

Monitoring in Small Firms: Experimental Evidence from Kenyan Public Transit

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Abstract

This paper examines whether moral hazard is a meaningful barrier to firm productivity and growth in low-income countries. We introduce monitoring devices into commuter minibuses in Kenya and randomize which minibus owners have access to the data using a novel mobile app. We find that treated vehicle owners modify the terms of the contract to induce higher effort and lower risk-taking from their drivers, resulting in lower firm costs, higher firm productivity, and firm expansion. These results suggest that moral hazard constrains firm productivity, and the proliferation of monitoring technologies could represent a boon for small firms in low-income countries.

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1 Introduction

Small and medium sized firms account for the majority of businesses in low-income countries, they employ over half of the population, and account for more than 40% of GDP (World Bank, 2021). Firms in low income countries also appear to stay small suggesting they face barriers to growth (Hsieh and Olken, 2014). Yet, the transition from an economy dominated by many small firms operated by small-scale entrepreneurs to one with larger firms that promote wage employment is an important step in a country’s economic development (McKenzie, 2017; Gollin, 2002). Therefore, identifying and relieving the many constraints that firms face has become a central focus for researchers and policymakers alike (Bloom et al., 2013; McKenzie, 2017; Brooks et al., 2018; Hardy and McCasland, 2020).¹

Any firm seeking to expand needs to grapple with the challenges associated with managing their work force. In particular, most firms cannot observe all dimensions of their employees’ behavior, leading to moral hazard that could harm firm productivity and lower profits. If firms and managers do not have systems in place that allow them to effectively monitor their workers, they may be hesitant to scale their business (Lucas, 1978).² Theoretical work has explored this mechanism: Shahe Emran et al. (2021) suggests that small firms do not expand because the cost of hiring and supervising someone else is much higher than doing the work themselves. Yet, empirical evidence on the consequences of moral hazard on firm growth is thin, and we know even less about the efficacy of monitoring technologies designed to overcome this barrier (Jayachandran, 2020; Bassi et al., 2021).³

In this paper, we identify the extent to which moral hazard limits firm productivity and demonstrate how monitoring technologies can boost firm growth. These technologies are becoming increasingly widespread, easy to use and cost effective – representing a promising avenue for firms who are typically hesitant to make investments in new technologies (Woodruff, 2018). Using daily data collected from small firms, we show that monitoring technologies allow firms to align their employees’ incentives with their own, substantially reducing firm costs, increasing profits, and spurring firm expansion.

We investigate these questions in the context of Kenya’s informal public transit indus-

¹See this IGC report for a comprehensive review.

²Lucas (1978) argues that firm size depends the number of workers that managers can effectively supervise (their ‘span of control’). Since monitoring may decrease a manager’s need for attention to an individual worker, the lack of monitoring may constrain a firm’s span of control.

³Bassi et al. (2021) study rental markets in Uganda. They speculate that small firms engage in complex rental arrangements with one-another to avoid merging and dealing with the challenges of managing and monitoring a larger labor force.

try, which is dominated by privately run minibuses. This industry is particularly relevant because these private firms struggle to grow beyond or two employees, and moral hazard is rampant. Minibus owners cannot observe how much revenue the minibus driver collects in passenger fares or whether he drives recklessly, which puts passengers at risk and can increase vehicle repair costs. While agency problems are central to this industry, they are not unique to public transit in Kenya.⁴ Most small businesses in low-income countries in sectors such as agriculture, the service industry, or manufacturing struggle to observe the amount of effort or output their employees produce, nor do they have recourse to sophisticated monitoring systems (Benjamin, 1992; International Labor Organization, 2019; Jayachandran, 2020).

To understand how monitoring affects firms, we develop a new monitoring system tailored to the industry that tracks driver effort and risk-taking choices. Our technology reveals driver actions but not revenue directly because it does not capture how many passengers are in the vehicle. Specifically, the system reports the driver's location, hours worked, distance driven, and a number of safety violations. We fit 255 minibuses with these tracking devices, working exclusively with owners who only manage a single minibus.⁵ We then conduct a randomized control trial (RCT), in which we provide half of the owners with access to the monitoring system for six months, while the other half continues to manage their drivers according to the status quo. Drivers in both groups are told that a tracking device is fitted in their vehicle but it is up to treated owners to reveal that they have access to the information.⁶

Interpreting the impacts of monitoring technologies requires observing and understanding the relationship between firms and their employees. In many informal transit systems around the world, minibus owners hire a driver on an informal daily contract, setting a revenue target for the driver to transfer at the end of the day. The driver retains the residual revenue, but he may not be rehired for the next day if he transfers less than the target; and the owner is liable for major expenses accrued during the day. This *target contract* is not unique to Kenya, and can be found between minibus owners and their drivers across the world (Cervero and Golub, 2007; Bruun and Behrens, 2014).

We develop a model that shows how this target contract is optimal given the constraints owners face, but is inefficient from a social planner's perspective.⁷ In other words, we show

⁴Blimpo (2014) documents problems of moral hazard in the motorcycle-taxi market in Benin and Togo; de Rochambeau (2020) studies information asymmetries in the Liberian trucking industry.

⁵About one third of owners in our baseline sample of the industry in Nairobi owned only a single minibus.

⁶Most drivers were already familiar with tracking devices due to wide use for security and recovery purposes after vehicles were stolen.

⁷The principal-agent model we develop accounts for the myriad contracting constraints frequently encountered in settings with relational contracts. First, the owner cannot observe effort and risk choices. Second,

that alternative contract arrangements such as debt contracts or wage contracts are suboptimal in environments where output is unobserved and drivers face limited liability. While the target contract is optimal, it incentivizes excessive risk-taking *and* high effort. This is because the principal cannot contract lower risk-taking in ways that are incentive compatible for the driver and maintain the flow of transfers from the driver to the owner. Monitoring technologies expand the contract space by making effort and risk observable to the owner, allowing the owner to specify the amount of effort and risk they want the driver to supply. As a result, profits rise primarily from less risk-taking, resulting in lower costs to the firm.

Our results are consistent with these predictions. We find that treated owners are able to effectively use the system to monitor their driver's activities more easily. While they retain the target contract structure, the parameters of this contract change: they slightly lower the driver's daily revenue target, and driving behavior is geared towards more effort and less risk-taking. Treated drivers work longer hours but engage in substantially less costly behavior such as off-road driving, earning about the same amount of revenue as before. This lowers maintenance costs and contributes to substantial increases in daily profit for the owners. After six months, profits increase by 13%, which is primarily driven by lower repair costs. These gains in firm profits more than offset the cost of the device, suggesting that a tracking device like the one we designed for this study would be a worthwhile investment if it were available on the market. Finally, we investigate whether firms use these technologies to expand their business. We find that treatment owners are 15 percentage points more likely to own an additional vehicle (an 11% increase) than control owners by the end of the study. This suggests that inadequate monitoring may represent a meaningful barrier to firm growth in low-income countries.

As these technologies become increasingly widespread, various institutions have expressed their concerns over their distributional consequences (West, 2021). We explore this by estimating the welfare implications of these devices. To quantify owner and driver welfare under the status quo and with the introduction of monitoring, we estimate the structural parameters of the model via simulated method of moments (SMM) using data from our experiment. We first estimate driver and owner welfare with data from the control group. Our estimates suggest the present-discounted contract surplus is large: the driver values the contract at about \$442 and the owner at about \$1,116. We then apply our SMM procedure to estimate the welfare effects under monitoring. Matching on reduced form moments from

the owner cannot observe the amount of revenue the driver collects, and can only rely on the transfer from the driver to determine whether to rehire him for the next day. Third, drivers are often liquidity constrained and thus subject to limited liability. Finally, contracts need to be self-enforcing.

the experiment, we estimate that the owner gains about \$41 from higher profits under similar revenue. This is very similar to their average willingness to pay of \$45 for the device at the end of the study. On the other hand, the driver's present-discounted value of the contract falls by 7% due to monitoring. This is primarily because they incur more disutility from having to drive in a less risky way. Thus, the total welfare effect of monitoring is positive but small. These welfare estimates do not factor in the benefits of a better working relationship between owners and drivers: in a survey we conducted 6 months after the experiment, 98% of drivers said they preferred driving with the device because it improved the level of trust with the owner, and owners devote 30% more to drivers in a trust game at endline.⁸

Our study contributes to a number of literatures. Our work speaks to a large literature documenting barriers to firm growth in low-income countries. Empirical research on small firm growth has identified three key challenges firms face: credit constraints, labor-market frictions, and managerial deficits (Bloom et al., 2010). Our paper most closely resembles the work on managerial deficits, which refers to the difficulties firms face managing day-to-day operations (including financial accounts and inventories), and incentivizing and monitoring workers. Most of the work in this field studies the impact of interventions that train firms on how to manage aspects of the business that do not involve employees (Bloom et al., 2013; Berge et al., 2015; McKenzie and Woodruff, 2017). One notable exception is Gosnell et al. (2020), who find that performance monitoring of Virgin Atlantic's airline captains improves labor productivity. Our paper focuses more directly on employee management through informal contracts, the role of moral hazard, and how providing information about employee behavior can change the firm's operations.

The paper also speaks to the vast theoretical literature on principal-agent relationships and contract formation in firms, which predominantly focuses on deriving the optimal contracts subject to various constraints (Holmström, 1979; Grossman and Hart, 1983; Hart and Holmström, 1986; Innes, 1990; Levin, 2003). We build on seminal empirical work by Hubbard (2000, 2003) and Baker and Hubbard (2004) who investigate how the introduction of onboard diagnostic computers affected the U.S trucking industry. Our study differs in three important ways from this earlier work. First, we generate exogenous variation in the usage of monitoring technologies by randomizing which companies receive data from a tracking device. Second, we capture high-frequency data on contracts and worker behavior. This al-

⁸We further discuss driver welfare considerations in Appendix A. Besides changes in the working relationship, our welfare evaluation also abstracts from welfare effects on passengers – an important consideration in light of how dangerous minibuses are. We explore this in a companion paper (Kelley et al., 2020). Monitoring did not significantly affect the number of accidents.

lows us to monitor how different dimensions of the contract and worker behavior change over time and how these changes affect firm profit. Finally, we study the impact of monitoring in a low-income country context, where relational contracts are more prevalent and monitoring devices reduce rather than eliminate information asymmetries. In this setting, we show empirically and theoretically that the impact of monitoring is fundamentally different.

Prior research suggests that monitoring systems may affect firms differently in low-income countries than in high-income countries. The quality of management practices is typically lower (Bloom et al., 2013), which could prevent firms from harnessing the benefits of monitoring technologies. Moreover, contract enforcement is weak and workers are poor, which could also limit the effectiveness of these systems. Our work demonstrates that this is not the case, but underscores how the impact of monitoring differs systematically in low-income countries because of these constraints. In particular, we do not find changes in the ownership structure (unlike Baker and Hubbard 2004) – contract change is more subtle, reinforcing Macchiavello and Morjaria (2015) findings about relational contracts. In closely related contemporary work, de Rochambeau (2020) finds that monitoring induces Liberian truck drivers to supply higher effort, although her focus is on intrinsic motivation.⁹

Finally, there is growing recognition that the informal transit industry has a large impact on various development outcomes. Research in this literature has focused on documenting the impact of policies that improve the efficiency of transportation networks within cities. This includes work by Hanna et al. (2017) and Kreindler (2020) that investigate the benefits of traffic congestion management policies. Tsivanidis (2019) documents large aggregate welfare gains from the introduction of the world’s largest Bus Rapid Transit system in Colombia. Recent work by Kelley et al. (2020) focuses on the impact of policies that improve the safety of informal transit systems. This build on previous work by Habyarimana and Jack (2011, 2015) who study how to mobilize passengers to improve minibus safety.

The rest of the paper is organized as follows. We describe features of the informal transit industry generally and specifically for Nairobi in Section 2. Section 4 then develops a theory of contracting in this industry. In Section 3 we describe the monitoring technology, the data collection, and the experimental design. We present reduced-form results of the experiment in Section 5. Section 6 provides results from our structural estimation, and Section 7 contextualizes its welfare implications. Finally, Section 8 concludes.

⁹Other work on monitoring in developing countries studies primarily external monitoring of firms and public service providers (Björkman and Svensson, 2009; Duflo et al., 2012, 2013). In related work in high-income countries, Liu et al. (2021) find that monitoring systems in Uber reduce driver moral hazard.

2 Context: The Matatus of Nairobi

Kenya's transportation industry is appealing to study the role of monitoring for firm growth for a number of reasons. First, it is broadly representative of informal transit systems around the world. Second, the dynamics we study between firms and employees can also be found in other industries where revenue is collected by the employee and remains unobserved by the firm. Third, monitoring technologies are becoming widespread and have the potential to change the way minibus owners run their businesses. Finally, this context allows us to overcome major data constraints that have limited researchers' ability to study how contracts respond to monitoring technologies in the real world.

Informal transit systems are the backbone of public transportation in low-income countries, often comprising more than two thirds of commutes (Godard, 2006).¹⁰ In Kenya, informal transit services are essential. Rough estimates suggest that 15,000 private minibuses called *matatus* circulate throughout the city. The industry employs over 500,000 people and contributes up to 5% of the country's GDP (Kenya Roads Board, 2007).

These informal transit industries are dominated by private entrepreneurs who typically own a small fleet of vehicles. Passengers embark at various points along the route and pay in cash (Bruun and Behrens, 2014).¹¹ Private entrepreneurs in Kenya primarily purchase 14-seat minibuses and license their vehicles to a single route. All routes in Nairobi are managed by a particular cooperative (Savings and Credit Cooperatives, SACCOs). These cooperatives usually leave the daily management of the vehicle to the owner but facilitate centralized organizational activities including scheduling, resolving internal disputes between owners, ensuring compliance with the National Transport and Safety Authority (NTSA) regulations, and providing financial services to owners and drivers. This system was put in place by the Ministry of Transport in 2010 with regulation that required all industry newcomers to join these cooperatives – in an effort to further formalize the industry and eliminate the presence of gangs that were becoming increasingly active in the sector (McCormick et al., 2013).

Owners typically hire a single driver to operate their vehicle along the designated route. An owner's day-to-day management consists of calling their driver, checking whether the vehicle needs to be serviced, and occasionally staging observers along the route to learn about the driver's activities. Drivers are hired on target contracts: the owner sets a daily

¹⁰Informal transit refers to all forms of privately-run public transportation services such as minibuses, vans, taxis, station wagons, three-wheelers, or motorcycles (Cervero and Golub, 2007).

¹¹Several attempts at introducing digital payment systems have failed, in part due to drivers resisting adoption.

revenue target at the beginning of the day and the driver is the residual claimant.¹² If the driver misses the target, the owner typically expects to receive the full day's revenue. If the owner deems the transfer to be too low, she will reconsider whether to rehire the driver for the next day. The owner sets the target based on vehicle characteristics, the route, and day-specific shocks such as weather conditions or special events (e.g. the beginning of the school year) (Behrens et al., 2015).

While this informal network of buses constitutes the only dependable transit system in Nairobi, the industry is widely perceived to be suffering from a number of inefficiencies (McCormick et al., 2013; Behrens et al., 2015; Mutongi, 2017). For example, a lack of regulation and enforcement creates incentives for drivers to operate on unlicensed routes, where they pay substantial fines when they are caught. Owners are unable to limit these events because they cannot easily observe their driver's activities – a management problem that deters owners from expanding their fleet and growing their business. Similarly, the presence of severe competition within a route leads to reckless driving and high vehicle maintenance costs. According to the World Health Organization's Global Status Report on Road Safety, approximately 3,000-13,000 people die annually from traffic incidents in Kenya, and at least 62% of cases involve matatus (Odero et al., 2003; WHO, 2013). Conditions have not improved in recent years. However, matatu owners are increasingly investing in the comfort of their vehicle, the aesthetics (e.g. colorful interior and exterior), the quality of the "experience" (e.g. helping passengers on and off the bus), and technology features such as TVs or free wifi (Reed, 2018). More attractive and comfortable vehicles charge up to twice the price of regular ones. Matatu fares vary between 0.5 and 1.5 USD for travel inside the city center, and between 1 and 5 USD for trips to the outskirts.

In recent years, companies offering GPS tracking services have started to enter the Kenyan market. Many insurance providers also mandate that minibuses install GPS trackers for security reasons.¹³ Despite their increasing availability, most medium and small-scale minibus owners had not installed them in their own vehicles at the time of the study because they were either prohibitively expensive (around \$600 per unit) or too complicated to operate. To fill this need, we worked with a Kenyan technology company to create a new monitoring system that was considerably cheaper and more flexible than other tracking systems. We describe the system in detail in Section 3.

¹²In Kenya, the driver is accompanied by a fare collector and they work as a team. For the purposes of this study, we treat them as a unit. The norm is for them to split the residual revenue evenly.

¹³See Business Daily Africa article "Vehicle tracking system gains popularity in Kenya", September 22, 2009, <https://www.businessdailyafrica.com/corporate/539550-661514-6k6toiz/index.html>.

3 Experimental Design

3.1 Tracking Device and Software

To understand the impact of monitoring on the matatu industry, we developed the *Smart-Matatu* monitoring system with a Kenyan technology company (Echo Mobile). We developed our own system because available alternatives on the market were either too costly or not sophisticated enough. The R&D process lasted more than one year, and benefitted from extensive discussions with small-scale matatu owners. The physical tracking units were procured for 125\$ from a company in the United States (CalAmp). The tracking device has a GPS and gyroscope, which capture the vehicle’s location and its vertical/lateral/forward and backward acceleration at 30-second intervals. The device relies on GPRS to send the information from the tracker to our servers via the cellphone network. The data is further processed on the server to provide daily measures of the vehicles’ mileage, the number of hours the vehicle’s ignition was on, average and maximal speed, and the number of speeding, over-acceleration, sharp braking and sharp turning alerts. Finally, an API call is generated each time the owner uses the app to request data from the server.

We also designed a novel mobile application to convey information from the tracker to owners in a user-friendly way (Figure 1). The app’s first tab is a map of Nairobi and presents the real-time location of the vehicle. By entering a specific time interval into the phone, the app can display the exact routes traveled by the matatu over this time period. This first tab conveys a more accurate measure of costly driving because owners can see if the driver is operating on roads that are known to damage vehicles. The second tab displays all the safety alerts that are captured by the device. The final tab conveys a summary of the driver’s effort and safety. The effort section lists the total mileage covered, and the duration the ignition was turned on that day. This provides treated owners with a more accurate measure of driver effort. Finally, the SmartMatatu app was also designed to collect daily information from both treatment and control owners, including the target; the amount the driver transferred; any repair costs incurred; and an overall satisfaction score for their driver’s performance.

3.2 Treatment Assignment

We conducted an extensive recruitment drive in late 2015 by contacting cooperatives operating across nine major commuter routes in Nairobi. We organized several large meetings with matatu owners, presenting the study’s goals and methodology. We registered inter-

ested owners that satisfied three conditions: they had to own only a single 14-seater matatu; they had to manage it themselves; and they had to employ a driver rather than driving the minibus themselves. We informed all owners that we would be placing a monitoring device in their vehicle free of charge, and they would be required to provide daily information about their business operations. We also mentioned that a random subset of owners would be selected to receive information immediately, while others would have to wait 6 months before gaining access to the information for a shorter two month period. It took approximately four months to recruit enough participants across these 9 major commuter routes. We successfully registered 255 owners, which we randomized into treatment (126) and control (129).

We conducted installations and trainings from November 2016 to April 2017 (Figure A.6). The field team scheduled a time to meet each owner individually at a location of their choosing. The owner was compensated for the time their vehicle spent off-road to perform the installation of the device with a one-time payment of 5000 KES (50 USD). We installed the trackers under the vehicle's dashboard to prevent tampering in both treatment and control vehicles. Our field team took both treatment and control owners aside and provided them with an Android smartphone with our SmartMatatu app pre-installed and trained them how to submit reports through the app. The app only allowed access to information for owners randomized into the treatment group, who received an additional 30 minutes of training on the features of the app's information section. We administered a small survey to the treatment owners at the end of their training to make sure they knew how to find all the information contained in the app. Despite this in-depth training, it took owners a few months to feel comfortable navigating the different tabs in the app. We offered continued support to treatment owners to help navigate the app. Finally, we granted control owners access to the information from the tracker for two months at the end of the 6-month study period.

At the same time another enumerator took drivers aside and explained that we were placing a tracking device in the vehicle, and we would be collecting data for research purposes. We did not mention, however, whether the information would be transferred to the owner. This meant that any subsequent changes we observed in driver behavior could only come from owners using the tracker data, rather than from receiving different information from the enumerators during the installation.

3.3 Data Collection

We collect data from three different sources. Enumerators conducted in-person baseline and endline surveys. Next, we gather a panel of daily responses from owners and drivers through our SmartMatatu app and SMS surveys, respectively. Finally the GPS tracker collects a wealth of data that we use to measure driving behavior.

We administer the baseline survey during the tracker installations. The owner baseline survey collects detailed information regarding basic demographics, employment history, features of the matatu, and their relationship with the current driver. Similarly the driver baseline asks about driver demographics, experience as a driver, unemployment spells, and their relationship with the current owner.¹⁴ We also use games to gauge drivers' risk aversion and driver/owner propensity to trust one another (Sprenger, 2015). To measure risk we ask respondents whether they prefer to receive 500 KES (5 USD) for certain or play a lottery to win 1500 KES. The trust game is similar to Berg et al. (1995): we present owners with 500 KES and asked them to select an amount to be placed back in an envelope. This amount is then tripled and delivered to a matatu driver who decide how much to keep for himself and how much to return to the owner. The amount the owner chooses to place in the envelope was recorded in the survey. At the end of the six month period, we also conduct an endline survey focusing on business investment decisions. Finally, we run a willingness-to-pay experiment, offering owners two additional months of monitoring information through the app.

Next, we collect daily data from owners and drivers. For owners, we rely on our Smart-Matatu app, which provides a novel means of collecting high-frequency data in a challenging environment. Owners in the study are reminded daily via a notification on their phone to report on that day's business activities through a form located on the app. They are asked to submit data on: the target amount assigned to their driver at the beginning of the day; the amount the driver delivered to the owner; any repair costs incurred; an overall satisfaction score for their driver's performance (bad, neutral, good); and whether the driver was fired/quit that day. Once the report is successfully submitted, owners received 40 KES via M-Pesa (a mobile phone-based money transfer service).

We collect similar information from drivers through SMS surveys (because the drivers are not provided with smartphones). Specifically, the message asks about whether the vehicle was on the road, the amount of revenue they collected, and the residual revenue they kept as a salary. We emphasize that all of the data they share remains confidential and they are

¹⁴If an owner-driver pair separated, we onboarded the new driver using the same baseline survey.

compensated 40 KES for each submission. We check for differential reporting by looking at the relationship between reported revenue and mileage for treatment and control drivers. We do not find that the relationships are statistically different from one another.

Finally we rely on the CalAmp tracking device data. We use the raw measures of acceleration to investigate changes in driver behavior. Specifically, we look at vertical and lateral acceleration to determine whether the driver is operating on bumpier stretches of road. Furthermore, we use the GPS data to calculate how far each vehicle is from the route they are licensed to be on at any point in time. This provides a measure of how far the driver is deviating from the actual route. Figure A.2 depicts the number of times vehicles licensed to one of the routes pass through a particular location. The figure illustrates that off-route driving is relatively common practice.

4 Model

We now describe a contract model of the owner-driver relationship in the informal transit industry. The defining features of this model are not unique to our setting and reveal important insights about a class of contracts that are prevalent in low-income countries. The goal of this model is threefold. First, it allows us to precisely describe the mechanics that lead this type of contract to be inefficient. Second, we can derive strong predictions about the effect of monitoring on the driver, the owner, and firm outcomes. Finally, the model provides the basis for the structural estimation of agents' welfare under the baseline contractual arrangement and after monitoring is introduced.

