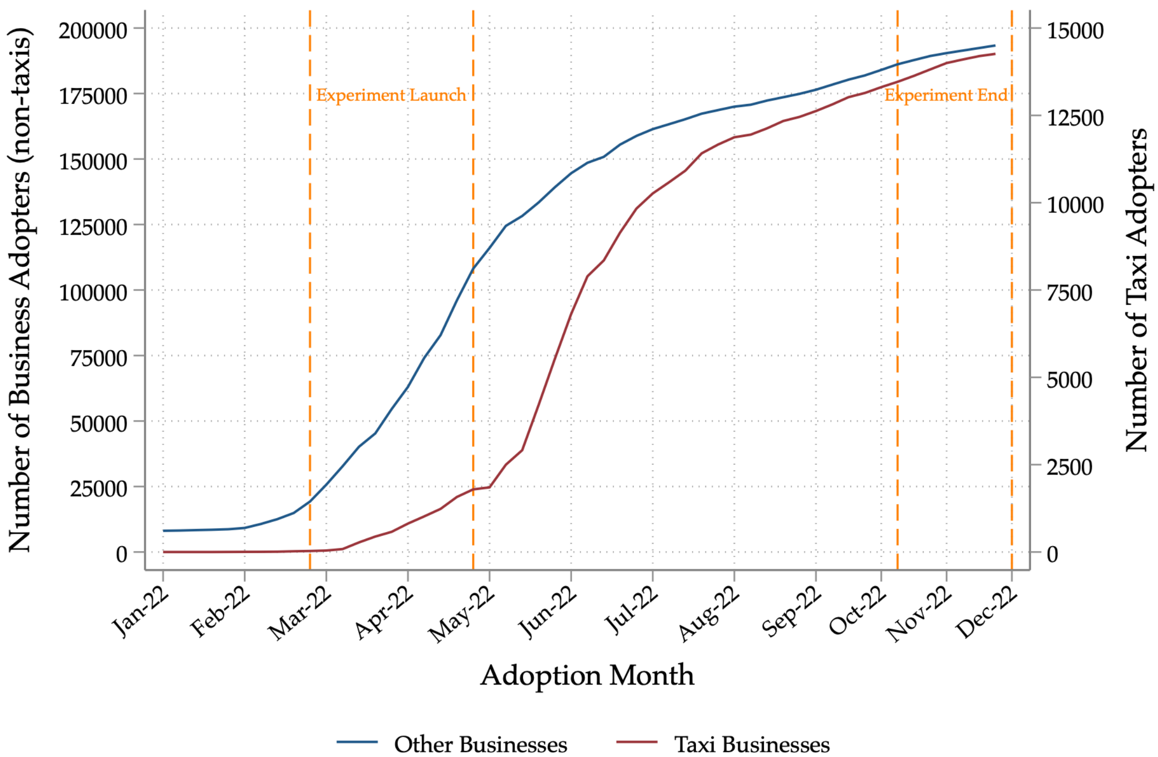


Figure 1: Digital Payments' Adoption in 2022 - *Author's calculations*

Notes: This figure illustrates the cumulative adoption of digital payment technology by businesses in Senegal throughout 2022, covering both taxi businesses and other industries. The adoption rate follows an S-shaped curve for both other businesses and taxi businesses. The experiment commenced on March 28, 2022, when the first taxi businesses were equipped with the technology, with the last taxi business onboarded by the end of April 2022. A week later, taxis outside the experiment were permitted to adopt the digital payment technology, while the control group remained on a waitlist for the time of the experiment. Throughout the year, all other businesses also had the opportunity to adopt the technology. The first endline survey was conducted on October 5, 2022, and the experiment randomizing access to digital payment technology concluded in late December 2022. By early 2024, approximately 17,000 taxis and 220,000 other businesses had adopted the technology, suggesting that the adoption rate as of October 2022 was about 75-80% of the potential business population.

Figure 2: Digital Payments for Taxis - Sénégal

Notes: These images illustrate the implementation of the technology within taxi vehicles. The technology utilizes a QR code visible from outside the vehicle, allowing potential customers to easily identify it. Drivers are provided with a sticker to place on their windshield, enhancing the visibility of the product. Additionally, drivers were equipped with the corporate mobile application and trained on how to use it by a dedicated mobile money agent. Passengers have the option to pay using their smartphones, or drivers can scan passengers' mobile money cards when they do not have smartphones. Businesses in different sectors were provided with the same QR code, which was presented as a sticker for display in their stores.

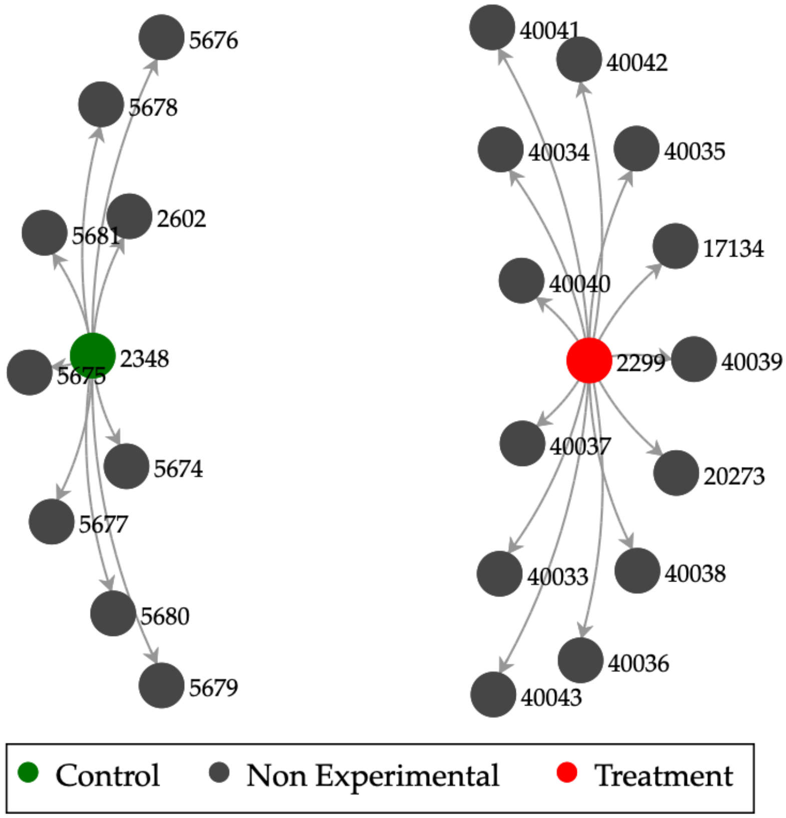
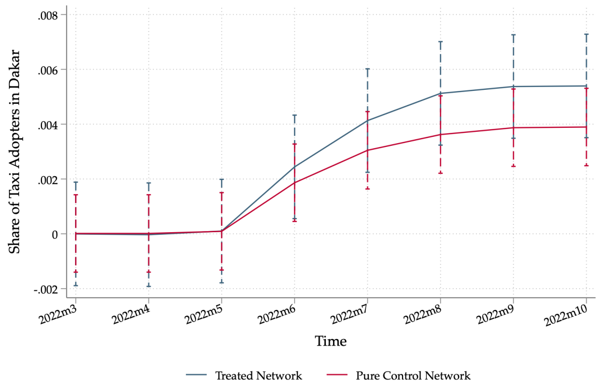
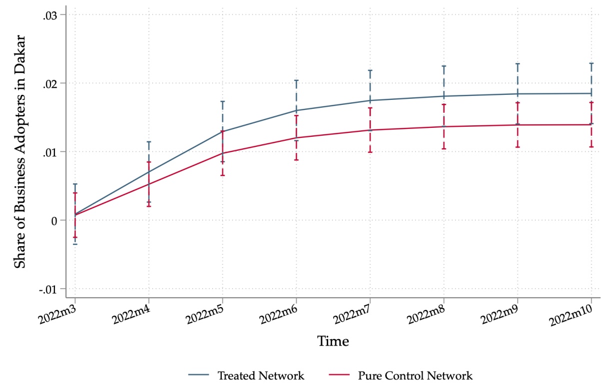


Figure 3: Illustration of the Experimental Design

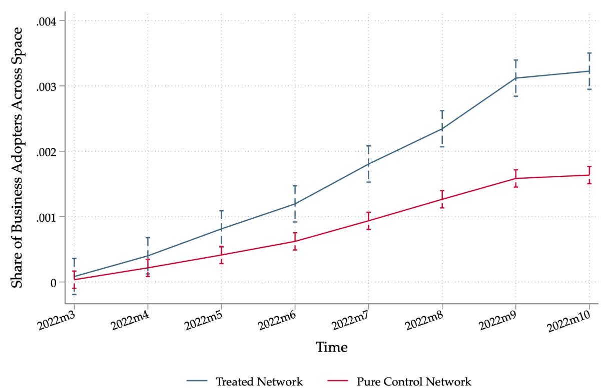
Notes: This figure illustrates and simplifies the experimental strategy. Some nodes, depicted as black dots, entered the experiment and were randomly assigned to either the treatment or control group. The study aims to quantify the likelihood of technology adoption among all users connected to an experimental node, whether treated or control, essentially comparing the adoption rates among the networks of treated versus control taxi businesses. In practice, networks often overlap, leading to network interference, an issue that is discussed in the estimation section 4.1.



