Measuring Informal Work with Digital Traces: Mobile Payphone Operators in Rwanda

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ABSTRACT

This paper illuminates the workings of an informal industry in one of the poorest countries in the world. I study payphone operators in Rwanda using 427 million digital traces recorded on the mobile phone network. I demonstrate how to extract economic behavior from these traces. They reveal every call that generates revenue, as well as operators' critical business decisions: entry, the daily decision of where and when to work, and exit. Over the period I study, thousands of informal workers enter the industry. New entrants learn to optimize their operations within the first two months. Patterns are suggestive of business stealing.

CCS CONCEPTS

•Applied computing→Economics;•Social and professional topics→Government technology policy

KEYWORDS

Informal work, measurement, mobile phones

1 Introduction

The informal sector represents 30-40% of economic activity in developing countries [11]. Estimates suggest there are 10 million street vendors in India [15], and street vending accounted for 12-24% of informal employment in a sample of African cities [13]. However, we know little about these industries. Informal work is difficult to measure via standard methods. Many informal workers are transitory, and forget or fail to disclose earnings when surveyed. Additionally, several experiments find that being surveyed alters the choices that respondents make afterwards [16]: high frequency surveys can contaminate the behavior they seek to measure. As a result, we know only coarse answers to even basic questions about informal industries. What is the daily pattern of wages for informal work? What is the learning curve for informal jobs? How do individuals—and industries—respond to shocks?

ICTD '20, June 17–20, 2020, Guayaquil, Ecuador

ACM ISBN 978-1-4503-8762-0/20/06. https://doi.org/10.1145/3392561.3397576

This paper studies mobile payphone operators in Rwanda, informal work that was common as mobile networks expanded. A person can become a payphone operator by purchasing a special handset from the mobile network operator, and going through basic training. Payphone operators earn a small margin on each transaction placed on their phone. Operators sit in market centers and street corners, next to airtime sellers and vegetable vendors.

A special feature of mobile payphones is that every transaction leaves a digital trace. This project uses 427 million digital traces left by the majority of payphone operators in Rwanda. Traces include every call—and thus every payphone interaction that generates revenue. I show how these records reveal the most important business decisions each operator makes: the decision to enter the market; the daily decisions of whether to work, where, when to start, when to take breaks, and when to end; and the decision to exit. These interactions paint a rich picture of each individual's business. Collectively, they reveal the competitive interactions in the entire industry. These records are collected passively, at close to zero cost.

This study takes a first step to describe the mobile payphone industry, and show how these records can be used to better understand informal work in developing societies. The job of a payphone operator is common, and is similarly illuminated in standard phone logs around the world [3]. To the extent that the same individuals choose between operating a payphone or engaging in other informal work, their decisions as payphone operators reveal the marginal outside opportunities available.

This complements a few studies. Futch and McIntosh [9] analyzes the impact of Rwanda's Village Phone payphone program, corroborating survey data with basic statistics from digital traces. Mann and Nzayisenga [12] analyze airtime sellers in Kigali through interviews. Donner [6] analyzes how diverse Rwandan microentrepreneurs use mobile phones. Hired drivers in rich countries (taxi or ride share) also generate digital trace data which has generated insight about self employment [4, 8, 5], but driving jobs are inaccessible to much of the world's poor.

2 Background

Payphones were common. 27% of Rwandans over 16 years used public phones by 2008, per a representative survey [14].

Payphones were cheaper, and were both substitutes and complements to personal mobile phones. Payphone use is actually higher among mobile phone owners—56% of adult mobile phone owners report using public phones [14]. Of those, 35% reported doing so because they were cheaper than personal mobile phones, and 6% because they did not require charging their phone's battery.

Rwanda had four types of payphones:

Landline payphones are mostly urban, similar to legacy payphones in developed countries.

Tuvugane ("let's talk") payphones were introduced in 2004. They are special handsets that look like landline phones but use the mobile phone network. To become an operator, one would apply, pay $272 for a handset, and complete basic training. Outgoing calls are billed in segments of 8 seconds. The mobile network sets a retail price, and charges operators a wholesale price discounted by 20%, which is electronically debited from their balance. Charging a price other than the retail price would require making small change, so would add friction. Incoming calls to payphones are rare. Some payphones are operated by shopkeepers in addition to their normal business; others are operated by street vendors. Operators may also sell phone credit. Operators could freely choose their work location until a government crackdown in 2008.

