Pre-Analysis Plan
Adoption and Impacts of Digital Payment Technologies: Evidence from Informal Transit*

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1 Introduction

Digital technologies have spread rapidly in much of the world. They are potentially a game-changer for firms, for many reasons. This project focuses on the following two important channels: (1) they increase traceability, mitigating information asymmetry within firms, and (2) they remove the transaction costs involved in cash payments (e.g., due to shortages of small change). By reducing moral hazard, digital technologies enable changes in the contracting space between employers and employees. This change may, itself, constitute a barrier to their adoption. To study their multidimensional issue, I conduct a randomized experiment by introducing digital payment technologies into widespread small businesses, taxis, in Senegal. In collaboration with one of the largest mobile money companies in the country, I test different options for digitizing payments and evaluate the impact of digital payment technologies in the informal transit sector.

2 Academic Contribution to the Literature

This project should contribute to at least three strands of the literature. **(1) Technology Adoption**. This project contributes to the broad literature on technology adoption in lower-income countries. This project focuses on the transportation sector, and isolates an understudied barrier to technology adoption, "moral hazard" – Atkin et al. (2017). The technology offered in this study is a digital payment app that discloses information on output and effort of drivers to owners. The large sample of employer-employee pairs will allow me to study mechanisms and contractual changes. **(2) Contract and Development.** This project will use existing insights about relationship value in contracts in

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the context of technology adoption. The extent to which contracts may affect technology adoption has been challenging to study in developing economies, and this project will contribute to a recently growing literature in organizational economics (Macchiavello and Morjaria (2015), Macchiavello and Morjaria (2021)). **(3) Transportation and Electronic Payments**. Transportation is a key sector in large developing cities and is often informal, unregulated, and dangerous. Relying on seminal empirical work in the US, Hubbard (2001), Hubbard (2003)), Baker and Hubbard (2004), this study will show to what extent electronic payments can increase productivity and lead to firm growth in a low-income setting. Further, there is still limited evidence of the importance of transaction costs for businesses (Aker et al. (2016), Suri and Jack (2016) focus on households), and transport-related research in developing economies has primarily focused on monitoring, Kelley et al. (2022), de Rochambeau (2021).

3 Sample and Treatment

3.1 Sample Population and Survey Timeline

This project focuses on private taxis in Dakar, Senegal. As in most developing cities, taxis are ubiquitous in Dakar (about 20,000 active taxis in 2019 - CETUD). The sector is mostly informal and includes two main stakeholders: the taxi business owner (principal) and the driver (agent). The owner constitutes the legal entity owning the taxi business. There are three types of owners: (1) most owners verbally contract with one driver and own a small fleet of 1-2 vehicles as a side activity (≈50%). (2) Some owners also drive their own taxi alone (≈25%) or (3) drive their taxi but also rent it to another driver/employee on their rest days (≈25%). In this context, the population studied is among the urban poor (PPI Index - IPA). From surveys, the extreme majority of taxi drivers and owners are male, did not complete primary education, more than half of drivers could not save any money in the past year, and most live in precarious conditions.

Listing Survey. The experimental sample includes all drivers and owners recruited through a listing survey from March to May 2022. Drivers were recruited in garages, car wash stations, meeting points, and on the streets of Dakar (during traffic jams). Owners not driving were primarily recruited by asking drivers about their owners' contact during the listing survey. Over 6,400 owners and drivers were listed, and we collected their basic characteristics to stratify the randomization. Out of the listing sample, we excluded from the experiment (1) drivers refusing to give their owners' contacts and vice versa ≈ 30% [1], (2) drivers that stated not having a smartphone during the listing ≈ 15%, (3) contacts provided but unreachable ≈ 10%, (4) secondary drivers (driving for multiple owners and

[1] Note that for drivers refusing to give their owners' contact, we still collected their basic information for prediction purposes. We then run a separate phone survey with this sample where we randomize whether we explicitly mention that their owners will access the visibility of their transactions. This intervention is to understand how visibility affects the willingness to provide their owners' phone numbers and thus access the product. We will also follow up with these drivers at endline to collect further characteristics about this sample.

taxis at the same time) - not considered during the listing, (5) owners with more than four taxis $\approx 1\%$. We then constituted pairs of owner-driver and included owners driving alone to be part of the experiment . Altogether, these excluded categories represent about 50% of the listing sample.