(a) Intra-Industry in Dakar



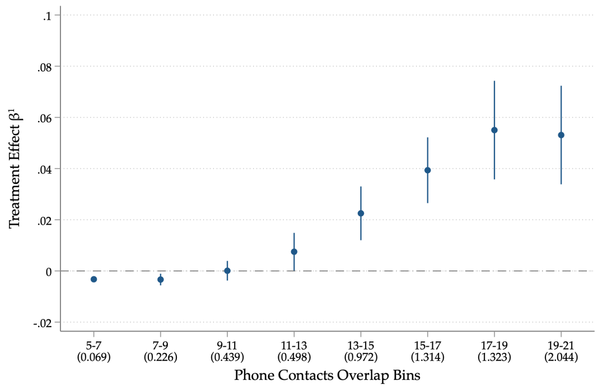
(b) Inter-Industry in Dakar



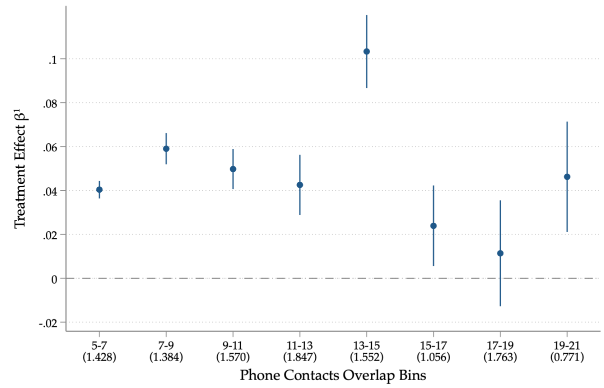
(c) Inter-Industry Across Space

Figure 4: Speed of Technology Diffusion Over Time Across Treatment Networks

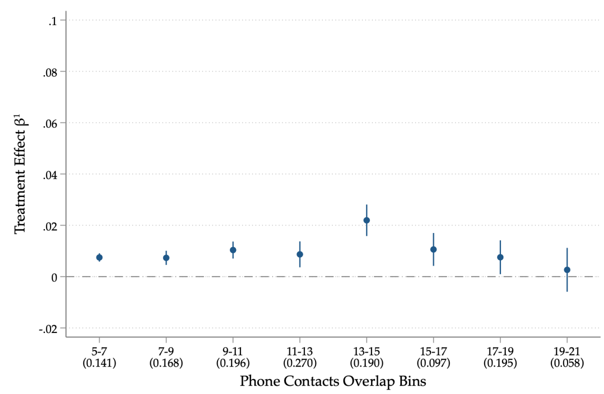
Notes: These three figures illustrate the adoption rates across three distinct outcomes: intra-industry adoption, inter-industry adoption in Dakar, and inter-industry adoption across space (outside Dakar). The scale of the y-axis differs across the three figures. For the "treated" first-order network, the figures plot the residualized monthly adoption rate over time for anyone connected to at over one treated taxi business (the median). This is calculated by considering the residuals from the regression of adoption on the number of connections. For the "pure control" first-order network, the figures show the residualized monthly adoption rate over time for individuals connected exclusively to control taxi businesses, with no treated businesses in their network. The figures also include 95% confidence intervals for each month, calculated using the standard errors for that month.



(a) Intra-Industry in Dakar



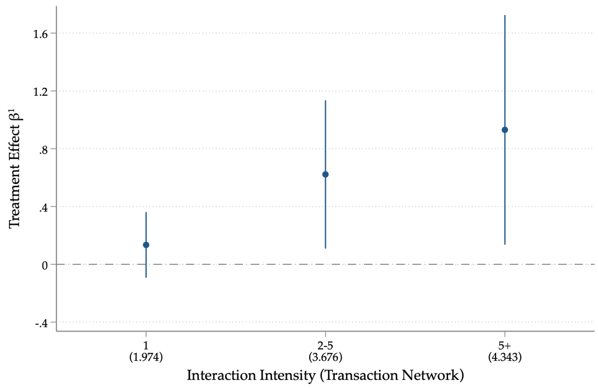
(b) Inter-Industry in Dakar



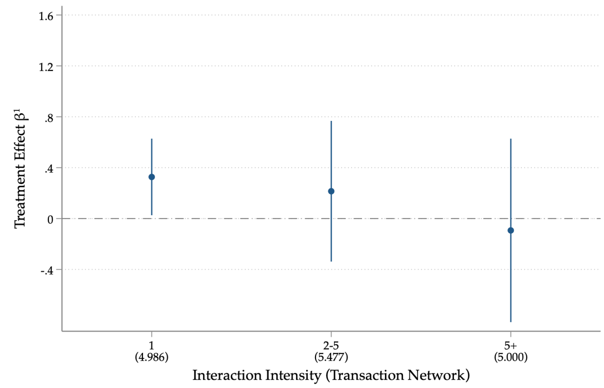
(c) Inter-Industry Across Space

Figure 5: Diffusion and Tie Length

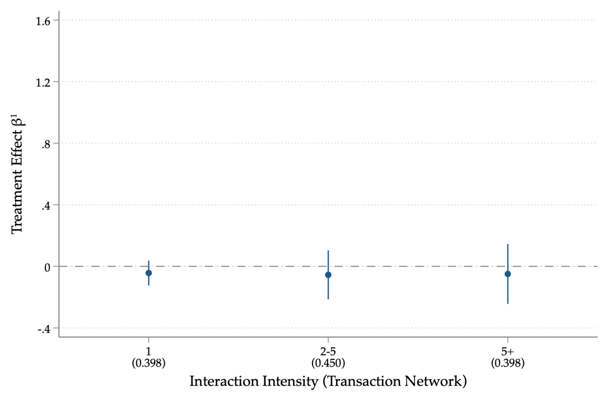
Notes: These three figures illustrate the spillover effects for three different dummy outcomes: intra-industry adoption, inter-industry adoption, and across-space adoption. Regressions are conducted for each outcome controlling for varying definitions of network connections, leveraging the phone contacts network, i.e., based on the tie length between the experimental subjects and the user. I apply the regression model $Adoption_i = \alpha + \sum_{ties} \beta^1_{ties} TreatedContacts_{ties} + \sum_{ties} \beta^2_{ties} TreatedControlContacts_{ties} + \epsilon_i$. The coefficient β^1_{ties} represents the treatment effect displayed on the graph. The control mean of adoption is displayed in parentheses on the x-axis, below the label: it is the adoption rate among users connected only to control subjects, with no treated contacts, for each specified tie length separately. The 95% confidence intervals are depicted as bars on the Figure. Robust-heteroskedastic standard errors. For example, the first bin defines a network link as having a 5-7% overlap share in phone contacts between an individual and an experimental subject. An individual's likelihood of adopting the technology increases by β^1_{ties} percentage points for each additional treated taxi business known with this longer tie (5-7% overlap), conditional on the number of such long tie connections to taxi businesses. Note that all coefficients and control means are multiplied by 100 to increase readability. The top 2% of drivers in terms of number of connections in the 8% overlap share cutoff network are dropped from these figures.



(a) Intra-Industry in Dakar



(b) Inter-Industry in Dakar



(c) Inter-Industry Across Space

Figure 6: Diffusion and Interaction Intensity

Notes: These three figures illustrate the spillover effects for three different dummy outcomes: intra-industry adoption, inter-industry adoption, and across-space adoption. Regressions are conducted for each outcome controlling for varying definitions of network connections, which leverage the transaction network, specifically based on the number of mobile money transfers between experimental subjects and users, termed interaction intensity. I apply the regression model $Adoption_i = \alpha + \sum_{ties} \beta^1_{ties} NumberOfTreated_{ties} + \sum_{ties} \beta^2_{ties} NumberOfTreatedControl_{ties} + \epsilon_i$. The coefficient β^1_{ties} represents the treatment effect displayed on the graph. The control mean of adoption is displayed in parentheses on the x-axis, below the label: it is the adoption rate among users connected only to control subjects, with no treated contacts, for each specified tie length separately. The 95% confidence intervals are depicted as bars on the Figure. For instance, the first bin defines a network link as having engaged in (made or received) just one mobile money transfer between a user and an experimental subject An individual's likelihood of adopting the technology increases by β^1_{ties} percentage points for each additional treated taxi business known with this longer tie (one transfer), conditional on the number of such long tie connections to taxi businesses. Note that all coefficients and control means are multiplied by 100 to increase readability.

Table 1: Technology Adoption Spillovers Within Firm Networks - 10% Phone Contact Overlap Cutoff

	(1)	(2)	(3)
	City-wide (Dakar)		Across-Space (Outside)
	Intra-Industry	Inter-Industry	Inter-Industry
Number of treated connections	0.02957***	0.10174***	0.01827***
	(0.00218)	(0.00359)	(0.00121)
	[0.00219]	[0.00366]	[0.00121]
Number of connections	-0.01751***	-0.06029***	-0.01070***
	(0.00124)	(0.00204)	(0.00069)
	[0.00124]	[0.00208]	[0.00069]
Obs	974145	974145	974145
Control Mean	0.398	1.422	0.168
Percent Change	7.431	7.155	10.874
Number of connections	22.774	22.774	22.774
RI p-values	[0.053]	[0.027]	[0.029]

Notes: This analysis examines spillover effects of being connected to treated taxi businesses, while controlling for the number of connections and the overall network size. The overlap share cutoff considered in this Table to define a connection is 10%. The regression model used is $Adoption_i = \alpha + \beta_1 NumberOfTreated_i + \beta_2 NumberOfTreatedControl_i + \epsilon_i$. Network standard errors, as calculated based on Leung (2020), SE_{nw}, are displayed in brackets [...]. These standard errors take into account the dependency graph and the correlated effects across the network. Specifically, the calculation considers first-order links, which means it accounts for whether units i and j are directly connected. Heteroskedastic-robust standard errors are provided above in parentheses (...). The stars are to describe p-value p reported from a t-test β/SE_{nw}, with *** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$.
RI p-values are computed from 1000 permutations of the treatment assignments under the sharp null hypothesis of no positive spillover effects (one-sided), using the T-score test statistic as derived in Athey et al. (2018).
The **Percent Change** represents the percentage change in the likelihood of adoption, i.e., β_1 divided by the control mean, which is the adoption rate among users who do not know any treated drivers. The number of experimental connections indicates the average number of connections to experimental taxi businesses. All coefficients, standard errors, and the control mean are multiplied by 100 to enhance readability.

Table 2: Adoption Within the Taxi Industry in Sub-Networks Elicited in Kinship Survey

	Adoption Within Taxi Industry (Dakar)						
Subnetwork	Family	Friends	Daily/Weekly Interactions	LendMoney	Clients	Casual Connections	Rare Interactions
Number of treated connections	-0.301	3.185**	1.931**	1.295	0.268	0.177	-0.393
	(0.764)	(1.415)	(0.843)	(1.039)	(1.189)	(0.384)	(1.262)
Number of connections	18.292	25.233*	8.440	5.087	-1.819	-2.044***	0.000
	(13.867)	(13.533)	(5.425)	(6.658)	(1.789)	(0.339)	(.)
Control Mean	4.485	9.636	6.952	8.211	1.282	1.810	2.521
Percent Change	-7	33	28	16	21	10	-16
Observations	2947	2007	4211	3034	415	5226	614

Notes: Network survey data collected in Sep-Dec 2023. This analysis investigates the spillover effects of being connected to treated taxi businesses, while controlling for the number of connections and overall network size across various sub-groups as defined in the kinship survey data. Friends and Family are self-reported by drivers. Family includes spouses, parents, siblings, children, cousins, and any close family members. Friends include reported friends in none of the previous categories. Daily/Weekly and Rare Interactions are people taxi businesses talk to daily/weekly, or never/almost never, respectively. LendMoney are people the taxi business would borrow money from (so people that could lend money to the taxi businesses). Clients are former or regular customers of the taxis. Casual Connections are people they could not remember based on names when asked. The employed regression model is $(First)Adoption_i = \alpha + \beta_1 NumOfT_i + \beta_2 NumberOfTC_i + \epsilon_i$. Robust-heteroskedasticity standard errors (HC3) are displayed in parenthesis. To enhance readability, All coefficients, standard errors, and the control mean are multiplied by 100.