To accurately reflect the informal transit environment, we combine several model components from the contract theory literature. Since drivers are relatively poor, we include a limited liability constraint as in Innes (1990). Because contract enforcement is limited, we require the driver's commitment to the contract to be self-enforcing, as in Levin (2003). The most novel component is to make output (or revenue) unobservable to the owner in addition to driver's choices. While this echoes the idea of costly state verification introduced by Townsend (1979), it generates new and interesting dynamics pertinent to the informal transit industry as well as other environments where the principal struggles to observe output.

We begin by setting up the model in the baseline environment without monitoring, and show how the resulting contract compares to a social-planner benchmark (an integrated owner-driver for whom the agency problem is of no concern). Finally, we show how the contract changes when monitoring technologies are introduced, which allows the owners to

observe some driver choices. We refer to the principal as the female owner (of the vehicle) and the agent as the male driver throughout the model.

4.1 Setup

A risk-neutral owner (principal) and risk-neutral driver (agent) engage in a daily relational contract. They value the contract at endogenous values V and U , respectively, and discount the future with a common factor δ . The driver chooses effort along two dimensions: effort to earn fares denoted by e , and effort to minimize costs by taking less risk, which we simply call “risk” and denote by r .¹⁵ He chooses (e, r) , incurring disutility $\psi(e, r)$. On the basis of these actions, nature draws revenue y from the revenue distribution $G(\cdot|e, r)$ as well as repair costs $c(r)$ from $F(\cdot|r)$. Repair costs depend on risk but not effort and accrue entirely to the owner. Conditional on effort and risk, the revenue and cost distributions are independent.¹⁶

The owner chooses whether to rehire the driver with some probability $p(\cdot)$ – the rehiring schedule. In the baseline environment without monitoring, this rehiring schedule depends only on the transfer: $p(t)$. If the owner has access to the monitoring technology, she can directly observe the driver’s effort and risk choices and may use these in the rehiring schedule $p(t, e, r)$. In contrast to standard contracting problems, the owner does not receive any information about revenue, even with a monitoring device.¹⁷ If the driver is fired he receives his outside option, and the owner pays a hiring cost h before drawing an identical driver.¹⁸

The timing of the game is as follows. At the beginning of the day, the owner and driver agree on the contract. The driver then makes driving choices (e, r) during the day. Based on (e, r) , nature draws revenue y as well as repair cost c . The driver then transfers $t(y)$ to the owner and keeps $y - t(y)$. Finally, the owner rehires the driver for the next day with

¹⁵Note that the use of “risk” is nonstandard in the literature, compared to, for example Ghatak and Pandey (2000). In our model, risk is a second effort dimension which has an additional cost to the principal, instead of having a mean-preserving effect on the variance of output. We nonetheless call this choice “risk” because it corresponds closely to actions such as a risky maneuver to overtake another car in traffic; driving offroad to bypass traffic, risking damage to the vehicle; or taking an unlicensed route, risking a fine.

¹⁶See Appendix Section D.2 for functional forms assumptions of the technology and preferences.

¹⁷This is an important feature of monitoring in informal transit. Even if the owner knows the exact number of trips a driver took there is no way to get a precise estimate of revenue because they do not know the number of passengers. Drivers said they were more comfortable with GPS technologies that revealed their choices of effort and risk, as opposed to technologies that allow owners to observe revenue directly, such as electronic payment systems (such as BebaPay, a failed Google venture).

¹⁸For expositional simplicity, we set $h = V$ in the theoretical section, but we estimate the hiring cost separately in the structural estimation. Our focus in this paper is moral hazard in stable owner-driver relationships so we do not study the interesting but separate problem of adverse driver selection. In any case, less than 15% of owners get a new driver over the course of the study, limiting the impact of adverse selection.

probability $p(t)$, or $p(t, e, r)$ in case of monitoring. Although reminiscent of a fixed rental contract, the resulting target contract is structurally different from known contracts in the literature. Limited liability prevents the driver from paying a rental price upfront. Hence the owner has to rely on a transfer at the end of the day based on uncertain revenue. This contract structure is not unique to our setting. It is common whenever workers are relatively poor and output is hard to observe.

4.2 Baseline Contract Without Monitoring

In the status quo contracting problem, the owner maximizes the expected sum of transfers and the future discounted value of the contract minus the cost of risk:

$$V = \max_{e, r, t(y), p(t)} \mathbb{E} [t(y) - c(r) + p(t(y))\delta V | e, r] \quad (1)$$

While the driver ultimately chooses effort and risk, the owner treats them as choice variables for the purpose of designing the contract, as is standard in contract theory.

This problem is subject to a number of constraints. First are the standard participation constraint and driver incentive compatibility constraint for their choice of effort and risk. Additionally, we add a limited liability constraint which restricts the driver from transferring more to the owner than what he made on a given day and a dynamic enforcement constraint that requires the driver to prefer honoring the contract as opposed to walking away at the end of the day. Finally, a “transfer constraint” restricts the transfer to the owner to be optimal from the driver’s point of view.

We define the rehiring schedule using a the daily target T , above which re-employment is guaranteed. Under the assumption that the owner prefers less risk than the driver, we solve for the optimal transfer and rehiring schedules:¹⁹

$$t(y) = \min \{y, T\}$$

$$p(t) = p_0 + \frac{t}{\delta U}$$

Under an optimal contract, the transfer schedule $t(y)$ requires the driver to transfer all revenue up to some target amount T , defined as the transfer at which re-employment is guaranteed. The driver retains any revenue beyond T . The corresponding rehiring schedule is linear up to the target, where it reaches certainty.

¹⁹See Appendix Section D.2 for more discussion about the justification and implications of this assumption.

The intuition for these schedules follows from the various goals the owner pursues. First, she seeks to maximize the transfer for any given revenue the driver achieves. To this end, the rehiring schedule must guarantee that the marginal benefit to the driver of one additional dollar transferred (which is the change in the rehiring probability times the discounted value of that relationship $p'(t)\delta U$) exceeds the direct value of keeping that dollar (which is just 1). This implies the slope of the rehiring schedule needs to surpass the inverse of the discounted value of the relationship ($1/\delta U$), as illustrated in Figure A.5.

Second, the owner seeks to incentivize the driver to select her preferred level of effort and risk. Since she cannot observe driving choices, she can only induce effort-risk bundles on the driver's incentive compatible set (see Panel A in Figure 2). This means her choice comes down to bundles with both higher effort and higher risk, or bundles with lower effort and lower risk. If she sets the slope of the rehiring schedule to $1/\delta U$, the driver chooses his bliss point. She *could* induce higher effort-risk bundles by setting a rehiring schedule that is steeper than $1/\delta U$. The driver would then find effort and risk more appealing because of its high return in terms of increased rehiring probability in case he misses the target. However, she *cannot* induce effort-risk bundles below the driver's bliss point by setting the rehiring slope below $1/\delta U$ because the driver would keep the marginal dollar rather than transfer it, without actually lowering effort and risk. Because we assume the owner prefers less risk than the driver (Panel B of Figure 2), she contents herself with the lower bound of risk induced by the minimal slope $1/\delta U$ and resigns herself to capturing as much revenue as possible. As shown in Panel C of Figure 2, this is her preferred bundle among those that are both incentive compatible and transfer compatible.²⁰

Inefficiency of baseline contract We assess the efficiency of the baseline contract by comparing it to the optimal decision of an integrated decision maker (or social planner), taking into account both the repair costs due to risk as well as the disutility of effort and risk. In Appendix D.3.2, we show that the baseline contract is inefficient compared to the social planner's solution due to excessive risk taking by the driver. Risk is oversupplied relative to the social optimum because the driver is not accounting for repair costs accruing the owner. Unlike many other principal-agent models, effort provision could be too high or too low depending on the degree of substitutability between effort and risk.²¹

²⁰The owner also needs to satisfy dynamic enforcement and limited liability, both of which are automatically satisfied under the linear rehiring and transfer schedules.

²¹If effort and risk are weakly substitutable then higher risk could induce higher effort than the social optimum level of effort e^* .

The failure of the contract to achieve the first-best outcome reflects the owner's inability to steer the driver away from his preferred mix of effort and risk. Hence, the owner may be able to use monitoring technologies to overcome this limitation and move the contract closer to the first best. We now turn to examining this possibility.

4.3 Introducing Monitoring

With monitoring, the owner now observes the driver's effort and risk choices and conditions her rehiring schedule on them as well as the transfer: $p(t, e, r)$ instead of $p(t)$. Therefore, the solution to rehiring schedule solution becomes

$$p(t, e, r) = \begin{cases} p_M + \frac{t}{\delta U_M} & \text{if } e = e_M \text{ and } r = r_M \\ 0 & \text{otherwise} \end{cases}$$

where (e_M, r_M) is the (owner mandated) effort-risk choice under monitoring. Even with monitoring, the contract retains its target structure. Since monitoring only reveals driver choices but not revenue, the owner must continue to provide transfer incentives, prohibiting the establishment of a wage contract.

Predicted effects of monitoring This result yields several predictions for how key outcomes will change under monitoring (a proof is in Appendix D.3.2):

1. **Effort will increase and risk will decrease:** Compared to the baseline contract, the owner can now explicitly contract on higher effort provision ($e_M > e_B$) and lower risk ($r_M < r_B$) moving the driver to a more profitable mix.
2. **Revenue may rise or fall:** The effect on revenues is ambiguous. The owner could settle on an effort-risk bundle that yields lower expected revenue if it also yields a larger drop in expected repair costs.
3. **Profits increase:** Profits will unambiguously increase driven by lower repair costs.
4. **The targets falls if revenue falls:** If the revenue collected by the driver falls, the optimal target will also fall as the owner needs to compensate the driver for lost salary.²²

²²There are two forces that influence the owner's decision to re-optimize the target. First, the driver is worse off from having to adopt a new effort-risk bundle that differs from the one he previously selected. This increases the risk that the driver does not make any transfer at all as he is less concerned about losing his job. The owner needs to compensate the driver for this loss by lowering the target, thereby increasing the

5. Ambiguous welfare effect: Finally, we show that monitoring may raise or lower overall welfare, depending on whether the contracted effort-risk bundle under monitoring confers higher or lower utility to the driver. While the owner is unambiguously better off, an interesting implication of the contract under monitoring is that the driver can be better off as well. This depends on how much the driver’s disutility of driving changes under monitoring: slightly higher disutility under the new effort-risk bundle may be compensated by a lower target, leaving the driver better off. This particular contract was not feasible without monitoring because it was not incentive compatible – the owner could not trust the driver to choose this bundle in exchange for this lower target. With the introduction of monitoring this contract is now enforceable.²³ We return to these calculations in Section 6.

5 Experimental Results

We now discuss the reduced-form impacts of the experiment. We first summarize descriptive statistics about owners and drivers in our sample, and provide evidence for basic features of our contract model. We then turn to a discussion of the impact of the intervention.

5.1 Descriptive Statistics

Baseline Survey and Balance We present baseline sample characteristics and treatment balance in Table 1. Owners are mostly self-employed men in their late thirties. They have eight years of industry experience on average, and five years of experience as matatu owners. Owners have worked with 1.85 drivers on average, and 79% of our sample has worked with at least one driver before the current one. Owners rate their drivers as being fairly honest and diligent. They set a daily revenue target at baseline of approximately \$31.30 (KES 3,130) and receive \$26 on average from the driver. These characteristics are balanced across

value of the job. Second, the owner will respond to a change in revenue. If expected revenue rises, the owner will increase the target in an effort to capture some of this surplus. However, if expected revenue falls, this reinforces downward pressure on the target. Therefore, while the overall impact of the target is ambiguous, we would expect the target to fall if the revenue distribution falls or remains largely the same.

²³To see this more concretely, imagine a point (e, r) on the driver’s incentive compatibility set and another point (e_m, r_m) (which we assume is on the same isoquant for convenience) $e < e_m$ and $r > r_m$. Now imagine that $c(r) >> c(r_m)$, but $\psi(e, r)$ is only slightly lower than $\psi(e_m, r_m)$. If the driver could credibly commit to supplying $\psi(e_m, r_m)$, the owner would optimally choose to lower the target, which would increase driver’s utility. However, because T is set before (e, r) are chosen, the owner knows the driver will not follow through on their commitment (which the owner cannot verify), which makes this agreement impossible.

treatment and control owners.

Drivers in our sample are exclusively male, they are a few years younger than owners and have lower levels of education. They have eight years of experience as matatu drivers on average, and have worked for six owners in the past. They have spent just over one year with the current owner, and rate the owners as fair. On average, drivers collect approximately \$77 (KES 7,700) in passenger fares throughout the day, and keep approximately \$9.60 for themselves as a salary. Driver characteristics are balanced, with the exception of driver age and experience (which are strongly correlated). We control for baseline characteristics to account for this imbalance.

The majority of matatu vehicles are imported Japanese minibuses that have been used for thirteen years. Some of them have special features such as free wifi, sound systems, or TVs. They were purchased for approximately \$6,675. Appendix Figure A.8 provides a visual of a matatu.

Empirical Contract Characteristics Our data shows that basic elements of the contract align closely with our model. First, we see that the transfer function has the piecewise linear shape: driver transfers increase linearly with revenue until the transfer amount reaches the target (Figure 3). We interpret the fact that drivers transfer less than total revenue as evidence for an (unmodeled) subsistence income. Note that including this subsistence level would not change the predictions of the model as it would simply constitute a renormalization of the revenue distribution. Therefore, for simplicity we do not include this feature formally in the model. However, we do account for the subsistence income in the structural estimation.²⁴

Second, the figure also shows that owners' satisfaction with their driver increases with the size of the transfer, as suggested by the rehiring schedule. While there are only 26 separations between owners and drivers over the course of our study, we find that they occur more frequently when the driver misses the target (Appendix Figure A.9). This provides evidence for the model prediction that owner rehiring is a function of the transfer.

²⁴As an alternative to subsistence income, risk aversion on the driver side would lead to a similar pattern in the transfer schedule. However, this would fundamentally complicate the solution the model: the driver's rehiring schedule would become a nonlinear function of the risk aversion parameter. Both the proofs of the propositions and the structural estimation rely on a linear rehiring schedule. Moreover, it is not clear whether introducing risk aversion would have any other benefits besides accommodating the pattern in the transfer schedule.

5.2 Treatment Take-Up

We investigate the degree to which owners engaged with the monitoring app and how the app affected self-reported management practices. We monitor owners' usage of the device by tracking the API calls that are generated every time the owner logs into the app and requests different pieces of information. We find that 70% of owners consult the app weekly, while 50% use it daily (Appendix Figure A.7).

We also confirm that owners are internalizing the information we provided through the app. At endline, we asked owners to state whether they knew the revenue earned, the number of kilometers driven, and the extent of off-road driving on the most recent day their vehicle was active (Table 2). Owners had the option of answering "don't know". We find that owners in the treatment group are 27 percentage points more likely to know about the number of kilometers driven and 45 percentage points more likely to know about the instances of off-route driving (columns 1 and 2). They are not more likely to know the vehicle's revenue, which we expect because our monitoring technology does not track the number of passengers who board the vehicle (column 3).

We also see that treated owners find it easier to monitor their drivers than control owners, and spend less time monitoring their drivers. We ask owners at endline to rate how challenging it is to monitor their employees on a scale from 1 (not hard) to 5 (very hard). Having access to the information reduces the reported difficulty level by just over 2 points (Table 2 Column 4). In other words, control owners maintain that monitoring is hard while treatment owners reveal that it is easy. Furthermore, we ask owners whether the amount of time they spend monitoring has increased or not in the last six months. We see that 72% of the sample report a decrease in the time they spend monitoring (Table 2 Column 5).

5.3 Results

To test the predictions of the model, we run the following regression using daily panel data for vehicle an owner-driver-matatu observation i on day d :

$$y_{id} = \alpha_d + \tau_{r(i)} + \sum_{m=1}^6 D_{im}\beta_m + \mathbf{X}'_i\gamma + \varepsilon_{id} \quad (2)$$

where y_{id} is an outcome of interest; D_{im} are treatment indicators by month since installation; β_m are our main parameters of interest, the effect of treatment assignment m months after installation; α_d are day fixed effects; $\tau_{r(i)}$ are route fixed effects; \mathbf{X}_i is a vector of baseline

characteristics;²⁵ and ε_{id} is an error term, which we allow to be arbitrarily correlated within i across days. This design allows us to examine the treatment effect as it evolves over the six months of the study.²⁶ This is important because it took a few months for owners to become comfortable with all the features of the monitoring app.

Effort We proxy driver effort by the number of hours the matatu is operating and find that operating hours increase by 0.98 hours per day on average by the third month after installation and rise steadily until the end of the study.²⁷ By month six, effort levels increase by 1.47 hours per day on average in the treatment group, a 9.9% increase in drivers' labor supply. This is a substantial increase in an environment where drivers are already working 14-hour days.²⁸ While this increase in effort leads to gains for the firm, we may worry about safety externalities for passengers and pedestrians exposed to drivers in their 15th hour. We show in a companion paper (Kelley et al., 2020) that there is no significant increase in safety-related outcomes. With more hours on the road, we also see the number of kilometers increase by 12 kilometers per day on average (10%), which corresponds to an extra trip to or from the city center.

These results are in line with the model predictions that treatment drivers will increase the amount of effort they supply and reduce the amount of risk they take in response to monitoring. This is because the monitoring device allows owners to see the amount of risk and effort drivers choose, and direct drivers towards a more favorable bundle. The results in Figure 4 support this prediction.

Risk Treatment drivers also appear to take substantially less risk. We find that treated drivers spend less time on these routes after the introduction of monitoring. Panel C in Figure 5 shows that they are about 400 meters closer to the licensed route on average than control drivers throughout the study period. Next, we investigate whether this change in the distance from the licensed route results in less side to side movement. This would indicate that treated drivers are taking less bumpy roads that are less damaging to the vehicle.²⁹

²⁵Specifically, we include as control variables the age of the matatu, the number of special features, owner age and sex, owner education, owner self-employment status, the number of other businesses the owner runs, owner years of matatu industry experience, and owner raven score.

²⁶It should be noted that this specification differs from the pre-specified regression, which pools all months of our data together and masks important dynamics.

²⁷The monitoring device powers on and off with the matatu, so we can track when the vehicle is operating.

²⁸There are no meaningful differences in the number of separations between treatment and control.

²⁹The largest repair costs owners frequently face are run-down break pads, damaged shock absorbers, and broken axles.

Taking fewer bumpy roads that jostle the vehicle will be visible in the acceleration data. Lateral acceleration measures tilting from side to side, while vertical acceleration captures movement upwards and downwards. We find that the distributions of lateral and vertical acceleration in the treatment group tightens around zero, consistent with a reduction in reckless and damaging driving. We can reject equality of treatment and control distributions by applying a K-S test, which returns a p-value below 0.001 for both measures of acceleration.

These findings are consistent with anecdotal evidence that one of the greatest sources of risky driving to operate on unlicensed routes. Drivers often use these routes as shortcuts to avoid traffic jams where they sit idly without picking up any passengers. These shortcuts are less appealing from the owner's perspective for a number of reasons. The roads are typically less well maintained and bumpier, which means vehicles are more likely to be damaged and repair costs will increase for owners. Furthermore, owners have to pay large fines when drivers are caught along these routes. When owners have access to the GPS technology, they can monitor where drivers are at any point throughout the day and mandate they stay on the designated routes.

Repair Costs In line with model predictions, these changes in driver behavior translate into lower repair costs. Figure 6 shows that repair costs reported by treatment owners decline steadily relative to control owners. By the third month, daily repair costs for treatment owners fall by \$1.25 (KES 125). By the sixth month, daily repair costs are \$2 (KES 200) per day lower for treatment owners. The magnitude of the effect is large: these reductions represent a 46% decrease in daily repair costs. They represent a major business expense for owners, which makes the impact of the monitoring technology significant.

It is also important to rule out any alternative explanations for these effects on repair costs. Specifically, it could be the case that drivers inflate repair costs, and the device reduces their incentive to do so because they are more likely to be caught. This is unlikely to be the case for larger repairs, however, because they are incurred directly by the owner and/or will be validated with the mechanic. We create an indicator for whether repair costs exceed 1000 KES (80th percentile). The probability of incurring a large repair cost decreases significantly (7-8 percentage points) (Appendix Figure A.3. This implies that the decrease in the repair costs that we observe cannot be entirely driven by inflated repair costs.

Revenue The top panel of Figure 7 shows that the effect on revenue is close to zero, and may be declining slightly. According to the model, the effect of treatment on revenue is ambiguous and depends on whether the effect of lower risk or higher effort dominates.

Owners may be willing to accept lower revenue if the reduction in repair costs from less risk more than offsets the reduction in expected transfers from lower revenue.

Target We find that treated owners set a slightly lower target than control owners. Figure 7 shows that by month six, the daily target amount is 135 KES (1.35 USD) below the control group, representing a 4.1% decrease (0.2 standard deviation). While the effect is not statistically significant, the downward trend is clearly visible. This steady reduction suggests that the information allows managers to re-optimize the terms of their employees' contracts. As a result of lowering the target, we see that drivers are able to make the target more often. Appendix Figure A.4 shows that the probability of making the target increases steadily throughout the study. Drivers are 10% more likely to make the target by the fourth month.

The fact that owners retain the target structure even under monitoring is consistent with our model predictions. They will now base their decision about whether or not to rehire the driver on the transfer the driver provides, as well as the effort and risk the driver supplies. A wage contract is not feasible because the tracking device does not reveal information about revenue, such that the owner must continue to provide incentives to the driver to make transfers. Similarly, a fixed rent contract is still infeasible in this context because limited liability prevents the driver from paying a rental price upfront. Our model also states that if revenue falls under the newly contracted effort-risk bundle, the owner should set a lower target to compensate the driver.

Profits We now turn to investigating the impact of the monitoring device on firm performance. Specifically, we are interested in determining whether the information we supplied allows companies to generate higher profits and ultimately expand their operations by adding more vehicles to their fleet. Company profits are measured by subtracting costs (repairs and driver salary) from total revenue. With revenues staying largely the same and repair costs falling significantly, we would expect profits to rise. Figure 9 shows that daily profits rise by approximately 12% in month four and five (\$4.40 per day) for treatment owners.

Taking the average gains over the study period and extrapolating to the full year (assuming matatus operate 25 days a month), owners can expect a \$1,200 increase in annual firm profits. The device cost \$125 (including shipping to Kenya), an amount that could be recovered in less than three months. It is worth mentioning, however, that this profit measure does not capture any additional gains from having to spend less time and effort monitoring the driver, nor does it account for any additional costs incurred from increases

in the firing probability. We discuss this further in Section 7.

The devices' return on investment suggest they are likely to be a worthwhile investment for owners in the short and long run. One of the reasons we do not see more matatu owners adopting them is because they did not exist in this form on the market at the time of our study. The options were either much more expensive (approximately 600 USD and monthly installments), or had more limited capacity. Without having tested their efficacy, owners were hesitant to make the investment, consistent with classic work on technology adoption (Foster and Rosenzweig, 1995). It is also worth mentioning that our profit gains are in line with some of the more successful business training programs documented in the literature. The cost of these trainings range from 20 to 740 dollars and last a few weeks at most (Bloom et al., 2013; McKenzie and Woodruff, 2017; Berge et al., 2015; de Mel et al., 2014; Valdivia, 2015). Our technology has the added benefit of requiring a single up-front payment for continued use. Moreover it requires relatively little coordination and training.

Growth Treatment firms are also more likely to grow their business than control firms. We measure firm growth by the number of vehicles that owners have in their fleet at endline. We find that treatment owners have 0.145 more vehicles in their fleet on average than control owners (Table 3), an 11 percent increase in fleet size. Table 3 also presents suggestive evidence that owners invested in the interior of their vehicles through the purchase of items such as higher quality seating, lighting, and sound systems.