Baseline Survey. We contacted 2,072 owners and 845 drivers in 12 batches to come to three tents located at three different locations in Dakar. The baseline survey took place from March to June 2022. Both owners and drivers came to the tents to be surveyed, with an attrition rate between the invitation to the survey actually taking place of about 15% [2]. Respondent's treatment arms were revealed at the end of the baseline survey so that we can rule out concerns of differential attrition / selection patterns across groups.

Follow-Up, Mystery Passengers, and Endline Surveys. The experimental sample will be contacted to conduct a follow-up survey and then an endline survey to collect the key outcomes, described below.

3.2 Treatments

Owners and drivers were invited to participate in the study and use the digital payments technology that aims at reducing transaction costs involved in cash payments (e.g., small-change shortages). The unit of randomization is the **taxi business owner**. In this setting, technology adoption is generally a joint decision between owners and drivers. In practice, the *intensive-margin* decision of using the technology is mostly on the driver's side.

QR codes are installed in taxis to allow passengers to pay securely via mobile money at a 1% fee for drivers. Drivers are also able to transfer payments to their owners at no fee. In collaboration with the largest mobile money company in Senegal, I designed the base technology with three options for varying the amount of information available to the owners on their drivers (see Figure A1):

1. *No Visibility (N-V)*: The owners do not access their drivers' transactions.
2. *Downside Visibility (D-V)*: The owners get notified each day via text at midnight of their drivers' total collection up to 5,000 FCFA (the estimated average daily digital collection). If the total balance is above 5,000 FCFA, the owners do not get notified of the surplus.
3. *Visibility (V)*: The owners get notified and can observe all the drivers' transactions[3]
4. *Pure Control*: no technology provided.

[2]Some drivers came but were, in fact, not eligible to receive the product; namely they did not have an Android smartphone (about 10%). We surveyed drivers without an Android smartphone so that we are able to analyze their data separately for robustness checks, i.e., running ITT and IV regression, including this sample.

[3]This option was initially the only one offered to other types of businesses accepting P2B mobile money payments.

Owners can receive digital transfers from drivers at no fee in the three treatment arms. The goal of these three treatment arms is to quantify one potential barrier for drivers to use the technology, which I call the ”moral hazard” barrier to technology adoption. We collected the willingness-to-pay (WTP) of owners for their randomized option, incentivized using the BDM (Becker–DeGroot– Marschak) method, where a price is drawn, and they are invited to complete their purchase only if the price is below their WTP. All participants were also asked to rank the three options. In theory, Option *No Visibility* should be preferred by drivers while Option *Visibility* may be preferred by owners depending on their (first and second-order) beliefs about their drivers. Option *Downside Visibility* might be a middle ground pleasing both parties as it allows drivers to credibly signal “bad days” to their owners, while not revealing the overall surplus on ”good days”.

Note that, at the time of writing this PAP, we plan to ”treat” the control group with either *full visibility* and *no-visibility* at endline, with the intent to conduct another round of follow-up in the future. The visibility group will be randomly sub-divided into two groups: whether we *nudge* the drivers *or* the owners about the possible contractual changes induced by the visibility to strengthen the treatment effect, and measure the trigger of the contractual change if any (see Figure A1). The content of the nudge will depend on preliminary data analysis and findings from the follow-up survey.

3.3 Randomization

We run the randomization on a computer[4], using the listing data. We randomized owner-driver pairs and owners driving alone across 12 batches, for logistical reasons - we wanted to limit the time between the listing survey and the baseline survey, to avoid losing respondents. All data from the listing was back-checked over the phone. More than 70 survey staff were involved in this activity of listing drivers, checking their data, constituting their pairs, calling them to come to the tents, and conducting the baseline survey.

We stratify the randomization on several dimensions:

- Proxy for **baseline digital usage** for the drivers, i.e., taxi-like transactions in the past 3 months. We computed a dummy variable for whether the driver made more than the median number of six taxi-like transactions pre-intervention using their mobile money personal wallet.

