Monitoring and Intrinsic Motivation: Evidence from Liberia's Trucking Firms

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Abstract

Information asymmetries make contracting difficult within firms. Standard principal-agent theory predicts that monitoring should unambiguously raise workers' effort. I test this prediction using a field experiment with Liberian trucking companies. Results show that drivers who are experimentally monitored provide more effort on average. However, a key finding is that this effect is heterogeneous across drivers: some drivers provide less effort as a result of monitoring and managers are therefore reluctant to monitor them. I outline several reasons for why this might be and show that decreasing effort may be a way for drivers to retaliate against the manager's decision to monitor them.

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1 Introduction

Information asymmetries make contracting difficult within firms. Increasingly available and affordable monitoring technologies have the potential to greatly reduce such asymmetries. Standard principal-agent theory predicts that these technologies should raise worker effort. However, new technologies may also undermine informal arrangements that have developed exactly to substitute for the effort incentives provided by formal contracting institutions. If so, the impact of modern monitoring technologies on worker effort is ambiguous.

In this paper, I evaluate the impact of a new monitoring technology on worker effort and a firm's decision of whether to employ the technology. Results are based on an experiment in the context of Liberia's trucking industry. The treatment offered managers the opportunity to install GPS tracking devices on randomly selected trucks at zero cost. The devices allow managers (principals) to better monitor drivers (agents) by reporting the position of trucks in real time. I first show how installed devices affect drivers' speeds without leading to higher accident rates or maintenance costs. I then show evidence that monitoring can be detrimental for some drivers, and that managers anticipate this by optimally choosing who they want to monitor. Finally, I present a simple theoretical framework to explore why this might be. I show evidence that intrinsically motivated drivers dislike being monitored and retaliate against their manager by decreasing their effort. This finding is key: it suggests that the adverse response of workers can be a barrier to organizational innovation within the firm.

Liberia's trucking industry is an ideal setting in which to study firms' monitoring choices and worker effort for several reasons. First, the combination of dirt roads and heavy rains makes route completion times variable and unpredictable. This unpredictability means that there is room for drivers to shirk without raising suspicion from their manager. Second, drivers take a set of decisions that affect the firm's performance, and that the manager cannot observe perfectly. These include the number and length of breaks, and whether to transport additional goods or individuals without the manager's approval. In the absence of a monitoring technology, the only information a manager can use to try to infer such driver "input" choices are "outputs" such as the total travel time.[1]

I conducted the experiment on a sample of 150 trucks based in Liberia's main transport hubs. GPS tracking devices were offered free of charge. The devices send the real-time positions of trucks to an online server through a mobile network. Managers can then access the online server on a computer or smartphone. The good network coverage and the large availability of smartphones in Liberia made it relatively straightforward for the managers to properly use the GPS trackers. The role of the GPS tracking devices and the managers' ability to track the truck was clearly explained to drivers at baseline.

Evidence from the experiment shows that monitored drivers completed their tasks 60 percent faster. This occurs in part because monitored drivers take shorter breaks,[2] but do not have more accidents or higher truck maintenance costs. Since, by construction, GPS tracking devices are only installed on trucks of the treatment group, the data collected by the devices cannot be used for measuring treatment effects. All estimates presented here are based on interviews with drivers and managers. The results hold whether managers' or drivers' estimates of speed and break times are used.

Despite the dramatic improvement in monitored drivers' performance, take-up of the monitoring devices was far from complete through the end of my data collection, a year after the start of the experiment. Managers chose not to install the devices on 35 percent of the trucks selected for treatment. This is because, for some drivers, monitoring is detrimental to the effort they provide. I show three pieces of evidence to support this finding.

First, I show that managers decide to install GPS tracking devices on the trucks of drivers who perform less well at baseline. Drivers who receive a GPS tracking

[1]Managers were unable to effectively align incentives of drivers with the firm's objectives before the experiment. Only two trucks in the sample used GPS trackers before the experiment. The literature has shown that performance pay may increase incentives of employees (e.g. Jensen and Murphy, 1990; Foster and Rosenzweig, 1994; Lazear, 2000; Lavy, 2009; Muralidharan and Sundararaman, 2011). However, only 21 percent of the truck drivers in the sample receive performance pay, and for these drivers the variable part of their pay only represents less than 5 percent of their total wage. While this might seem surprising at first, a risk-averse worker may not agree to a performance pay in a case where many factors affect the output and are out of his control. In fact, when asked if they would like a performance-pay, the drivers answered that they would find it "unfair".

[2]Estimated breaks are times when the driver stops for being stuck in the mud, for deliveries or for personal reasons.

device ex ante complete their routes less fast, are more likely to have accidents, and are more likely to break the rules set out by their managers.[3] Additionally, managers report worse relationships at baseline with the drivers they later decide to monitor.

Second, the treatment effect on drivers' propensity to follow the rules of the business is adverse for drivers who provided high levels of effort at baseline. This is particularly the case for rules that are not easily observable with the GPS tracker, such as carrying unauthorized passengers or goods. Monitoring the drivers significantly decreased the propensity of drivers with high levels of effort at baseline to follow these unobservable rules.

Third, the drivers who provided high levels of effort at baseline reported a significant deterioration in their relationship with the managers after monitoring was introduced.

These last two pieces of evidence suggest that monitoring drivers who provide effort at baseline would be counter-productive for the firm, which helps explain why managers on average choose not to install monitoring devices on such drivers' trucks. This evidence that Liberian managers on average accurately judge which workers to monitor—the combination of the first and second two pieces of evidence—suggests that simply making monitoring technologies available can increase firm productivity.[4]

Finally, I shed light on potential mechanisms driving the results. I show that the empirical evidence points towards a tit-for-tat mechanism, where drivers' intrinsic motivation is negatively affected by the manager's decision to monitor. In other words, the manager's decision to monitor undermined the preexisting manager-driver informal arrangement.

Overall, this paper demonstrates that, while monitoring technologies can dramatically increase the productivity of certain drivers, their use may be counter-productive for other workers. Thus, blind application of monitoring devices to the entire worker-base may produce a suboptimal effect on overall productivity, contrary to the predictions of classical principal-agent theory. This suggests that the

[3]Rules include "do not carry unauthorized passengers or goods" and "do not use the truck for personal reasons".

[4]Evidence suggests that management choices are not always optimal in developing countries (Bloom et al., 2013). My findings show that in choosing which drivers they wanted to monitor, managers on average made the optimal choice.

adverse response of workers to innovation can be a barrier to technology adoption within the firm. This paper contributes to the literature on the agency problem in the workplace, on the adverse effect of incentives, on contingent management, on the technology diffusion process and on the understanding of high transport costs in developing countries.

An existing literature on the agency problem has shown that information asymmetries in the workplace can in some contexts partly be overcome with informal arrangements, such as relational contracts (e.g. Greif, 1993; McMillan and Woodruff, 1999; Brown et al., 2004; Macleod, 2007; Macchiavello and Morjaria, 2015), face-to-face interaction (Startz, 2018), or referrals (Burks et al., 2015). In this paper, I study how monitoring can help solve a key agency problem when informal arrangements fail and when the principals are not able to perfectly observe agents. This relates to the literature specifically on the effect of monitoring on an agent's effort. Monitoring has been shown to have a positive effect on the performance of workers in different contexts in developing countries, such as health care provision (Björkman and Svensson, 2009) or education (Duflo et al., 2012).[5]

The line of work that is the closest to this project is the work by George Baker and Thomas Hubbard and the more recent paper by Kelley et al. (2018). In several papers (Hubbard, 2000, 2003; Baker and Hubbard, 2003, 2004) Baker and Hubbard study the impact of the introduction of On-Board Computers (OBCs)[6] in trucking companies in the Unites States. Kelley et al. (2018) study the introduction of GPS trackers on taxi drivers in Kenya. In both cases, the authors show that the introduction of the technology helped solve the moral hazard issue within the firm. My work differs from theirs in that, due to the unobservable nature of some of the driver's tasks in my setting, informal arrangements partially substitute for formal contract enforcing institutions. This is important because in such settings monitoring may undermine informal arrangements and may be counter-productive. In the context of this study I find counter-productive effects of monitoring that were not considered in previous literature.

[5]This has also been shown in developed countries, for example (Jackson and Schneider, 2015) show that monitoring has a positive impact on the effort of workers in auto repair shops.

[6]GPS tracking devices are a particular case of OBCs. OBCs can be more sophisticated, and in some cases are able to provide additional information than the position of the truck, such as fuel and battery levels, or other measures of driver performance.