There are a number of reasons why the monitoring device could have encouraged treatment owners to grow their businesses more actively. First, these effects could be driven by the cost savings and profit gains that owners reaped, which may have made it easier to take a loan for a second bus. Second, owners also report that managing their vehicles has become easier, which could have lowered the mental burden of taking on a second bus (Table 2, Column 5 and 6). Finally, owner's perceptions of their drivers' performance has improved (Table 4). Treatment owners' assessment of whether their drivers' skills have improved increases by 0.6 points (where they could be assigned a -1 for worse driving, 0 for no change, and 1 for better driving). Owners also report that drivers are significantly more honest, and they trust their drivers more. These broad performance improvements could make the prospect of expanding to a second bus less daunting.

Salary Finally we consider the monetary gains to drivers. Figure 9 shows that the impacts on driver salary per hour are close to zero. While not a formal prediction of the model, the effect of the tracking device on driver take-home pay is ambiguous. The impact will

depend on how revenue changes, and how much the owner adjusts the target. However, it is important to note that this is not the only metric that informs driver welfare. We need to also consider how changes in driving behavior and the relationship with the owner affect the driver, which we discuss in the next section.

6 Structural Estimation

The previous section provides reduced-form evidence for the effect of monitoring on driver behavior, firm outcomes, and contract parameters. As firms adopt these technologies more extensively, it is also important to understand their distributional consequences. To this end, we estimate the structural model introduced in Section 4 via Simulated Method of Moments (SMM). First, we calibrate the model using the control group (the “status quo”) and demonstrate that the model provides predictions that closely fit the data.³⁰ Second, we use this calibration and re-estimate the model to match the reduced form changes from the experiment. This allows us to estimate the change in welfare for both the owner and the driver.

6.1 Simulated Method of Moments

We search for the unknown model parameters that minimize the weighted distance between observed outcomes in the data and their simulated counterparts. The three unknown model parameters are driver disutility from their chosen effort and risk, owner firing costs, and the driver’s outside option $\theta \equiv (\psi(e_B, r_B), h, \bar{u})$.³¹ The SMM estimator is:

$$\hat{\theta} = \arg \min_{\theta} [\hat{m}_D - \hat{m}_S(\theta)]' W [\hat{m}_D - \hat{m}_S(\theta)]$$

where \hat{m}_D is the vector of moments calculated from the data, $\hat{m}_S(\theta)$ is the analogous vector of endogenous moments simulated from the model for any given choice of θ , and W is the

³⁰Specifically, we numerically solve the owner’s maximization problem, which is Equation (1) after applying the optimal transfer and rehiring schedules:

$$V = \max_{T \in \mathcal{Y}} \delta V + T - G(T|e, r) \left(1 + \frac{V}{U}\right) \{T - \mathbb{E}[y|e, r, y \leq T]\} - \mathbb{E}[c(r)|r].$$

³¹In addition, we use observed data to estimate other model parameters such as daily repair costs $E[c(r)]$ and the CDF of revenue $G(y|e, r)$.

weighting matrix.³² To first study the baseline contract, we match on five moments which are observed in the data to their simulated counterparts: the target, the driver take home salary, the owner’s net transfer, the rehiring probability, and driver welfare, for which we use the average reported price to forego their current contract.

In the second exercise (i.e. valuing the monitoring effect) we use a single moment: the change in the target observed under treatment. We only require a single moment because we keep two of the three unknown model parameters fixed from the previous estimation.³³ For both exercises, we run this simulation 500 times, where each simulation draws samples with replacement from the observed empirical distribution of revenue to create the bootstrapped distribution (see Appendix Section E for more detail).

6.2 Status Quo Estimation

Table 5 summarizes the results of the status-quo model estimation. Starting with the parameter estimates, driver daily disutility of baseline effort and risk choices is estimated to be equivalent to approximately \$5, while we estimate firing costs to be equivalent to 51 days of lost profits. Both of these values are reasonable, as firing costs likely reflect a combination of idle days for the vehicle and the cost of finding a new driver. The driver’s outside option is estimated to be \$7.07, which is approximately equal to the average unskilled daily wage in our context.³⁴

The model also does a good job of matching the observed moments in the data. The target is matched nearly exactly, while expected profits and driver welfare are well within one standard deviation of what we observe in the data. Predicted driver salary is \$0.69 below observed salary, a relatively small difference. The only moment which the model fails to match by a meaningful margin is the firing probability, where the model predicts 0.6% of days will result in a separation versus the observed 0.1%.³⁵

Finally, we can examine owner and driver welfare under the status quo. The model shows that the contract confers substantial welfare to the owner and the driver. Drivers receive \$442 above their outside option while owners benefit \$1,116 from this relationship with the

³²The optimal weighting matrix given by the inverse variance-covariance matrix of the data moments.

³³Appendix Table A.2 shows robustness of our estimation to matching on treatment effects for salary and profits in addition to the target.

³⁴Appendix Figures A.10 to A.13 investigate the sensitivity of the model outcomes are to different values of the model parameters. These Figures show that our calibration is robust to other reasonable parameter choices.

³⁵To assess the overall fit of the model, we use an over-identification test of the model’s overall fit. We find that we cannot reject the model ($p = 0.54$).

driver. While drivers do not reach the target every day, their residual claim on days where they do is substantially higher than their outside option. Owners have high repair costs but induce large transfers even when drivers miss the target.³⁶

6.3 Valuation with Monitoring

Our second exercise aims to estimate how the introduction of monitoring affects owner and driver welfare. We hold the driver's outside option and the owner's firing costs fixed from the status quo estimation as these parameters are not expected to change under monitoring.³⁷ The final unknown model parameter is driver disutility under monitoring. The SMM procedure first calculates new model outcomes under monitoring, and calculates the simulated treatment effects by comparing the new simulated outcomes to the ones previously estimated under the status quo. The procedure estimates what value of driver disutility produces a simulated treatment effect for the target that best matches the observed treatment effect in the data.

Table 6 displays the results of the second SMM estimation. The fit of the simulated moments of the treatment effects is somewhat lower than what we observe under the status quo. The target treatment effect match is nearly perfect (which is expected given that the estimation was exactly identified using this moment), while the treatment effect on the firing probability is also close. The predicted profit treatment effect (\$1.18 increase) is smaller than the observed profit treatment (\$3.62) though not statistically significant, while the predicted salary treatment effect is higher (\$0.93 versus \$0.23). That is, our model slightly underestimates the benefits to the owner and overestimates the benefits to the driver.³⁸

Most interestingly, this exercise estimates the changes in driver and owner welfare. From the theoretical model, we have a clear prediction that owner welfare will rise after the introduction of monitoring. In contrast, the effect of monitoring on driver welfare and total welfare is ambiguous. It depends on how driver disutility changes as the status quo bundle of effort and risk shifts from (e_B, r_B) to (e_M, r_M) under monitoring. When driver disutility increases only slightly or falls, driver welfare *rises*. This outcome was not possible without

³⁶See Appendix Figures A.10 to A.13 for sensitivity of the model outputs to different parameter values

³⁷We also rely on data from the treatment group to calculate expected repair costs and the CDF of revenue.

³⁸One explanation for this under-estimation is that the monitoring device may provide owners a weak signal of revenue, making it harder for drivers to withhold revenue when they fall below the target. While treated owners are slightly more likely to report that they know the revenue the driver collected on a given day (Table 2), the effect is small and insignificant. Despite the absence of this effect, treated drivers may expect their owners to have a better sense of the revenue they earn. This could prompt them to transfer more to the owner, thereby lowering the driver's salary and increasing the owner's profits.

monitoring because it could only be achieved by the owner setting a lower target, and the driver committing to a more favorable effort-risk bundle. Committing to such a bundle was not credible in the absence of monitoring.

Figure 10 Panel (b) illustrates these dynamics for different costs. When driver disutility increases by less than 10%, the driver is better off with monitoring than without. As driver disutility increases between 10% and 25%, monitoring lowers driver welfare but still raises overall welfare as the gains to the owner are larger than the losses to the driver. However, once driver disutility increases beyond 25%, driver losses dominate the owner’s gains causing overall welfare to fall. Our SMM procedure estimates driver disutility increasing by 22% (to \$6.08). If the disutility function is convex, this effect is consistent with the reduced-form increases in both mileage (11%) and driving time (10%). This means driver welfare falls by \$31 while owner value increases by \$41, leading to a small overall welfare improvement of \$10. These structural estimation results suggest that monitoring leads to small efficiency gains, with some redistribution from the driver to the owner. It is worth highlighting that there is some uncertainty on the overall welfare impacts (which we discuss more below), though it does seem to be the case that the owner benefits substantially while the driver does not.

To evaluate the plausibility of the owner’s valuation of the monitoring device, we can compare our estimates to our findings from a willingness-to-pay experiment conducted at the end of the study. We estimate the owners’ average willingness to pay for the monitoring system to be \$44.67 as compared to the model estimate of \$41.10. This suggests the model captures the benefits of monitoring to the owner well.

7 Discussion of Welfare

While we find that owners end up offering a welfare-reducing contract to drivers in this case, this did not have to be the case as we discuss above. Moreover, there is an important caveat to this finding. These welfare estimates do not account for changes in the intangible relationship between owners and drivers. The relationship between owners and drivers is notoriously fraught with mistrust: under the status quo, owners often suspect that drivers are cheating them and driving the matatu recklessly; conversely, drivers often complain that owners second-guess their reports, and refuse to give them the benefit of the doubt when things go awry. In focus groups with drivers during the development of the monitoring system, many drivers brought up that trust between owners and drivers could increase under

monitoring.

We complement drivers' welfare estimates with SMS survey responses that we collected from drivers six months after the study finished.³⁹ Out of the 60% of drivers who responded, one quarter said the tracking device improved the relationship with their owner while nearly three quarters reported no change (only 3% reported a worse relationship). 96% said they preferred driving with the tracker. While this evidence may suffer from interviewer demand effects and selection, it does indicate that monitoring may have conferred non-pecuniary benefits to the driver. Consistent with this interpretation, we find that treatment owners transferred a larger amount to their driver in a trust game at endline (Table 4, Column 1). This evidence suggests that an improvement in the owner-driver relationship may have counteracted some of the costs drivers' incurred from monitoring.⁴⁰

The welfare implications associated with these monitoring technologies are further complicated by how they interact with the public transit passengers and other road users. One of the motivations for this research initiative was to understand whether these technologies could improve road safety as Kenya's matatu sector is notoriously unsafe. While we explore the implications of GPS technologies on road safety in a companion paper, it's important to highlight that the welfare impacts that we estimate in this paper have the potential to change dramatically if passengers/pedestrian welfare is also considered. Weighing driver welfare relative to consumer welfare is beyond the scope of this research.

8 Conclusion

A firm's success rides heavily on the performance of its employees. It is therefore important that firms design contracts and manage their employees in ways that align the employees' incentives with their own. This becomes more challenging when firms cannot observe the amount of effort employees invest, nor the amount of output they produce. In theory, firms can use monitoring technologies that reveal the performance of their workers more accurately

³⁹At this point we had given control owners two months with app access as well, so no distinction can be drawn between treatment and control drivers. Response frequency was balanced across treatment and control drivers.

⁴⁰Integrating the idea of trust in the model and quantifying its importance for welfare is beyond the scope of this paper. But it is interesting to consider a model in which owners and drivers are risk-averse (even though it limits the tractability of the model), so that uncertainty in the returns affects their utility. Monitoring may then lower this uncertainty and improve welfare. Alternatively, one could attempt to model owner and driver utility as a function of deception: there could then be a psychic cost to the driver of deceiving the owner, and the owner suffers from revealed deception. Monitoring would lower the scope for deception and thereby improve welfare.

to overcome this constraint. In practice, however, the impact of such monitoring technologies is unclear.

In this paper, we investigate the impact of monitoring devices on firm productivity. This question is particularly relevant as small firms struggle to expand in low income countries, and information technologies are becoming ubiquitous. To this end, we implement a randomized control trial where we introduce a monitoring device to 255 firms operating in Kenya's transit industry. We design a novel mobile application that provides information to 125 treatment firms regarding: the location of the vehicle, number of kilometers driven, number of hours the ignition was on, and the number of safety violations incurred. We confirm that 70% of owners consult the app weekly. Owners also report that monitoring their drivers has become significantly easier. We use daily surveys from vehicle owners and drivers over six-months to track the impact of reducing asymmetric information on firm outcomes.

Firms use the monitoring device to demand a new bundle of effort and risk from the driver that was previously impossible to incentivize. The driver responds by driving an additional hour per day, and engaging in less off-road driving on bumpy routes that damage the minibus. Vehicle repair costs fall by 42%, and firm profits increase by 13%. These gains more than offset the cost of the device, suggesting that a tracking device like the one we designed for this study would be a worthwhile investment if it were available on the market. We also investigate whether this improved profitability, and better management, fuel business growth. We find that treatment owners have 0.145 more vehicles (11%) on average than control owners after 6 months.

We do not see the owners changing the contract structure they offer. Firms reduce the transfer they demand from drivers to compensate them for the higher disutility they incur under the new effort-risk bundle, but the target contracts remains. This suggest that this class of inefficient contracts could remain widespread in this industry where revenue is unobserved— at least until monitoring technologies can reveal the amount of revenue employees earn throughout the day.

To identify the distributional consequences of these technologies we estimate the target contract model via simulated method of moments. We find that owners' welfare increases by approximately \$41 with the introduction of monitoring. While our model predicts that drivers could be better off under monitoring, our setting is one where the disutility from new effort and risk bundle outweighs the gains from a lower target. It is worth highlighting that these losses may be compensated by greater trust between owners and drivers.

Taken together, these results provide compelling evidence that monitoring devices can

help firms overcome inefficiencies created by moral hazard. These results are particularly relevant for small firms, and policy makers focused on helping firms expand. We know that firms struggle to grow in low income countries for a number of reasons, and this paper identifies another important barrier that is relatively understudied empirically: moral hazard in labor contracting. We demonstrate that introducing cost-effective monitoring technologies can be a worthwhile investment.

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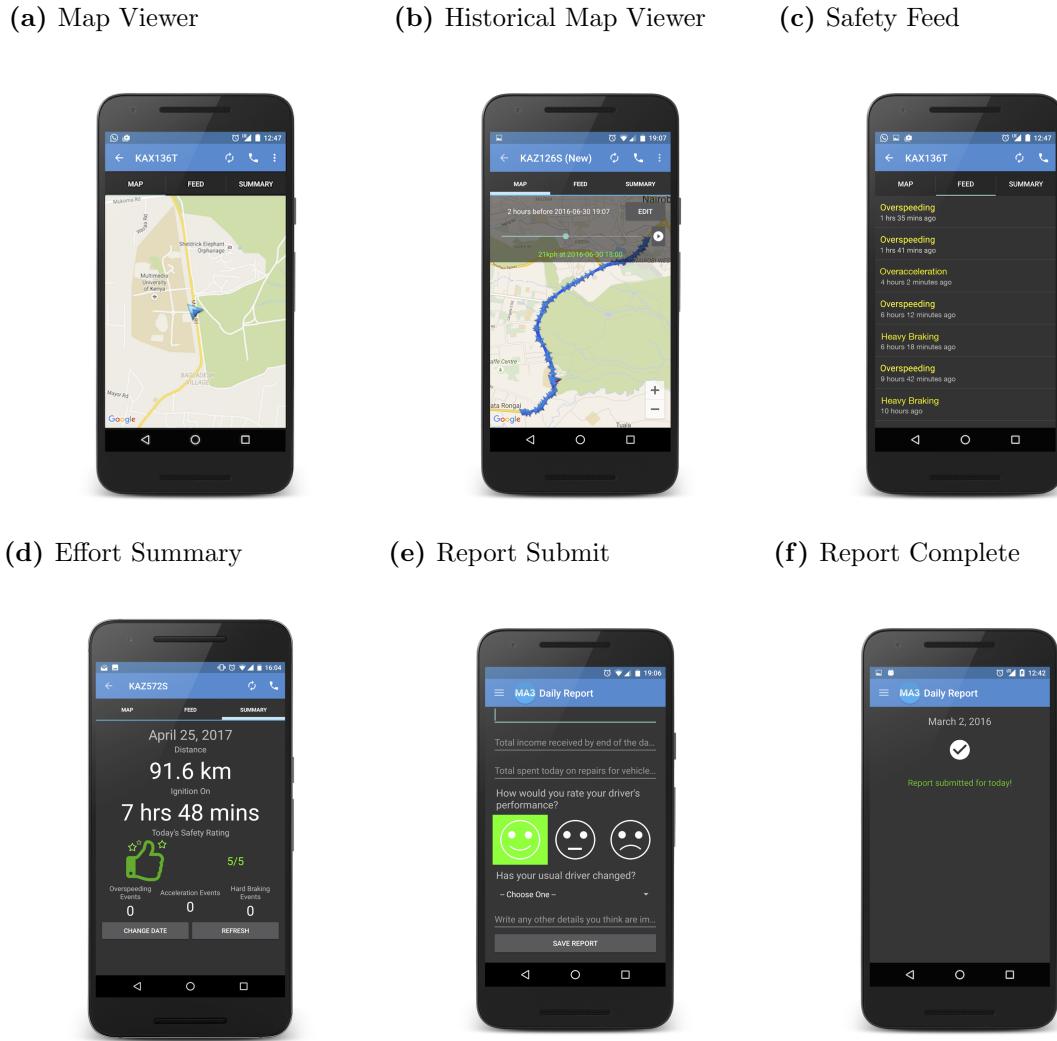
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Figures

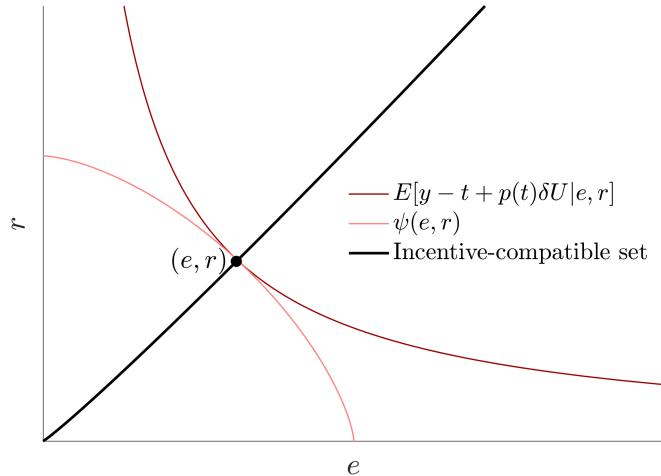
Figure 1: Mobile app “SmartMatatu”



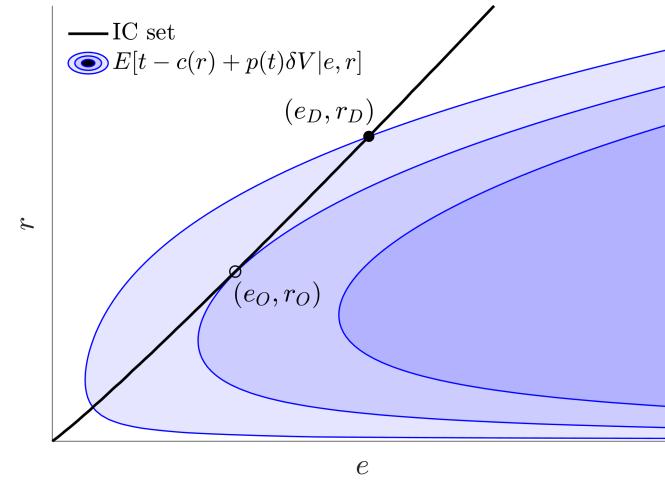
Notes: Android mobile app “SmartMatatu” developed by Echo Mobile in collaboration with matatu owners. Panels A and B: map viewer of real-time matatu location with historical playback of past locations over several hours for a given day. Panel C: Safety feed with speeding, acceleration, and hard braking alerts. Panel D: Daily effort summary, with mileage in kilometers, number of hours ignition on as a measure of hours worked, and summary safety rating relative to other drivers on the route. Panels E and F: Reporting for both treatment and control owners of daily target, transfer received, repair costs, satisfaction with driver, and notification in case the driver changed.

Figure 2: Baseline and monitoring contract intuition

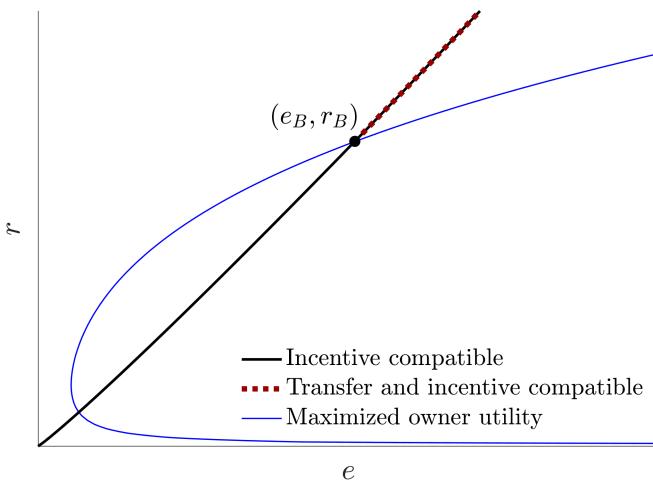
(a) Driver utility in (e, r) space.



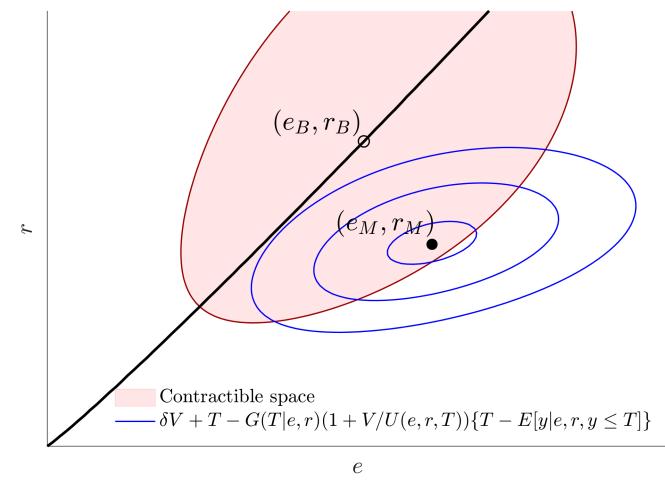
(b) Assumption 2 implies $(e_D, r_D) > (e_O, r_O)$.



(c) Incentive compatible contracting choice (e_B, r_B) .