Village Phones (see [9]) were introduced by the NGO Grameen in 2005. They were standard Nokia handsets connected to a long range antenna and a car battery, which allows them to be used in remote villages at the fringes of the mobile network. The program was imported from Bangladesh where it was successful; but in Rwanda, Tuvugane phones were already providing some of these services. Microfinance loans were available to finance the purchase of the phone. The program started with a 50 phone pilot from May 2005 to October 2006, and was subsequently expanded.

Standard mobile phones could also be informally rented out by their owners. However, if an operator used a standard phone plan, he would pay the standard retail rate, which is higher than both the retail and wholesale rates for payphone plans. Thus, standard phone owners are unlikely to rent out their phones to the same scale as the official payphone categories. Although I observe standard mobile phones in my digital trace data, this data does not differentiate between transactions by the owner or by a person renting the phone, so I do not consider this type of sharing.

3 Materials and Methods

I observe every transaction over nearly every mobile phone in the country using call detail records from Rwanda's dominant operator, from January 2005 to May 2009. This operator held above 88% of the market for personal mobile phones, and most of the payphone market. The data includes metadata for 5.3 billion transactions, including each call and text message, with the duration, an anonymous identifier for each account, the handset model, and the location of the tower used. From January 2005 to August 2008 I also observe the charge. I infer each individual's phone plan using the billing model developed in [2].

I obtain data on the going price for day labor at each market center from the Rwandan government market information service.

I corroborate this data with Research ICT Africa's nationally representative household survey of ICT usage [14], and a Rwandan government household survey (EICV).

I identify payphone accounts using data on accounts and devices:

Tuvugane payphones include a special account bound to a particular handset model (Tellumat M744 and M762). To identify these payphones, I first select accounts whose mode handset was either of these two models (N=7017). For accounts that were active before July 2008, I also have billing information. Since the billing structure for Tuvugane payphones was unique, I remove the small number of individuals who may happen to have the same model but do not operate it as a payphone by removing those for which the mode plan was not the local payphone plan (leaving N=7004).

Village Phones use two common handset models (Nokia 1110i or 1100) connected to a large antenna, so the handset model is not an identifying feature. They do have a unique billing structure however. I use the inferred Village Phone billing structure to identify these phones. Since plan inference is imperfect, I then further restrict the sample by handset. From the phones with mode plan Village Phone (N=1400) I remove devices for which fewer than 10 accounts are represented (N=977), and then restrict to the two specified models (N=825). Because billing information is only available through July 2008 and the handset information available after that point does not uniquely identify Village Phones, I can only identify those that entered before then.

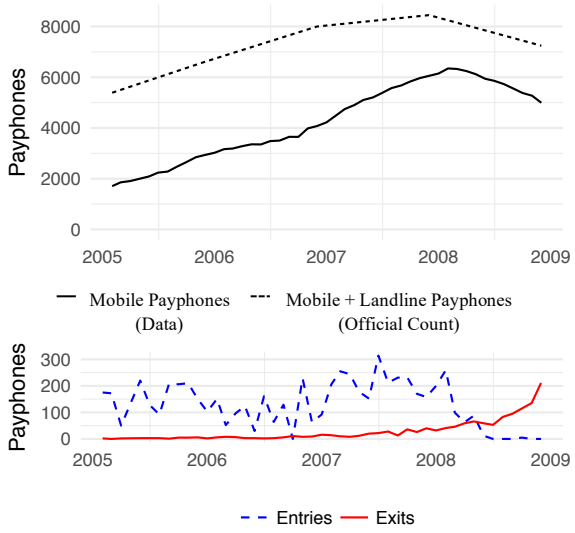

Figure 1. Counts of payphone operators

Figure 1 shows the count of payphone accounts observed in the data (mobile), and reported by the regulator (mobile and landline). The difference shrinks over time, consistent with landline payphones becoming less prominent as the mobile network grows.

Transactions. For each call placed through a payphone, I compute the gross and operator revenue. For months where actual charges are not available, I compute the billed amount based on the plan.

Location. I identify a payphone's daily location using a form of triangulation, based on the cell towers used to transmit calls [10]. I match each payphone's location to the nearest market center, using data from the Rwandan Trade Map project.