In that respect, this paper adds to the literature on motivational crowding out and adverse effects of extrinsic incentives. While several papers find that extrinsic incentives increase agent's effort (Esteves-Sorenson and Broce, 0; DellaVigna, 2009), some papers find the opposite effect. Existing studies document how monetary incentives crowd out motivation in blood donations (Mellström and Johannesson, 2008), day-care pick-ups (Gneezy and Rustichini, 2000a), recruitment of public health workers (Deserranno, 2019), and the lab (Gneezy and Rustichini, 2000b). A few studies also find that monitoring crowds out effort in the lab (Falk and Kosfeld, 2006; Dickinson and Villeval, 2008), particularly when monitoring is not perfect and some tasks remain unmonitored (Békir et al., 2015; Belot and Schröder, 2016). These studies conclude that monitoring induces a direct cost on the agent which prompts retaliation against the principal through lower effort.[7] There is to my knowledge no existing evidence on the implications of motivational crowding out for firms, and of the adverse effect of monitoring in the field.[8]

Models explaining the possibility of adverse effect of incentives were developed in theoretical papers, such as Holmstrom and Milgrom (1991), Bénabou and Tirole (2003), Sliwka (2007) and Ellingsen and Johannesson (2008). In this paper, I explore several of the approaches developed in the theoretical literature.

My findings suggest two things: (i) monitoring employees can crowd out their effort and (ii) managers are aware of and act on the phenomenon. In this regard, this paper contributes to the literature on contingent management practices. The employer-worker relation and how optimal management practices interact with this relation is studied by Amodio and Martinez-Carrasco (2018), Bandiera et al. (2015) and Blader et al. (2019). In my study, managers base their decision to monitor drivers or not on their relationship with drivers. This confirms the findings of Grund and Harbring (2013), who show that in an employment relationship, control is negatively correlated with trust.

The technology diffusion process is often slower than economists expect. Recent

[7]This precision is important. It distinguishes monetary incentives—which have no direct negative impact on the agent—from monitoring.

[8]Gneezy and Rustichini (2000b) show that paying high-school students to do voluntary work can crowd out their effort. That I know of, this is the closest evidence in the literature on the adverse effect of incentives in an employer-employee relationship. See Frey and Jegen (2000) for a survey of empirical evidence in the fields of both economics and psychology.

papers have found that reasons for this include firms' lack of information about the technology (Bloom et al. 2013), a misalignment of incentives within the firm (Atkin et al. 2017), or competition among firms (Hardy and McCasland 2019). An implicit assumption in these papers is that the adoption of new technologies unambiguously raises firm productivity. However, this paper shows that new technologies may interfere with existing employer-employee agreements which guaranteed optimal behavior from both sides. This suggests that as long as the norms shaping these agreements have not changed, the adverse response of workers to innovation can be a barrier to technology adoption within the firm.

Finally, this paper relates to the literature on transport costs. Authors have shown that transport costs are high in developing countries, particularly in Africa (Teravaninthorn and Raballand, 2009). Atkin and Donaldson (2015), Bergquist and Dinerstein (2020) and Lall et al. (2009) shed light on the significant role played by intermediaries and low competition in the transport sector in explaining high transport costs. This paper is the first to document the role of moral hazard between traders and transporters in explaining high transport costs.

The paper is organized as follows. Section 2 presents the context of the experiment, Section 3 details the experimental design and Section 4 describes the effect of the treatment on treated drivers. Section 5 presents empirical evidence of the adverse effect of monitoring. Section 6 discusses the potential mechanisms at play. Section 7 concludes.

2 Background

Liberia's trucking industry is particularly prone to asymmetries of information between drivers and managers.

2.1 Liberia

The civil war in Liberia which ended in 2005 put the economy to the ground. As a result, in 2016 (when this study was being conducted) the economy was still very young. Most firms had not been operating for more than ten years, and workers—who were either soldiers or refugees during the war—were often not well educated. It is often difficult for firms or workers to bring a disagreement to court and written contracts are uncommon.[9] In the data collected for this project, only half of the driver-manager contracts are covered by written agreements. In such a context, managers rely extensively on their personal networks to hire employees.

2.2 The transport industry in Liberia

Liberia is connected to the international market through its main port of entry based in the capital, Monrovia, where most trucking companies are based. These companies find clients (mainly traders or producers), distribute imported goods to inland markets and collect local goods for international exports. A few other companies operate from other cities, mainly transporting goods that are locally produced and consumed.

Despite it being the main mode of transportation within the country, Liberia's road network is not well developed. The country's main axis connects the three main cities but still leaves a large share of the population unconnected to a paved road. Moreover, Liberia ranks 14th in terms of average rainfall per year. As a result, vehicles get often stuck in the mud.[10] The combination of heavy rains and a poor road network makes travel times very uncertain and transport companies have a hard time predicting the time it will take for goods to be delivered.[11]

2.3 Information asymmetries in trucking firms

Information asymmetries arise when managers are not able to perfectly monitor workers. When trucks leave the parking lot, managers are not able to know for certain the location of the truck until it reaches its destination and the client confirms the delivery. During that time, drivers choose the speed of the truck, the number and length of breaks without managers being able to see or control these decisions.

Discussions with the managers before the beginning of the experiment revealed different approaches to monitoring drivers prior to the experiment. Most of the managers I talked to mentioned that they could not rely on any information, and as such had no choice but to trust their drivers. To keep track of where the goods are, most managers require their drivers to call them regularly and update them on

[9] In 2016, Liberia ranked 220 over 235 countries on the World Bank's doing business indicator.

[10] See the top panel of Figure A.1 in the Appendix for a map of Liberia's main roads. The bottom panel of Figure A.1 in the Appendix shows a common situation after a strong rain.

[11] In contracts between transport companies and their clients, very few stipulate a date of arrival. Most clients pay a flat rate for the goods to be delivered in a "timely manner".

their position. There are three network providers in Liberia, which together cover almost entirely the road network, but separately each one only covers some areas. A truck driver, who often relies on only one network, lacks a signal in some sections of the journey. This provides him with a great reason to not continuously update his manager on the location of the truck (or to avoid answering the phone). Another obvious issue with this approach is that even in the case in which he can get in touch with the driver, the manager is not able to confirm the information that he is given.[12]

Very few companies used GPS tracking devices prior to the experiment. Information and cost barriers combined with the poor development of the mobile network contribute to the low take-up of the technology in the past. Local GPS trackers are expensive and have not proven to be fully functioning, in part because the mobile network necessary to use the device has been very slow to develop and until recently did not cover the main roads.[13] At baseline, only 25 percent of managers knew what a GPS tracker was before being told.

In other contexts, information asymmetries have been shown to be at least partially solved with performance pay. In the context of trucking companies, drivers receiving a performance pay have a wage based on the time they take to complete a trip, the number of trips completed per month, or other observable measures of performance. Only 21 percent of the drivers in my sample received a wage based on performance, and for these drivers the variable part of their wage only represents less than 5 percent of their total wage. While this might seem surprising at first, there are at least two known reasons for why performance pay is not always the optimal solution. First, incentivizing multi-tasking agents on observable tasks may distort the driver's incentives and prove inefficient for a profit-maximizing firm (see Holmstrom and Milgrom, 1991). Second, a risk-averse worker may not agree to a performance pay in a case where many factors affect the output and are out of his control (see Chapter 2 in Gibbons and Roberts, 2012). In fact, when asked if they would like to be paid based on their performance, drivers answered that they would

[12]One manager said he had developed a system to monitor his driver. He had asked businesses on the road—managed by family, or friends—to watch the road and notify him when the truck went by. While this approach could in theory solve at least in part the agency problem, it requires an extensive network of friends and family along the road.

[13]A quick survey of the local options for GPS trackers determined that the cheapest device available in Liberia is priced at US$ 1,500.

find it "unfair".

In the past, managers have not been able to perfectly align drivers' incentives with the optimal actions for the benefits of the firm. The experiment I describe in the next section measures to what extent the introduction of a monitoring device solves the agency problem.

3 Experimental Design

In this section I describe the recruitment of trucking companies, the randomization of the treatment and its implementation as well as the data collection.

3.1 Sample of Companies

Firms were recruited in the sample using a combination of different methods detailed in Section A.1 of the Appendix. All the firms that we reached who had at least one truck were given the opportunity to participate in the study. Out of the 76 firms for which we had contact information of, 62 agreed to participate in the experiment (82%). These 62 companies represent 152 trucks and 160 driversfootnoteHere, only drivers that are not managers are counted. These are the drivers of interest for the experiment. Since there is no census of trucking companies in Liberia, it is hard to know what share of the total population the sample represents, but I am confident that it represents a significant share of the overall universe of trucking companies in Liberia.[14]

Table 1 presents summary statistics for these firms. The baseline interviews were conducted during the rainy season, which means that not all drivers had completed trips in the month prior to the interview, and when they did their speed was unusually low compared to the dry season. On average, a trip—which is defined as the journey from origin to destination—lasts 54 hours, but the time spent on a trip varies a lot across trips. The average speed of drivers at baseline is 12 kilometers per hour (around 7.5 miles per hour). However, this only reflects the average speed of trucks during the rainy season, and the average speed of the control group during the dry season is significantly higher, at 33 kilometers per hour. The average speed referred to here includes all types of breaks the drivers may take. Most drivers are always

[14] According to Dablanc (2010), Mali had 1,864 trucks in 2006, or 0.13 trucks per thousand people or 0.35 trucks per $ million GDP. Scaled to Liberia in 2016, this is equivalent to 600-735 trucks.

assigned to the same truck, which means that in most cases treatment is at the driver level.[15]

< Table 1 here. >

3.1.1 Treatment Randomization

The treatment was rolled out in two phases.