- Proxy for **baseline knowledge/beliefs**: business type (owners driving or not), number of taxis (dummy for whether they have one or multiple taxis), and length of the relationship (dummy equal to one if more than two years of relationship, the median).

- Proxy for **baseline risk aversion**: riskiness of work strategy, i.e., whether the taxi drivers circulate throughout the city or wait for passengers in a fixed place.

The stratified randomization code was run for each separate batch. The control group constitutes about 40% of the sample, while the treatment groups are split into three groups

[4]We used the Stata command `randtreat` to stratify the randomization.

($\approx$ 20 % each) to maximize power, according to power calculations conducted before the survey.

Table B1 describes the randomization balance of the initial sample contacted, and we will run separate balance tests on the effective experimental sample. Not surprisingly, since the treatment status is randomly assigned, there is no imbalance across key variables.

4 Research Questions

Primary research questions:

1. To what extent do existing information asymmetries in the informal transit sector prevent technology adoption, contractual changes, and business growth?

2. What are the impacts of digital payment technologies on productivity, prices, business growth, and network adoption (technological complementarities)?

3. What are the impacts of digital payments as monitoring technologies on the contracting space in a widespread principal-agent relationship in lower-income countries, i.e., the taxi business? To what extent can potential changes be explained by standard principal-agent models?

Secondary research questions:

4. What are the distributional consequences and welfare implications of digital payment technologies on within-business relationships?

5. To what extent do norms and social networks push adoption and contractual changes?

5 Empirical Analysis

5.1 Primary Outcomes

5.1.1 Technology adoption

- *Intensive margin* (technology usage on the driver side): it is ambiguous *a priori*. Drivers may use monitoring technology to signal their productivity, and thus use it further under visibility. They may conversely be able to manipulate the revenue collected by using it less under visibility than under non-visibility/downside visibility. This "visibility" effect should not last as the equilibrium changes in the market (increase in overall adoption), and passengers adopt further.
- *Extensive margin*. The extensive-margin decision of adopting the technology is usually a joint decision between the owner and the driver. In this experiment, we had no way to contact the owner without the driver's consent. Therefore, for the sample of drivers who refused to provide us with their owners' contact information, we conducted a sub-experiment to test the impact of transaction visibility on accepting to give their owner's contact: some drivers were randomly told whether their owners could see their transactions or not. This experiment will be used to test the null hypothesis of information asymmetry/moral hazard as a barrier to technology adoption on the driver's side.

5.1.2 Productivity gains

The outcomes in this section will be measured at **driver-level outcomes**. For the following outcomes, I will pool data from the three sub-treatment arms (varying visibility) – unless otherwise noted. I will rely primarily on survey data.

1. **Transaction costs of cash payments**: both at the *intensive-margin* - small-change shortages, defined by the following variables: frequency of substantial time lost looking for cash/small changes, price cut because of small change shortages, total money lost because of small-change, as estimated by the driver, and *extensive-margin*: number of passengers refused because they could only pay digitally and a dummy whether they refused any passengers because of digital money.
2. **Digital gains for businesses** The digital payment technology could be effective at improving revenues by at least two mechanisms:
   - *Supply-side*: by reducing the time lost associated with using cash (e.g., looking for changes), the taxi drivers could be able to do more trips in a given day / not refuse a passenger for not having change.
   - *Demand-side*: passengers could prefer taking a taxi with digital payments than without digital payments (it may or may not come at the expense of the control group, depending on whether the passengers would have taken a taxi or not).

3. **Pricing Strategy**: whether final prices will be a multiple of 500 or not. The slope of the supply curve may transition from stair-step fashion to a more linear supply curve. Price data were collected from mystery passengers.

4. **Overall Business Profits**. They will be measured from a re-collection of all the costs and revenues collected by the drivers in the past three days (at follow-up and endline survey), but also asking for average profit directly - De Mel et al. (2007) and money saved thanks to the digital technology. Un-incentivized willingness-to-pay will also be measured and considered as an outcome.