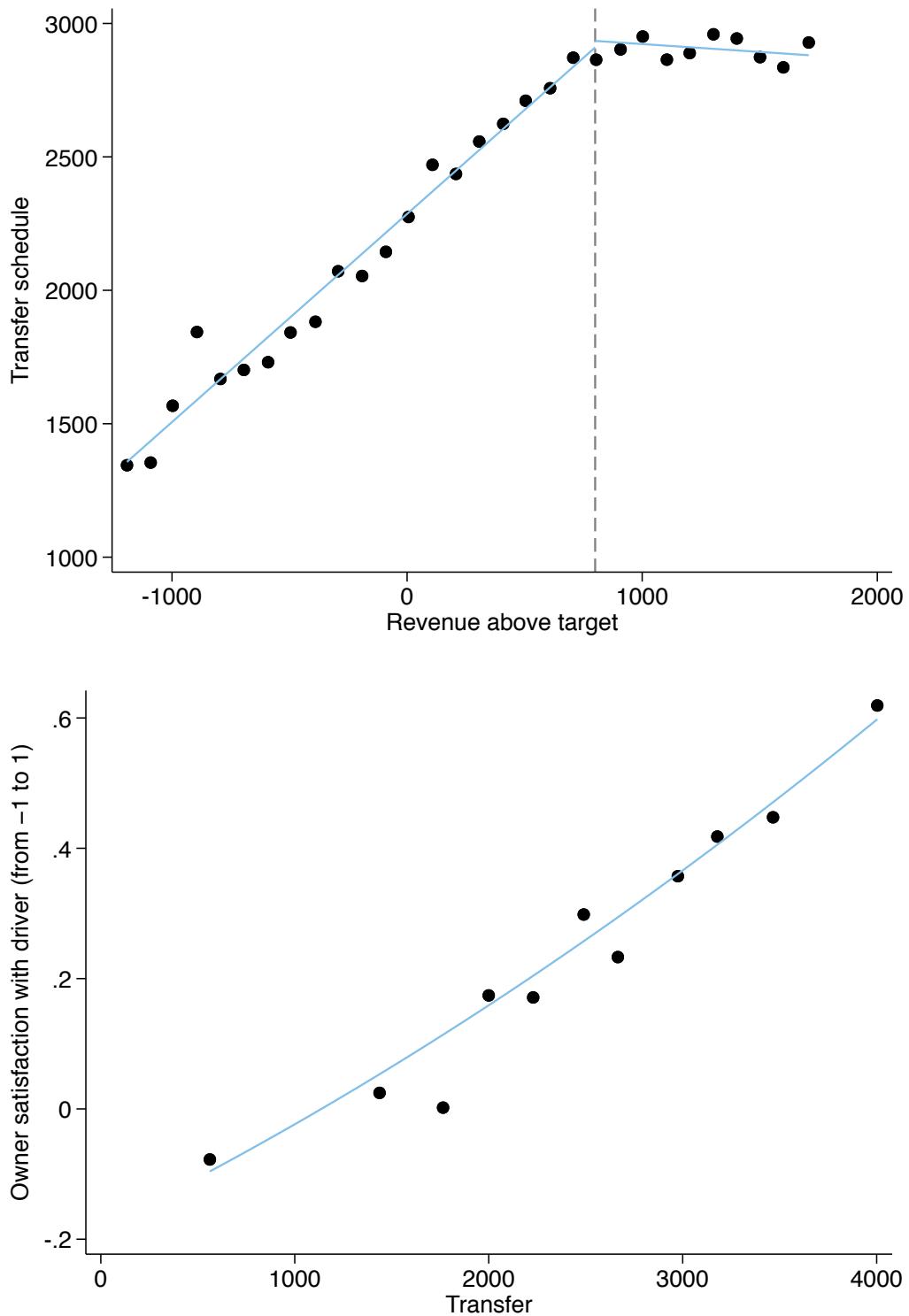


(d) Monitoring shifts effort/risk to (e_M, r_M) .



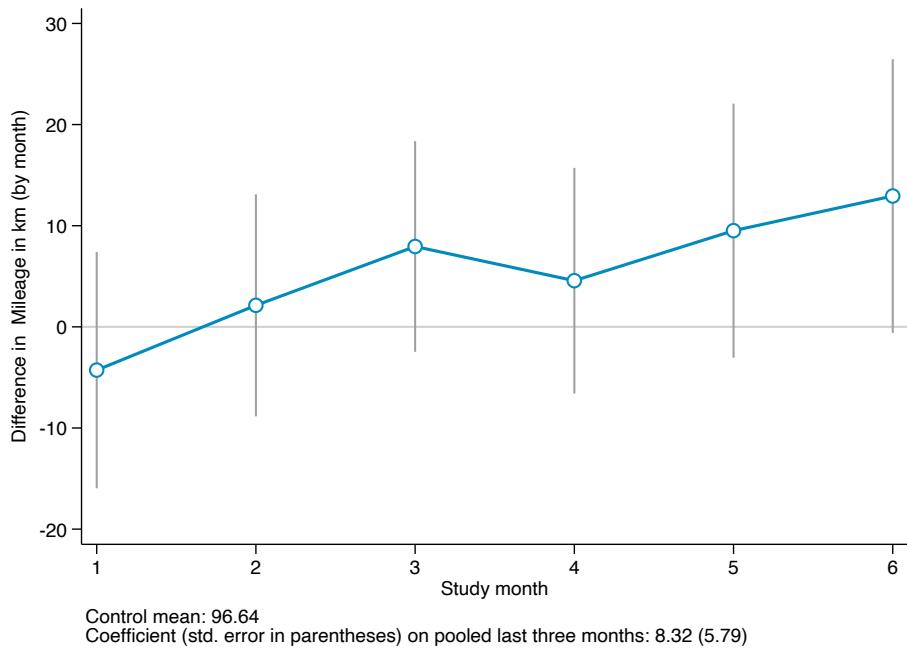
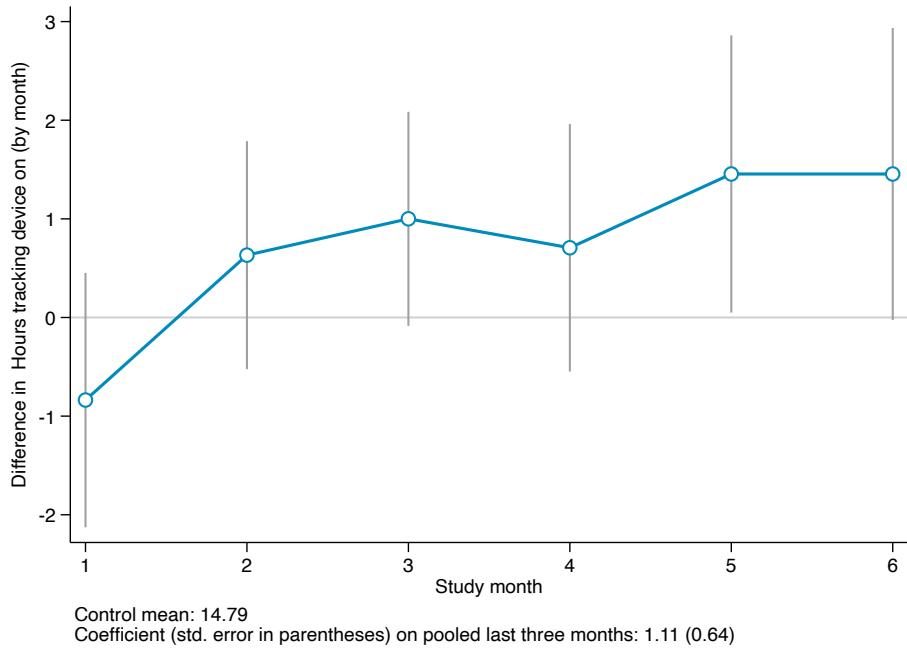
Notes: Panel A: The owner can only induce effort-risk bundles on the incentive compatible set. Panel B: The owner constrained bliss point (e_O, r_O) is below the driver bliss point (e_D, r_D) due to Assumption 2. Panel C: The baseline contracted bundle (e_B, r_B) coincides with the driver bliss point. Panel D: With Monitoring, effort rises and risk falls; the owner faces a tradeoff in effort and the target.

Figure 3: Estimated transfer schedule and owner satisfaction in response to transfer



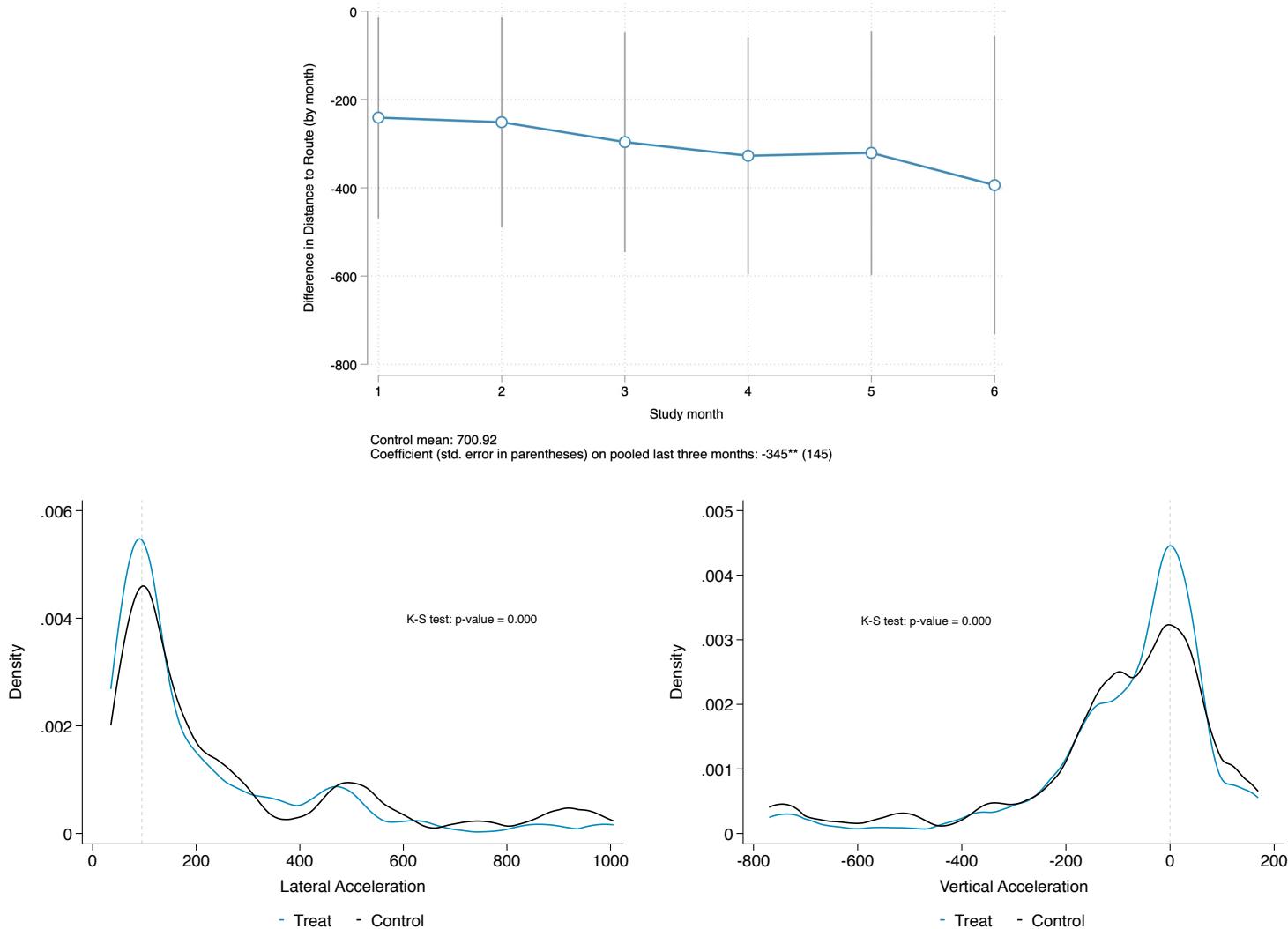
Notes: Top panel: The empirical transfer schedule closely resembles the shape $t(y) = \min\{y, T\}$ as in the Lemma. The slope extends beyond the target because of subsistence income, which we include in the structural estimation (see text). Bottom panel: Owner satisfaction rises substantially with the transfer, as suggested by $p(t) = p_0 + \frac{t}{\delta U}$. In Appendix Figure A.9, we also show that rehiring falls with transfers below the target.

Figure 4: Treatment effects on effort



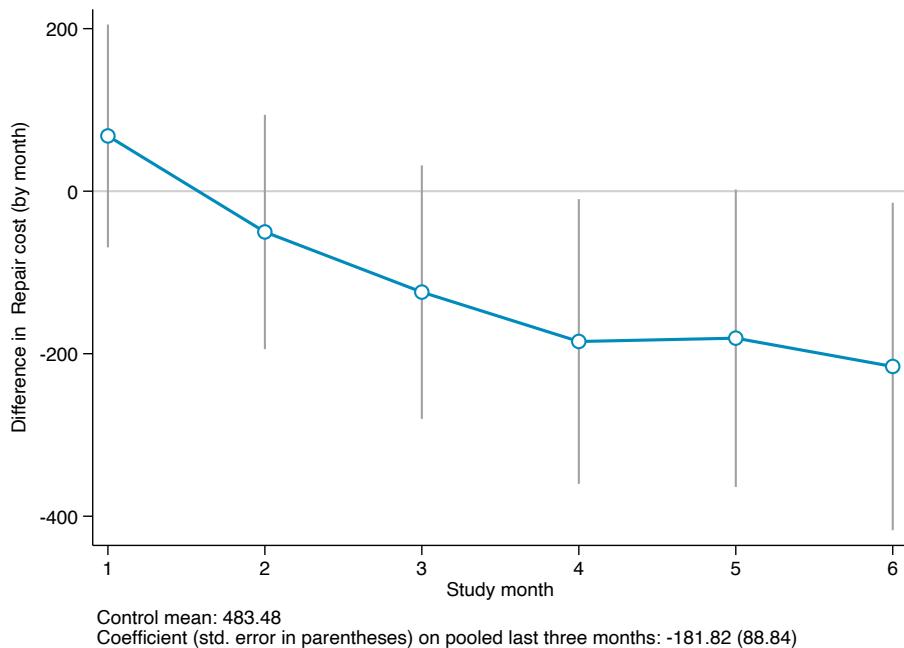
Notes: OLS estimates according to Equation 2. Top panel: Hours tracking device on corresponds to working hours of driver. Bottom panel: Daily mileage captured by tracking device. Standard errors for 95% confidence intervals clustered at the matatu level (255 clusters).

Figure 5: Treatment effects on risk taking



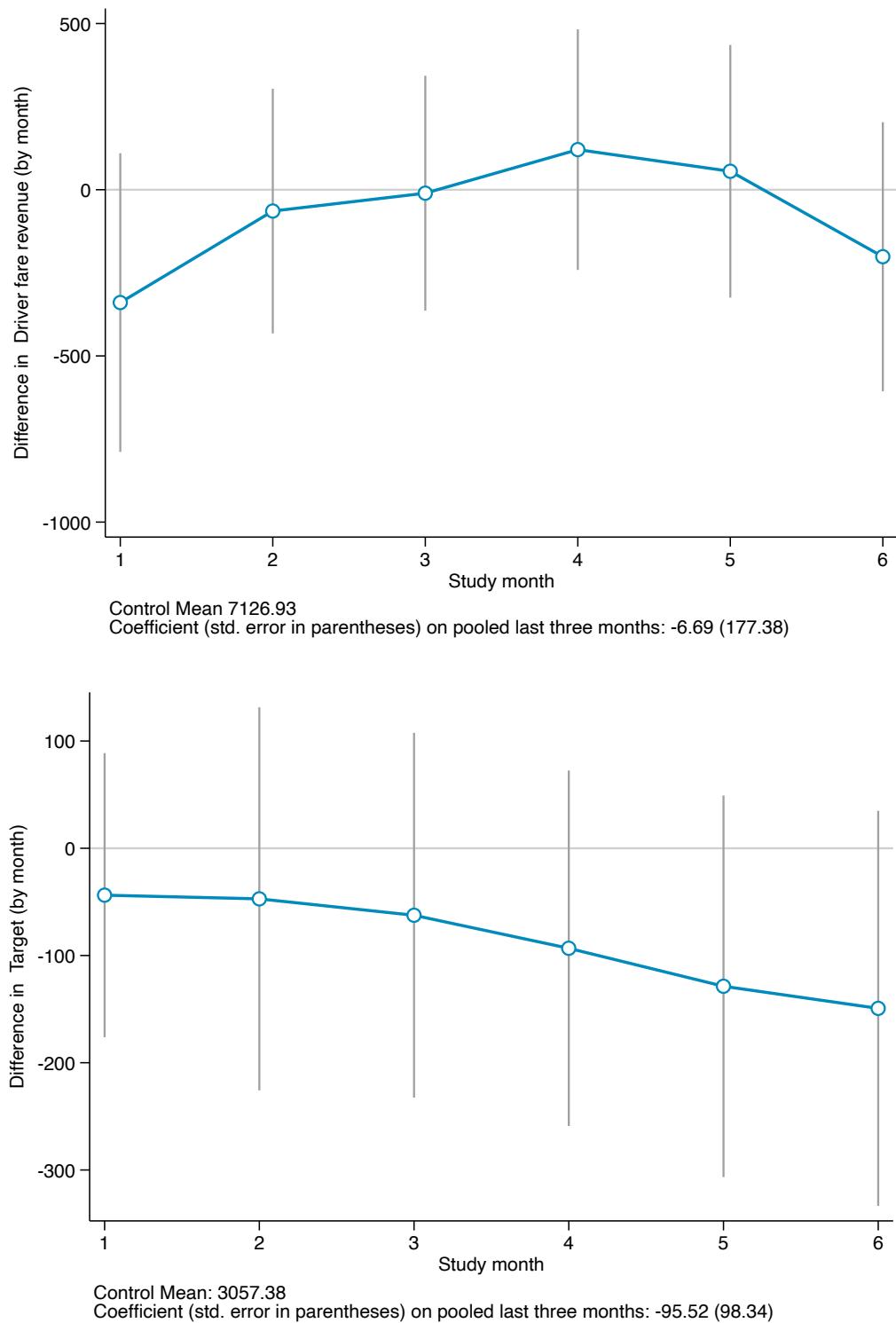
Notes: OLS estimates according to Equation 2. Top panel: Distance to licensed route in meters captured by tracking device. Middle panel: Treatment and control distributions of lateral acceleration. Standard errors for 95% confidence intervals clustered at the matatu level (255 clusters). Bottom panel: Treatment and control distributions of vertical acceleration. Kolmogorov-Smirnov test of equality of distributions.

Figure 6: Treatment effects on costs



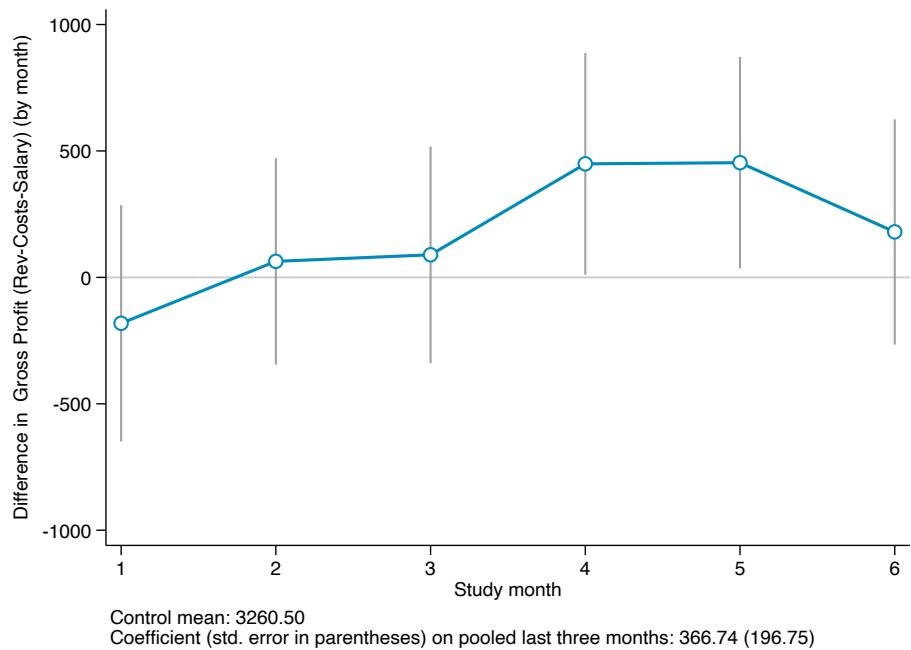
Notes: OLS estimates according to Equation 2. Top panel: Treatment effect by month on gross profit, defined as revenue minus repair costs minus driver residual claim (salary). Standard errors for 95% confidence intervals clustered at the matatu level (255 clusters).

Figure 7: Effect of monitoring on revenue and target



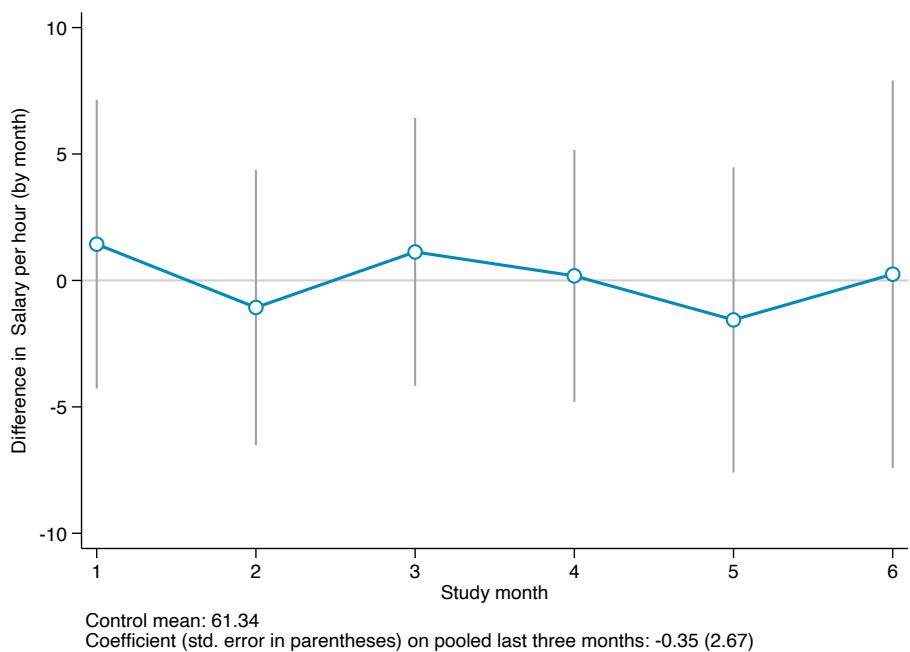
Notes: OLS estimates according to Equation 2. Treatment effects by month on daily revenue. Standard errors for 95% confidence intervals clustered at the matatu level (255 clusters).