Table 3: Technology Diffusion For Connected Taxis Via Customers

	(1) Adoption Intra-Taxi Industry	(2) Adoption Intra-Taxi Industry
Number of treated connections - Social	10.97***	11.65***
	(3.577)	(3.570)
Number of treated connections - Non-Social	2.947***	2.974***
	(0.219)	(0.217)
Number of connections - Social	-8.807***	-9.160***
	(2.632)	(2.636)
Number of connections - Non-Social	-2.102***	-2.119***
	(0.159)	(0.158)
Control Mean Social	65.306	64.646
Control Mean Not Social	55.312	54.321
Percent Change - Social	16.80	18.02
Percent Change - Not Social	5.33	5.47
F-stat # Treated Social = # Treated Non-Social	4.99	5.85
Number of connections - Social	0.098	0.101
Number of connections - Non-Social	23.679	23.876
Number of Shared Customers - Social	3.316	3.324
Number of Shared Customers - Non-Social	2.725	2.957
Customer Definition	$\geq$ 3 transactions	All
Observations	7877	7926

Notes: This table uses the sample of taxis connected to other taxi drivers based on shared customers, as a measure of the sensitivity to strategic complementarities. To separate strategic complementarities from social learning, I define two types of connections among this sample of taxis sharing customers: Social and Non-Social. 'Social' and 'Non-Social' categories denote whether taxi businesses have more than 8% overlap in phone contacts with the connected taxi driver. The first column includes only customers who appear at least twice or more with the same taxi (a loose definition of frequent customers). The second column includes all customers who have ever paid the taxi. Heteroskedastic-robust standard errors. The **Percent Change** represents the percentage change in the likelihood of adoption, i.e., β_1 divided by the control mean 'social', which is the adoption rate among users who do not know any 'social' treated drivers. All coefficients, standard errors, and the control mean are multiplied by 100 to enhance readability.

Table 4: Local Technology Diffusion Around Garages - 75-meter-radius

	(1) Adoption Intra-Taxi Industry	(2) Adoption Inter-Industry
Number of treated connections - Social	0.555	7.096^{***}
	(5.469)	(2.489)
Number of treated connections - Non-Social	-0.0616	0.540
	(0.243)	(0.940)
Number of connections - Social	2.831	-4.067^{***}
	(2.707)	(1.209)
Number of connections - Non-Social	0.00375	-0.153
	(0.106)	(0.418)
Control Mean Social	20.000	3.333
Control Mean Not Social	1.594	2.226
Percent Change - Social	2.77	212.87
Percent Change - Not Social	-3.86	24.25
F-stat # Treated Social = # Treated Non-Social	0.01	7.46
Number of connections - Social	0.013	0.013
Number of connections - Non-Social	3.663	3.663
Number of garages	21	21
Observations	34725	34725

Notes: Sample of residents within a 75 meter radius around taxi garages. All garages with at least one mobile money agent within this radius are kept. Location is defined from the mobile money withdrawal and deposit history of each user in the country. Clustered SE at the garage level. Most users are assigned to one garage, and I dropped individuals with multiple garages to clustered SE at the garage level. Robustness not dropping these individuals altogether are also conducted with qualitatively very similar results. Social connections are defined by sharing more than 8% overlap share of phone contacts with the taxi driver in the garages. Only garages that are within the radius distance of a mobile money agent are considered. The **Percent Change** represents the percentage change in the likelihood of adoption, i.e., β_1 divided by the control mean 'social', which is the adoption rate among users who do not know any 'social' treated drivers. To enhance readability, all coefficients, standard errors, and the control mean are multiplied by 100.

Table 5: Technology Diffusion Via Remote Interactions

	Adoption			
	(1)	(2)	(3)	(4)
	Thies	Touba	Mbour	Kaolack
Number of treated connections - Migrant	-0.0167	-0.0715	-0.326**	0.0315
	(0.0609)	(0.0493)	(0.145)	(0.130)
Number of treated connections - Non-Migrant	0.0654***	0.0507***	0.0864***	0.0201
	(0.0188)	(0.0118)	(0.0211)	(0.0188)
Number of connections - Migrant	-0.0956*	-0.00000832	0.323**	-0.130**
	(0.0497)	(0.0428)	(0.152)	(0.0612)
Number of connections - Non-Migrant	-0.0261**	-0.0257***	-0.0535***	-0.00956
	(0.0111)	(0.00622)	(0.0122)	(0.0107)
Control Mean Migrant	0.71	0.58	0.78	0.52
Control Mean Non-Migrant	0.45	0.39	0.47	0.49
Percent Change - Migrant	-2.37	-12.28	-41.99	6.10
Percent Change - Non-Migrant	14.53	13.18	18.57	4.13
Number of connections - Migrant	1.02	1.44	0.40	0.30
Number of connections - Non-Migrant	9.93	16.79	13.03	11.60
Observations	49958	72196	35420	34556

Notes: This table presents the analysis from separate spillover regressions of the outcome *AdoptionInCity* (Y) on the number of treated connections known, while controlling for the total number of connections, whether this taxi business migrated to that city or not: $AdoptionInCityX_i = \alpha + \beta_1 MigrantTreatedContacts_i + \beta_2 NonMigrantTreatedContacts_i + \beta_3 MigrantTreatedControlContacts_i + \beta_4 NonMigrantTreatedControlContacts_i + \epsilon_i$. The network links are defined as follows: first-order link to a 'migrant' (taxi businesses that migrated to their city throughout the time of the experiment) and first-order link to a 'non-migrant' (taxi businesses that did not migrate to their city throughout the time of the experiment). The **Percent Change** represents the percentage change in the likelihood of adoption, i.e., β_1 divided by the control mean Migrant, which is the adoption rate among users who do not know any treated drivers that migrated. For all these separate regressions, the sample is restricted to (1) users residing in the specific city of interest, i.e., individuals who have been located in the city throughout the experiment according to mobile money data, and (2) users who have at least one experimental subject in their network.
To enhance readability, all coefficients, standard errors, and the control mean are multiplied by 100.

Table 6: Technology Diffusion Across Geographic Areas: Impact of Temporary Migration of Business Owners to the Capital City, Dakar

	Adoption		
	(1)	(2)	(3)
	All Living Outside	Visited Dakar	Did Not Visit Dakar
Number of treated connections	0.0556***	0.00111	0.0664***
	(0.00577)	(0.0174)	(0.00612)
Number of connections	-0.0324***	-0.00121	-0.0386***
	(0.00327)	(0.00991)	(0.00347)
Control Mean	0.47	0.27	0.51
Percent Change	11.90	0.41	12.96
Number of connections	15.01	8.87	16.45
Observations	305221	58065	247156

Notes: This analysis investigates the spillover effects of being connected to treated taxi businesses, while controlling for the number of connections in the experiment, among the users living outside of Dakar. The regression model is $Adoption_i = \alpha + \beta_1 TreatedContacts_i + \beta_2 TreatedControlContacts_i + \epsilon_i$. Robust-heteroskedasticity standard errors (HC3) are displayed in parenthesis. The first column, labeled "All Living Outside," restricts to all users located outside of Dakar as per the mobile money data throughout the duration of the experiment. The second column focuses on users who migrated to Dakar at least once, while the third column is restricted to users primarily located outside of Dakar, who did not migrate to Dakar during the experiment.
To enhance readability, all coefficients, standard errors, and the control mean are multiplied by 100.

Table 7: Adoption Inter Industry in Sub-Networks Elicited in Kinship Survey data

	Adoption Across Industry (Dakar)						
Subnetwork	Family	Friends	Daily/Weekly Interactions	LendMoney	Clients	Casual Connections	Rare Interactions
Number of treated connections	-0.097	0.207	0.092	0.439	3.384	1.664***	-1.627
	(0.665)	(1.072)	(0.663)	(0.808)	(2.099)	(0.562)	(1.850)
Number of connections	-3.163***	9.447	-0.591	-1.413	-9.973***	-5.664***	0.000
	(0.784)	(10.071)	(2.760)	(3.716)	(3.408)	(0.582)	(.)
Control Mean	3.322	5.758	4.672	4.715	3.205	3.474	5.882
Percent Change	-3	4	2	9	106	48	-28
Observations	2947	2007	4211	3034	415	5226	614

Notes: Network survey data collected in Sep-Dec 2023. This analysis investigates the spillover effects of being connected to treated taxi businesses, while controlling for the number of connections and overall network size across various sub-groups as defined in the kinship survey data. Friends and Family are self-reported by drivers. Family includes spouses, parents, siblings, children, cousins, and any close family members. Friends include reported friends in none of the previous categories. Daily/Weekly and Rare Interactions are people taxi businesses talk to daily/weekly, or never/almost never, respectively. LendMoney are people the taxi business would borrow money from (so people that could lend money to the taxi businesses). Clients are former or regular customers of the taxis. Casual Connections are people they could not remember based on names when asked. The employed regression model is $(First)Adoption_i = \alpha + \beta_1 NumOfT_i + \beta_2 NumberOfTC_i + \epsilon_i$. Robust-heteroskedasticity standard errors (HC3) are displayed in parenthesis. To enhance readability, All coefficients, standard errors, and the control mean are multiplied by 100.