5.1.3 Contractual change

1. **Contractual change**: The emerging contract is in itself a key empirical question of this study. Theory leads to hypothesizing different possible scenarios. (1) A change in the contract structure, **transitioning to a risk-sharing or a wage contract**; (2) A change in contract terms, e.g., an increase in the transfer fee; (3) A change of opinion about what the optimal contract should be, in the absence of switching costs (measured as a mental exercise at endline). The nature of changes, enabled under full or downside visibility, will depend on owners' and drivers' baseline characteristics (in particular, risk aversion and limited liability, as measured in an index), baseline beliefs, and/or contractual norms about the current contract.[5]

2. **Employee's behavioral response to contractual change**: we plan to measure effort and risk-taking behavior via proxies. *Effort*: number of days and hours worked; productivity (number of passengers, total collected, etc.), *Risk-taking*: reparation costs, night shifts, accidents.

5.2 Secondary Outcomes

1. **Network adoption**: Despite the cost associated with using cash, cash could remain efficient as long as the majority is still using it: does the technology adoption spark more digital payments for the respondents, but also within the social network? We will analyze the number of socially and financially "connected" individuals adopting the technology / using digital payments, taxi drivers or not. That may differ across the level of competition (e.g., whether a driver is part of an association or not).

2. **Savings**: as measured in the survey and the administrative mobile money data (partial savings). Two effects may induce more savings:

   (a) Behavioral savings and cash-on-hand:

   - the absence of cash-on-hand could prevent drivers from spending during their day and allow for more significant savings. Daily consumption will be measured.

[5] Note that owners may decide to implement contractual changes with existing drivers or new ones (entry), based on drivers' type - baseline productivity.

- a recent literature - Jakiela and Ozier (2016); Carranza et al. (2022) - has also underlined the importance of social pressure / tendency to share earnings to relatives when visible. The technology may reduce such behavior by removing the driver's cash-on-hand, thus increasing savings. Unclear which way this may go *a priori*: it may well be easier to transfer via mobile money, even though cash may be more visible. We will distinguish within the household vs. outside the household.

(b) Traceability and greater financial management: whether they keep records of transactions. Better management may allow drivers to better save their own money.

A change in savings could, in turn, relax limited liability constraints under all treatment arms and thus affect the employer-employee relationship described in Section 5.1.3. This change is in the forms of, for instance, default on transfer, stress associated with the transfer, satisfaction with the relationship, or trust.

3. **Contractual norm**: About 50 taxi owners also the president of associations were automatically provided the technology to facilitate the rollout in this setting. These presidents were randomized into "full visibility" vs. "non-visibility" treatment arms. We will test whether being a driver in an association with a president treated with full visibility increases the likelihood of contractual change. The idea is that the president of associations may spread contractual norms more easily.

4. **Trust and Altruism**: the visibility offered by the technology may affect intrinsic behavioral preferences between owners and drivers. We will measure trust in two main ways: (1) we will ask explicitly for first-order and second-order measures of trust, on a scale of 0 to 10, (2) we will ask questions on actions related to trust between two people: keeping the taxi home, willingness to get a GPS tracker, owners lending money to their drivers, asking for maintenance invoices, etc. To measure altruism, we will conduct an incentivized dictator game, not informing the other parties about the amount sent – Koch and Normann (2008).

5. **Safety**

   - *Actual safety*: any robbery in the past three months. I hypothesize robbery and the amount of money robbed on treated drivers to reduce, as money is now partly collected digitally in such taxis.[6]
   - *Subjective safety*: the extent to which drivers are worried about getting robbed should be reduced.

6. **Distributional/welfare implications**: ultimately ambiguous, will depend on key model parameters (e.g., risk aversion, limited liability, baseline relationship). At baseline and endline, we will measure revealed preferences for the three visibility options.

[6]An unlikely side effect might be that the product is perceived as signaling wealth to robbers, thus increasing robbery. But I believe this is unlikely ex-ante.