In August 2016, firms were recruited and the owner of the truck was asked to sign a Memorandum of Understanding giving the authorization to install a GPS tracking device on all the trucks in his company.[16] Managers and drivers were then interviewed, and upon completion of the interviews of all manager and drivers of a company, the company's trucks were randomly assigned to treatment and control groups. The randomization procedure is detailed in Section A.2 of the Appendix. At the end of this randomization, 104 trucks (68% of all trucks) where assigned to the treatment group and 48 trucks where in the control group.

Despite the treatment being entirely free for the firms and extensive efforts from the mechanics to install the devices, by March 2017 (7 months after the beginning of treatment) only 55 of the 104 trackers had been installed (53% of the treatment group).

At the beginning of the study, a Memorandum of Understanding between the research team and a donor was signed which ensured funding for the GPS trackers in exchange for the guarantee that at least 100 GPS trackers be installed before June 2017. Given the size of the sample and the low take-up, expectations were revised and both parties agreed to a second randomization round which would ensure that more GPS trackers would be installed, while still having a group of pure control trucks. The second randomization assigned an additional one third of the control group to the treatment group. At the end of the second randomization, 19 more

[15]In the analysis that follows, all drivers have been kept in the sample. Dropping drivers who change trucks does not alter results

[16]For legal reasons, the owner's approval is necessary to start the installation. Most of the time the owner of the truck is the manager. The MoU detailed all the interviews the drivers and the managers would have to go through, as well as the procedure of GPS installation. For the firm to participate in the study, the owner had to give his approval for the interviews, and for the potential installation of GPS trackers. Drivers were then individually asked for consent to be interviewed.

trucks were assigned to the treatment, bringing the total number of treatment trucks to 123 (81% of all trucks).[17]

By the end of April, the number of trackers installed reached 80 out of the 123 assigned to treatment (65%). Despite strong efforts to install GPS trackers, no trackers were installed between May and September 2017.

Figure 1 shows the timeline of installation of the GPS trackers. Part of the revised agreement with the donor was also to hire a new mechanic after the second randomization. This new mechanic turned out to be more efficient at contacting the managers to install the trackers, and he installed some of the trackers that had been assigned to treatment during the first wave of randomization. While there appears to be some progression in the first months after the assignment of trucks to treatment, after a year, the number of installations seems to have reached a limit. Table 2 shows that treatment and control groups are balanced.[18]

< Figure 1 here. >

< Table 2 here. >

3.1.2 GPS Trackers and Installation

All the trucks in the treatment group were assigned a GPS tracker with a label stating the license plate of the truck they were assigned to (or other form of truck identification) as well as the name of the driver. To make sure that a truck in the control group did not wrongly receive a GPS tracker, the mechanic was asked to verify the license plate of the truck and the name of the driver before starting the installation.

GPS trackers used for the purpose of this study are small black boxes of around 3 inches width by 2 inches length. To be properly functional, GPS trackers must be installed inside the truck's dashboard by a professional mechanic. The GPS tracker is directly connected to the battery of the truck, which allows it to stay on even when

[17]While the second wave of randomization is not ideal on a statistical power point of view, it occurred late enough that it allowed to conduct interviews and to measure the impact of the trackers before the second wave. See following section for more details.

[18]This balance table is based on the first randomization, since this is the one that is used for identification in preferred estimations. Balance mostly holds after the second wave of randomization as well. The balance table for the second randomization can be provided upon request. Driver fixed effects are included in all specifications.

the engine is turned off. The tracker turns off soon after the battery of the truck is disconnected from the truck (which is pretty common in Liberia when the truck is parked, to avoid battery theft).[19] The installation takes about 30 minutes to 2 hours, depending on the truck. The mechanics were hired by the research team, and were sent to the truck's parking space, so that the tracker and the installation were completely free of charge for the company. Figure A.2 in the Appendix shows a picture of a tracker, and a mechanic working on the dashboard to install the tracker.

Once the GPS tracker is properly installed on the truck, it sends the position of the truck through a mobile network to an online server. The combination of mobile networks used covers most of the road network, ensuring that the position of the truck is precisely reported over time. When the truck goes through a geographical area not covered by a network, the manager has to infer the position of the truck with the positions recorded before and after. This does not happen often enough that it has been reported as an issue by the managers. The server stores the history of recorded positions. Codes of access for the online platform to access the data were given to the owner of the truck.[20] A printed manual for using the online platform was also provided to the owner, as well as telephone numbers they could reach if they needed help. In the cases in which the owner was not the direct manager of the driver, the owner shared access codes with the manager. The bottom picture of Figure A.2 shows an example of a common trip recorded on the platform.

It quickly became apparent that the drivers were unhappy about the GPS tracking devices. To ensure that the devices were installed on the trucks according the manager's willingness, and not the driver's, the mechanics were asked to follow this procedure:

1. Mechanics contacted the driver assigned to the truck, and scheduled a meeting for the installation.
2. If the first step failed and the tracker could not be installed, the mechanics contacted the manager and asked him to schedule the meeting with the driver.
3. If the two first steps failed, the mechanics repeated the two first steps the following week.

[19] Other more complex trackers are able to give other type of information such as the oil level. The GPS tracking devices used in this study do not; they only give information on the location of the truck.

[20] Driver were not given the codes to access the the online platform.

The mechanics received a wage partly based on the number of devices installed. In addition, an independent enumerator verified that the mechanic contacted the drivers and showed up at meetings.[21] When a tracker failed or mysteriously disappeared, it was immediately replaced by a new tracker.[22]

3.2 Data Collection

Interviews were conducted both before and after the first wave of randomization of the GPS trackers, with both managers and drivers.

3.2.1 Manager interviews

Managers were first interviewed at baseline, upon recruitment of the firms. These rounds of interviews lasted from the end of August to the end of October 2016. After the baseline, follow-up interviews were completed regularly. Four rounds of follow-ups were completed: January 2017, February 2017, March 2017 and April 2017. The first three follow-ups were therefore completed between the first and second rounds of randomization, and the last one is the only round that captures the effect of the second randomization. [23]

The content of baseline and follow-up interviews of managers were very similar. They included questions on the manager (the interviewee), the business, the transport sector, the truck(s) of the business, each driver hired by the business and the drivers' trips that the manager could recall. For each trip completed in the month before the interview that they could remember, the managers were asked questions about the origin and destination, estimated time of completion, the types and length of breaks, the commodity transported, technical issues and whether there was another truck from the same company on the trip.[24] The baseline interviews were all conducted in person. Follow-up interviews were done in person or on the phone at the convenience of the manager.

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[21]While the mechanics sometimes failed to show up at meetings, significant effort was done to correct these errors. By the end of the treatment period, all failures of installation where due to a failure from the company's side.

[22]Fewer than five trackers were reported to fail during the experiment.

[23]The Intent-to-treat variable in the estimations reflects the re-assignment of trucks to treatment in the last round. Dropping the last round does not change the estimates presented in this paper.

[24]To limit the length of the interview, we limited the number of trips to three per driver. If the driver completed more than three trips in the last month, the manager was asked about the three main trips completed.

3.2.2 Driver interviews

Drivers were interviewed at baseline, in the same period that the manager baseline was completed. There was one follow-up interview for drivers, in late March to early April 2017. All the estimations based on driver interviews therefore pick-up the effect of the GPS trackers assigned on the first wave of randomization.

Driver interviews were shorter than managers interviews and included questions on the drivers (the interviewee) and the past trips they could recall. For each trip completed in the past month, the drivers were asked the origin and destination, estimated time of completion, the types and length of breaks, the commodity transported, technical issues and whether the was another truck from the same company on the trip.[25]

In addition to the questionnaire, enumerators where trained to explain to drivers the role of the GPS tracking device and the manager's ability to track the truck at baseline.[26] Driver interviews were all carried out in person during the baseline and follow-up, except when an in-person was not feasible.

3.2.3 Distance and speed

Given that the GPS trackers are only installed on the trucks of the treatment group, their data cannot be used for measuring treatment effects.

For this reason, I use data collected from interviews to estimate speed of drivers, and the length of breaks. For each trip, interviewees are asked about origin and destination, the time it took them to complete, and an estimate of the time they spent on breaks. Interviewees could report different types of breaks: breaks for delivery of goods, breaks for technical reasons (for example when the truck is stuck in the mud of the road), and personal breaks. This last category was let vague on purpose, and includes anything else that the drivers stop for (for example eating, sleeping, or visiting family). To calculate speed, I additionally used a distance measure that is based on the distance between origin and destination locations as calculated by

[25]To limit the length of the interview, we also limited the number of trips to three per driver. Note that since driver interviews and the manager interviews are not overlapping in time (except for the baseline), it is not possible to directly compare the data on trips from drivers and managers interviews.

[26]Not informing the drivers about the GPS tracking devices would have put drivers at risk of being reprimanded or disciplined by their managers.