Online Appendix

Nationwide Diffusion of Technology Within Firms' Social Networks

Deivy Houeix

A Appendix Figures

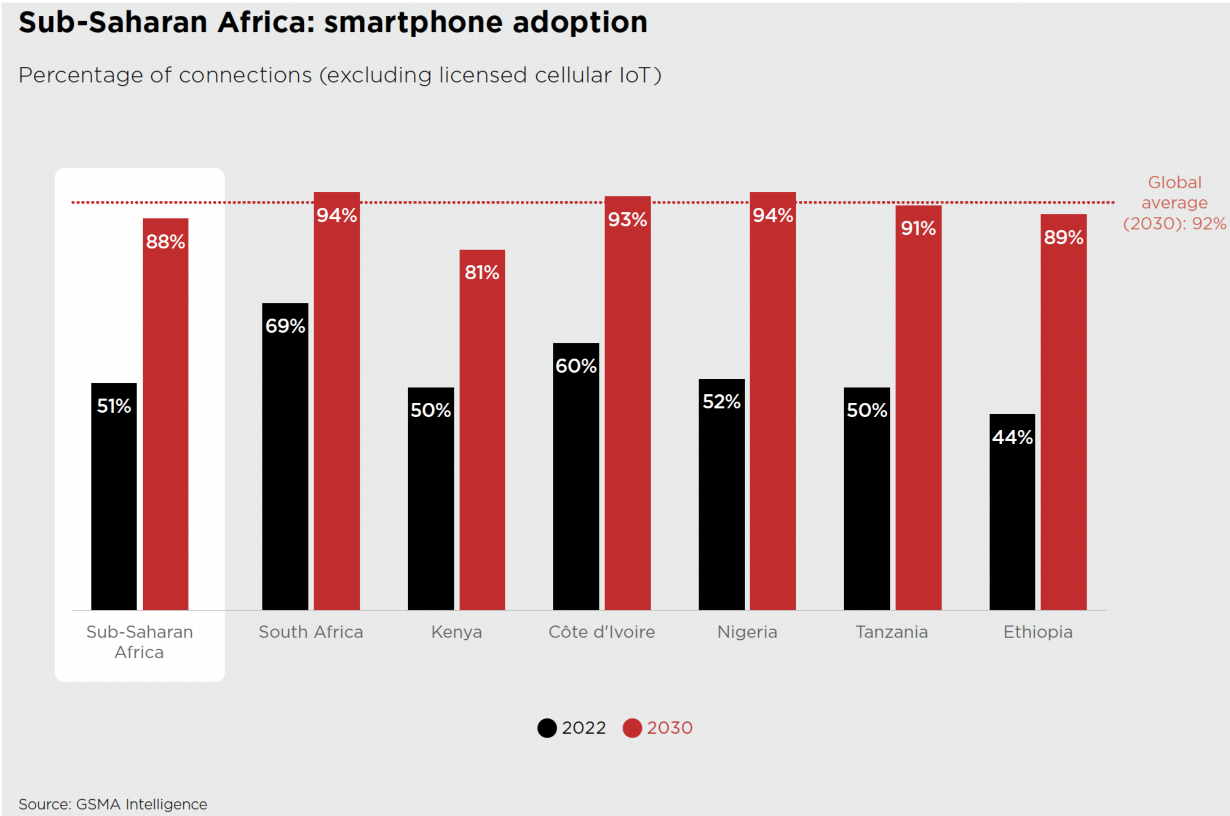


Figure A1: Smartphone Adoption in Sub-Saharan Africa

Notes: This graph is sourced from the GSMA Intelligence 2023 report, "The Mobile Economy Sub-Saharan Africa 2023," on page 15 of 46. The report gathers data and forecasts smartphone adoption across several African countries. Cote d'Ivoire, which is similar to Senegal in size and geography, reports a 60% smartphone adoption rate for the entire country, a statistic that is likely much higher in urban areas.

Figure A2: Experimental Design

Notes: This figure outlines the experimental design. Each taxi driver was initially listed at various locations including garages, car wash stations, meeting points, and on the streets of Dakar (e.g., during traffic jams). The listing was comprehensive enough to cover most parts of the city, and a large portion of the taxi drivers working in the city were approached (it is estimated that about 30% of the drivers were approached, with some refusing to be surveyed, others not interested, and some not eligible, as detailed in Section 2.4.2). Subsequently, taxi owners and drivers were invited to specific locations in Dakar to be surveyed and randomized into the treatment. The primary experimental variation involved randomizing access to the technology. The treatment was then subdivided into three different "observability" treatment arms for owners to monitor their drivers' transactions in various ways. For this paper, these sub-treatments are pooled together as most of the sample considered here consisted of taxi businesses operated solo.

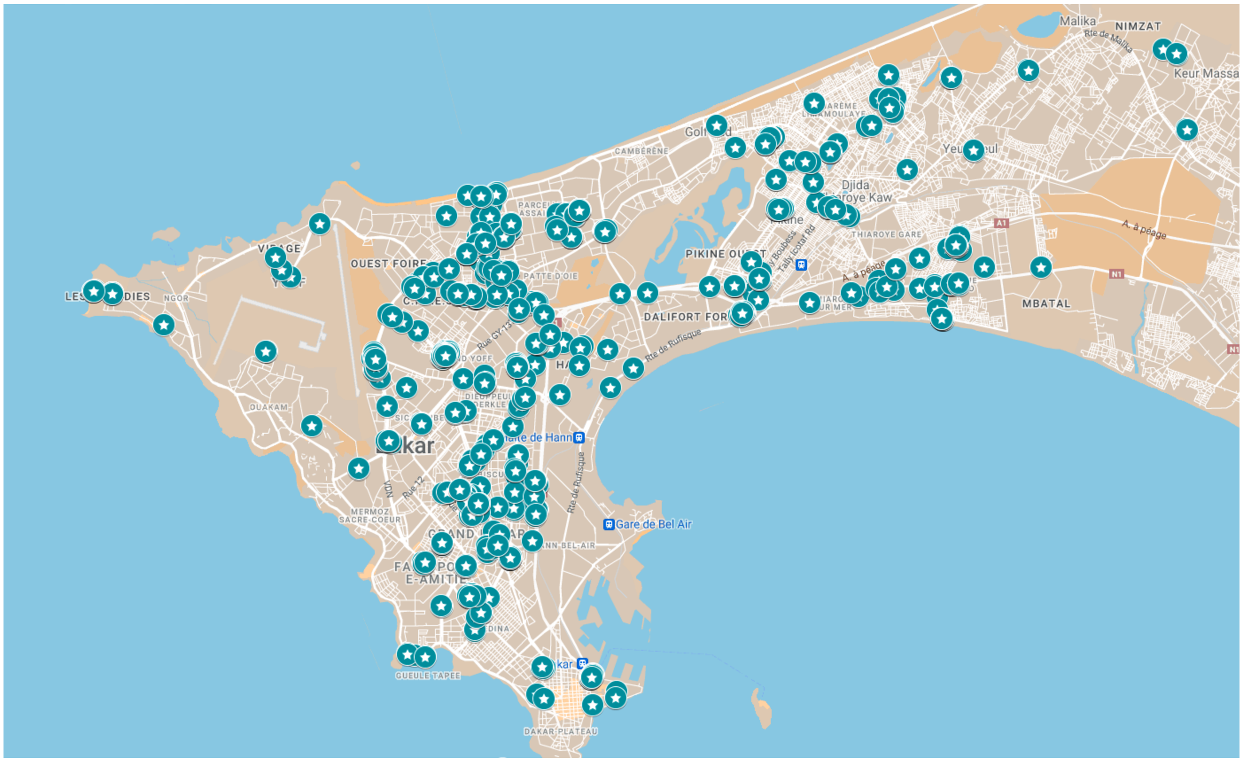


Figure A3: Listing Survey Activity in Dakar - March/April 2022

Notes: The figure displays a map of Dakar, capital city of Senegal. Each blue dot is the GPS location of the listing survey conducted before the experiment. Drivers were recruited in garages, car wash stations, meeting points, and on the streets of Dakar (e.g., during traffic jams). The extent of the listing was so broad that it covers most part of the city and a large portion of the taxi drivers working in the city were approached (among which some refused to be surveyed, some were not interested, some were not eligible, as described in Section 2.4.2). Owners not driving were primarily recruited by asking drivers about their owners' contact information during the listing survey.

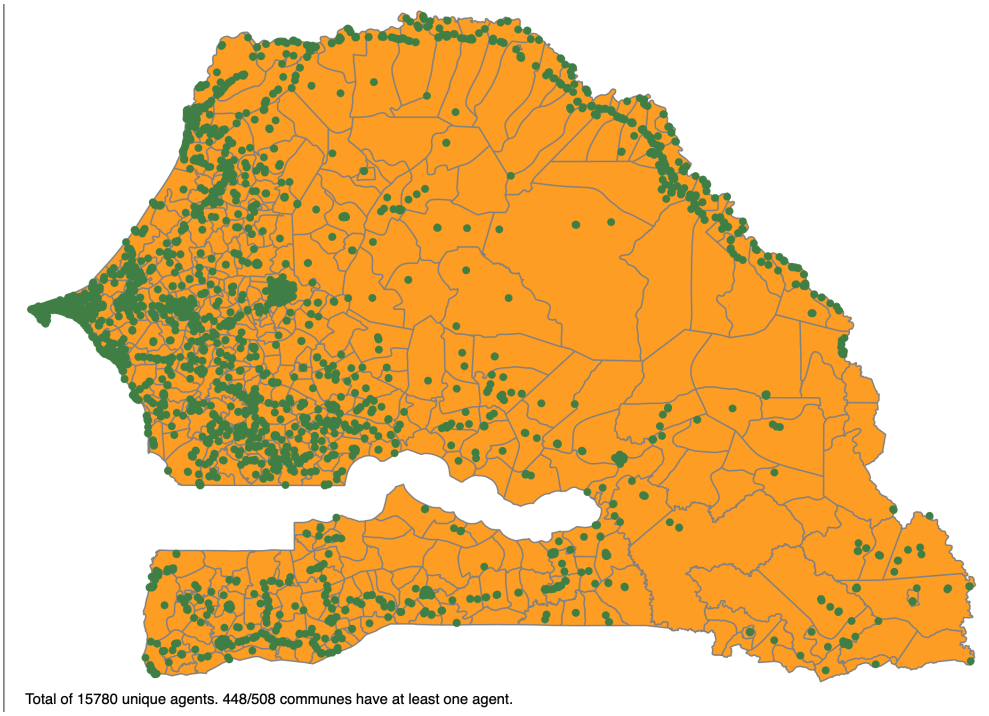


Figure A4: Mobile Money Agents in Senegal in 2022

Notes: This Figure represents a map of Senegal. Each green dot is the GPS location of a mobile money agent for the main mobile money platform. There are over 15,000 unique agents in Senegal from this mobile money company, which covers the full set of urban cities and the extreme majority of communes/villages.

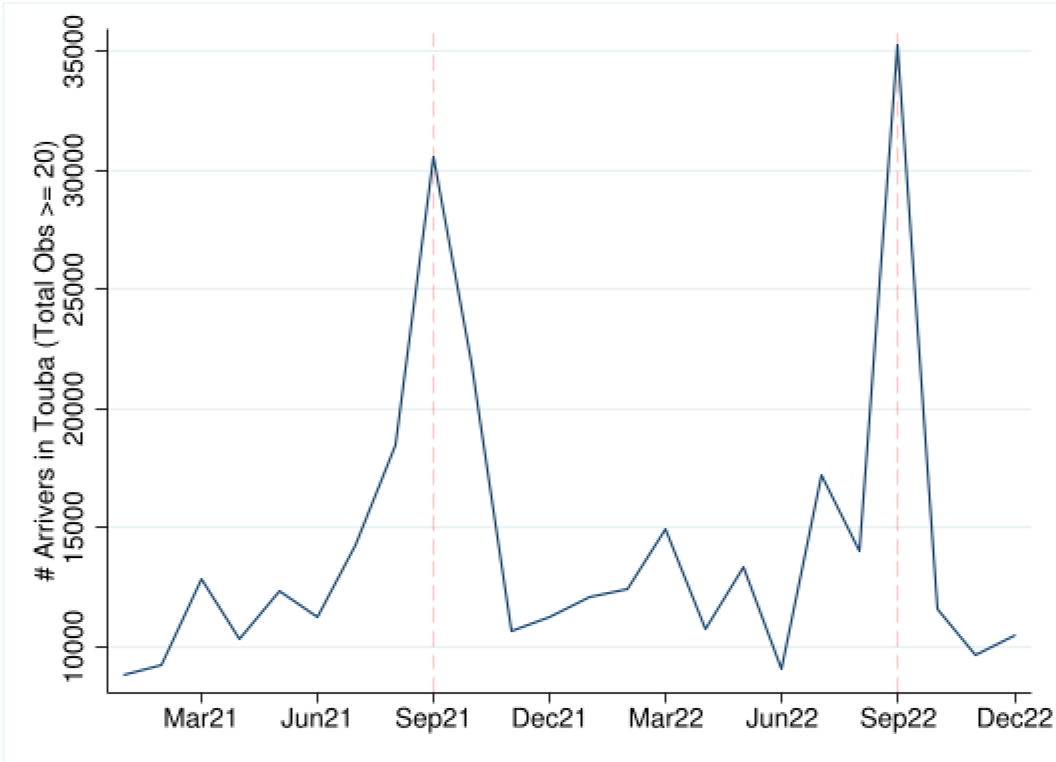


Figure A5: Location Data - Arrivals in Touba

Notes: This Figure represents the number of arrivers in Touba over each month from February 2021 to December 2022, as measured via the withdrawal/deposit of mobile money to agents located in the city of Touba. There are peaks of arrivals in the months of September, which is directly consistent with the pilgrimage dates happening every year in this city.