5.3 Heterogeneity Analysis

We plan to explore heterogeneity along the following dimensions measured at baseline, directly grounded in theory:

- Willingness-to-pay for the technology
- Level of transaction costs involved in cash payments
- Predictors pre-specified and directly used to stratify the randomization
  1. Owners and drivers' proxy for risk aversion and actual risk aversion parameters (measured at baseline): a high-risk aversion coefficient will predict a higher likelihood of changing the contract structure towards a risk-sharing type of contract.
  2. Age of the relationship: the longer the relationship, the higher the value of the existing contract, and the less likely the contractual change will occur.
  3. Owners' type: whether they are drivers themselves or not. Theory would hypothesize that owners not driving would know less about their drivers, and thus information may play a larger role.
  4. Owners' number of taxis (dummy for whether they have one or several taxis, typically 2). Owners with several taxis/drivers would be able to better compare relative performance and distinguish between the nature of a bad shock (individual vs. market-level).
  5. Digital usage at baseline: dummy for whether they used taxi-like transactions more than six times (median) in the past three months before the launch of the experiment.
- Other proxies for relationship value: trust, relationship links (e.g., kinships), and the number of refusals before finally providing the owners' phone numbers.
- Owners' beliefs and heterogeneity of beliefs between owners and drivers will affect the contract scheme – Dumav et al. (2022).
- Preferences for the visibility option as a proxy for how much people anticipate contractual changes and costs/benefits from the visibility as monitoring technology.
- Drivers' limited liability, as proxied by savings.
- Drivers' outside option, as proxied by wealth.

Last but not least, heterogeneity analysis will also take into account attrition as an outcome variable, i.e., pairs may split or not as a result of the treatments. Such an outcome would be interesting but may complicated causal inference. We plan to run regressions both on the full sample and the sample that remained pairs.

5.4 Regression Analysis

This section describes the estimation strategy. The most general estimating equations we use are:

Taxi business-level regressions:

$$y_j = \beta T_j + \gamma X_j + \epsilon_j \tag{1}$$

$$y_j = \beta_1 T_j^1 + \beta_2 T_j^2 + \beta_3 T_j^3 + \gamma X_j + \epsilon_j \tag{2}$$

Taxi driver-level regressions:

$$y_{ij} = \beta T_{ij} + \gamma_1 X_j + \gamma_2 X_{ij} + \epsilon_{ij} \tag{3}$$

where i indexes drivers, and j indexes businesses (taxi business owners). Standard errors are clustered at the business level in Equation (3). y_{jk} and y_{ijk} denotes business-level and driver-level outcomes of interest, respectively, and X_{ijk} and X_{jk} are driver and business-level covariates, as discussed below[7]. Finally, T^1, T^2, and T^3 denote the three different visibility treatment arms (full, downside visibility, and no visibility) described above. T denotes the pooled treatment of receiving access to digital payments on driver-level outcomes. Each of the corresponding coefficients estimates the average causal effect of each treatment arm on the outcome of interest. In alternative specifications, we will look at effects within the sample of treated respondents to compare taxi businesses with the technology and conduct pairwise comparisons across groups.

There are two main sets of analyses we will run.

- Analysis using follow-up and endline survey sample. For outcomes related to (1) the various transaction costs involved in cash payments and (2) relationships between owners and drivers (measured on both sides).
- Analysis using administrative data. Digital transaction data will be analyzed to (1) measure the first-stage (T on usage) and (2) identify contracts, i.e., financial transfers between owners and drivers (available for the subset of the sample using mobile money for such transfers).

For our core analyses, we will use heteroskedasticity-robust standard errors and will intend to remove any contamination bias, as described in Goldsmith-Pinkham et al. (2022).

5.5 Controls

I will include specifications with no covariates. For all regressions, we will then use machine learning techniques to select the controls. Potential controls include:

[7] I propose specifications without strata fixed effects to limit sample size loss from attrition due to the absence of smartphones, described in Section 3.1. I will perform randomization inference as a robustness check.

- *Driver-level covariates*: an index of estimated driver wealth (an index constructed following the PPI Index in Senegal), a dummy for whether they saved in the past three months, a dummy for whether they prefer visibility or not, their risk aversion parameter and their willingness-to-pay for the technology (all collected at baseline).
- *Business-level covariates*: A dummy indicating the type of contracts within the taxi business (salary / risk-sharing), a dummy for whether there were issues such as defaulted payments in the past. In addition, we will test for balance across a larger set of individual- and business-level variables, and we will show robustness in controlling for any that are significantly imbalanced.