Google Maps.[27]

Providing a precise estimation of the length of a trip or a break is not an easy exercise, which led to a lot of measurement error. Observations with unrealistic speed estimates were dropped. The reliability of the data from interviews and how it affects the results are discussed in a greater length in the next section, which explains the effect of the treatment on treated drivers.

3.2.4 Observable and Non-Observable Rules

At baseline, managers were asked which rules they asked the drivers to follow. For each business, a list of rules is then generated which allows us to ask both managers and drivers whether the driver follows each of these rules. The rules generally vary from one business to another. In order to exploit variation in whether a driver follows these rules, I generate a variable for whether the driver follows the rules of the business.[28] I also separate these rules between *observable* and *non-observable*rules. Observable rules are rules that a GPS trackers helps monitor. Conversely, a non-observable rule cannot be monitored, even with a GPS trackers. Observable rules mainly include: "do not drive at night", "do not drive during the rain", "report upon arrival to a major city". Non-observable rules mainly include: "do not carry unauthorized passenger or goods", "do not fight on the job", "do not drink alcohol on the job".

4 Results of the Experiment

4.1 Econometric Specification

The key variation that I exploit is within drivers over time. I collected data before and after the randomization of treatment, which allows me to use a difference-in-difference regression framework with driver fixed effects. To capture seasonal variation and infrastructure differences among roads I also use season and road fixed effects. For each specification in this section I estimate both the intent-to-treat estimate and the local average treatment effect.

[27]Given Liberia's road network, there is often only one route to go from one city to another. In case Google Maps offered two itineraries, the most common route was confirmed by managers of trucking companies. In those cases, the distance difference was not high and the results are unaltered using one route or the other.

[28]At baseline, about a third of drivers are reported as infringing one of these rules.

The main specification I use is at the trip level. The regression estimation is

$$y_{itr} = \alpha_i + \beta_r + \gamma_t + X_{itr} + \delta T_{it} + \epsilon_{itr}$$

Where y_{itr} is the output for driver i at time t on road r; α_i, β_r, γ_t are driver, road, and time fixed effects; X_{itr} are trip controls (the type of goods transported, technical issues during the trip, and whether there were several trucks from the same company on the trip); T_{it} is the treatment variable, which takes the value one when the truck of driver i was assigned to treatment at time t. δ is the coefficient of interest. To compute the local average treatment effect on the treated, I instrument the treatment take-up with the assignment to treatment.[29]

One concern with this specification is that the treatment may affect the number of trips the driver completed, and biases the number of observations in each group. To avoid this concern, in a second specification I reduce the number of observations at the driver-period level (rather than at the trip level). Results from these second specification are similar to the ones from the main regression, so I will only refer to those in the empirical results. More details about this specification and the resulting regression tables can be found in Section A.3 of the Appendix.[30]

4.2 Effect of Monitoring on Driver Performance

According to standard principal-agent theory, a monitoring device should increase workers' efficiency along measures of effort monitored by the device. In this section, I study the effect of GPS tracking devices on speed and length of breaks.

4.2.1 Effect on Speed

The first output I explore is the average speed of drivers. By construction, only the treated group of trucks has a GPS tracker, so the average speed is estimated with information from interviews (completion time, destination and origin). I compute separate estimates based on drivers and managers interviews.

[29]In all tables, two stage regressions are done using 2SLS.

[30]The speed and break estimates are based on the trips completed in the month prior to the interview. In some cases the driver had not completed any trip, or the interviewee was reluctant to recount the event so that the estimations are not based on a full panel. The estimation at the driver level helps cope with this concern. Note that there I do not observe differential attrition between treatment and control in the trips recounted.

For clarity, tables in this section present the specifications in the same order. Columns (1), (2) and (3) show “Instrumental Variable” estimates, which is the local average treatment effect on the treated. Columns (4), (5) and (6) show “Reduced Form” estimates, also called intent-to-treat estimates, which is the effect of assignment to treatment. Columns (1) and (4) have season fixed effects, columns (2) and (5) have season, driver and road fixed effects, and columns (3) and (6) have the same fixed effects as (2) and (5), and additional trip controls that can affect a driver’s speed (fixed effect on types of goods transported, technical issues during the trip, and whether another truck from the same company was on the trip). The top panel is based on interviews with managers, while the bottom panel is based on interviews with drivers.

Table 3 shows the effect of the treatment on speed of drivers. the top panel shows that the installation of the GPS tracker significantly increases the average speed of the drivers, as estimated by their managers. The local average treatment estimate indicates that, according to managers, monitoring devices increased the speed of treated drivers by about 19.8 kilometers per hour, once controlling for seasonality, driver fixed effects, road fixed effects and controls. Due to the low take-up of the treatment—which is explored in the next section—the intent-to-treat estimates are about one-third smaller. Being assigned to treatment increased the average speed of the driver by 6.9 kilometers per hour.

< Table 3 here. >

Note that adding controls in Column (2) and (3) increases the value of the coefficient compared to Column (1). This is because firms prefer sending the trucks with a GPS tracker (trucks in the treatment group) on roads where they know the drivers have a lot of opportunities to shirk. As a result, the roads that drivers take are not balanced between treatment and control groups, and adding the fixed effect changes the coefficient. While the effect of treatment also exists when road fixed effects are not added, the preferred specification includes road and driver fixed effects, as well as controls.

To ensure that these results do not come from a bias in the managers’ interviews, I compute estimates based on drivers interviews. Managers might be biased if, in order to keep a good relationship with the research team, managers over-estimate the effect of the tracker.[31] If this is the case, estimates from the top panel of Table 3 may be over-estimating the effect.

The bottom panel of Table 3 shows the same specification, but in this case speed was estimated from the drivers interviews. While drivers can also be biased in answering the interviews, they would intuitively want to under-estimate the effect of the tracker.[32] Estimates from the bottom panel of Table 3 show that the effect of the treatment on speed based on drivers interviews is very similar to the ones from the top panel. The local average treatment estimate indicates that, according to drivers, monitoring devices increased the speed of drivers by about 18.5 kilometers per hour, while the intent-to-treat estimate is 8.9 kilometers per hour.

4.2.2 Effect on Breaks

The installation of monitoring significantly increases the average speed of treated drivers. In this section, I explore whether this effect is due to drivers reducing the length of breaks. I measure the length of breaks as the percentage of the total trip spent on breaks. Here, breaks include all sorts of reasons to stop, such as times when the driver stops for being stuck in the mud, for deliveries or for personal reasons.

Table 4 shows the effect of the treatment on the length of breaks. The top panel of Table 4 shows the estimate of the effect of monitoring on breaks as a percentage of the total trip, using managers' interviews. The bottom panel of Table 4 shows the same estimation using drivers' interviews. Both tables show that GPS trackers reduced the time of the trip spent on breaks, between 9 and 14 percent.

< Table 4 here. >

Decomposing the output per type of breaks shows that the reduction in breaks comes from the driver spending less time on personal breaks, compared to other types of breaks. Estimates are shown in Table A.3 of the Appendix.[33]

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[31] For example, it could be that managers were exaggerating the effect of trackers, thinking it might increase their chances to get trackers for their trucks in the control group—although it was made clear from the beginning that this would not be the case. Note that nor the managers nor the drivers were told the purpose of the research, but the managers could have guessed that the speed was one of the outputs of interest.

[32] Given that, as pointed out in Section 6, drivers on average prefer not to be monitored, they would want to convince the research team that monitoring drivers have no effect on their performance.

[33] Note that, even with a GPS tracker, the manager can only infer which type of break the driver

4.2.3 Effect on accidents, maintenance costs and technical problems

One immediate concern of a reduction in "personal" breaks is that it may have a detrimental effect on the capacity of the driver to drive safely. However, it is worth noting that in this context drivers are always accompanied by co-drivers called "carboys". The role of carboys is to ensure that there is always a driver, even when the driver rests. Carboys are usually training to become drivers themselves, are much younger than the main drivers, and have little to no responsibility during the trip other than driving. As such, managers expect trucks to only stop for fuel, deliveries, or other truck imperatives.

To further show that the increase in speed did not have a detrimental effect, Table A.2 presents estimates of the treatment effect on the number of accidents, maintenance costs and technical problems. The coefficients are small and not significant.

Estimates reveal that the tracking devices significantly increase monitored drivers' average speeds, without leading to higher accident rates or maintenance costs. In the following sections, I explore why managers refused to install monitoring devices on selected trucks.

5 Empirical Evidence

5.1 Baseline characteristics on treatment take-up

Among the trucks selected for treatment, managers decided which drivers will and will not receive a GPS tracker. In this section, I show that the managers decided to install a GPS tracker on the trucks of drivers that showed lower levels of effort at baseline.

Figure 2 shows how drivers in the treatment group compare at baseline according to treatment take-up. On every panel, the top line presents the average and the 95% confidence interval for drivers for whom the manager refused to install a GPS tracking device. The bottom line presents the same information but for drivers who received a tracker. The figure is based on interviews from managers, since they are the ones deciding who to monitor or not.