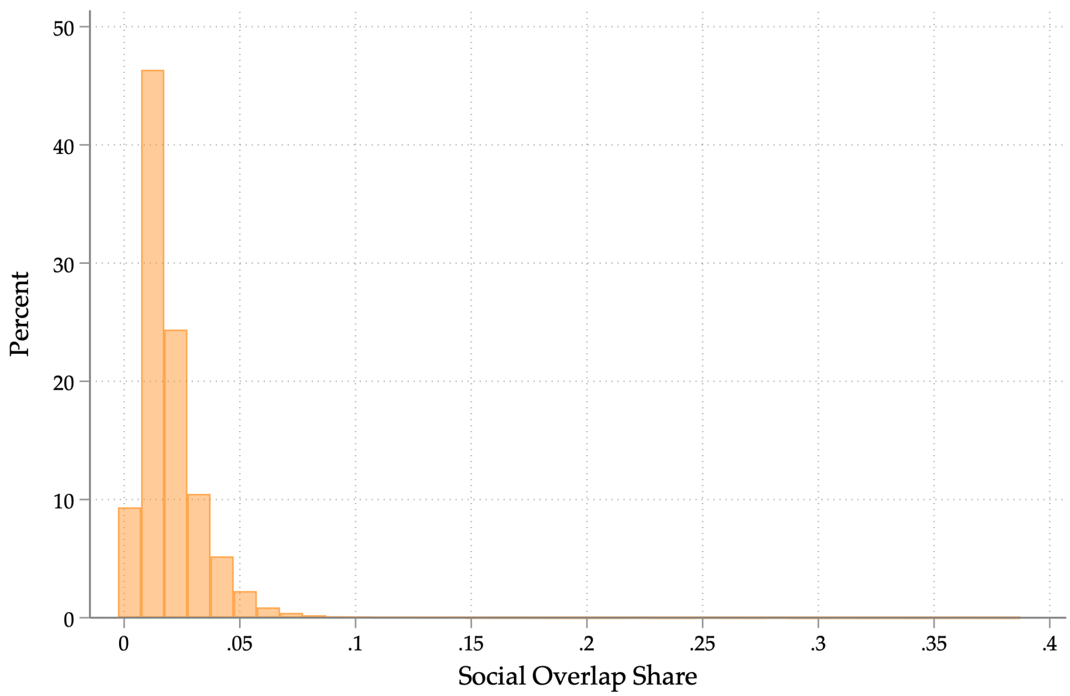


Figure A6: Overlap Share in Phone Contacts' Network

Notes: This Figure plots the distribution of phone overlap share for the entire set of users connected to the taxi businesses in the experiment. I trimmed at 0.4 to show how skewed the distribution is between two typical users, unlikely to be socially connected.

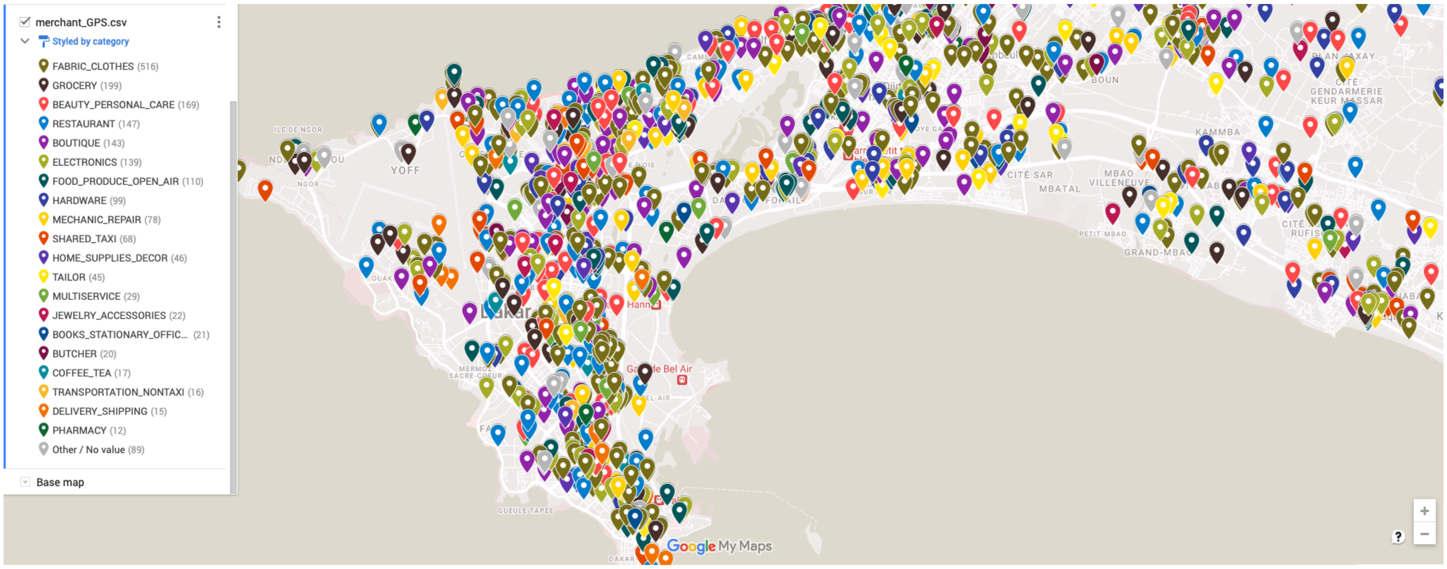


Figure A7: Technology Diffusion in Dakar Throughout the Experiment

Notes: This map shows the technology diffusion, for a randomly selected sample of businesses, across the capital city of Dakar with the firm's sectors. Each colored dot shows the location of a business who adopted the digital payment technology during the time of the experiment.

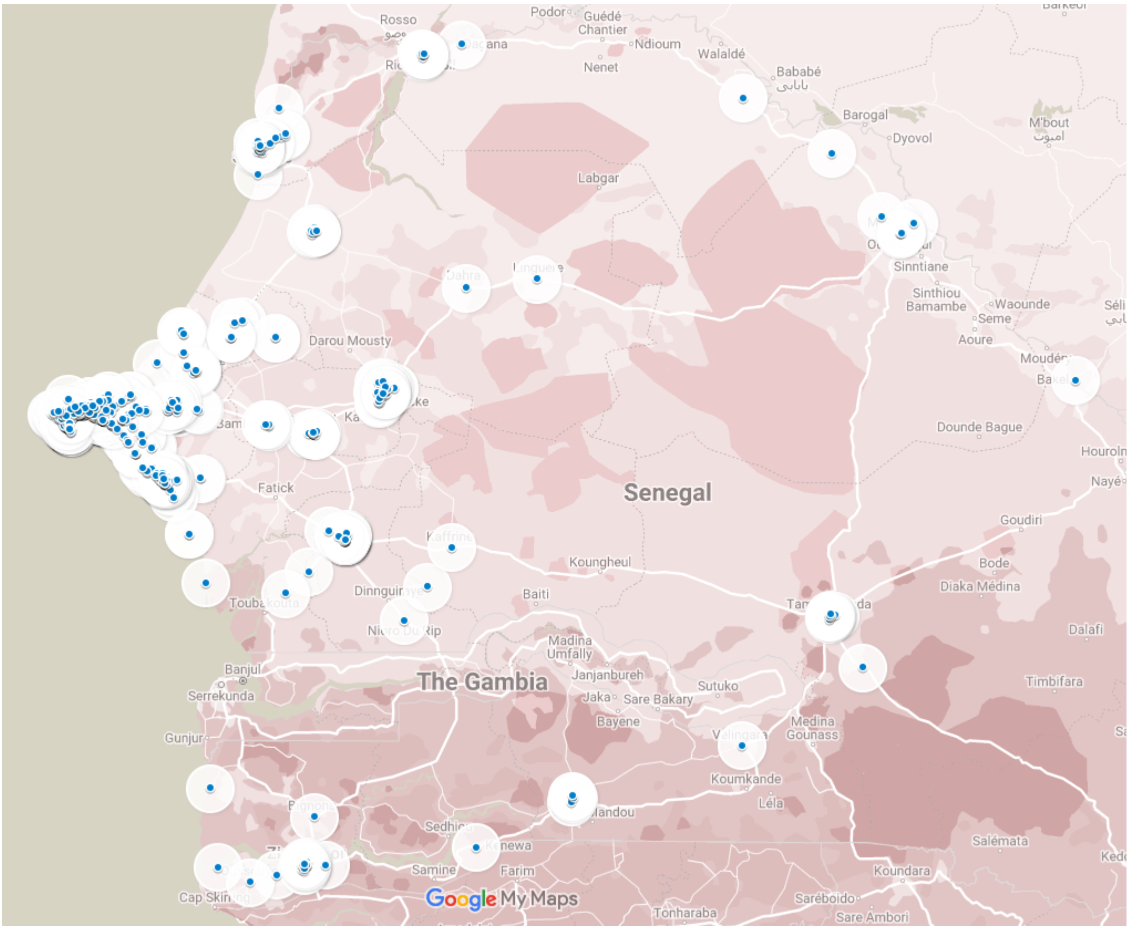


Figure A8: Technology Diffusion Inter-Industry Across Space Throughout the Experiment

Notes: This map shows the technology diffusion, for a randomly selected sample of businesses, across many different urban cities in Senegal, beyond the capital city of Dakar, where the experiment took place. Each blue dot shows the location of a business who adopted the digital payment technology during the time of the experiment.