Figure 8: Treatment effects on profits



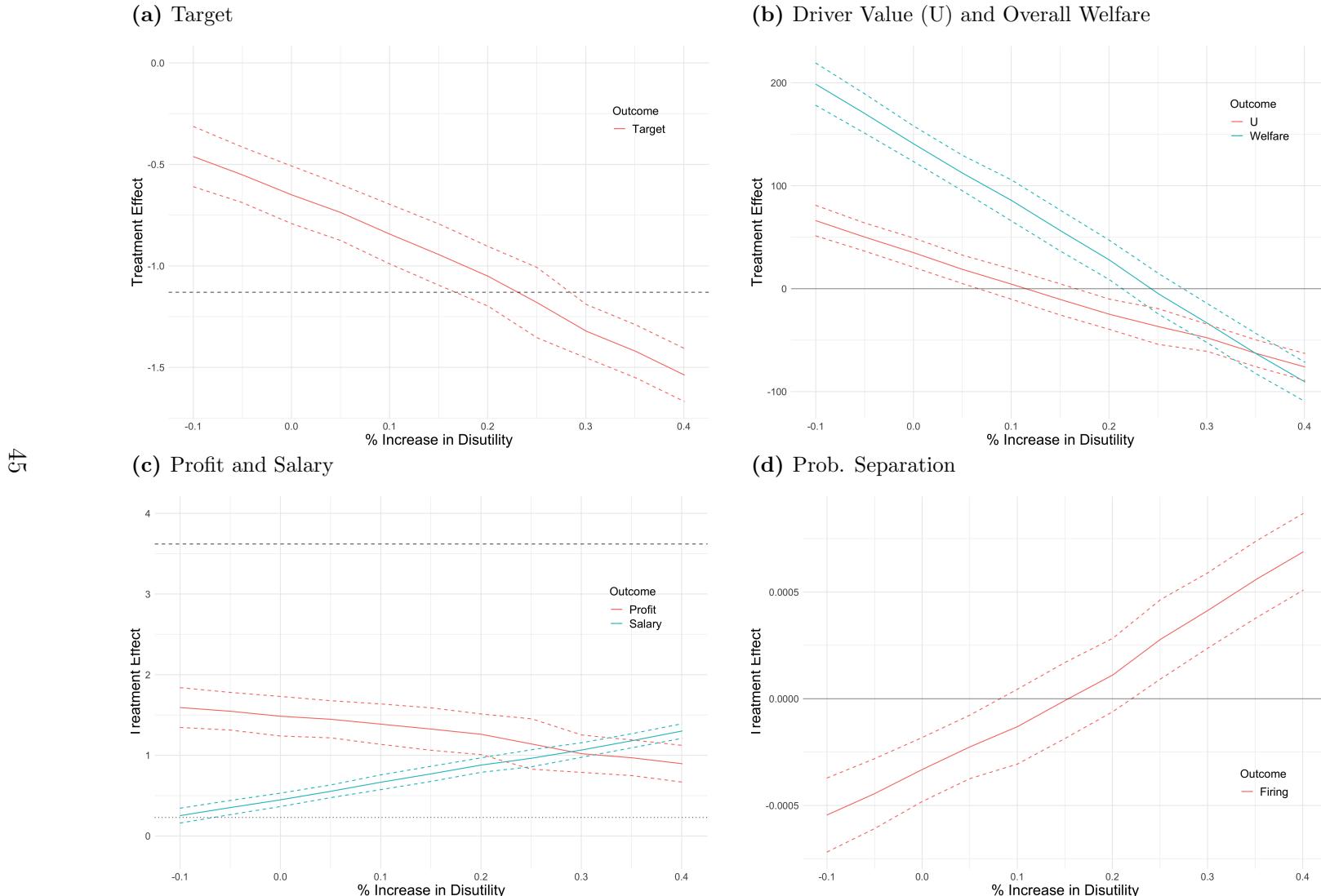
Notes: OLS estimates according to Equation 2. Treatment effect by month on gross profit, defined as revenue minus repair costs minus driver residual claim (salary). Standard errors for 95% confidence intervals clustered at the matatu level (255 clusters).

Figure 9: Treatment effects on salary per hour



Notes: OLS estimates according to Equation 2. Treatment effect by month on driver salary per hour. Standard errors for 95% confidence intervals clustered at the matatu level (255 clusters).

Figure 10: Predicted Treatment Effects by Increased Work Cost



Notes: Figures plot the model predicted treatment effect for different increases in driver work cost under monitoring. Dashed or dotted lines show observed values where applicable; in panel (c) the dashed line is the observed profit treatment effect while the dotted line is the observed salary treatment effect. Other input parameters are fixed per those stated in the main model calibration table.

Tables

Table 1: Summary statistics on owners, drivers, and matatus

	All				Treatment	Control	p-Value
	Mean	Std. Dev.	Min	Max	mean	mean	difference
Owners							
Age	36.72	7.87	18	68	37.16	36.29	0.377
Female	0.18	0.38	0	1	0.17	0.18	0.939
Years of education	11.65	2.88	0	14	11.52	11.77	0.501
Self-employed (yes/no)	0.78	0.41	0	1	0.77	0.79	0.689
Years industry experience	7.78	6.34	0	34	7.82	7.74	0.927
Years matatu owner	4.56	4.16	0	26	4.47	4.66	0.715
Number past drivers	1.85	1.73	0	10	1.94	1.77	0.437
Owner Raven's score	4.56	1.55	0	8	4.63	4.49	0.452
Owner rating: driver honesty	7.70	1.45	4	10	7.61	7.78	0.345
Owner rating: driver diligence	8.19	1.46	3	10	8.08	8.29	0.239
Baseline target	31.31	4.44	20	50	31.56	31.06	0.376
Baseline transfer	25.96	7.96	0	50	25.94	25.98	0.969
Drivers							
Age	35.71	7.25	21	58	37.19	34.27	0.001
Years of education	11.06	2.78	0	14	10.86	11.26	0.252
Years driving experience	7.89	5.89	0	37	8.75	7.05	0.021
Number of past owners	5.50	4.87	0	50	5.36	5.64	0.649
Months with current owner	14.77	19.90	0	180	14.25	15.27	0.684
Driver Raven's score	4.28	1.38	0	8	4.23	4.33	0.552
Driver risk choice	6.65	2.99	1	10	6.70	6.60	0.803
Driver rating: owner fairness	8.23	1.53	2	10	8.40	8.07	0.088
Baseline revenue	76.99	16.38	30	150	77.10	76.89	0.918
Baseline residual revenue	9.59	2.67	3	20	9.54	9.64	0.765
Matatus							
Age of matatu	13.06	4.27	2	26	13.46	12.67	0.142
Number of special features	1.38	0.89	1	8	1.40	1.37	0.825
Purchase price (USD)	6675	2849	1800	30000	6396	6947	0.123
Observations	255				126	129	

Notes: All values in 100s of Kenyan Shillings (KES, approximately \$1). Data from baseline survey. Years of education constructed from categories, assuming partial completion (elementary: 4 years; high school: 10 years; university: 14 years; technical college: 12 years). Ratings of honesty and diligence (owner) and fairness (driver) range from 1 to 10. Driver risk choice based on a standard risk lottery game. p-value of t-test comparing means in treatment and control groups.

Table 2: Treatment effects on reported knowledge and monitoring behavior

	(1) Know mileage	(2) Know off-route	(3) Know revenue	(4) Difficulty monitor	(5) Monitoring time
Treatment	0.27 (0.07)	0.45 (0.07)	0.04 (0.07)	-1.85 (0.16)	-0.72 (0.05)
Control Mean of DV	0.47	0.40	0.61	4.02	-0.01
Controls	X	X	X	X	X
Route FE	X	X	X	X	X
Matatu N	187	187	187	190	190

Notes: OLS regressions of outcome on treatment indicator, controlling for route fixed effects, the age of the matatu, the number of special features, owner age and sex, owner education, owner self-employment status, the number of other businesses the owner runs, owner years of matatu industry experience, and owner raven score. “Know mileage”: whether the owner knows the approximate number of kilometers a driver drove on a given day. “Know off-route”: the owner knows when the driver is off the licensed route. “Know revenue”: the owner know the approximate amount of revenue the driver made. “Difficulty monitor”: how hard it is to monitor the driver’s behavior, from 1 (very easy) to 5 (very hard). “Monitoring time”: whether the owner’s time spent monitoring the driver has increased (1), stayed the same (0), or fallen (-1) over the last six months. Data from additional question added to endline after one quarter of endlines were already completed, hence only up to 190 out of 255 observations (balanced across treatment and control; three non-responses to first three questions). Robust standard errors. Stars indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 3: Treatment effects on business investment

	(1) Number vehicles	(2) New interior
Treatment	0.129 (0.076)	0.074 (0.057)
Control Mean of DV	1.22	0.21
Controls	X	X
Route FE	X	X
Matatu N	245	240

Notes: OLS regressions of outcome on treatment indicator, controlling for route fixed effects, the age of the matatu, the number of special features, owner age and sex, owner education, owner self-employment status, the number of other businesses the owner runs, owner years of matatu industry experience, and owner raven score. “Know mileage” ask whether the owner knows the approximate number of kilometers a driver drove on a given day. “Know off-route”: the owner knows when the driver is off the licensed route. “Know revenue”: the owner know the approximate amount of revenue the driver made. “Number vehicles”: the number of vehicles the owner owns at endline. “New interior”: major investment into interior of vehicle. Data from endline survey. Robust standard errors. Stars indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 4: Perceptions of treatment at endline

	(1) Trust amount	(2) More honest	(3) Performance rating	(4) Better driving
Treatment	33.80 (15.12)	0.71 (0.05)	0.11 (0.17)	0.63 (0.06)
Control Mean of DV	151.61	0.04	7.21	0.04
Controls	X	X	X	X
Route FE	X	X	X	X
Matatu N	244	190	246	190

Notes: OLS regressions of outcome on treatment indicator, controlling for route fixed effects, the age of the matatu, the number of special features, owner age and sex, owner education, owner self-employment status, the number of other businesses the owner runs, owner years of matatu industry experience, and owner raven score. “Trust amount”: amount in KES the owner gives to the driver in a trust game at endline. “More honest”: change in honesty of transfer amount since baseline, either less honest (-1), the same (0), or more honest (1). “Performance rating”: overall performance rating of the driver at endline, ranging from 1 (poor) to 10 (excellent). “Better driving”: the owner’s judgement of overall driver performance at endline, worse (-1), about the same (0), or better (1). Data from endline survey; trust and performance rating added after a quarter of endlines were already completed, hence only up to 190 out of 255 observations (balanced across treatment and control; three non-responses to first three questions). Robust standard errors. Stars indicate statistical significance at the 1% ***, 5% **, and 10% * levels.

Table 5: Model calibration under baseline contract

Panel A: Assumptions			
Input	Symbol	Value	Justification
Repair Costs	$E[c(r)]$	4.9	Average repair costs seen in the control group
Revenue Distribution	$G(\cdot)$	—	Empirical distribution calculated from control group data
Discount Factor	δ	0.99	

Panel B: SMM Parameter Estimates			
Input	Symbol	Value	Interpretation
Disutility	$\psi(e^*, r^*)$	4.99 (0.01)	Disutility equivalent to 5 dollars
Firing Cost	h	51.44 (0.50)	Total firing costs equivalent to 51 days lost profits
Outside Option	\bar{u}	7.07 (0.04)	Approximately the average unskilled daily wage

Panel C: Matched Moments and Predictions			
Outcome	Prediction	Observed	Difference
Target	30.13 (0.09)	30.12 (0.35)	0 (0.36)
Expected Profit	22.41 (0.14)	23.25 (0.89)	-0.843 (0.9)
Expected Salary	19.26 (0.03)	19.94 (0.32)	-0.69 (0.32)
Prob. Separation	0.0064 (0.00011)	0.0011 (0.0002)	0.0054 (0.0002)
Driver Contract Value minus Outside Option	442.12 (2.53)	446.18 (184.62)	-4.06 (184.64)
Owner Value	1116.27 (15.03)	—	—
Total Welfare	1558.39 (15.44)	—	—

Notes: Simulated method of moments (SMM) calibration for work cost, firing cost, and outside option. Matched on five moments: observed target profits, salary, separation probability, and driver contract value. All values are in 100s of Kenyan Schillings. Observed salary includes estimated fare collector salary.

Table 6: Reduced-form versus structural treatment effect estimation

Panel A: Assumptions			
Input	Symbol	Value	Justification
Repair Costs	$E[c(r)]$	2.7	Previous value of 4.9 minus observed treatment effect reduction of 2.2
Revenue Distribution	$G(\cdot)$	—	Empirical distribution calculated from treatment group data
Discount Factor	δ	0.99	
Firing Cost	h	51.44	Fixed from previous value
Outside Option	\bar{u}	7.07	Fixed from previous value

Panel B: SMM Parameter Estimates			
Input	Symbol	Value	Interpretation
Disutility	$\psi(e^*, r^*)$	6.08 (0.07)	Increase of 1.09 (22%) from previous value

Panel C: Predicted vs. Observed Treatment Effects			
Outcome	Pred.Treat	Obs.Treat	Difference
Target	-1.14 (0.14)	-1.13 (0.87)	-0.01 (0.88)
Expected Profit	1.18 (0.2)	3.62 (1.96)	-2.44 (1.97)
Expected Salary	0.93 (0.03)	0.23 (0.35)	0.7 (0.35)
Prob. Separation	0.0002 (0.00016)	-0.01 (0.01)	0.01 (0.01)
Driver Contract Value minus Outside Option	-30.98 (3.38)	—	—
Owner Value	41.1 (22.25)	—	—
Total Welfare	10.12 (22.65)	—	—

Notes: All values are in 100s of Kenyan Schillings. Work cost estimated via simulated method of moments matching the observed target treatment effect.

Online Appendix for “Monitoring in Target Contracts: Theory and Experiment in Kenyan Public Transit”

Erin Kelley, Gregory Lane, and David Schönholzer

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A Ethics Statement

This paper is focused on Kenya's public transit industry, a sector dominated by small-scale entrepreneurs that typically own 1-2 minibuses ("matatus") which they rent out to drivers on a daily basis. Over the past 10 years new technologies have entered the market and changed the way minibus owners manage their businesses. Most notably are the arrival of GPS technologies that help matatu owners track their vehicles. When we launched the study in 2014 these technologies were still relatively new. Private businesses were encouraging owners to purchase tracking devices, and designing applications that customers could download to monitor matatu's progress (Kalan, 2013). Finally, a number of banks were requiring that matatu owners install GPS trackers in their minibuses before approving a loan for a new bus.

While these new technologies were spreading rapidly, there were no active studies investigating their impact on the transportation industry as a whole. As a result, we felt that it was important to document their impact on matatu owners, drivers and passengers/commuters. The latter are an important group to consider as the minibus industry is notoriously unsafe and road traffic accidents are becoming the leading cause of death among 18-25-year olds in low-income countries (WHO, 2013). We explore these dynamics on road safety in a companion paper.

A priori there were two major concerns about the impact of the device on matatu drivers. First, there was a concern that drivers could lose their jobs, or some of their income as a result of the information that we provided to matatu owners. After more than a year of piloting in the field we collected sufficient evidence to suggest these outcomes were unlikely. Extensive conversations with owners and drivers highlighted that drivers hold significant market power because finding reliable drivers that owners can trust is not easy. In most cases of owner-driver separations, drivers reported leaving voluntarily for a better paying job from another owner. Furthermore, of the relationships that were terminated by the owner, drivers reported being able to find a similarly paying job quickly and without difficulty. Conversely, owners reported significant difficulties in finding drivers to operate their matatus. Therefore, we expected that owners would not financially punish their drivers in response to this information.

Despite these assurances, there remained some risk to drivers along this dimension. To minimize the chance that matatu drivers were negatively affected by the intervention we set up a hotline that drivers could use to contact us at any time. We informed them at baseline that they should use this number to notify us if the owners threatened to act in a harmful

manner. We hired a well-established matatu driver's advocate to attend the baseline surveys and explain the value of this resource. This helped build the requisite trust with drivers. We also made monthly phone calls to each driver to check-in on business operations. These precautions were successful. We did not record any instance of drivers using the hotline or reporting abusive behavior. Moreover, driver income was not affected by our intervention (and if anything, it increased ever so slightly).

The second concern we had is that owners would use the GPS technology to mandate a new level of effort and risk that drivers would find burdensome and make them worse off. *A priori*, however, the effect on this outcome was ambiguous. When owners have access to a GPS technology they can monitor dimensions of driver behavior that were previously unobserved. This broadens the contracting space and could result in the owner choosing an effort/risk/target profile that is more appealing to the driver, leaving the driver better off.

While we find that owners end up offering a welfare reducing contract to drivers in this case, there is an important caveat to this finding. These welfare estimates do not account for the intangible relationship between owners and drivers. The relationship between owners and drivers in is notoriously fraught with mistrust. Matatu drivers often complain that owners second-guess their reports, and refuse to give them the benefit of the doubt when things go awry. Drivers were initially the ones who communicated to the research team that monitoring devices could make these interactions much easier. Other proponents of monitoring technologies also suggest they can foster better working relationships by increasing employers' trust in their employees (Pierce, Snow, and McAfee, 2015). We have some suggestive evidence of this in our data. In a qualitative survey we conducted six months after the experiment concluded, we find that 65% of drivers said the tracking device made their job easier (26% said nothing changed). We also see that owners share an additional 30 KES with drivers in a trust game that we played at endline – a 30% increase. This suggests that the effects of new technologies on worker well-being are more nuanced than what our welfare estimates capture.

The welfare implications associated with these monitoring technologies are further complicated by how they interact with the consumers of public transit and other road users. One of the motivations for this research initiative was to understand whether these technologies could improve road safety. Kenya's matatu sector is notoriously unsafe: drivers often over-accelerate, speed, stop suddenly, and turn sharply in order to collect more passengers. Matatus account for 11% of registered vehicles but 70.2% of passenger casualties (Macharia et al., 2009). Buses in the US on the other hand account for 1% of registered vehicles and

0.4% of casualties (U.S. Department of Transportation, 2016). While we explore the implications of GPS technologies on road safety in a companion paper, it's important to highlight that the welfare impacts that we calculate in this paper have the potential to change dramatically if passengers/pedestrian welfare is also considered. Weighing driver welfare relative to consumer welfare is beyond the scope of this research.

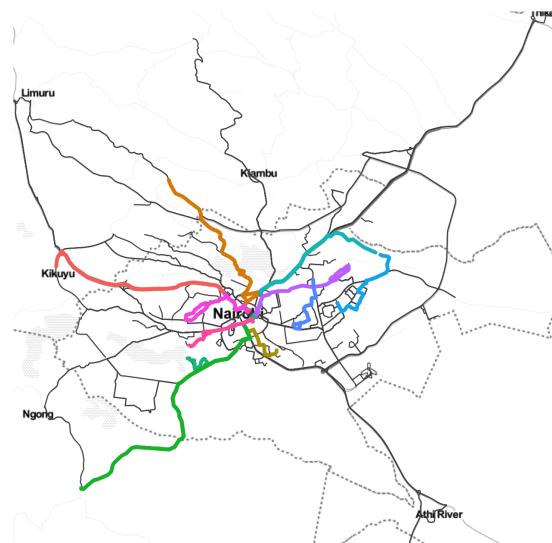
B Appendix Figures

Figure A.1: Metropolitan Nairobi matatu route maps

(a) Designated bus routes in Nairobi (black)

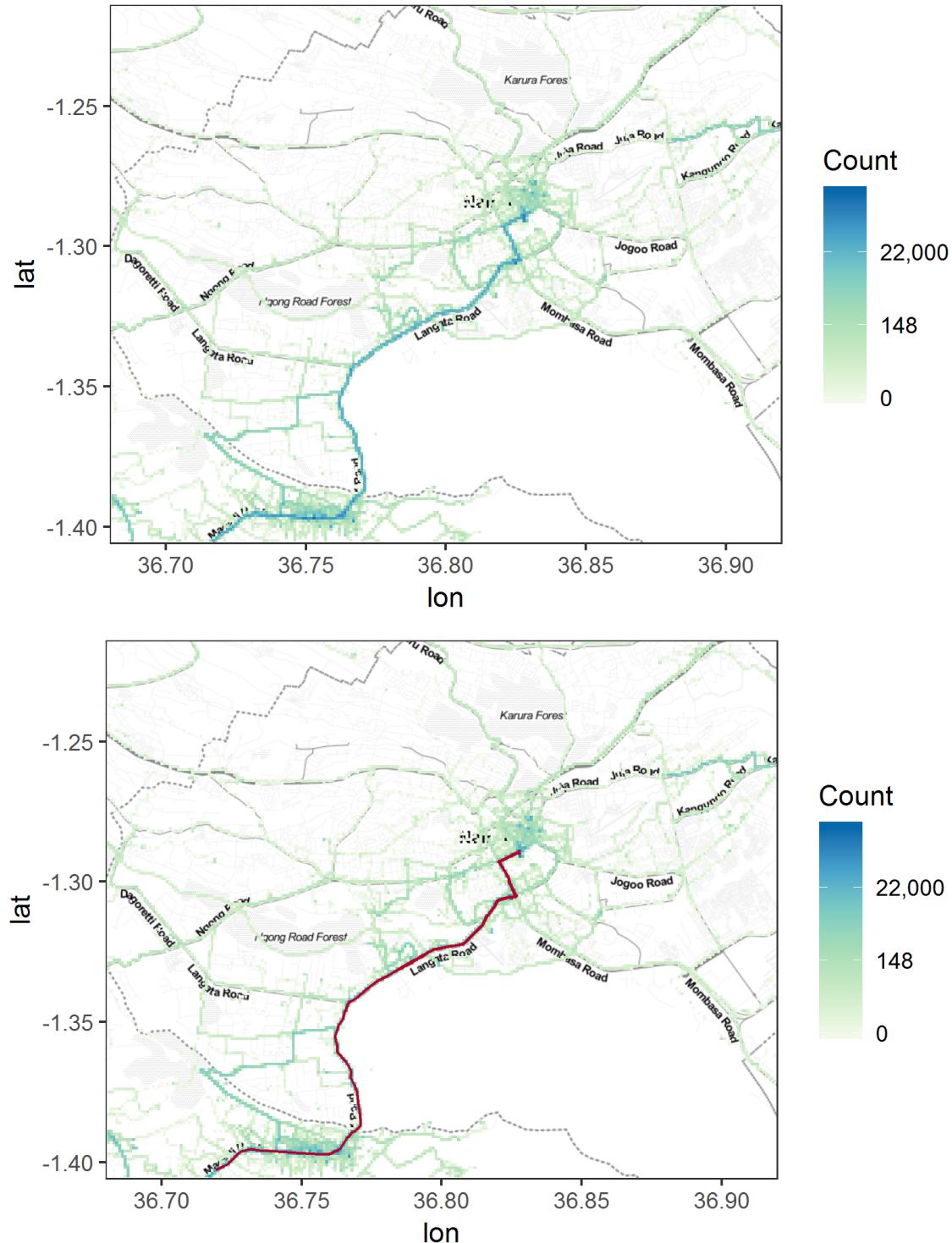


(b) Designated bus routes in Nairobi (black) and routes in our sample (colored)



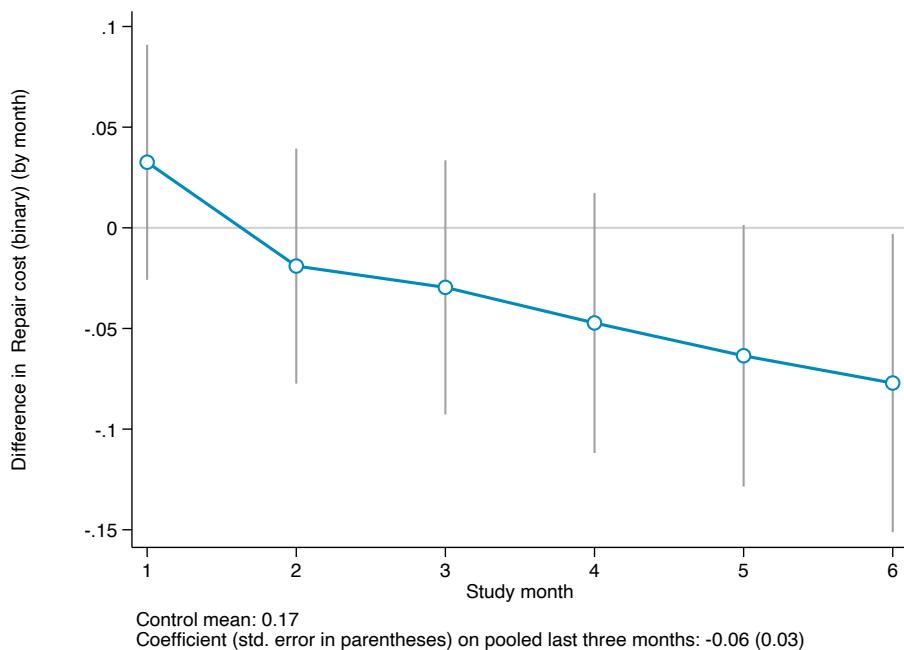
Notes: Map of all routes in the Nairobi metropolitan areas. Panel A: all routes documented in the Digital Matatus project (digitalmatatus.com). Panel B: Our 255 participants are spread across the highlighted eleven routes.