Finally, I will use these variables to conduct a heterogeneity analysis, as specified above.

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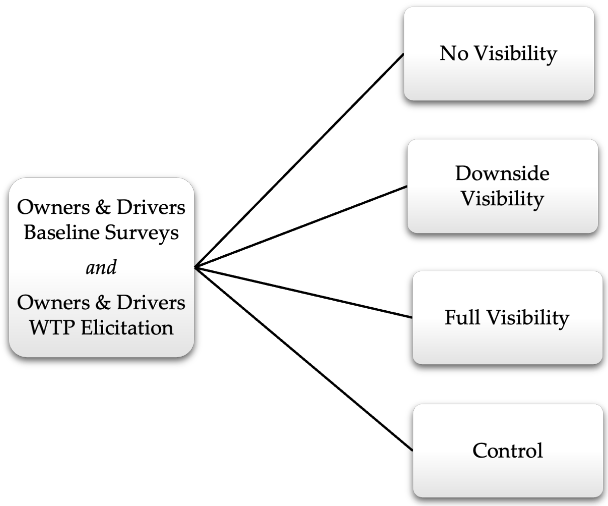
Appendices

A Figures

Figure A1: Experimental Design



B Tables

Table B1: Balance Table - Initial Full Sample

	(1) V	(2) D-V	(3) N-V	(4) Control	F-Test	N
Panel A. Variables Used To Stratify						
Owners not driving	0.22	0.23	0.24	0.25	(0.40)	2072
	(0.42)	(0.42)	(0.43)	(0.43)		
Owners driving his own taxi alone	0.59	0.58	0.60	0.58	(0.20)	2072
	(0.49)	(0.49)	(0.49)	(0.49)		
Owners driving, with at least one driver	0.18	0.20	0.17	0.17	(0.62)	2072
	(0.39)	(0.40)	(0.37)	(0.38)		
Owns only one taxi	0.97	0.95	0.96	0.95	(0.78)	2012
	(0.17)	(0.21)	(0.20)	(0.21)		
Long relationship (>2y)	0.46	0.44	0.40	0.42	(0.53)	843
	(0.50)	(0.50)	(0.49)	(0.49)		
Dummy for risk aversion	0.19	0.18	0.18	0.18	(0.07)	1977
	(0.39)	(0.38)	(0.38)	(0.39)		
High-users of digital transactions	0.45	0.45	0.40	0.43	(0.74)	1982
	(0.50)	(0.50)	(0.49)	(0.49)		
Panel B. Other Listing Variables						
Age of the relationship	3.44	3.81	2.83	3.37	(1.70)	835
	(4.11)	(4.85)	(3.25)	(3.73)		
Number of taxis	1.04	1.06	1.05	1.07	(1.18)	2012
	(0.24)	(0.30)	(0.23)	(0.39)		
Owner or driver in taxi association	0.35	0.32	0.35	0.33	(0.53)	2063
	(0.48)	(0.47)	(0.48)	(0.47)		
Owners having taxi property paperwork	0.84	0.90	0.86	0.85	(2.07)	2072
	(0.36)	(0.30)	(0.35)	(0.36)		
Owner: Digital taxi-like transactions IN in past 3mo	8.81	7.76	7.77	7.76	(0.58)	1584
	(19.06)	(11.30)	(10.98)	(10.18)		
Driver: digital taxi-like transactions IN in past 3mo	7.54	8.36	6.34	6.62	(1.40)	837
	(9.36)	(17.18)	(7.05)	(7.89)		
Owners: All digital transactions IN/OUT in past 3mo	71.63	81.40	73.59	77.53	(0.58)	2072
	(95.42)	(162.74)	(99.14)	(110.90)		
Drivers: All digital transactions IN/OUT in past 3mo	49.28	57.39	53.15	50.16	(0.57)	837
Number of Obs	437	398	422	815		2072

V: Full Visibility // D-V: Downside Visibility // N-V: No Visibility of the owner on their driver's transactions.
F-Test ANOVA reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Variables used to stratify are described in Section 3.3.
Digital transactions are actual mobile money transactions observed in the administrative data. All other variables are collected during the listing.