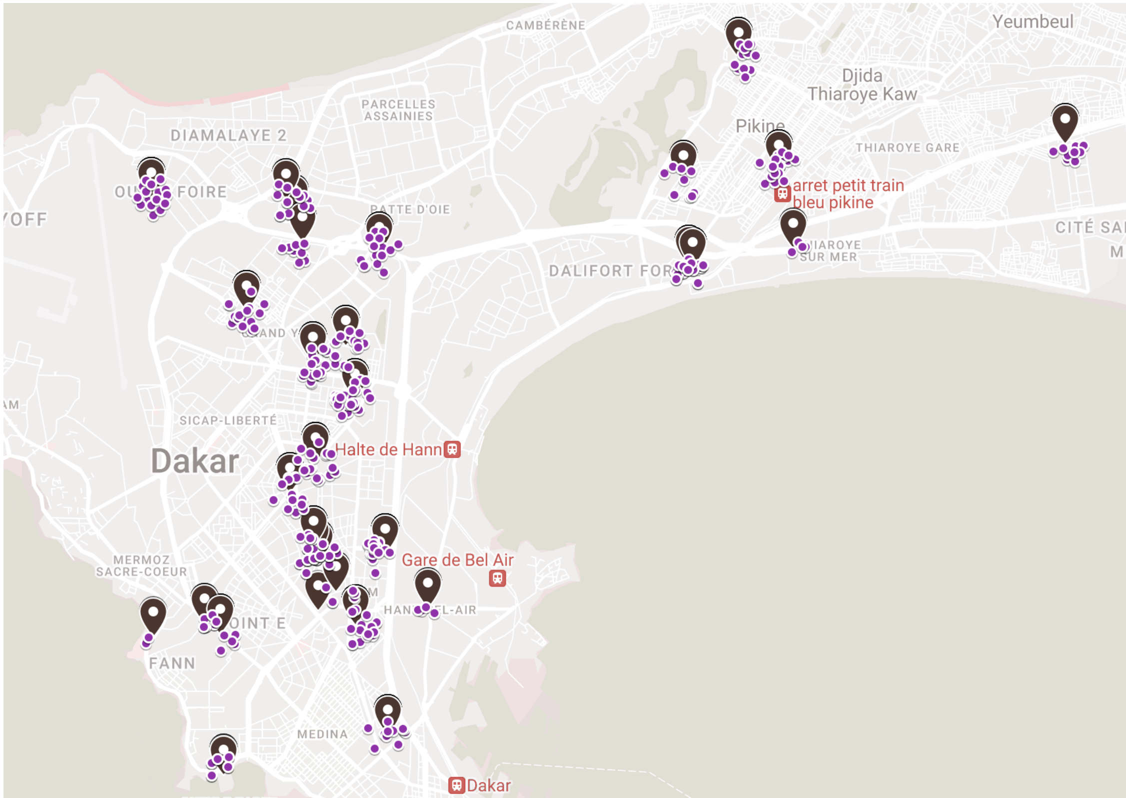


Figure A9: Local Technology Adoption Spillovers Nearby Taxi Garages

Notes: This figure displays a map of Dakar, pinpointing the geo-locations of a subset of taxi garages where at least one taxi driver participated in the experiment. Each garage was manually coded to define a neighborhood. Mobile money agents within a 200-meter radius were identified and tagged, in this illustration in purple. For these tagged agents, I compiled a dataset of inhabitants living in proximity to these agents to delineate the residents of each neighborhood. For these residents, I then analyzed their propensity to adopt the technology depending on the number of treated taxi businesses and the total number of experimental taxi businesses within their neighborhood.

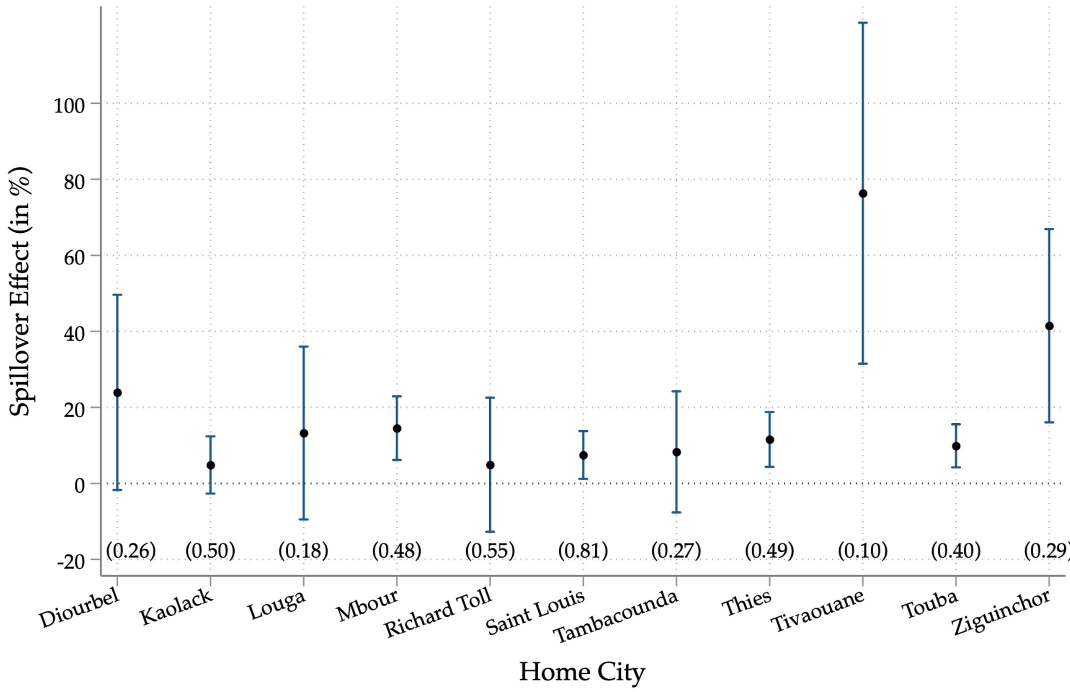


Figure A10: Diffusion Across Multiple Cities

Notes: This figure presents the coefficients from separate spillover regressions of the outcome *AdoptionInCity* on the number of treated connections known, while controlling for the total number of connections (both treated and control): $AdoptionInCity = \alpha + \beta_1 NumberOfTreated + \beta_2 NumberOfTreatedControl + \epsilon$. In the y-axis, I display the coefficient β_1 normalized by the control mean of adoption in the city (the adoption rate among users connected only to control subjects, with no treated connections). This control mean is also displayed in parentheses below each bar, multiplied by 100. A connection is defined using the 10% overlap in the phone contact network. The 95% confidence intervals are displayed as bars on the figure. For all these separate regressions, the sample is restricted to (1) users residing in the specific city of interest, i.e., individuals who have been located in the city throughout the experiment according to mobile money data, and (2) users who have at least one experimental subject in their network. Only cities with at least 20 adopters in the first-order network connected to the experimental sample that migrated are considered.

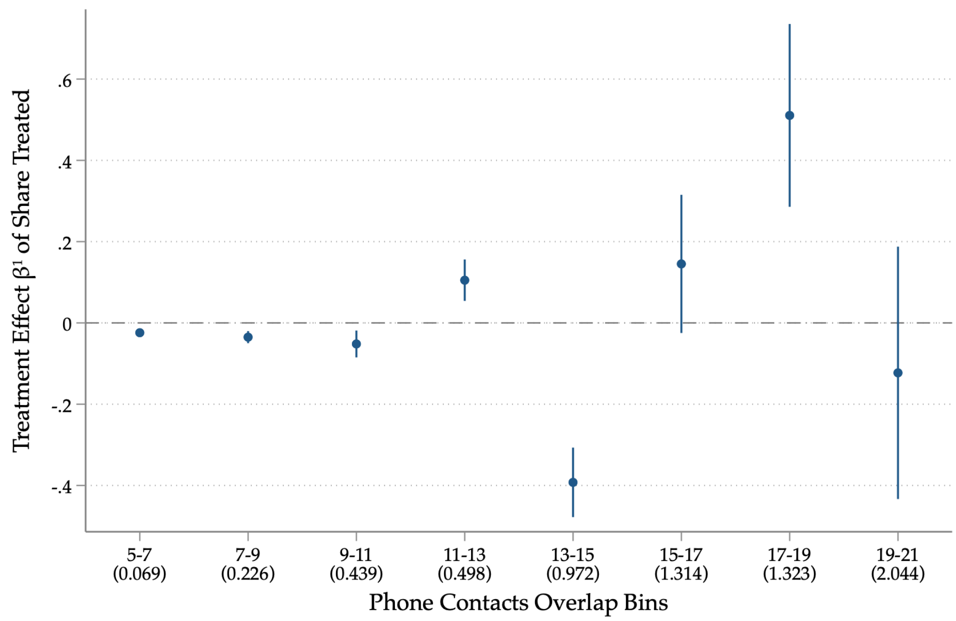


Figure A11: Intra-Industry Diffusion and Share of Treated, Across Tie Length

Notes: These three figures illustrate the spillover effects for intra-industry adoption. Regressions are conducted controlling for varying definitions of network connections, leveraging the phone contacts network, i.e., based on the tie length between the experimental subjects and the user. I apply the regression model $Adoption_i = \alpha + \sum_{ties} \beta^1_{ties} ShareOfTreatedContacts_{ties} + \sum_{ties} \beta^2_{ties} TreatedControlContacts_{ties} + \epsilon_i$. The coefficient β^1_{ties} represents the treatment effect displayed on the graph. I dummied out when the share was missing (the individual did not know anyone with a particular overlap social link in the experiment). The control mean of adoption: the adoption rate among users connected only to control subjects, with no treated contacts, for each specified tie length separately is displayed in parentheses on the x-axis, below the label. The 95% confidence intervals are depicted as bars on the Figure. Robust-heteroskedastic standard errors. For example, the first bin defines a network link as having a 5-7% overlap share in phone contacts between an individual and an experimental subject. An individual's likelihood of adopting the technology increases by β^1_{ties} percentage points when all taxi business known get treated (share=1) under this longer tie (5-7% overlap), conditional on the number of such long tie connections to taxi businesses (note that all coefficients and control means are multiplied by 100 to increase readability). The top 2% of drivers in terms of number of connections in the 8% overlap share cutoff network are dropped from this figure.