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is taking based on the truck's location. According to informal discussions with managers, this was relatively easy to do.

< Figure 2 here. >

The figure clearly shows that managers chose to install GPS tracking devices on drivers who showed lower performance at baseline. At baseline, according to managers, drivers who received the tracker were slower, were less able to follow the rules of the firm (such as not transporting unauthorized passengers or goods, or not using the truck for personal reasons), and were more likely to have accidents. During interviews, managers are asked to rate their relationship with their drivers on a scale from 0 to 10. Managers decided to install monitoring devices on drivers who received a lower "relationship index". The most statistically significant differences between the two groups comes from the rules infringed, and the number of accidents.[34]

Figure 2 together with the results from Section 4 show that, within the treatment group, managers selected drivers who performed less well at baseline to receive a GPS tracker, and that on those drivers the effect of monitoring was positive. I now explore the heterogeneity of the treatment effect.

5.2 Treatment heterogeneity

In this section I separately examine the effect of the treatment on drivers who provided a high level of effort at baseline and on drivers who provided a low level of effort at baseline.

The specification is as follows

$$\begin{gathered} y_{it} = \gamma_t + HighEffort_i Wetseasont + LowEffort_i Wetseasont + \\ + HighEffort_i Dryseasont + \delta_1 T_{it} HighEffort_i \\ + \delta_2 T_{it} LowEffort_i + \epsilon_{it} \end{gathered}$$

Where y_{it} is the output for driver i at time t. γ_t is a time fixed effect, $HighEffort_i$ is a dummy that takes the value one when the driver provides high effort at baseline, $LowEffort_i$ is a dummy that takes the value one when the driver provides low effort at baseline and T_{it} is a dummy for treatment. The coefficients of interest are

[34]Since the sample is restricted to the drivers in the treatment group, it is not surprising that these differences are not all statistically significant, although they all are in the expected direction. The variable "Does the driver infringe any of the rules?" is statistically significantly different between the two groups at the 5% level, while the number of accidents is significant at the 10% level. More detail on this can be found in Table A.5 of the Appendix.

δ_1 δ_2, the effect of treatment on both types of drivers.[35]

To measure whether the driver provided an overall high or low level of effort at baseline, I base my predictions on baseline characteristics in the following way. In the treatment group, I select the variables which best predict take-up of treatment.[36] I then regress the take-up variable on these selected characteristics and use the coefficients to generate a "propensity to be treated" on both the treatment and control groups. This propensity to be treated reflects the manager's belief about the driver's effort at baseline, and the probability that the driver receives a tracker, conditional on him being in the treatment group. Drivers with a low propensity to be treated are drivers who provided a high level of effort at baseline, and conversely drivers with a high propensity to be treated are drivers who provided a low level of effort at baseline.

Figure A.3 in the Appendix shows the histogram of treated and not treated drivers with respected to the "propensity to be treated" index. As expected, treated drivers are especially numerous in high levels of the index, while drivers who were not treated tend to be in lower levels of the index. However, there a number of overlapping indexes, meaning that while managers on average correctly chose who to monitor, some low propensity drivers nevertheless received a GPS tracker. This allows to estimate the effect of monitoring on these drivers.[37]

Figure 3 presents the results on whether the driver follows the rule of the business, as measured by drivers.[38] Drivers are asked how many times they infringed the rules

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[35]Note that the estimation includes dummies for high and low effort at baseline. This ensure that the heterogeneity effect is not driven by high and low propensity drivers being different types of drivers to begin with. The omitted category of drivers in the regression is (Low Effort, Dry Season).

[36]This is done through a lasso estimation of the take-up on a group of baseline characteristics. The four variables selected are the average breaks taken by the drivers, whether the driver had an accident in the year before the interview, whether the driver infringes the rules of the business, and the rate of relationship between the manager and the driver. All characteristics are based on manager interviews.

[37]One concern here might be that adoption is driven by unobservables. Given that the propensity to be treated score is based on the same variables with the same corresponding coefficients in the control and the treatment groups, the heterogeneity is well-identified (similar groups are compared across treatment and control). Also note that results are robust to different ways of generating the "propensity to be treated score". For example, results are robust to the linear regression being replaced by a logit regression, and all characteristics kept in the regression (instead of keeping those selected by the lasso).

[38]Table A.6 in the Appendix shows the corresponding estimation results. Driver interviews are used here to avoid the interview bias described in Section 4.

of the business in the month preceding the interview. The top panel of Figure 3 shows that while treatment seems to have a negative effect on the probability of the driver to infringe the rules of the business for drivers with a high propensity to be treated, this effect increases the probability to infringe the rules of business of drivers with a low propensity to be treated.[39]

< Figure 3 here. >

The two bottom panels of Figure 3 show that the effect is different for rules that managers can partially monitor with the GPS trackers—such as using the truck for personal reasons—and rules that they cannot—such as carrying unauthorized passengers or goods. Drivers with a high propensity to be treated tend to shirk less on both types of rules. However, drivers with a low propensity to be treated—drivers who provided a high level of effort at baseline—tend to increase the number of times they infringe rules that are not easily monitored by managers. These drivers do not significantly change their behavior on observable tasks.

This effect–that agents shirk on rules that are not easily observable by principals as a result of monitoring–reflects the findings of the literature (Békir et al., 2015; Belot and Schröder, 2016). When monitoring is not perfect and some tasks remain unobservable to the principal, it leaves room for the agent to shirk without the principal noticing. A more detailed discussion about the behavior of the driver is included in Section 6.3.

5.3 Effect of monitoring on relationships

During interviews, managers are asked to rank between 0 and 10 their relationship with their drivers, and drivers are asked the same question with respect to their manager. Figure 4 shows the heterogeneity of the effect with respect to the "propensity to be treated" index. The top panel shows the heterogeneous effect of treatment on both types of drivers on their relationship according to their manager. The bottom panel shows the same heterogeneity but according to drivers. Managers' relationship index improves as a result of treatment for drivers with a high propensity to be treated. However, the relationship index according do drivers is deteriorated for drivers of low propensity to be treated.

[39] Another way to present the results is to split the drivers into two separate groups: high propensity and low propensity. Results hold if regressions are run separately for the two groups.

< Figure 4 here. >

These results show that monitoring is counter-productive for drivers who provided a high level of effort at baseline. When monitored, these drivers report that their relationship with their manager has deteriorated, and they tend to shirk more, particularly on tasks that are not easily observable by managers.

6 Theoretical Framework

While GPS trackers clearly incentivized some drivers to exert higher levels of effort, the previous section shows that some drivers decreased the effort they provided as a result of the technology. This section introduces a framework that details possible mechanisms behind this effect.

6.1 General Framework

A manager wants to hire a driver on a job for which the output will depend on the driver's effort along two dimensions, effort e_1 on task 1 and effort e_2 on task 2. The driver chooses the effort he provides on both tasks (e_1, e_2), incurs the cost of effort $cost(e_{1,}e_2)$, and gets the wage w. After the driver chooses his effort level (e_1, e_2), the signals (s_1, s_2) are generated which are observed by the manager. s_1 and s_2 are noisy signals of e_1 and e_2 .

Now assume that the manager can ex-ante choose a costless monitoring technology $m \in [0, 1]$ which improves the quality of the signal of task 1, but has no effect on the signal of task 2: $s_i = e_i + \epsilon_i$, where ϵ_1 and ϵ_2 are independent random variables, with $\epsilon_1(m) \sim \mathcal{N}(1, \sigma_1(m)^2)$ and $\sigma_1' < 0$, and $\epsilon_2 \sim \mathcal{N}(1, \sigma_2^2)$.

The timing of the game is the following. The manager chooses the monitoring technology m. Given m, the driver chooses his optimal level of effort $(e_1^*(m), e_2^*(m))$. The manager observes the signals s_1 and s_2 and forms a guess about the true levels of effort. The game will be solved by backward induction.

Assume the manager has a prior about the distribution of the driver's effort, $e_i \sim \mathcal{N}(e_i^0, (\sigma_i^0)^2)$. By Bayesian updating, the manager forms a guess about the effort provided by the driver based on his prior and the signals he receives.

$$\begin{cases} \mathbb{E}[e_1|s_1] = & \frac{(\sigma_1(m))^2 e_1^0 + (\sigma_1^0)^2 s_1}{(\sigma_1(m))^2 + (\sigma_1^0)^2} \\ \mathbb{E}[e_2|s_2] = & \frac{(\sigma_2)^2 e_2^0 + (\sigma_2^0)^2 s_2}{(\sigma_2)^2 + (\sigma_2^0)^2} \end{cases} \tag{1}$$

Note that the beliefs of the manager only enter the utility of the driver, not the manager. Knowing that the manager updates his beliefs through (1), the driver chooses his optimal level of efforts. Assume the driver is paid a fixed wage w, and that the efforts (e_1, e_2) and signals of effort $(s_{1,}s_2)$ affect the utility of the driver through a function f , which also depends on the monitoring choice of the manager m.[40] Given the wage w and the monitoring technology chosen by the manager, the driver will choose the level of effort (e_1, e_2) to maximize his expected utility.