Figure A.2: Device location



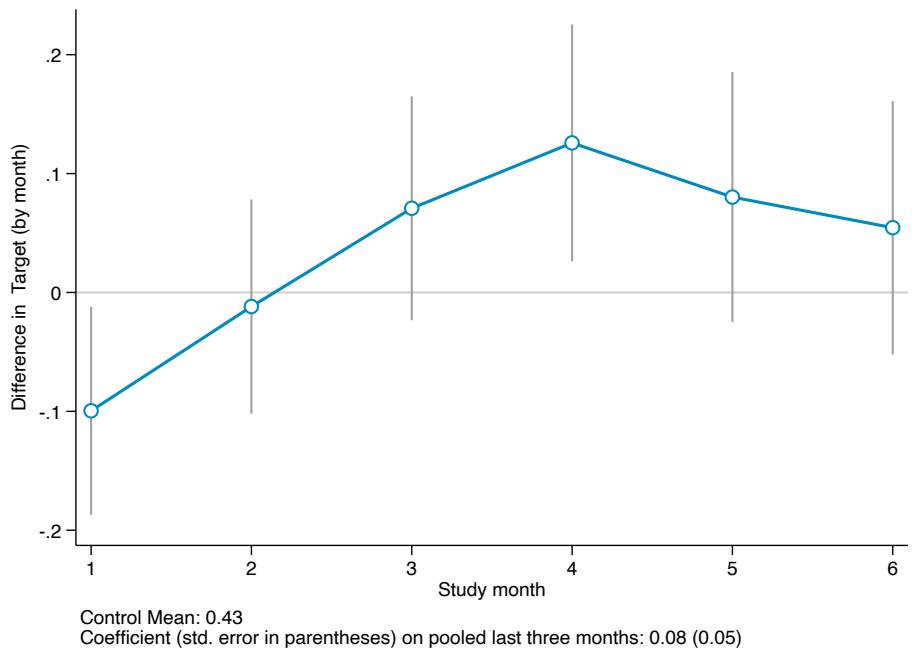
Notes: These maps use data from the trackers that were installed in vehicles licensed to operate on Route 126 (Ongata-Rongai line). We count the number of times that vehicles passed through particular geographic cell on the map. A deeper shade of blue demonstrates that more vehicles passed through that particular cell. The second panel overlays the designated route that vehicles are supposed to be on (red). Any colored cells⁶outside of the designated route are instances of off-route driving.

Figure A.3: Treatment effects on large repair costs



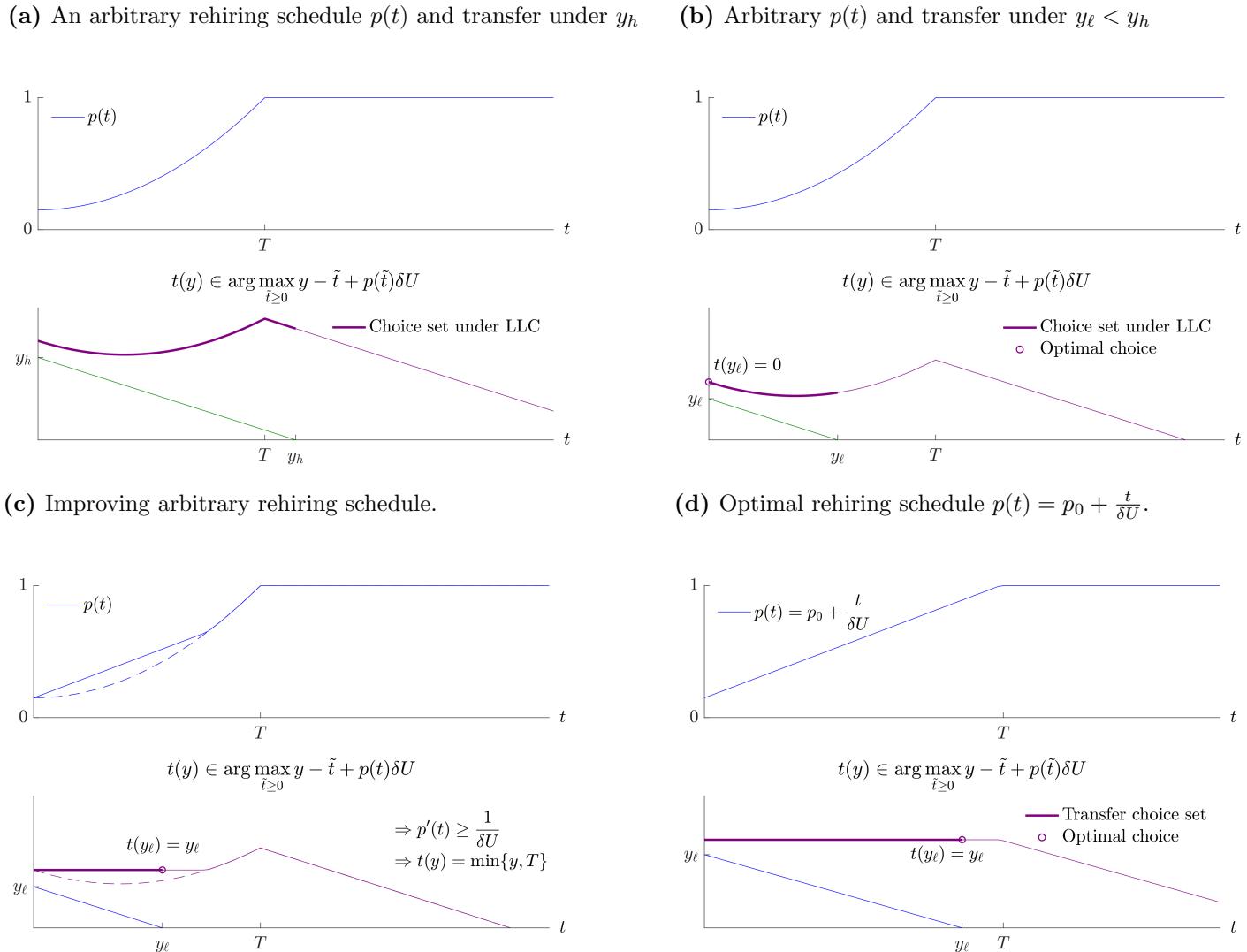
Notes: OLS estimates according to Equation 2. Treatment effect by month on probability of incurring a large repair cost (in excess of 1000 KES – the 85th percentile of repair costs). Standard errors for 95% confidence intervals clustered at the matatu level (255 clusters).

Figure A.4: Treatment effects on probability of making the target



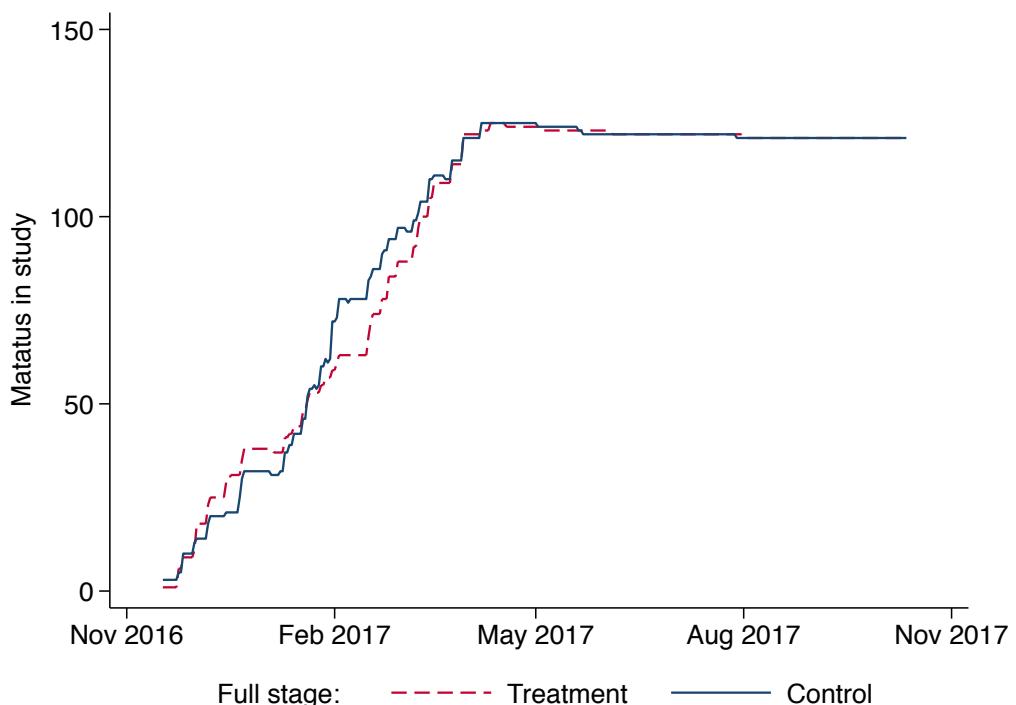
Notes: OLS estimates according to Equation 2. Treatment effect by month on probability of making the target. Standard errors for 95% confidence intervals clustered at the matatu level (255 clusters).

Figure A.5: Setting the transfer and re-hiring schedules



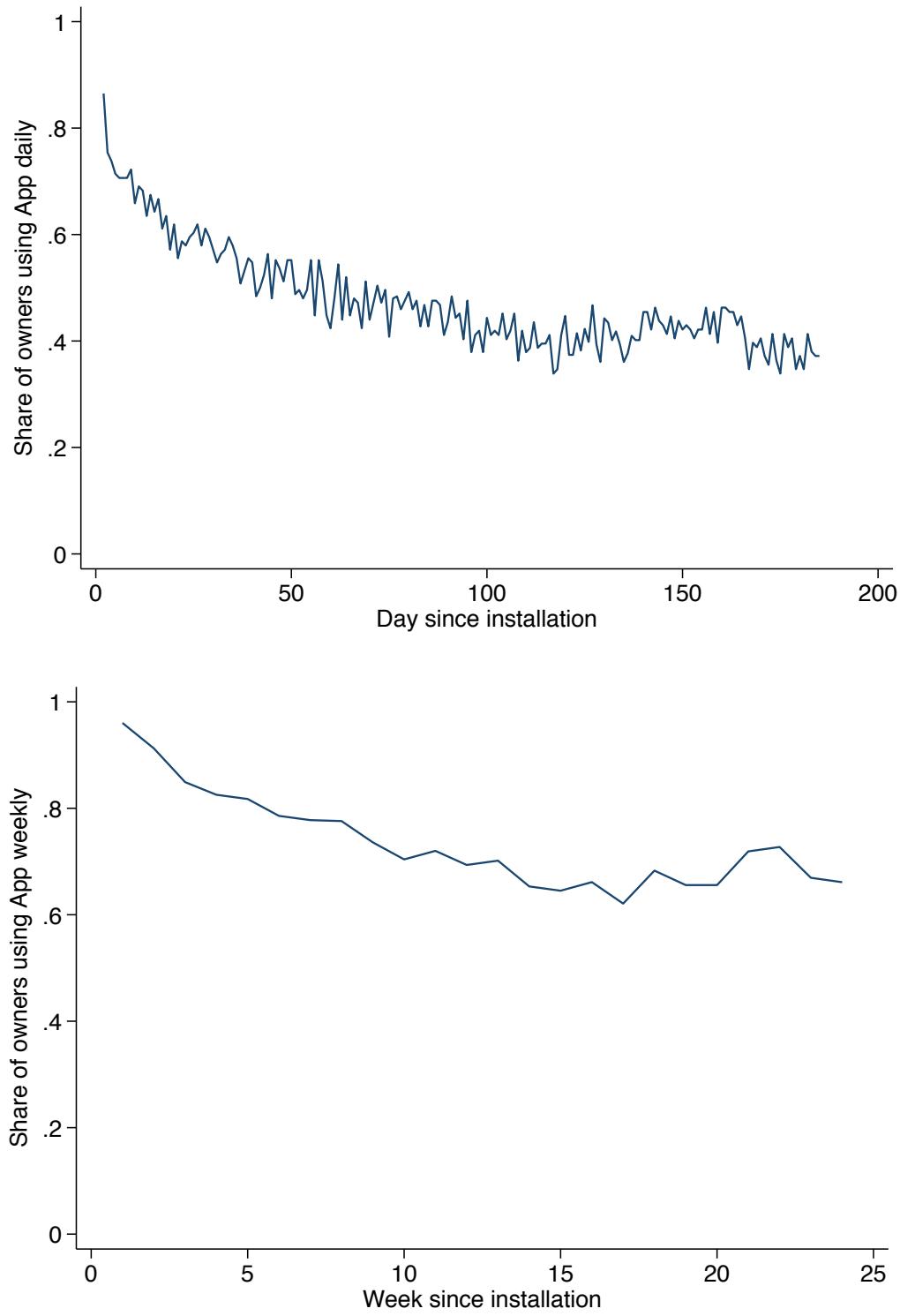
Notes: Intuition for the transfer and rehiring schedules in the Lemma. Panel A shows some arbitrary rehiring schedule with target T under a high realized revenue y_h . Under this rehiring schedule, the driver chooses the transfer that maximizes his utility in the transfer problem from the bold purple line; hence, he will choose to transfer T . If he instead only makes $y_\ell < y_h$, he will transfer zero under this rehiring schedule, as in Panel B. If the owner had instead guaranteed a minimal slope of $1/\delta U$ in the flat part of $p(t)$, the owner would have received y_ℓ instead, as in Panel C. A steeper slope offers no transfer benefits, and thus the owner would choose the schedule $p_0 + \frac{t}{\delta U}$ to maximize the driver's transfer to her.

Figure A.6: Installation timeline



Notes: Number of matatus that were fitted with tracking devices (and hence were added to the study) per week. The first installation took place in November 2016, and continued until April 2017. On average, the field team was able to fit trackers to 15 matatus per week. As a result it took approximately five months to finish installations.

Figure A.7: App usage since installation



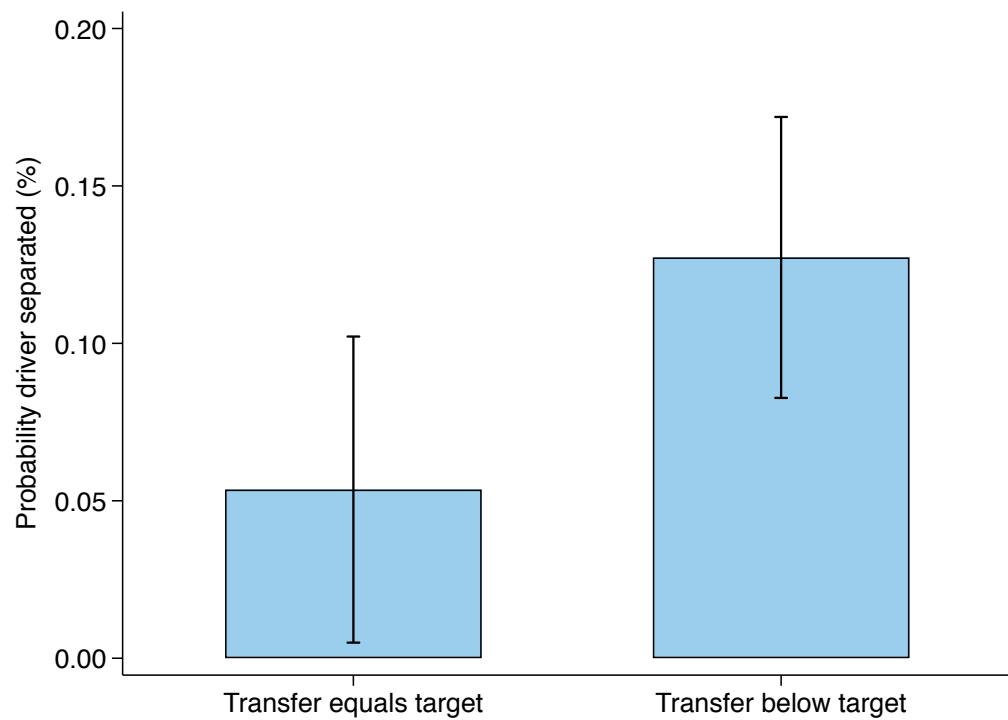
Notes: To measure device usage, we capture whether any API calls were made in a day. An API call is generated each time the owner requests data from the server, such as when logging in or refreshing a screen. The top panel looks at usage by week, whereas the bottom panel looks at usage per day.

Figure A.8: Example of vehicles used in study: 14-seater minibus



Notes: A typical 14-seater matatu in downtown Nairobi.

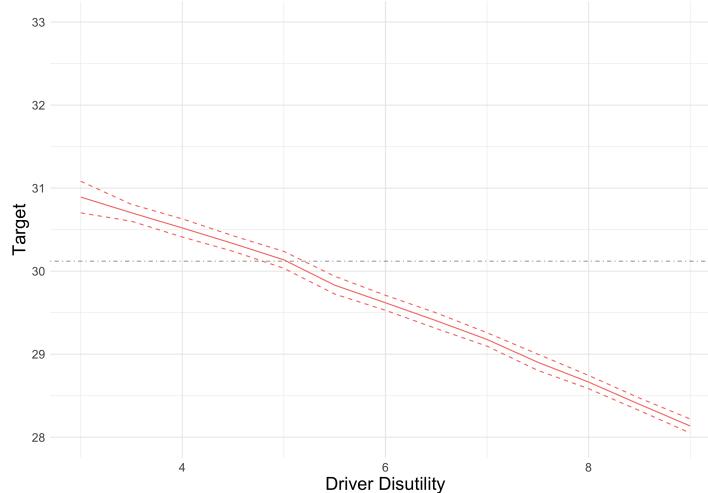
Figure A.9: Probability fired as a function of transfer



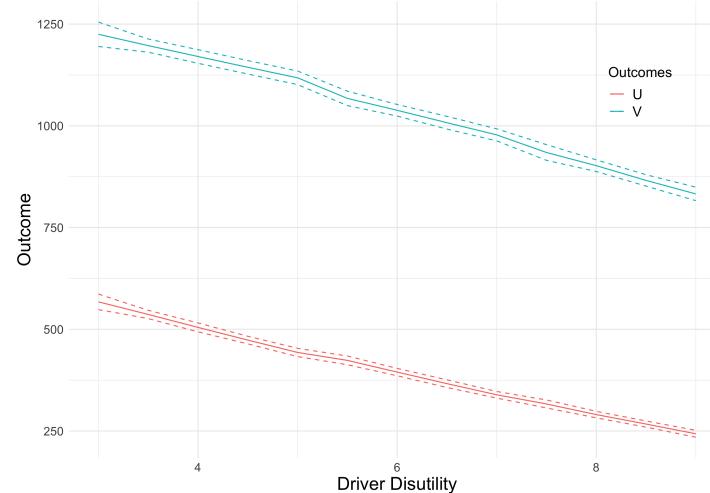
Notes: Daily share of drivers separated from owners, conditional on whether the transfer equals the target or is below the target. In total, 26 out of 255 drivers separated from their owner over the six month period. xxx add this code to analyze_data.do

Figure A.10: Model Calibration Sensitivity to Work Costs

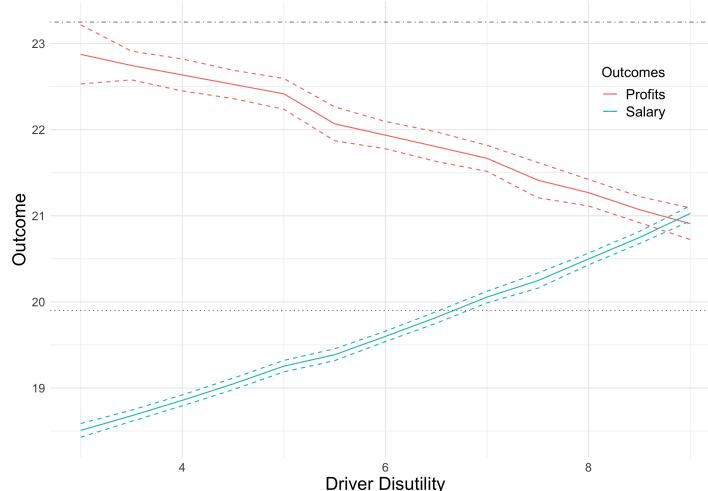
(a) Target



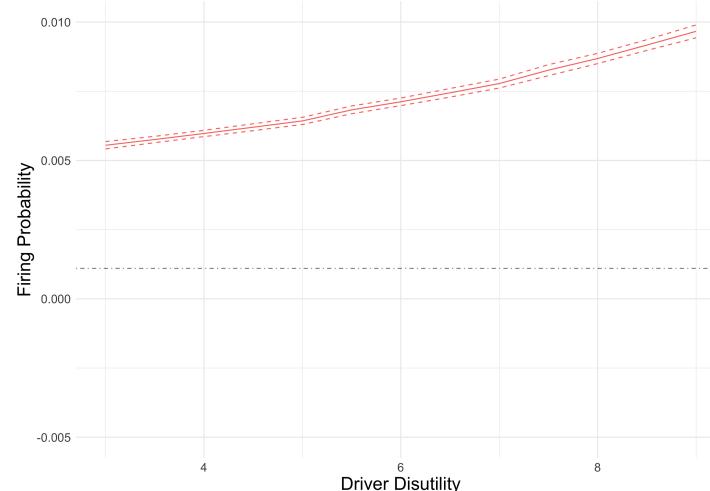
(b) Owner and Driver Value



(c) Salary and Profit

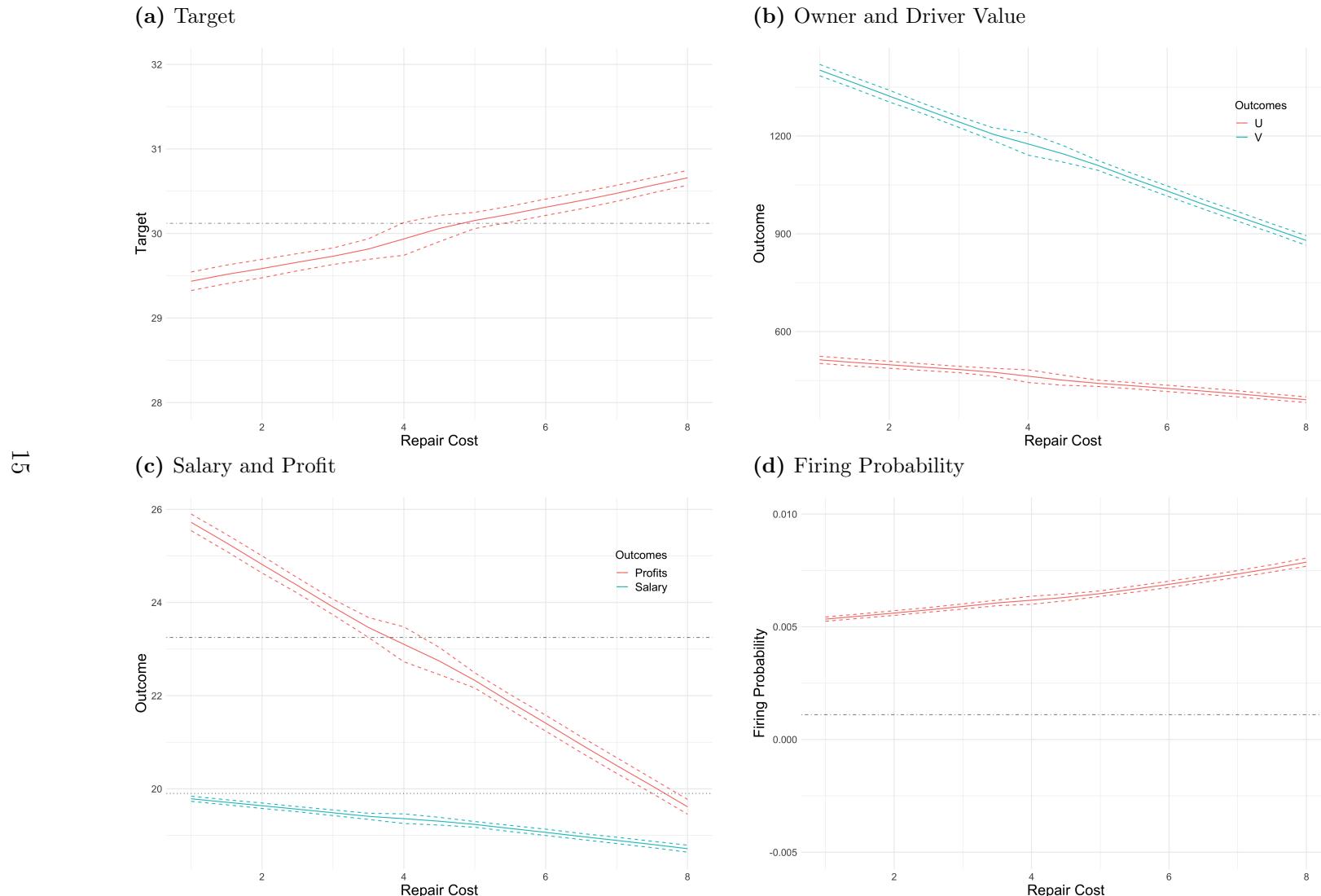


(d) Firing Probability



Notes: Figures plot the model predicted values for different input values of driver work cost ($\psi(e, r)$). Dashed or dotted lines show observed values where applicable. Other input parameters are fixed per those stated in the main model calibration table.