B Appendix Tables

Table B1: Balance Table - Experimental Sample of Taxi Businesses

	(1) Control	(2) Treatment	(3) t-stat	(4) N
Attrition Between Listing and Baseline	0.24	0.26	(1.02)	3026
	(0.43)	(0.44)		
Panel A. Taxi Businesses				
Owners Not Driving Their Taxi	0.17	0.16	(-0.51)	2269
	(0.38)	(0.37)		
Owners Driving Their Taxi	0.49	0.52	(1.32)	2269
	(0.50)	(0.50)		
Taxi Drivers (Non-Owners)	0.29	0.28	(-0.79)	2269
	(0.45)	(0.45)		
Part of a Taxi Association	0.38	0.41	(1.05)	2269
	(0.49)	(0.49)		
Daily Hours Worked	10.61	10.61	(0.03)	2269
	(2.56)	(2.65)		
Panel B. Individual Characteristics				
Male Respondent	1.00	1.00	(0.84)	2269
	(0.07)	(0.05)		
Education Level: Less Than Primary	0.67	0.68	(0.55)	2269
	(0.47)	(0.47)		
Literacy (Read And Write)	0.70	0.70	(-0.11)	2269
	(0.46)	(0.46)		
Wealth Index - PPI Poverty Line 2011	62.83	63.94	(1.39)	2269
	(18.77)	(16.88)		
Saved Money In The Past 3 Months	0.57	0.56	(-0.40)	2269
	(0.50)	(0.50)		
Panel C. Network Characteristics				
# of Mobile Money Connections (In & Out)	58.85	53.74	(-1.68*)	2269
	(75.42)	(57.64)		
# of Personal Mobile Money Transfers Per Connection	2.57	2.53	(-0.51)	2269
	(1.45)	(1.68)		
# of Phone Contacts	599.69	579.67	(-0.83)	2269
	(532.77)	(506.64)		
Growth of Phone Contacts From Feb24 to Apr24	0.04	0.04	(0.12)	2269
	(0.17)	(0.17)		
Share of Urban Social Connections (10% overlap)	0.82	0.82	(0.18)	2269
	(0.07)	(0.08)		
Share of Dakar Social Connections (10% overlap)	0.45	0.45	(-0.18)	2269
	(0.13)	(0.13)		
Number of Obs	920	1349		2269

This table compares the taxi businesses' baseline characteristics across treatment groups. Treatment: Digital payment technology provided to the taxi owner and their driver(s).
The following regression is run: $Y_i = \alpha + \beta Treated_i + \epsilon_i$. Robust-heteroskedastic standard errors, clustered at the business level. t-Test reported with the following significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Digital transactions and phone contacts are observed in the administrative data. All other variables are collected during the baseline survey, and missing responses (refused to answer or don't know) are dummied out from the regression. The PPI Index described is a wealth aggregated index, specific to Senegal, as described in Poverty Probability Index (PPI). In Panel C, a social connection is defined as sharing at least 10% of phone contacts with another person. Location data is determined using mobile money agent locations and users' baseline withdrawal and deposit histories.

Table B2: Cross-Validating Social Networks via Encrypted Phone Contacts

	(1) Wife	(2) Family	(3) Friends	(4) Casual Connections	(5) Professional Contacts	(6) Daily/Weekly Interactions	(7) Rare Interactions	(8) Shared Information	(9) Discussed Technology
Overlap Share	23.77	14.44	9.06	4.13	7.27	11.83	5.42	11.29	12.34
	(22.83)	(12.87)	(7.17)	(5.91)	(6.95)	(10.81)	(4.92)	(10.31)	(10.63)
Observations	121	1221	1115	1725	881	2407	209	2439	817

Notes: This table presents summary statistics of the overlap share for each relationship type to validate the accuracy of the overlap measures (mean and standard deviation in parentheses), linking a random subset of the phone contact overlap data to the survey data. The survey was with all experimental participants, asking them about a randomly selected subset of 16 mobile money recipients and senders. Participants described their relationship with these 16 individuals, including discussion frequency (daily/weekly or rarely/never) and conversation content (general information sharing vs. explicit discussions about technology). Casual connections refer to people participants could not remember by name when asked.

Table B3: Summary Statistics - Phone Contact Network ($\geq$10% Overlap Cutoff)

	(1) Urban	(2) Rural	(3) Dakar	(4) Experiment Taxi Businesses
# of Phone Contacts	684.29	523.22	737.04	587.51
	(721.31)	(538.25)	(781.98)	(515.65)
Share of Urban Social Connections	0.86	0.81	0.86	0.82
	(0.22)	(0.29)	(0.21)	(0.07)
Share of Dakar Social Connections	0.53	0.51	0.55	0.45
	(0.31)	(0.34)	(0.31)	(0.13)
Observations	2946029	562341	1546224	2165

Notes: The social network is constructed from all the mobile money users identified in the contact network of experimental taxi businesses, for computational readons. While the exact number of contacts for each user is known, the encryption process prevents identifying the actual contacts. Therefore, in rows 2 and 3 of this table, a social connection is defined as sharing at least 10% of phone contacts with another person. Location data is determined using mobile money agent locations and users' withdrawal and deposit histories. Specifically, the most frequently used agent's location in 2021 and 2022 (mode) is used to determine each user's likely place of residency.

Table B4: Phone Contacts Overlap Network Matrix Across Industries

	Beauty	Boutique	Delivery	Electronics	Fabric	Grocery	Hardware	Jewelry	Mechanic	Restaurant	Tailor	Taxi
Beauty	.129	.034	.013	.044	.06	.046	.041	.055	.042	.063	.062	.083
Boutique	.075	.122	.015	.05	.08	.065	.084	.022	.034	.041	.009	.099
Delivery	.013	.021	0	.011	.019	.041	.011	.014	.065	.016	.014	.09
Electronics	.047	.043	.059	.054	.029	.037	.03	.037	.042	.024	.015	.073
Fabric	.052	.032	.054	.054	.063	.045	.041	.018	.054	.035	.017	.082
Grocery	.024	.054	.019	.061	.062	.063	.054	.023	.072	.082	.018	.079
Hardware	.046	.029	.009	.042	.035	.024	.098	.019	.052	.029	.01	.08
Jewelry	.017	.013	.001	.067	.08	.06	.062	.029	.033	.018	.121	.086
Mechanic	.026	.017	.002	.032	.045	.031	.042	.043	.151	.028	.049	.087
Restaurant	.05	.062	.05	.064	.069	.057	.069	.012	.044	.036	.032	.092
Tailor	.031	.03	.022	.051	.037	.033	.033	.163	.053	.046	.015	.085
Taxi	.005	.005	.001	.006	.008	.007	.004	.002	.016	.003	.001	.246

Notes: This Table shows the phone contacts overlap matrix across industries. Using the phone contacts of each user, it shows the share of businesses within the phone contacts of business owners with a minimum 10% overlap share. It reads as follows: column 1, row 1 shows the share of businesses in beauty/care in the phone contacts of beauty/care business owners. Column 2, row 1 shows the share of "boutique" in the contacts of beauty/care business owners with at least 10% overlap, etc. For computational reasons, this relies on a partial and potentially biased subset of the data of the network data, of users connected to at least one taxi business in the experiment. Hence, this is only used descriptively to motivate the study.

Table B5: Kinship Survey in the Transaction Network - Summary Statistics

	Share
Panel A. Nature of the Relationships	
Family	0.23
	(0.16)
Friends	0.16
	(0.15)
Any Business	0.34
	(0.20)
Taxi Drivers	0.10
	(0.11)
Taxi Drivers Same Garage	0.01
	(0.04)
Business Owners	0.19
	(0.15)
Both Personal and Professional	0.23
	(0.17)
Casual Interactions - Do Not Remember	0.42
	(0.23)
Panel B. Frequency of Conversations in Past 3 Months	
Every Day	0.37
	(0.26)
Every Week	0.31
	(0.23)
At Least Once a Month	0.21
	(0.21)
Less Than Once a Month	0.06
	(0.12)
Never	0.02
	(0.07)
Would Borrow Money To If Needed	0.51
	(0.29)
Panel C. Information Sharing	
Generally Share Important Advice/Information	0.74
	(0.28)
Discussed or Recommended the Digital Payment Technology	0.12
	(0.18)
Observations	1952

Notes: This table displays summary statistics about the kinship survey data collected from September to December 2023 among RCT-taxi businesses. The survey involved businesses successfully followed up with and who consented to participate in this kinship survey. Sixteen links were identified for each respondent. Eight links were randomly selected from the pre-experiment transaction network, while the other eight were chosen from transactions occurring during or after the experiment. Respondents were asked to define their relationship and several survey questions with each of these links.

Table B6: Technology Adoption Spillovers Within Firm Networks - Transaction Network

	(1)	(2)	(3)
	City-wide (Dakar)		Across-Space (Outside)
	Intra-Industry	Inter-Industry	Inter-Industry
Number of treated connections	0.32359***	0.25764**	-0.04676
	(0.10403)	(0.12510)	(0.03413)
	[0.11681]	[0.13128]	[0.03603]
Number of connections	2.64048***	0.65681***	0.01034
	(0.18711)	(0.14555)	(0.02543)
	[0.16199]	[0.20457]	[0.02740]
Obs	107570	107570	107570
Control Mean	1.956	4.926	0.418
Percent Change	16.543	5.230	-11.187
Number of connections	1.177	1.177	1.177
RI p-values	[0.098]	[0.102]	[0.850]

Notes: This analysis examines spillover effects of being connected to treated taxi businesses, while controlling for the number of connections and the overall network size. The full transaction network is considered in this Table to define a connection. The regression model used is $Adoption_i = \alpha + \beta_1 NumberOfTreated_i + \beta_2 NumberOfTreatedControl_i + \epsilon_i$. Network standard errors, as calculated based on Leung (2020), SE_{nw}, are displayed in brackets [...]. These standard errors take into account the dependency graph and the correlated effects across the network. Specifically, the calculation considers first-order links, which means it accounts for whether units i and j are directly connected. Heteroskedastic-robust standard errors are provided above in parentheses (...). The stars are to describe p-value p reported from a t-test β/SE_{nw}, with *** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$.
RI p-values are computed from 1000 permutations of the treatment assignments under the sharp null hypothesis of no positive spillover effects (one-sided), using the T-score test statistic as derived in Athey et al. (2018).
The **Percent Change** represents the percentage change in the likelihood of adoption, i.e., β_1 divided by the control mean, which is the adoption rate among users who do not know any treated drivers. The number of experimental connections indicates the average number of connections to experimental taxi businesses. All coefficients, standard errors, and the control mean are multiplied by 100 to enhance readability.