The driver's utility and the maximization of his ex-ante expected utility can be written

$$U = w - cost(e_1, e_2) + f(e_1, e_2, s_1, s_2, m)$$

$$\max_{e_1,e_2} \mathbb{E}[U] = w - cost(e_1, e_2) + F(e_1, e_2, m)$$

Where $F(e_1, e_2, m) = \mathbb{E}[f(e_1, e_2, s_{1,}s_2, m)|e_1, e_2]$ is the ex-ante expected value of f given the driver's choice of effort. If first and second order conditions are satisfied, there exists a solution to the driver's problem, and the implicit function theorem yields the optimal levels of effort $(e_1^*(m), e_2^*(m))$ that solve the maximization problem.

The derivative of the optimal level of effort with respect to the monitoring choice can be written

$$\begin{cases} \frac{\partial e_1^*}{\partial m} & = \frac{F_{13}[F_{22}-cost_{22}]-F_{23}[F_{12}-cost_{12}]}{[F_{12}-cost_{12}]^2-[F_{11}-cost_{11}][F_{22}-cost_{22}]} \\ \frac{\partial e_2^*}{\partial m} & = \frac{F_{23}[F_{11}-cost_{11}]-F_{13}[F_{12}-cost_{12}]}{[F_{12}-cost_{12}]^2-[F_{11}-cost_{11}][F_{22}-cost_{22}]} \end{cases} \tag{2}$$

The signs of the expressions above will determine whether monitoring increases or decreases the effort provided by the driver. Note that from the second order

[40] Note that in theory, the wage w could depend on (s_1, s_2) (such as performance-pay). However, if the driver is risk-averse, the signal is noisy and the driver has a high enough outside option, there are situations in which the only contract the driver would accept is a contract that does not depend on the signal of performance x. Since this is the situation observed in this context, we will focus on this case here. The wage is pinned down by the market and may depend on the experience of the driver or on the relationship between the driver and the manager. This assumption can be relaxed although the model then becomes less tractable.

conditions of the driver's optimization problem, we know that

$$\begin{cases} [F_{12} - cost_{12}]^2 - [F_{11} - cost_{11}][F_{22} - cost_{22}] < 0 \\ F_{22} - cost_{22} < 0 \\ F_{11} - cost_{11} < 0 \end{cases} \tag{3}$$

Given $(e_1^*(m), e_2^*(m))$, the manager chooses the monitoring technology m to maximize his profits. His maximization problem can be written

$$\max_m \Pi = G(e_1^*(m), e_2^*(m)) - w \tag{4}$$

Where $G(.,.)$ is the manager's payoff function and is increasing in both arguments. Note that from (4) above, the monitoring choice of the manager only affects his profits through the level of effort chosen by the driver.[41] The choice of the manager to monitor or not the driver will then depend on how monitoring affects effort (the signs of the expressions in (2)), and on the shape of the function G.

6.2 How monitoring decreases effort on non-monitored tasks

In this section, I explore the mechanisms behind a key empirical finding—how monitoring can decrease the effort provided by drivers on tasks that are not monitored. I will not explore the other more commonly known effect of monitoring—how it can increase the effort provided on monitored tasks. A more complete model that incorporates both effects is discussed in Section (A.4) of the Appendix.

Each subsection below explores a different mechanism for why monitoring can decrease the effort provided by the agent on task 2, the task that is not being monitored. I then discuss which mechanism best fits the results of the experiment.

6.2.1 Multi-tasking

The mechanism described here is based on the case where the driver's tasks are substitutes in cost. Following the multi-tasking agent theory developed by Holm-

[41] One could think of other ways monitoring can affect the manager's profits through, for example, better resource management. Since, in these mechanisms, monitoring often generates an increase in the manager's profit, they are not the focus of this section which tries to explain the counter-productive effect of monitoring. These types of mechanisms are excluded by this framework but could be easily included in the manager's profit function.

strom and Milgrom (1991), if the two tasks are substitutes in cost and if the agent is incentivized to produce more effort on one task, the agent will mechanically shift his effort away from other tasks.

To see this in the model, assume the driver wants to send signals of high levels of effort to the manager.[42] The function f can then be written as a classic pay-per-performance scheme.

$$f(e_1, e_2, s_1, s_2, m) = \mu_1 \mathbb{E}[e_1|s_1] + \mu_2 \mathbb{E}[e_2|s_2]$$

Where $\mathbb{E}[e_i|s_i]$ is the manager's belief about the effort on task i given the signal he receive s_i, and μ_i is the weight on that belief. The ex-ante expected value of f can then be written

$$\begin{aligned} F(e_1, e_2, m) &= \mathbb{E}[f(e_1, e_2, s_1, s_2, m)|e_1, e_2] \\ &= \mathbb{E}[\mu_1 \mathbb{E}[e_1|s_1] + \mu_2 \mathbb{E}[e_2|s_2]|e_1, e_2] \end{aligned} \tag{5}$$

Combining (5) and (1), the second order derivatives F_{13}, F_{23} and F_{12} can be computed, and substituted into (2). Combining the resulting inequalities with the first order conditions in (3)

$$\begin{cases} \frac{\partial e_1^*}{\partial m} > 0\text{; and} \\ \frac{\partial e_2^*}{\partial m} < 0 \text{ if and only if } \mu r^2 \sigma_1'(m) \sigma_1(m) e_1 cost_{12} < 0. \end{cases} \tag{6}$$

From the first inequality above, monitoring unambiguously increases the driver's effort on the monitored task. The intuition behind this finding is that if the signal s_1 becomes more informative about the real value of effort e_1 chosen by the driver, then when the manager updates his belief about effort, he will give the signal a higher relative importance compared to his prior. This means that if the manager decides to monitor the driver, the driver's return to providing effort on the monitored task increases.

[42]Here, I am being agnostic about what motivates the driver to care about the values of signals of effort. The driver may be incentivized by future interactions with the manager, or by pure intrinsic motivation. In theory the driver could also receive a wage based on the signal, and the results would be unchanged (the reward would then enter the manager's profit function, which is not the case we solve here).

In the second inequality of (6), since $\sigma_1'(m) < 0$, the sign of $\frac{\partial e_2^*}{\partial m}$ depends solely on the shape of the function $cost$. If we assume the tasks are substitutes in cost ($cost_{12} > 0$), then monitoring decreases effort provided on the non-monitored task ($\frac{\partial e_2^*}{\partial m} < 0$). This is because in the mechanism described here, monitoring increases the returns to effort on the monitored task, which, if efforts are substitutes in cost, shifts effort away from the non-monitored task.

6.2.2 Tit for tat

In this section the mechanism explored is one where the driver retaliates against a harmful action of the manager. Assume the driver does not like being monitored and, if monitored, wants to retaliate against the manager by lowering his profits. In this case if the manager decides to monitor he also creates an incentive for the driver to reduce effort.

Let the utility of the driver depend not only on his own payoff, but also on the payoff of the manager. Similarly as in the inequity aversion literature, let the driver's weight on the manager's payoff be conditional on the manager's choice to monitor.[43]

$$F(e_1, e_2, m) = -mC + \gamma(m)\Pi(e_1, e_2) \tag{7}$$

Where C is a monitoring disutility and the weight $\gamma(m)$ in front of the manager's profit Π is decreasing in m. Monitoring induces a direct disutility to the driver C and deteriorates how much the driver cares about the manager's payoff through $\gamma(m)$.

From (7), the second order derivatives F_{13}, F_{23} and F_{12} can be computed, and substituted into (2). Combining the resulting inequalities and (3), under some assumptions on the shape of the manager's benefit function G, monitoring decreases the effort provided on the non-monitored task ($\frac{\partial e_2^*}{\partial m} < 0$).[44] When this assumption is verified, monitoring incentivizes the driver to reduce the profit of the manager and, as a result, the driver decreases the effort he provides.

[43]In the literature on inequity aversion (see for example Charness and Rabin, 2002 and Fehr and Schmidt, 1999) an individual's weight in front of another individual's payoff is conditional on their relative payoff.

[44]From (3), a sufficient condition for $\frac{\partial e_2^*}{\partial m} < 0$ to hold is that $G_{12}(e_1, e_2) > \frac{cost_{12}(e_1,e_2)}{\gamma(m)}$.

6.2.3 Signaling intrinsic motivation

Following Bénabou and Tirole (2006), assume here that the driver is intrinsically motivated to provide effort and that in addition the driver also cares about the manager's opinion of his intrinsic motivation. The manager uses both signals of effort to guess the intrinsic motivation of the driver, who values this guess. By monitoring, the signal of effort on the monitored task becomes more informative compared to the non-monitored task. The driver's return to providing effort on the non-monitored task therefore decreases, even without efforts being substitutes in cost (such as in Section 6.2.1).