Figure A.11: Model Calibration Sensitivity to Repair Costs

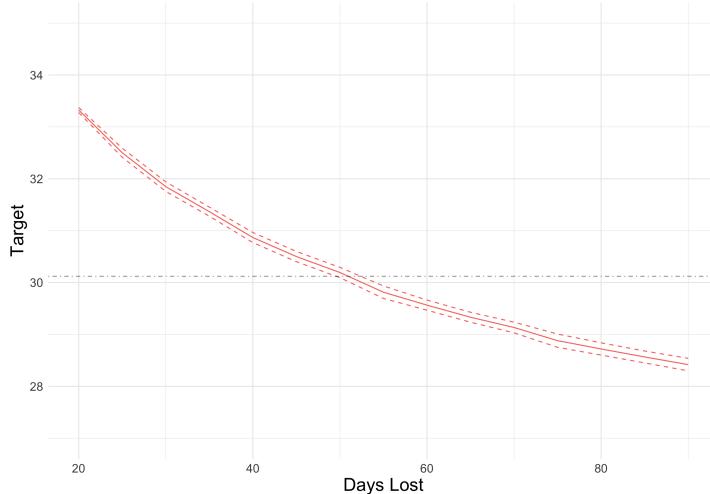


Notes: Figures plot the model predicted values for different input values of expected repair costs ($\mathbb{E}[c(r)]$). Dashed or dotted lines show observed values where applicable. Other input parameters are fixed per those stated in the main model calibration table

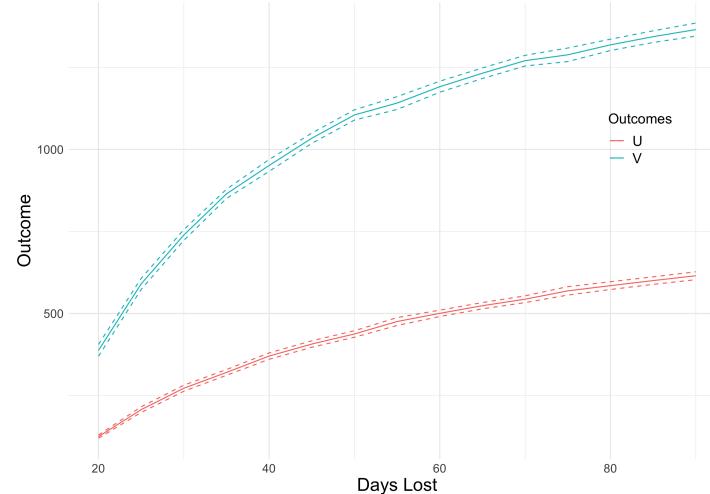
Figure A.12: Model Calibration Sensitivity to Firing Costs

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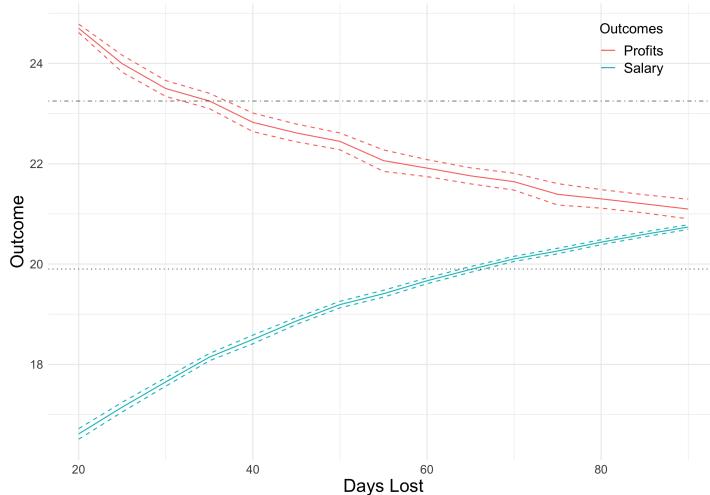
(a) Target



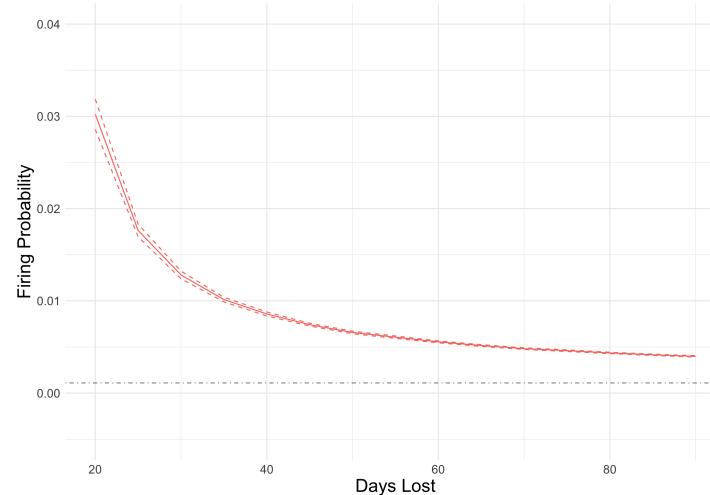
(b) Owner and Driver Value



(c) Salary and Profit



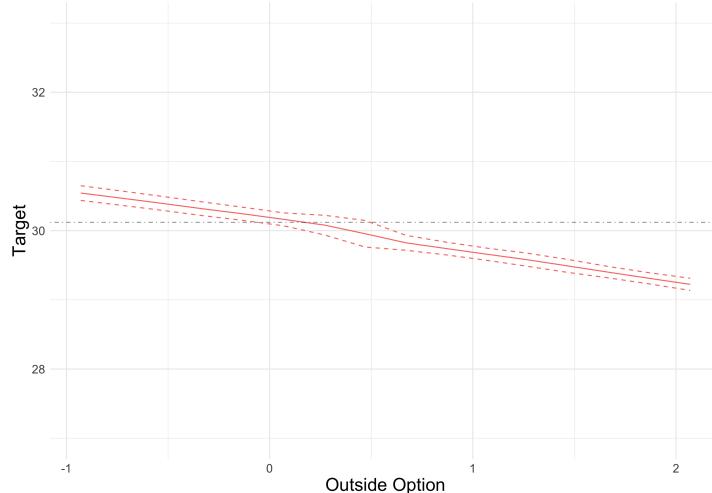
(d) Firing Probability



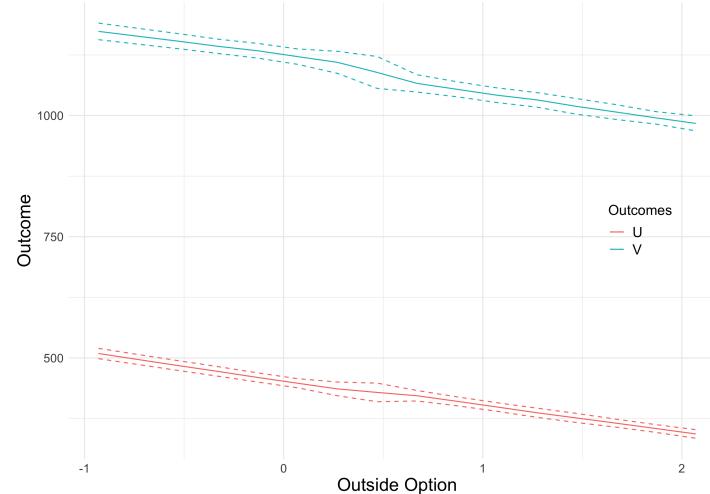
Notes: Figures plot the model predicted values for different input values of firing costs (h). Dashed or dotted lines show observed values where applicable. Other input parameters are fixed per those stated in the main model calibration table

Figure A.13: Model Calibration Sensitivity to Outside Option

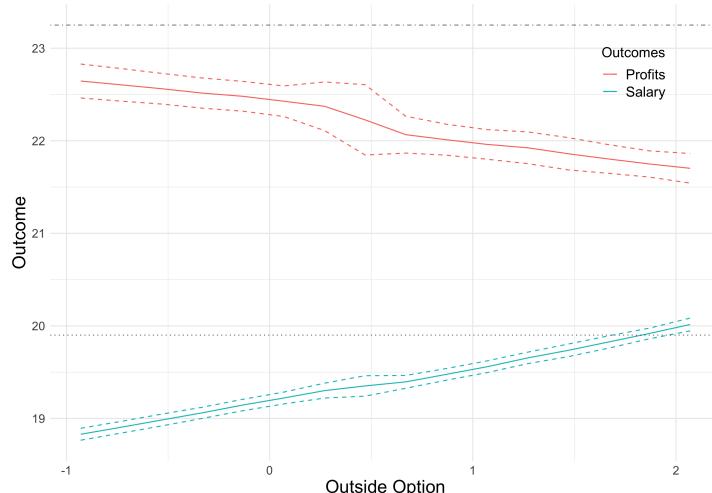
(a) Target



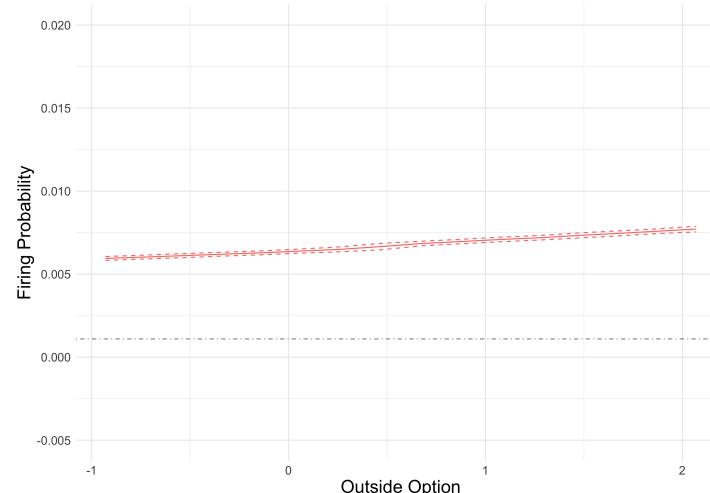
(b) Owner and Driver Value



(c) Salary and Profit



(d) Firing Probability



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Notes: Figures plot the model predicted values for different input values of outside option (u). Dashed or dotted lines show observed values where applicable. Other input parameters are fixed per those stated in the main model calibration table

C Appendix Tables

Table A.1: Treatment effects on target, costs, profits, mileage and hours worked

	(1) Target	(2) Repair costs	(3) Gross profit	(4) Mileage (kilometers)	(5) Device on (hours)
Treatment × Month 1	-0.10 (0.04)	67.97 (69.96)	-181.60 (238.35)	-4.28 (5.96)	-0.84 (0.66)
Treatment × Month 2	-0.01 (0.05)	-50.18 (73.55)	63.27 (208.06)	2.13 (5.60)	0.63 (0.59)
Treatment × Month 3	0.07 (0.05)	-124.21 (79.55)	89.19 (218.80)	7.94 (5.31)	1.00 (0.55)
Treatment × Month 4	0.13 (0.05)	-184.97 (89.35)	449.04 (223.61)	4.56 (5.69)	0.71 (0.64)
Treatment × Month 5	0.08 (0.05)	-180.89 (93.37)	453.49 (213.32)	9.51 (6.41)	1.45 (0.72)
Treatment × Month 6	0.05 (0.05)	-215.73 (102.80)	179.75 (227.27)	12.93 (6.90)	1.45 (0.76)
Control Mean of DV	0.43	483.48	3260.50	96.64	14.79
Controls	X	X	X	X	X
Day FE	X	X	X	X	X
Route FE	X	X	X	X	X
Matatu N	237	238	216	254	254
Matatu-Day N	15,888	15,881	10,406	45,654	45,654

Notes: OLS regressions as in Equation 2. “Target”: daily revenue target set by owner. “Repair costs”: owner-reported daily repair costs. “Gross profit”: Revenue minus repair costs minus driver residual claim (salary). “Mileage (kilometers)”: Daily mileage as measured with tracking device. “Device on (hours)”: number of hours the tracking device reported the ignition to be on as a measure of driver work hours. Controls include the age of the matatu, the number of special features, owner age and sex, owner education, owner self-employment status, the number of other businesses the owner runs, owner years of matatu industry experience, and owner raven score. Data are from daily panel collected from owner in-app reports and aggregated tracking device data. Standard errors clustered at the owner/driver/matatu level. Stars indicate statistical significance at the 1% ***, 5% **, and 10% * levels. xxx express all values in dollars instead SEK.

Table A.2: Simulated vs. Actual Treatment Effects

Panel A: Assumptions			
Input	Symbol	Value	Justification
Repair Costs	$E[c(r)]$	2.7	Previous value of 4.9 minus observed treatment effect reduction of 2.2
Revenue Distribution	$G(\cdot)$	—	Empirical distribution calculated from data
Discount Factor	δ	0.99	
Firing Cost	h	51.44	Fixed from previous value
Outside Option	\bar{u}	7.07	Fixed from previous value

Panel B: SMM Parameter Estimates			
Input	Symbol	Value	Interpretation
Disutility	$\psi(e^*, r^*)$	4.53 (0.03)	Decrease of 0.46 (9%) from previous value

Panel C: Predicted vs. Observed Treatment Effects			
Outcome	Pred.Treat	Obs.Treat	Difference
Target	-0.47 (0.07)	-1.13 (0.87)	0.66 (0.87)
Expected Profit	1.6 (0.13)	3.62 (1.96)	-2.02 (1.96)
Expected Salary	0.27 (0.05)	0.23 (0.35)	0.04 (0.35)
Prob. Separation	-0.0005 (0.00008)	-0.01 (0.01)	0.01 (0.01)
Driver Contract Value minus Outside Option	63.06 (7.46)	—	—
Owner Value	130.98 (11.65)	—	—
Total Welfare	194.04 (9.84)	—	—

Notes: All values are in 100s of Kenyan Schillings. Work cost estimated via simulated method of moments matching the observed target, salary, and profit treatment effects.

D Model Details

D.1 Owner Problem

The fully specified owner problem is given by

$$V = \max_{e,r,t(y),p(t)} \mathbb{E} [t(y) - c(r) + p(t(y))\delta V | e, r]$$

subject to

1. $U = \mathbb{E} [y - t(y) + p(t(y))\delta U | e, r] - \psi(e, r) \geq \bar{u}$
2. $(e, r) \in \arg \max_{(\tilde{e}, \tilde{r}) \in \mathcal{S}} \mathbb{E} [y - t(y) + p(t(y))\delta U | \tilde{e}, \tilde{r}] - \psi(\tilde{e}, \tilde{r})$
3. $t(y) \leq y$
4. $y - t(y) + p(t(y))\delta U \geq y$
5. $t(y) \in \arg \max_{\tilde{t} \geq 0} y - \tilde{t} + p(\tilde{t})\delta U,$

where the owner's expectation is over the joint distribution of y and c . While the driver ultimately chooses effort and risk, the owner treats them as choice variables for the purpose of designing the contract, as is standard in contract theory. The first two constraints are standard participation constraints and (driving) incentive compatibility constraints. Driver utility is the expected sum of the residual revenue and the future discounted value of the contract minus the disutility of effort and risk. The participation constraint restricts driver utility to be at least as great as his outside option. For now, we assume that this outside option is normalized to zero, $\bar{u} = 0$, which we relax in our structural estimation. The third constraint is the limited liability constraint, which restricts the driver from transferring more to the owner than what he made on a given day. The fourth constraint ensures dynamic enforceability: the driver has to prefer to honor the terms of the contract ex post over renegeing. The fifth and last constraint restricts the transfer to the owner to be incentive compatible: $t(y)$ has to be an optimal transfer from the driver's point of view.⁴¹

⁴¹Since firing the driver is costly to the owner, she may have an incentive to renege on the agreed-upon rehiring probability $p(t)$ and rehire him despite a negative outcome of the rehiring lottery. For simplicity, we do not explicitly model this possibility. It would require the driver to form beliefs about the likelihood that the owner will renege, and then for the owner to take this into account when considering the contract. While it may be possible to incorporate this incentive into the model, we are likely to arrive at similar conclusions in terms of contract dynamics with respect to driver choices and the transfer problem. For the contract not to unravel, we assume that frequent renegeing would be inferred over time by the driver and he would switch to a strategy of transferring nothing to the owner.

D.2 Assumptions

D.2.1 Technology and Preferences

We make the following assumptions about the functional forms of technology and preferences:

Assumption 1. *Technology and preferences obey:*

- *$G(y|e, r)$ is twice continuously differentiable with respect to all arguments with density $g(y|e, r)$.*
- *The distribution of revenue y has the monotone likelihood ratio property (MLRP), which implies the first-order stochastic dominance (FOSD) property: for all y , we have that $G_s(y|e, r) \leq 0$ for $s \in \{e, r\}$.*
- *Effort and risk are weak substitutes with $G_{er}(y|e, r) \geq 0$ and $G_{ss}(y|e, r) > 0$ for $s \in \{e, r\}$.*
- *Driver disutility is twice continuously differentiable with partials $\psi_s(e, r) > 0$ for all $(e, r) > 0$, $\psi_{er}(e, r) > 0$ and $\psi_{ss}(e, r) > 0$ for $s \in \{e, r\}$.*

D.2.2 Relative Preferences for Risk

The solution to this contracting problem can be greatly simplified with an assumption about the driver's risk preferences relative to the owner. To this end, we define the *incentive-compatible set*

$$\mathcal{I} = \left\{ (e, r) \in \mathcal{S} : \frac{\int_0^{\bar{y}} y g_e(y|e, r) dy}{\int_0^{\bar{y}} y g_r(y|e, r) dy} = \frac{\psi_e(e, r)}{\psi_r(e, r)} \right\}$$

as the optimal effort-risk bundles that the driver would choose for a given disutility budget – he equates the ratio of marginal benefits from an additional unit of effort and risk to the ratio of marginal costs. See Panel A of Figure 2 for an illustration. Among these bundles, we can then define the driver's bliss point to be:

$$(e_D, r_D) = \arg \max_{(e, r) \in \mathcal{S}} \mathbb{E}[y|e, r] - \psi(e, r),$$

which is the driver's preferred effort-risk bundle if he were to find the vehicle at the side of the road and did not have to worry about repair cost or contract concerns. We then make the following assumption:

Assumption 2. *Relative costliness of risk:* At any bundle $(e, r) \in [e_D, \bar{e}] \times [r_D, \bar{r}]$, the owner prefers less risk than the driver.

This assumption reflects the prevalent sense among owners that drivers engage in excessive risk-taking. The owner would prefer an effort-risk bundle skewed more towards effort because the costs of risk-taking accrues exclusively to them. See Panel B of Figure 2 for an illustration of this assumption: the owner's indifference curves in blue reflect the fact that she always prefers higher effort but faces a tradeoff with respect to risk. Higher risk-taking increases revenue and the expected transfer she receives, but it also increases repair costs. The assumption states that the owner prefers the driver to choose a bundle with less risk because at the driver's bliss point the costs of risk outweigh the potential benefits.

Under this assumption, the rehiring schedule collapses to a single parameter which acts as a contractual shorthand in our setting: the daily target T , above which the next day's re-employment is guaranteed. In contrast, without this assumption, the rehiring schedule would depend on the functional form of revenue. The target is also a key parameter in our structural estimation below.

D.3 Proofs

D.3.1 Lemmas

Lemma (Minimal linear contract). *Under Assumptions 1 and 2, in any solution to the baseline contracting problem without monitoring, the following schedules are optimal:*

$$t(y) = \min \{y, T\}$$

and

$$p(t) = p_0 + \frac{t}{\delta U}$$

for $t \leq T = (1 - p_0) \delta U$ and $p(t) = 1$ for $t > T$, where $p_0 \in [0, 1]$.

Proof. The proof proceeds in two steps: in step 1, we show that under Assumption 1 the minimally optimal slope of $p(t)$ is $\frac{1}{\delta U}$ – that is, a $p(t)$ with lower slope than $\frac{1}{\delta U}$ cannot be optimal. In Step 2, we then show that under Assumption 2 this minimal slope is preferred to higher slopes.

We begin with Step 1. Define the target $T = \min \{t \in \mathcal{Y} : p(t) = 1\}$. For this to exist, we need that there exists a t for which $p(t) = 1$. Suppose this were not the case so that

the optimal $p(t) < 1$ for all t . Then, in particular, $p(\bar{y}) < 1$. However, the owner would be strictly better off by setting $p(\bar{y}) = 1$: she would capture a higher continuation value without lowering transfer or driving incentives for the driver. Hence, $p(t) = 1$ for some $t \leq \bar{y}$ and T exists.

We next show that the minimal slope is necessary to induce maximal transfers for any given realization of $y \in \mathcal{Y}$. According to the LLC, $t(y) \leq y$. Note that whenever $t(y) = y$, it has to hold that for any $t, t' \in [0, T]$ and $t > t'$, the driver always transfers the larger amount t if $p(t)$ satisfies the following condition:

$$y - t + p(t)\delta U \geq y - t' + p(t')\delta U$$

$$\frac{p(t) - p(t')}{t - t'} \geq \frac{1}{\delta U}$$

and in this case $t(y) = \min \{y, T\}$.