Table B7: Technology Adoption Spillovers Within Firm Networks - 12% Phone Contact Overlap Cutoff

	(1)	(2)	(3)
	City-wide (Dakar)		Across-Space (Outside)
	Intra-Industry	Inter-Industry	Inter-Industry
Number of treated connections	0.04768***	0.14566***	0.03027***
	(0.00382)	(0.00517)	(0.00177)
	[0.00382]	[0.00525]	[0.00178]
Number of connections	-0.02811***	-0.08541***	-0.01756***
	(0.00217)	(0.00295)	(0.00101)
	[0.00217]	[0.00300]	[0.00101]
Obs	555533	555533	555533
Control Mean	0.640	1.206	0.148
Percent Change	7.450	12.078	20.451
Number of connections	24.432	24.432	24.432
RI p-values	[0.049]	[0.011]	[0.009]

Notes: This analysis examines spillover effects of being connected to treated taxi businesses, while controlling for the number of connections and the overall network size. The overlap share cutoff considered in this Table to define a connection is 12%. The regression model used is $Adoption_i = \alpha + \beta_1 NumberOfTreated_i + \beta_2 NumberOfTreatedControl_i + \epsilon_i$. Network standard errors, as calculated based on Leung (2020), SE_{nw}, are displayed in brackets [...]. These standard errors take into account the dependency graph and the correlated effects across the network. Specifically, the calculation considers first-order links, which means it accounts for whether units i and j are directly connected. Heteroskedastic-robust standard errors are provided above in parentheses (...). The stars are to describe p-value p reported from a t-test β/SE_{nw}, with *** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$.
RI p-values are computed from 1000 permutations of the treatment assignments under the sharp null hypothesis of no positive spillover effects (one-sided), using the T-score test statistic as derived in Athey et al. (2018).
The **Percent Change** represents the percentage change in the likelihood of adoption, i.e., β_1 divided by the control mean, which is the adoption rate among users who do not know any treated drivers. The number of experimental connections indicates the average number of connections to experimental taxi businesses. All coefficients, standard errors, and the control mean are multiplied by 100 to enhance readability.

Table B8: Technology Adoption Spillovers Within Firm Networks - 8% Phone Contact Overlap Cutoff

	(1)	(2)	(3)
	City-wide (Dakar)		Across-Space (Outside)
	Intra-Industry	Inter-Industry	Inter-Industry
Number of treated connections	0.01191***	0.05005***	0.00898***
	(0.00147)	(0.00303)	(0.00111)
	[0.00147]	[0.00305]	[0.00111]
Number of connections	-0.00730***	-0.03100***	-0.00544***
	(0.00084)	(0.00172)	(0.00063)
	[0.00084]	[0.00173]	[0.00063]
Obs	1814028	1814028	1814028
Control Mean	0.271	1.501	0.187
Percent Change	4.396	3.334	4.801
Number of connections	22.336	22.336	22.336
RI p-values	[0.145]	[0.190]	[0.205]

Notes: This analysis examines spillover effects of being connected to treated taxi businesses, while controlling for the number of connections and the overall network size. The overlap share cutoff considered in this Table to define a connection is 8%. The regression model used is $Adoption_i = \alpha + \beta_1 NumberOfTreated_i + \beta_2 NumberOfTreatedControl_i + \epsilon_i$. Network standard errors, as calculated based on Leung (2020), SE_{nw}, are displayed in brackets [...]. These standard errors take into account the dependency graph and the correlated effects across the network. Specifically, the calculation considers first-order links, which means it accounts for whether units i and j are directly connected. Heteroskedastic-robust standard errors are provided above in parentheses (...). The stars are to describe p-value p reported from a t-test β/SE_{nw}, with *** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$.
RI p-values are computed from 1000 permutations of the treatment assignments under the sharp null hypothesis of no positive spillover effects (one-sided), using the T-score test statistic as derived in Athey et al. (2018).
The **Percent Change** represents the percentage change in the likelihood of adoption, i.e., β_1 divided by the control mean, which is the adoption rate among users who do not know any treated drivers. The number of experimental connections indicates the average number of connections to experimental taxi businesses. All coefficients, standard errors, and the control mean are multiplied by 100 to enhance readability.

Table B9: Technology Adoption Spillovers Within Firm Networks - 10% Phone Contact Overlap Cutoff

	(1)	(2)	(3)
	City-wide (Dakar)		Across-Space (Outside)
	Intra-Industry	Inter-Industry	Inter-Industry
Share of treated connections	-0.01258	0.68631***	0.12234***
	(0.01705)	(0.03399)	(0.01238)
	[0.01706]	[0.03401]	[0.01238]
Number of connections	-0.00077***	-0.00263***	-0.00035***
	(0.00002)	(0.00006)	(0.00003)
	[0.00003]	[0.00007]	[0.00003]
Obs	974145	974145	974145
Control Mean	0.398	1.422	0.168
Percent Change	-3.162	48.264	72.819
Number of connections	22.774	22.774	22.774
RI p-values	[0.481]	[0.025]	[0.022]

Notes: This analysis examines spillover effects of being connected to treated taxi businesses, while controlling for the overall network size. The overlap share cutoff considered in this Table to define a connection is 10%. The regression model used is $Adoption_i = \alpha + \beta_1 ShareOfTreated_i + \beta_2 NumberOfTreatedControl_i + \epsilon_i$. Network standard errors, as calculated based on Leung (2020), SE_{nw}, are displayed in brackets [...]. These standard errors take into account the dependency graph and the correlated effects across the network. Specifically, the calculation considers first-order links, which means it accounts for whether units i and j are directly connected. Heteroskedastic-robust standard errors are provided above in parentheses (...). The stars are to describe p-value p reported from a t-test β/SE_{nw}, with *** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$.
RI p-values are computed from 1000 permutations of the treatment assignments under the sharp null hypothesis of no spillover effects (one-sided).
The **Percent Change** represents the percentage change in the likelihood of adoption, i.e., β_1 divided by the control mean, which is the adoption rate among users who do not know any treated drivers. The number of experimental connections indicates the average number of connections to experimental taxi businesses. All coefficients, standard errors, and the control mean are multiplied by 100 to enhance readability.

Table B10: Summary Statistics - Taxi Customer Networks

	Mean	SD	Min	Max
Panel - Taxi Customers				
Avg # of unique taxis	3.18	4.61	1	46
Avg # of transactions	3.28	4.79	1	46
Share of taxis with regular customers ($\geq$ 3)	.19	.39	0	1
Number of Obs	434891			

Notes: Transactions network data pre-experiment and business transactions from January 22 to August 2023 for the universe of businesses who adopted the technology. All taxi businesses, in and outside garages. The share of taxis with regular customers considers the taxis having customers with at least 3 different transactions.

Table B11: Local Technology Diffusion Around Garages - 100-meter-radius

	(1) Adoption Intra-Taxi Industry	(2) Adoption Inter-Industry
Number of treated connections - Social	-1.859	5.791***
	(3.182)	(2.079)
Number of treated connections - Non-Social	-0.0897	1.384
	(0.202)	(1.169)
Number of connections - Social	4.326***	-3.365***
	(1.446)	(1.023)
Number of connections - Non-Social	0.0214	-0.563
	(0.0873)	(0.526)
Control Mean Social	15.493	1.408
Control Mean Not Social	1.284	3.064
Percent Change - Social	-12.00	411.14
Percent Change - Not Social	-6.99	45.17
F-stat # Treated Social = # Treated Non-Social	0.33	5.67
Number of connections - Social	0.011	0.011
Number of connections - Non-Social	3.442	3.442
Number of garages	27	27
Observations	72284	72284

Notes: Sample of residents within a 100 meter radius around taxi garages. All garages with at least one mobile money agent within this radius are kept. Location is defined from the mobile money withdrawal and deposit history of each user in the country. Clustered SE at the garage level. Most users are assigned to one garage, and I dropped individuals with multiple garages to clustered SE at the garage level. Robustness not dropping these individuals altogether are also conducted with qualitatively very similar results. Social connections are defined by sharing more than 8% overlap share of phone contacts with the taxi driver in the garages. Only garages that are within the radius distance of a mobile money agent are considered. The **Percent Change** represents the percentage change in the likelihood of adoption, i.e., β_1 divided by the control mean 'social', which is the adoption rate among users who do not know any 'social' treated drivers. To enhance readability, all coefficients, standard errors, and the control mean are multiplied by 100.

Table B12: Local Technology Diffusion Around Garages - 200-meter-radius

	(1) Adoption Intra-Taxi Industry	(2) Adoption Inter-Industry
Number of treated connections - Social	-0.559	2.618
	(1.989)	(1.548)
Number of treated connections - Non-Social	0.0244	0.735
	(0.129)	(0.765)
Number of connections - Social	3.739***	-1.860**
	(1.039)	(0.763)
Number of connections - Non-Social	-0.0151	-0.273
	(0.0544)	(0.382)
Control Mean Social	7.477	2.336
Control Mean Not Social	0.773	3.139
Percent Change - Social	-7.48	112.05
Percent Change - Not Social	3.16	23.42
F-stat # Treated Social = # Treated Non-Social	0.09	2.14
Number of connections - Social	0.007	0.007
Number of connections - Non-Social	3.339	3.339
Number of garages	34	34
Observations	207372	207372

Notes: Sample of residents within a 200 meter radius around taxi garages. All garages with at least one mobile money agent within this radius are kept. Location is defined from the mobile money withdrawal and deposit history of each user in the country. Clustered SE at the garage level. Most users are assigned to one garage, and I dropped individuals with multiple garages to clustered SE at the garage level. Robustness not dropping these individuals altogether are also conducted with qualitatively very similar results. Social connections are defined by sharing more than 8% overlap share of phone contacts with the taxi driver in the garages. Only garages that are within the radius distance of a mobile money agent are considered. The **Percent Change** represents the percentage change in the likelihood of adoption, i.e., β_1 divided by the control mean 'social', which is the adoption rate among users who do not know any 'social' treated drivers. To enhance readability, all coefficients, standard errors, and the control mean are multiplied by 100.

Table B13: Adoption Inter Industry Across Space in Sub-Networks Elicited in Kinship Survey

Subnetwork	Adoption Across Industry (Outside) Family	Friends	Daily/Weekly Interactions	LendMoney	Clients	Casual Connections	Rare Interactions
Number of treated connections	-0.088	-0.409	0.068	-0.064	-0.253	0.134	-0.574
	(0.295)	(0.286)	(0.187)	(0.269)	(0.750)	(0.154)	(0.650)
Number of connections	-0.518	-0.114	-0.406**	-0.446*	-0.134	-0.420***	0.000
	(0.340)	(0.170)	(0.174)	(0.229)	(1.007)	(0.148)	(.)
Control Mean	0.664	0.588	0.342	0.569	0.641	0.245	0.840
Percent Change	-13	-70	20	-11	-40	55	-68
Observations	2947	2007	4211	3034	415	5226	614

Notes: Network survey data collected in Sep-Dec 2023. This analysis investigates the spillover effects of being connected to treated taxi businesses, while controlling for the number of connections and overall network size across various sub-groups as defined in the kinship survey data. Friends and Family are self-reported by drivers. Family includes spouses, parents, siblings, children, cousins, and any close family members. Friends include reported friends in none of the previous categories. Daily/Weekly and Rare Interactions are people taxi businesses talk to daily/weekly, or never/almost never, respectively. LendMoney are people the taxi business would borrow money from (so people that could lend money to the taxi businesses). Clients are former or regular customers of the taxis. Casual Connections are people they could not remember based on names when asked. The employed regression model is $(First)Adoption_i = \alpha + \beta_1 NumOfT_i + \beta_2 NumberOfTC_i + \epsilon_i$. Robust-heteroskedasticity standard errors (HC3) are displayed in parenthesis. To enhance readability, All coefficients, standard errors, and the control mean are multiplied by 100.