Following Bénabou and Tirole (2006), let the function f be

$$f = \mu(\gamma_1 e_1 + \gamma_2 e_2) + \lambda \mathbb{E}[\mu | s_1, s_2, m]$$

Where the first term $\mu(\gamma_1 e_1 + \gamma_2 e_2)$ represents the intrinsic motivation of the driver, and μ is the weight in front of this intrinsic motivation. The second term $\mathbb{E}[\mu | s_1, s_2, m]$ is the manager's guess about that weight, given the signals of effort he observes. The ex-ante expected value of f can then be written

$$\begin{aligned} F(e_1, e_2, m) &= \mathbb{E}[f(e_1, e_2, s_1, s_2, m) | e_1, e_2] \\ &= \mu(\gamma_1 e_1 + \gamma_2 e_2) + \lambda R(e_1, e_2)] \end{aligned} \tag{8}$$

Where $R(e_1, e_2, m) = \mathbb{E}[\mathbb{E}[\mu | s_1, s_2, m] | e_1, e_2]$ is the driver's ex-ante expectation of the manager's guess about his intrinsic motivation. The derivatives F_{13}, F_{23} and F_{12} which will determine the sign of $\frac{\partial e_2^*}{\partial m}$ depend on the shape of the function $R(e_1, e_2, m)$. To guess the value of μ, the manager relies on the first order conditions of the driver's maximization problem

$$\max_{e_1, e_2} \mathbb{E}[U] = w - cost(e_1, e_2) + \mu(\gamma_1 e_1 + \gamma_2 e_2) + \lambda R(e_1, e_2)]$$

For tractability, assume that the cost function takes the following form

$$cost(e_{1,} e_2) = \frac{1}{2} k_1 e_1^2 + \frac{1}{2} k_2 e_2^2$$

The first order conditions of the driver's utility optimization problem are

$$\begin{cases} 0 = & -k_1 e_1 + \mu\gamma_1 + \lambda R_1(e_1, e_2, m) \\ 0 = & -k_2 e_2 + \mu\gamma_2 + \lambda R_2(e_1, e_2, m) \end{cases} \tag{9}$$

Assume the manager knows the parameters k_1, k_2, γ_1, γ_2 and λ in the equations above. Through Bayesian inference, the manager generates a guess about the value of μ based on (1) and (9).[45] The driver's ex-ante expectation about his guess takes the form

$$\mathbb{E}[\mathbb{E}[\mu|s_1, s_2, m]|e_1, e_2] = A(m)e_1 + B(m)e_2 - \tfrac{\lambda}{k_1}A(m)R_1 - \tfrac{\lambda}{k_2}B(m)R_2 \tag{10}$$

Where $A(m)$ and $B(m)$ are functions of the parameters k_1, k_2, γ_1, γ_2 and of the manager's decision to monitor m, and are respectively increasing and decreasing in m.[46]

Following the same methodology as in Bénabou and Tirole (2006), equation (10) is a linear differential equation in $R(e_1, e_2, m) = \mathbb{E}[\mathbb{E}[\mu|s_1, s_2, m]|e_1, e_2]$, and

$$\begin{cases} R_1(e_1, e_2, m) = A(m) \\ R_2(e_1, e_2, m) = B(m) \end{cases} \tag{11}$$

Combining (11) and (8), F_{13}, F_{23} and F_{12} can be computed, and substituted into (2). The resulting inequalities and the second order conditions (3) ensure that

$$\frac{\partial e_2^*}{\partial m} < 0$$

Intuitively, as the signal from the monitored task becomes more informative about the driver's intrinsic motivation, the signaling impact of one additional unit of effort on the non-monitored task decreases.

[45] Here the manager has no prior on the value of μ. We don't need this assumption to match the empirical findings, but it can be easily incorporated in the model.

[46] $A(m) = \frac{k_1 \frac{1}{\gamma_1} \frac{k_2}{\gamma_2} (\sigma_2)^2}{\frac{k_2}{\gamma_2}(\sigma_2)^2 + \frac{k_1}{\gamma_1}(\sigma_1(m))^2}$ and $B(m) = \frac{k_2 \frac{1}{\gamma_2} \frac{k_1}{\gamma_1} (\sigma_1(m))^2}{\frac{k_2}{\gamma_2}(\sigma_2)^2 + \frac{k_1}{\gamma_1}(\sigma_1(m))^2}$

6.3 Discussion

While the experiment discussed here was not designed to directly test for evidence of one of the three mechanisms above, in this section I discuss how the results point towards one of the mechanisms.

If multi-tasking was the only mechanism at play, the only reason why drivers would decrease their effort on the non-monitored task would be to trade-off their effort towards the monitored task. However, in the empirical findings, the drivers who increase their effort on monitored task—drivers who provided a low level of effort at baseline—are not the same drivers that are decreasing their effort on non-monitored tasks—drivers who provided a high level of effort at baseline. Therefore, multi-tasking does not seem to be the only mechanism at play.

If drivers wanted to signal their intrinsic motivation, as described in the Section 6.2.3 above, then monitoring would allow a better signaling and drivers, particularly those that are intrinsically motivated, would benefit from monitoring and want to be monitored.[47] However, this was not the case in practice. The mechanic who installed the GPS trackers had a hard time with the drivers and often had to call the managers for back-up. This is reflected in the take-up rate of the experiment, which was 65%. In addition, among the treatment group, the drivers whose trucks did not receive the trackers were the ones who provided a high level of effort at baseline, presumably the intrinsically motivated drivers. This contradicts a pure intrinsic motivation story where drivers, and in particular good drivers, would want the GPS trackers to be installed.

The tit-for-tat mechanism is consistent with the evidence presented in previous sections. As a result of being monitored, some drivers exert less effort and their relationship with their manager is deteriorated, as shown in Section 5.3. This is also consistent with the qualitative evidence collected after the experiment. Drivers reported being unhappy with their manager's decision to monitor them and managers reported having had complaints, particularly from good drivers. Drivers were not outspoken to the research team about why they dislike monitoring, but discussions with them and the managers revealed that they see monitoring as an obstruction to the driver's personal freedom.

[47]In the theory described above, this can be seem by computing $\frac{dU(e_1,e_2,m)}{dm}$, which is positive.

In conclusion, of the mechanisms displayed here, the evidence points towards a tit-for-tat mechanism. However, the evidence does not allow to rule our that other mechanisms may also be at play.[48]

7 Conclusion

The experiment demonstrates that the introduction of GPS monitoring to Liberian trucking firms results in significantly increased route completion speeds for monitored drivers. However, the effect of monitoring varies from driver to driver. These effects can be explained by segmenting the drivers into certain heterogeneous groups. Specifically, drivers who ex-ante provided a low level of effort have high productivity returns on monitoring treatment. Conversely, drivers who ex-ante provided a high level of effort show counter-productive effects of monitoring on individual productivity. I show that the empirical evidence is consistent with a theory of workers' retaliation against the manager's decision to monitor them. This study indicates that productivity gains from technology adoption can be challenged by the presence of informal arrangements between principals and agents. This effect is especially pronounced in developing countries, where parties extensively rely on informal arrangements.

This experiment was not designed to test technology adoption by the firm in the long term. However, it suggests that GPS tracking devices may allow firms to hire drivers for whom informal arrangements were not feasible ex-ante, without a corresponding loss of productivity. This experiment also implies that compensating drivers for the adoption of new technology, or having it imposed by a third party (like the government) may prevent its adverse effects. Testing causally these conclusions is left for future projects.

The conclusion to be drawn here is that blind application of monitoring technology may produce a sub-optimal effect on overall productivity. To maximize productivity gain, the choice of which drivers to monitor should take into consideration the motivations of each individual worker, which are on average well

[48] Another mechanism which is not described here is one where the manager's decision to monitor the driver is a signal to the driver about the belief or the type of the manager. However, if this mechanism was at play, the drivers would react (positively) to the manager's decision not to install the GPS tracker. However, in our experiment, this was not the case. Drivers in the treatment group who did not receive a tracker behave similarly to drivers in the control group.

approximated by managers.