We can now show that there is no way to lower effort and risk incentives below the minimal slope. To this end, define the “transfer set” $\mathcal{T} = \{y \in [0, T] : t(y) = y\}$ to be all revenue realizations for which the rehiring schedule $p(\cdot)$ induces transferring all revenue. Hence, $p(y)\delta U \geq y$ whenever $y \in \mathcal{T}$. Let the complement to the transfer set be $\mathcal{Y} \setminus \mathcal{T} = \bigcup_{i=1}^I \mathcal{X}_i$ where $\mathcal{X}_i = (t_i, x_i]$ are connected sets with lower bound $t_i = \max \{y \in \mathcal{T} : y < x_i\}$ and $t(y) = t_i < y$ whenever $y \in \mathcal{X}_i$. Revenue realizations that fall into an interval \mathcal{X}_i trigger transfers at the lower bound of \mathcal{X}_i because all revenue beyond this lower bound has a higher direct return to the driver than its return in terms of increased future discounted contract value $p(t)\delta U$. We now split the owner’s objective function $\mathbb{E}[y - t + p(t)\delta U | e, r]$ into intervals \mathcal{T} and \mathcal{X}_i for $i = 1, \dots, I$:

$$\begin{aligned} \mathbb{E}[y - t + p(t)\delta U | e, r] &= \mathbb{E}[p(y)\delta U | e, r, y \in \mathcal{T}] \Pr(y \in \mathcal{T}) \\ &\quad + \sum_{i=1}^I \mathbb{E}[y - t_i + p(t_i)\delta U | e, r, y \in \mathcal{X}_i] \Pr(y \in \mathcal{X}_i) \\ &= \int_{y \in \mathcal{T}} \delta U p(y) g(y | e, r) dy \\ &\quad + \sum_{i=1}^I \left\{ [p(t_i)\delta U - t_i] \Pr(y \in \mathcal{X}_i) + \int_{y \in \mathcal{X}_i} y g(y | e, r) dy \right\}. \end{aligned}$$

The marginal effect of increasing $s \in \{e, r\}$ on the owner's utility is then

$$\int_{y \in \mathcal{T}} \delta U p(y) g_s(y|e, r) dy + \sum_{i=1}^I \int_{y \in \mathcal{X}_i} y g_s(y|e, r) dy.$$

All that is left to do in Step 1 is to show that this marginal effect is bounded from below by application of the minimal slope of $p(\cdot)$. Since $p(\cdot)$ only appears in the first term (i.e. those in the transfer set), we can ignore the second (i.e. the one with the non-transfer sets \mathcal{X}_i). According to the definition of \mathcal{T} , $p(y)\delta U \geq y$. Together with the MLRP, this implies that

$$\int_{y \in \mathcal{T}} \delta U p(y) g_s(y|e, r) dy \geq \int_{y \in \mathcal{T}} y g_s(y|e, r) dy,$$

meaning that there is no way to incentivize less effort and/or risk with any choice of $p(\cdot)$: marginal incentives are bounded from below by $\int_{y \in \mathcal{Y}} y g_s(y|e, r) dy$.

We now move to Step 2: that under Assumption 2, the owner never benefits from inducing higher effort or risk with a steeper rehiring schedule $p(t)$. To see this, write owner utility under at least minimal slope (i.e. with $p(t) \geq p_0 + \frac{t}{\delta U}$) as:

$$X(e, r) = \mathbb{E}[t - c(r) + p(t)\delta V|e, r] \quad (3)$$

$$= \int_0^T [y + p(y)\delta V] g(y|e, r) dy + (1 - G(T|e, r)) [T + \delta V] - \mathbb{E}[c(r)|r] \quad (4)$$

and the corresponding marginal effect of effort and risk:

$$X_s(e, r) = \int_0^T [y + p(y)\delta V] g_s(y|e, r) dy - G_s(T|e, r) [T + \delta V] - \frac{\partial \mathbb{E}[c(r)|r]}{\partial s}.$$

It remains to be shown that $\sum_{s \in \{e, r\}} \psi_s(e, r) X_s(e, r) \leq 0$ for all $(e, r) \geq (e_D, r_D)$. If this inequality holds, then the owner's marginal utility in the direction of the driver's disutility gradient is negative: as the driver exerts more effort and risk past his bliss point (e_D, r_D) in the preferred direction of the driver, the owner's utility falls.

We construct an upper bound of this marginal effect by setting (a) $T = \bar{y}$, (b) $p(y) = 0$ if $y \leq y^*$ and 1 otherwise, where y^* is defined as the smallest y for which $g_s(y|e, r) \leq 0$ for all $y \leq y^*$, and (c) $V = \frac{\mathbb{E}[y|e, r]}{1-\delta}$. In this way, the owner captures all of the marginal benefit of effort and risk, which maximizes the returns to the owner. We then have

$$X_s(e, r) < \frac{\partial \mathbb{E}[(1 + \phi_s)y - c(r)|e, r]}{\partial s}$$

with $\phi_s = -\frac{\delta}{1-\delta}G_s(y^*|e, r)$. The right-hand side expression is the result of applying the extreme conditions (a)-(c) from the last paragraph, where the owner receives maximal marginal returns to effort and risk. According to Assumption 2, we then have for all $(e, r) \geq (e_D, r_D)$:

$$\sum_{s \in \{e, r\}} \psi_s(e, r) X_s(e, r) < \sum_{s \in \{e, r\}} \psi_s(e, r) \frac{\partial \mathbb{E}[(1 + \phi_s)y - c(r)|e, r]}{\partial s} \leq 0,$$

with the latter inequality holding because it corresponds to the owner's directional derivative falling as we move up the incentive compatible set.

□

D.3.2 Propositions

The social planner ("owner-driver") problem is

$$(e^*, r^*) \in \arg \max_{(e, r) \in \mathcal{S}} \mathbb{E}[y - c(r) + \delta W|e, r] - \psi(e, r)$$

where W is the owner-driver's continuation value. The baseline contract without monitoring compares as follows to the social planner's solution:

Proposition 1 (Inefficiency of baseline contract). *Let (e_B, r_B) be the driver's baseline effort-risk profile without monitoring. Under Assumptions 1 and 2, the following properties hold in the baseline contract:*

- The driver takes excessive risk $r_B > r^*$.
- Effort may be over- or undersupplied: $e_B \stackrel{<}{>} e^*$.
- Welfare is suboptimal: $\mathbb{E}[y - c(r_B)|e_B, r_B] - \psi(e_B, r_B) < \mathbb{E}[y - c(r^*)|e^*, r^*] - \psi(e^*, r^*)$.

Proof of Proposition 1

Proof. Using the Lemma, we can write the driver's problem as: $\delta U - T + \mathbb{E}[y|e, r] - \psi(e, r)$. Thus, the FOCs for the driver and the owner-driver are, respectively:

$$\begin{aligned} \frac{\partial \mathbb{E}[y|e^*, r^*]}{\partial r} - \frac{\partial \mathbb{E}[c(r^*)|r^*]}{\partial r} &= \frac{\partial \psi(e^*, r^*)}{\partial r} \\ \frac{\partial \mathbb{E}[y|e_B, r_B]}{\partial r} &= \frac{\partial \psi(e_B, r_B)}{\partial r}, \end{aligned}$$

while

$$\frac{\partial \mathbb{E}[y|e,r]}{\partial e} = \frac{\partial \psi(e,r)}{\partial e}$$

holds for both the driver and the owner-driver.

Write

$$\frac{\partial \mathbb{E}[y|e,r]}{\partial r} - \mu \frac{\partial \mathbb{E}[c(r)|r]}{\partial r} = \frac{\partial \psi(e,r)}{\partial r}$$

as the marginal problem that nests both the driver's and the owner-driver's optimal risk problem: note that $\mu = 0$ is the driver's problem and $\mu = 1$ is the owner-driver's problem.

We now use the Implicit Function Theorem (IFT) to show that $\frac{\partial r}{\partial \mu} < 0$, which implies the first part of the statement, i.e. $r_B > r^*$.

Define $H : \mathcal{S} \rightarrow \mathbb{R}^2$ in the following way:

$$\begin{aligned} H_1(e, r) &= \frac{\partial \mathbb{E}[y|e,r]}{\partial e} - \frac{\partial \psi(e,r)}{\partial e} = 0 \\ H_2(e, r) &= \frac{\partial \mathbb{E}[y|e,r]}{\partial r} - \mu \frac{\partial \mathbb{E}[c(r)|r]}{\partial r} - \frac{\partial \psi(e,r)}{\partial r} = 0 \end{aligned}$$

We can now apply the IFT:

$$\begin{aligned} \begin{bmatrix} \frac{\partial e}{\partial \mu} \\ \frac{\partial r}{\partial \mu} \end{bmatrix} &= - \begin{bmatrix} \frac{\partial H_1}{\partial e} & \frac{\partial H_2}{\partial e} \\ \frac{\partial H_1}{\partial r} & \frac{\partial H_2}{\partial r} \end{bmatrix}^{-1} \begin{bmatrix} \frac{\partial H_1}{\partial \mu} \\ \frac{\partial H_2}{\partial \mu} \end{bmatrix} \\ &= \frac{1}{A} \begin{bmatrix} \left\{ \frac{\partial^2 \psi(e,r)}{\partial r \partial e} - \frac{\partial^2 \mathbb{E}[y|e,r]}{\partial r \partial e} \right\} \frac{\partial \mathbb{E}[c(r)|r]}{\partial r} \\ \left\{ \frac{\partial^2 \mathbb{E}[y|e,r]}{\partial e^2} - \frac{\partial^2 \psi(e,r)}{\partial e^2} \right\} \frac{\partial \mathbb{E}[c(r)|r]}{\partial r} \end{bmatrix} \end{aligned}$$

where $A = \frac{\partial H_1}{\partial e} \frac{\partial H_2}{\partial r} - \frac{\partial H_1}{\partial r} \frac{\partial H_2}{\partial e} > 0$. Thus, for $\frac{\partial r}{\partial \mu} < 0$ we need the following to be true:

$$\begin{aligned} \left\{ \frac{\partial^2 \mathbb{E}[y|e,r]}{\partial e^2} - \frac{\partial^2 \psi(e,r)}{\partial e^2} \right\} \frac{\partial \mathbb{E}[c(r)|r]}{\partial r} &< 0 \\ \Leftrightarrow \frac{\partial^2 \mathbb{E}[y|e,r]}{\partial e^2} &< \frac{\partial^2 \psi(e,r)}{\partial e^2} \end{aligned}$$

which holds according to Assumption 1. $\frac{\partial e}{\partial \mu} > 0$ holds in case

$$\frac{\partial^2 \psi(e,r)}{\partial r \partial e} > \frac{\partial^2 \mathbb{E}[y|e,r]}{\partial r \partial e},$$

which may or may not be true according to Assumption 1.

□

Proposition 2 (Effects of monitoring). *Let (e_M, r_M) be the driver's effort-risk profile under monitoring. Under Assumptions 1 and 2, the target contract with monitoring has the following properties:*

1. One solution for the rehiring schedule is:

$$p(t, e, r) = \begin{cases} p_M + \frac{t}{\delta U_M} & \text{if } e = e_M \text{ and } r = r_M \\ 0 & \text{otherwise} \end{cases}$$

2. Compared to the baseline contract:

- Higher effort provision $e_M > e_B$ and lower risk $r_M < r_B$.
- Revenue may rise or fall: $E[y|e_M, r_M] \leq E[y|e_B, r_B]$.
- Profits increase: $\mathbb{E}[y - c(r_M)|e_M, r_M] > \mathbb{E}[y - c(r_B)|e_B, r_B]$.
- The target falls if revenue falls: $T_M < T_B$ if $E[y|e_M, r_M] \leq E[y|e_B, r_B]$.
- The welfare effect is ambiguous:

$$\mathbb{E}[y - c(r_B)|e_B, r_B] - \psi(e_B, r_B) \geq \mathbb{E}[y - c(r_M)|e_M, r_M] - \psi(e_M, r_M).$$

Proof of Proposition 2

Proof. To incentivize maximal transfers for any realization of y , the slope of the rehiring schedule continues to be bounded from below: that is, for any t, t' with $t > t'$ in $[0, T]$, where $T = \inf \{t : p(t, e, r) = 1\}$, it has to hold that

$$\frac{p(t, e, r) - p(t', e, r)}{t - t'} \geq \frac{1}{\delta U}.$$

The rehiring schedule also continues to be bounded from above by this slope. To see this, consider some rehiring schedule $\hat{p}(t, e, r)$ with higher than minimal slope. This implies there exists some $y \in \mathcal{Y}$ such that $\hat{p}(y, e, r) = 1$ but $p(0, e, r) + \frac{y}{\delta U} < 1$ and hence $\hat{T} = \inf \{\hat{p}(t, e, r) = 1\}$. For every such rehiring schedule, there exists another with equal expected rehiring probability but at minimal slope, i.e. $\mathbb{E}[p_0 + \frac{t}{\delta U}|e, r] = \mathbb{E}[\hat{p}(t, e, r)|e, r]$ with $T = (1 - p_0)\delta U > \hat{T}$. Because the target of the minimal slope rehiring schedule is strictly higher while the rehiring probability is the same, the owner will strictly prefer the minimal slope rehiring schedule.

To complete the argument for the functional form of the rehiring schedule, note that the owner can induce a particular (e_M, r_M) by setting $p(t, e, r)$ such that

$$\mathbb{E}[y - t + p(t, e_M, r_M) \delta U_M | e_M, r_M] - \psi(e_M, r_M) \geq \mathbb{E}[y - t + p(t, e, r) \delta U | e, r] - \psi(e, r)$$

for all $(e, r) \in \mathcal{S}$. If such a $p(t, e, r)$ exists, then setting $p(t, e, r) = 0$ for all $(e, r) \neq (e_M, r_M)$ satisfies this constraint. Existence of this sufficient $p(t, e, r)$ is guaranteed by the expected dynamic enforcement constraint $U_M \geq \mathbb{E}[y|e, r] - \psi(e, r)$. Putting together the bounds on the slope of the rehiring schedule and the condition on (e, r) that induce a positive rehiring probability, it follows that

$$p(t, e, r) = \begin{cases} p_M + \frac{t}{\delta U_M} & \text{if } e = e_M \text{ and } r = r_M \\ 0 & \text{otherwise} \end{cases}$$

is a solution to the problem.

For the second part of the Proposition, the owner problem with minimal slope is:

$$\max_{(e, r) \in \mathcal{S}, T \in \mathcal{Y}} \delta V + T - G(T|e, r) \left(1 + \frac{V}{U(e, r, T)} \right) \{T - \mathbb{E}[y|e, r, y \leq T]\} - \mathbb{E}[c(r)|r]. \quad (5)$$

subject to the participation constraint and the expected dynamic enforcement constraint. To show that $e_M > e_B$ and $r_M < r_B$, we first show that the first derivatives with respect to e and r have the required sign at (e_B, r_B) : owner utility rises with larger e and falls with larger r . We then argue that they continue to do so in the relevant subset of \mathcal{S} until they either run up against a constraint or reach an interior solution by crossing zero. Partial derivatives with respect to $s \in \{e, r\}$ are:

$$\begin{aligned} & -G_s(T|e, r) \left(1 + \frac{V}{U(e, r, T)} \right) \{T - \mathbb{E}[y|e, r, y \leq T]\} \\ & + G(T|e, r) \frac{V}{U(e, r, T)^2} \frac{\partial U}{\partial s} \{T - \mathbb{E}[y|e, r, y \leq T]\} \\ & + G(T|e, r) \left(1 + \frac{V}{U(e, r, T)} \right) \frac{\partial \mathbb{E}[y|e, r, y \leq T]}{\partial s} - \frac{\partial \mathbb{E}[c(r)|r]}{\partial s}, \end{aligned}$$

where $U(e, r, T) = (\mathbb{E}[y|e, r] - \psi(e, r) - T) / (1 - \delta)$. The first and the third additive term are always positive. The second term is zero at (e_B, r_B) . The fourth term is always zero for e . Hence the partial with respect to e is positive at (e_B, r_B) , as desired. For the partial with

respect to r at (e_B, r_B) to be negative, we need the last term (i.e. expected marginal cost of risk) to outweigh the sum of the first and the third term. This is guaranteed by Assumption 2.

As we move into (e, r) with $e > e_B$ and $r < r_B$, the second term of the partial with respect to e becomes negative and grows at a faster rate than the first and the third term, guaranteeing that it eventually crosses zero. The second term of the partial with respect to r becomes positive for (e, r) with $e > e_B$ and $r < r_B$. But Assumption 2 guarantees that the partial as a whole remains negative for all $(e, r) \geq (e_B, r_B)$, and hence it will cross zero (or hit a constraint) at some $r < r_B$.

The result that profit increases follows directly from it being collinear with owner utility; (e_B, r_B) being in the owner's choice set; and owner utility increasing strictly when moving towards (e_M, r_M) .

To see that revenue may rise or fall, note that (e_M, r_M) is in the set $\mathcal{S}_M = (e_B, \bar{e}] \times (0, r_B)$ and recall that $G_{e,r}(e, r) \geq 0$ from Assumption 1, which implies that the isoquant at (e_B, r_B) is downward sloping. Hence, the intersection of \mathcal{S}_M with both the upper contour set and the lower contour set of (e_B, r_B) in terms of $E[y|e, r]$ is non-empty. In the upper contour set, revenue rises, while in the lower contour set, it falls.

To see whether the target T_M is greater or smaller than the baseline target T_B , note that the partial of (5) with respect to T is:

$$\begin{aligned} M(e, r, T) &= 1 - g(T|e, r) \left(1 + \frac{V}{U(e, r, T)} \right) \{T - \mathbb{E}[y|e, r, y \leq T]\} \\ &\quad + G(T|e, r) \frac{V}{U(e, r, T)^2} \frac{\partial U}{\partial T} \{T - \mathbb{E}[y|e, r, y \leq T]\} \\ &\quad - G(T|e, r) \left(1 + \frac{V}{U(e, r, T)} \right) \left\{ 1 - \frac{\partial \mathbb{E}[y|e, r, y \leq T]}{\partial T} \right\} \end{aligned}$$

If $T \rightarrow \bar{y}$, then $M(e, r, T) < 0$, and if $T \rightarrow 0$, then $M(e, r, T) > 0$. By the intermediate value theorem, it is zero at some value in between. None of our assumptions restrict $M(e_B, r_B, T)$ to be positive or negative; hence it is ambiguous in general.

However, in case revenue falls $E[y|e_M, r_M] \leq E[y|e_B, r_B]$, the target has to fall as well. To see this, we apply the Implicit Function Theorem to $M(e, r, T) = 0$ at all (e, r) in the intersection of the lower contour set running through (e_B, r_B) and the lower quadrant given by $[e_b, \bar{e}] \times [0, r_b]$, which we denote by \mathcal{S}_Q . We then show that the total effect on the target

of moving from (e_B, r_B) to (e_M, r_M) is negative:

$$\begin{bmatrix} \frac{\partial T}{\partial e} \\ \frac{\partial T}{\partial r} \end{bmatrix} \cdot \begin{bmatrix} e_M - e_B \\ r_M - r_B \end{bmatrix} = - \begin{bmatrix} \frac{\partial M(e, r, T)/\partial e}{\partial M(e, r, T)/\partial T} \\ \frac{\partial M(e, r, T)/\partial r}{\partial M(e, r, T)/\partial T} \end{bmatrix} \cdot \begin{bmatrix} e_M - e_B \\ r_M - r_B \end{bmatrix} < 0$$

evaluated at all $(e, r) \in \mathcal{S}_Q$. This depends specifically on the sign of the partials of $M(e, r, T)$. First, consider that lower expected revenue implies a lower optimal target. To see this, consider the lower bound: if expected revenue were near zero, then so is the target. Since, by assumption, revenue falls, the partial terms involving changes in revenue caused by the change in effort and risk are negative. Therefore, while the partial effect of the change in effort is negative and partial effect of the change in risk is positive, the sign of the dot product depends only on terms that move with $U(e, r, T)$. Because we are moving away from the incentive compatible set, the effort-risk bundle is increasingly less favorable to the driver, lowering his valuation of the contract.

Finally, to see that the welfare effect is ambiguous, note that welfare is just profit minus disutility of work $\psi(e, r)$. While profit rises unambiguously, we do not know whether $\psi(e_M, r_M)$ is greater or smaller than $\psi(e_B, r_B)$ under the maintained assumptions, and in particular whether it overcompensates for the rise in profit.

□

E Structural Estimation Details

The structural estimation numerically solve the owner's maximization problem, which we simplify by applying the Lemma to Equation (1):

$$V = \max_{T \in \mathcal{Y}} \delta V + T - G(T|e, r) \left(1 + \frac{V}{U} \right) \{T - \mathbb{E}[y|e, r, y \leq T]\} - \mathbb{E}[c(r)|r] \quad (6)$$

where

$$U = \frac{\mathbb{E}[y|e, r] - T - \psi(e, r)}{1 - \delta}$$

is the driver's contract valuation under the target contract. Equation (1) makes explicit that V is the maximal value of the owner's objective function. Hence, solving for V involves finding the fixed point of this equation.

To find the target T that maximizes owner utility numerically, we need to empirically specify five terms. Two are calibrated from the data: the distribution of revenue $G(\cdot)$ and the expected repair costs $\mathbb{E}[c(r)|r]$. Expected daily repair costs are fixed at \$4.99 (the mean in the control group) and the CDF of revenue $G(y|e, r)$ is sampled from the underlying data from the control group. We also assume a common discount factor of 0.99. Three are unobservable parameters that need to be estimated: the driver's outside option \bar{u} , firing costs h , and driver disutility from effort and risk $\psi(e, r)$ evaluated at (e_B, r_B) and (e_M, r_M) . Because we evaluate $\psi(e, r)$ only at these two points – the effort-risk bundle at baseline (e_B, r_B) and under monitoring (e_M, r_M) – we do not need to make any functional form assumptions to estimate. We use simulated method of moments to simultaneously pin down these parameters and solve for the optimal target. We then use this output to evaluate the owner's contract valuation V specified in Equation (6).

Armed with these estimates of structural parameters under the status quo, we then turn to evaluating the welfare effect of monitoring. We update our calibrations of the expected costs $\mathbb{E}[c(r)|r]$ and the revenue distribution $G(\cdot)$ using the observed treatment effects, and re-run the estimator with these new inputs. This allows us to estimate the change in contract valuation for both the owner and the driver.

More specifically, our SMM procedure estimates the unobserved parameters $\theta \equiv (\psi(e_B, r_B), h, \bar{u})$. SMM searches for the unknown parameters to minimize the weighted distance between a subset of the contract outcomes we can observe in the data and their simulated counterparts.

The SMM estimator is:

$$\hat{\theta} = \arg \min_{\theta} [\hat{m}_D - \hat{m}_S(\theta)]' W [\hat{m}_D - \hat{m}_S(\theta)]$$

where \hat{m}_D is the vector of moments calculated from the data, $\hat{m}_S(\theta)$ is the analogous vector of endogenous moments simulated from the model for any given choice of θ , and W is the weighting matrix.⁴² We include two different sets of moments for the two exercises below (i.e. baseline contract evaluation and monitoring valuation). To study the baseline contract, we use five moments

$$\hat{m} = (\hat{T}, \hat{\mathbb{E}}[y - t|e, r], \hat{\mathbb{E}}[t - c(r)|e, r], \hat{\mathbb{E}}[p(t)|e, r], \hat{U})'$$

using either estimated means from the data for \hat{m}_D or simulated means based on parameter guesses for $\hat{m}_S(\theta)$.⁴³ For the first moment, \hat{T}_D is the average target observed in the data, while $\hat{T}_S(\theta)$ is the numerically optimal target in Equation 6 for a given θ and a “bootstrapped” distribution of revenue $\tilde{G}(\cdot)$. Similarly, the next three moments use the average driver residual claim, the owner’s net transfer, and the rehiring probability on the data side, and simulated counterparts using θ and $\tilde{G}(\cdot)$ on the simulated side. The final moment is driver welfare, for which we use the average reported price to forego the current contract as the data moment and the model expression for driver welfare evaluated at θ as the simulated moment.

In the second exercise (i.e. valuing the monitoring effect) we use a single moment: the change in the target \hat{T} . We only require a single moment because we keep the outside option (\bar{u}) and firing costs (h) from the status quo estimation fixed. For both exercises, we run this simulation 500 times, where each simulation samples with replacement from the observed empirical distribution of revenue to create the bootstrapped distribution $\tilde{G}(\cdot)$.⁴⁴

⁴²We use the optimal weighting matrix given by the inverse variance-covariance matrix of the data moments.

⁴³In principle it would be possible to estimate the parameters using only three moments, however using all five moments allows us to conduct an overidentification test of the model.

⁴⁴If we estimate the model matching all three treatment effects, we find that both owner *and* driver valuation increase (see Appendix Table A.2). This result requires driver disutility to fall by 9% under the new bundle of effort and risk. This is consistent with the model’s predictions, that allow for the possibility that both owner and driver welfare could increase with the introduction of monitoring. However, given the high number of working hours under the status quo, it seems unlikely that driver disutility falls with the observed increase in effort.