Work Spells. Transactions on any given payphone tend to be densely packed, so it is possible to infer work spells (accounting for days taken off, and breaks taken during the day). I infer work spells by clustering these transactions using DBSCAN, an unsupervised machine learning algorithm, which clusters groups of transactions that are close in time, allowing for outlier usage that is not part of a spell [7]. I define a spell as having at least 5 calls with gaps of less than 1 hour. I cluster all work spells for every payphone in my data, to define the timespans worked: see Figure 2 for an example.[1]

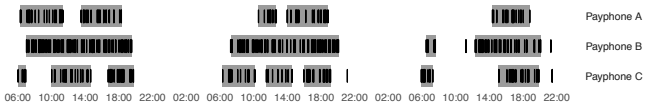

Figure 2. Identifying work spells. *Calls from three nearby payphones over three days. Calls are denoted by vertical lines, and inferred work spells are shown in gray.*

3 Results

Payphones were cheaper than personal phones. At the beginning of my data in 2005, a 30 second peak call was 49% cheaper on Tuvugane than on a personal phone. That difference eroded over time—to 24% by 2006 and 21% after February 2008.

Substitution between payphones and personal mobile phones is price sensitive. Calls on personal mobile phones are discounted on Sunday mornings. Personal mobiles bunch their calls during the discount period, leading to a drop when the discount ends. There is no such discount on Tuvugane payphones; these calls have a slight amount of reverse bunching, with more calls after the personal discount ends (see Figure 3).

[1] This measure represents an underestimate of the hours worked, because an individual may start working prior to the first transaction, or stop working after the last transaction. But calls during work spells are tightly bunched, so that the resulting bias appears to be slight.

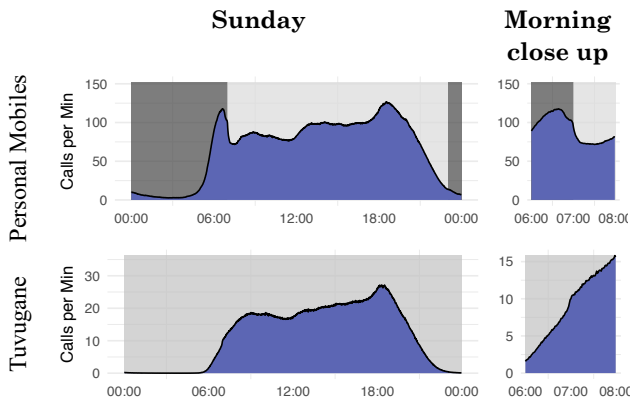

Figure 3. Substitution between personal mobile phones and payphones. *Shading represents discount relative to personal mobile peak rate, and shape represents the average number of calls initiated per minute from January 2005 to October 2007.*

Most payphone operators keep regular hours. The call data reveals the structure of work for payphone operators. Operators work an average of 62% of days; the median payphone-day starts a bit after sunrise at 8:08 AM and ends after sunset at 7:08 PM. The average daily revenue is $0.85, which is only slightly higher than the daily consumption per capita of $0.66 (EICV 2005-2006). This is a lower bound of total revenue, because operators may also be selling mobile phone credit or working other jobs simultaneously (for example, store owners sell other goods [9]). Taking into account only spells of the day where the operator is working, the median wage is $0.11 per hour.

	Mean	
Proportion of days worked	0.62	
	Median	**SD**
Hour Started	8.14	3.70
Hour Finished	19.18	3.70
Hours Worked	9.74	4.11
Duration Out (minutes)	17.63	17.70
Daily Revenue	$0.85	$0.96
Implied Hourly Wage	$0.11	$0.11

Table 1: Daily usage, by phone-day

3.2 Learning the Trade

Thousands of individuals became payphone operators from 2005 to 2008, as shown in Figure 1. Call data provides some insight into how these individuals learned where and how to work.

Figure 4 plots different measures as a function of the days since the account was opened. New operators settle into a routine quickly. The likelihood of working reaches a pattern after two weeks (panel a). Operators also quickly learn how to find demand: the probability of switching markets is high in the first few days, and by week 3 has declined dramatically (panel b). The fraction of time during work spells occupied by calls (congestion) increases

over time (panel c). As a result of being able to find demand, the implied hourly wage rises (panel d).

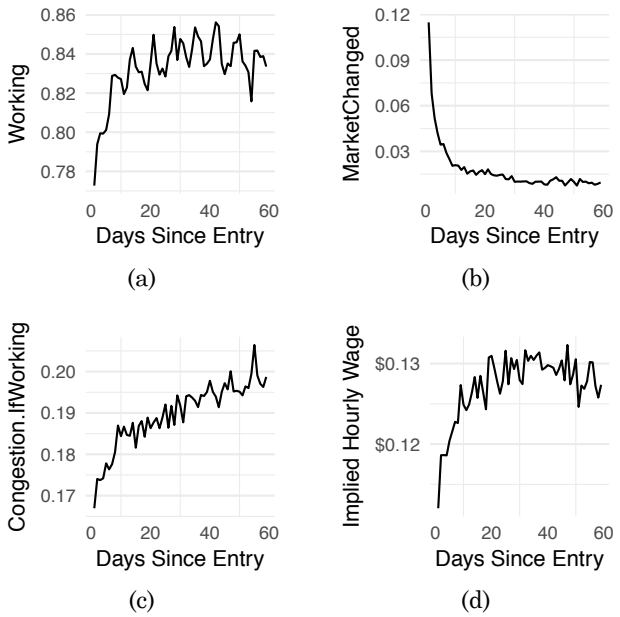

Figure 4: Behavior by time since starting

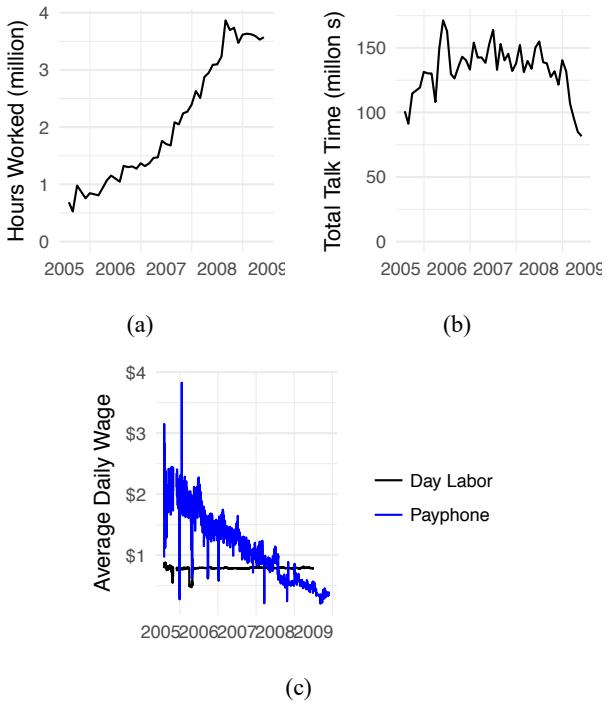

Figure 5: Industry trends

3.2 Industry Trends

What drove thousands of individuals to become payphone operators? It could have resulted from increasing demand for calls: payphones were both a complement to and substitute of the growing personal mobile phone network.

However, while the number of payphones doubled from 2006 to 2008 and number of hours worked by payphone workers increased dramatically (see Figure 5 a), the total duration spoken through them was fairly flat (Figure 5 b).

This is suggestive of business stealing: as the market matures, more workers chase the same amount of business, though further work would need to confirm. Business stealing is hypothesized to be common among informal vendors: in many developing countries, many vendors sell identical products at similar prices in adjacent locations. If duplication is wasteful, it may represent a drag on welfare. That could result if entry is too easy: overentry can occur in markets where prices do not sufficiently adjust [1]. There is little scope for price adjustment in the mobile payphone market, as prices are set by the operator. It could still be that entry improved welfare, if consumers sufficiently dislike waiting or walking to the nearest available payphone.[2] The resulting daily wages from operating a payphone fell over time, to below the daily wage from day labor (Figure 5 c). It is after this point in 2008 that payphone operators exit in large numbers.

[2] [9] likewise finds that profits are higher among Village Phones that have fewer Village Phones nearby, for a given level of remoteness.

In 2008, the payphone industry faced two additional shocks. The mobile network reduced personal phone calling prices, making payphones relatively less attractive. And, as part of a broader effort to regulate street vending, the government ordered Tuvugane operators in Kigali to work only in fixed locations [17]. This shakeup is likely to have contributed to the drop in entry, and uptick in exit in 2008 (seen in Figure 1).

4 Conclusion

This study shows how digital traces can illuminate an entire informal industry. This paper presents broad trends on the payphone industry in Rwanda. The industry is also present in many other countries, where it is also monitored in similar detail by cellular networks. While this paper is exploratory, this type of measurement can be combined with interviews, experiments, or policy changes to better understand informal work. Follow up work could address big questions: how do workers learn to be effective at their jobs? What is the nature of competition in these markets? How should policy respond to informal work?

ACKNOWLEDGMENTS

Thank you to Craig McIntosh and Jesse Shapiro for helpful conversations, and to Nathan Eagle for data. Daniel Björkegren acknowledges the W. Glenn Campbell and Rita Ricardo-Campbell National Fellowship at Stanford University, and Microsoft Research for support. The data used was deemed to not be classified as human subjects by the author's IRB.

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