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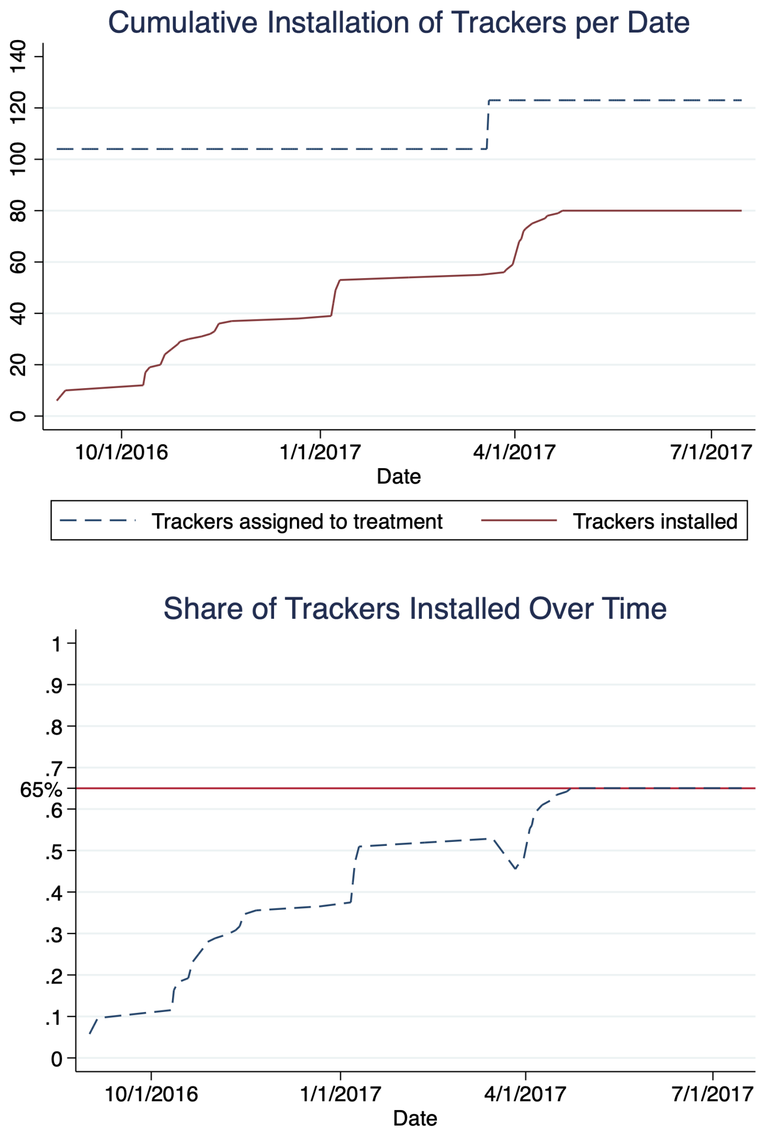
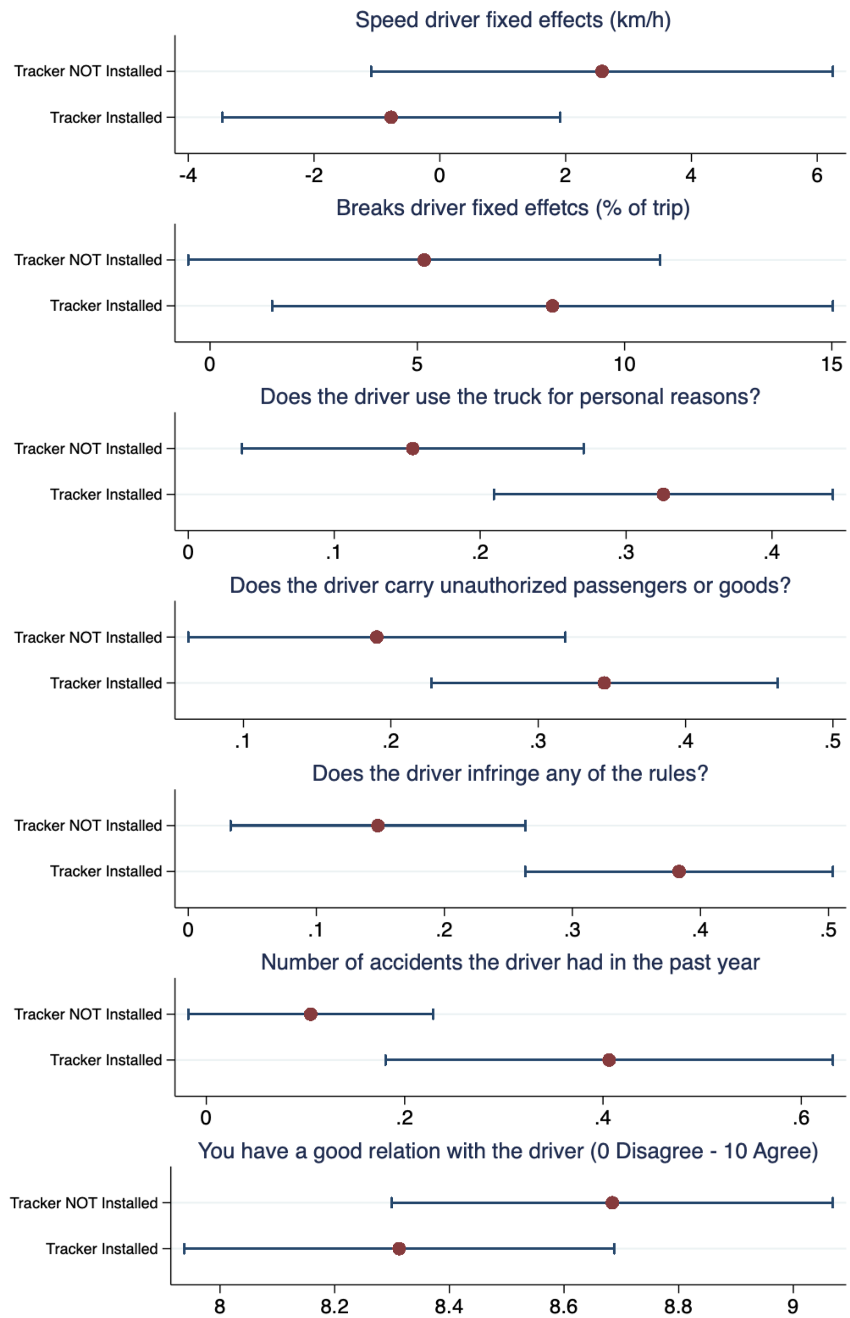
Figure 1: Timeline of GPS tracker installation



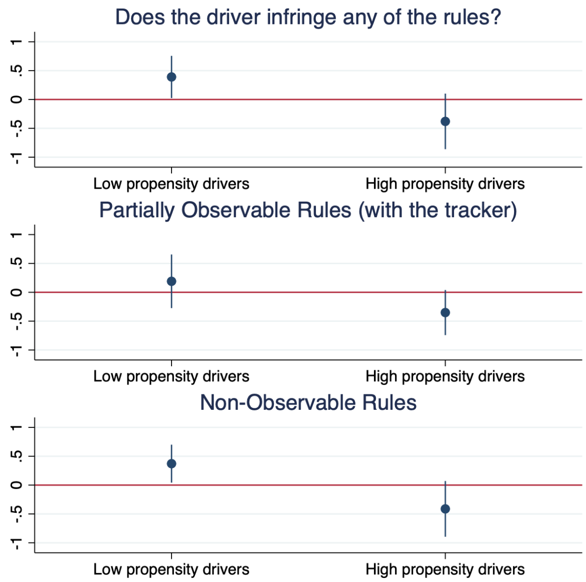
These figures depict the installation of trackers over time. The top figure shows the cumulative number of GPS trackers, compared to the number of trucks assigned to treatment as part of the two-wave randomization. The bottom figure shows the share of GPS trackers installed over time, which converges to the long-term value of 65%. Sudden increases in the number of trackers installed correspond to trucks several becoming available, a change in the mechanic's pay scheme, and the second randomization (which was combined with a change in mechanic).

Figure 2: Baseline Comparison by Treatment Take-Up



This figure represents baseline comparisons between drivers of the treatment group who had their GPS tracker installed, and those that did not. All data is based on managers interviews.

Figure 3: Effect of Treatment on Driver Effort by Propensity to be Treated Score Index



Data from baseline interviews with drivers. Coefficients are treatment-on-the-treated estimates and include driver-type by season fixed effects. Standard errors are robust. 95% Confidence Intervals.

Figure 4: Effect of Treatment on Driver-Manager Relations by Propensity to be Treated Score Index

Data from baseline interviews. The top graph is based on interviews with managers, bottom graph is based on interviews with drivers. Coefficients are treatment-on-the-treated estimates and include driver-type by season fixed effects. Standard errors are robust. 95% Confidence Intervals

Table 1: Summary Statistics at Baseline

	Mean	SD	Obs.
Managers			
How many trucks does the business own?	3.98	5.92	62
Is transport the only activity of the business?	0.65	0.48	62
Is transport the main activity?	0.76	0.43	62
Is the business officily registered?	0.71	0.46	62
What is the total number of employees?	16.18	31.87	62
Does the business deliver goods outside the country?	0.21	0.41	62
Gender of the interviewee (Male=0; Female=1)	0.02	0.13	62
Is the manager Liberian?	0.92	0.27	62
Is the manager a driver?	0.44	0.50	62
Do you give rules to the drivers in your business?	0.95	0.23	55
Does your business hire carboys?	0.56	0.50	62
How many tires did your business purchased last month?	4.15	4.30	62
Did the business ever pay for overloading?	0.27	0.45	62
Has this business ever been a victim of theft?	0.35	0.48	62
Trucks			
Did the business import this truck?	0.66	0.48	152
Was it a second-hand truck when the business acquired it?	0.84	0.37	152
Amount paid for maintenance in the past month (USD):	607.05	1112.73	152
Price of truck when bought (1k USD)	23.88	21.42	90
Drivers			
Is the driver a full time employee of the firm?	0.86	0.35	160
Did this driver ever have an accident while working for you?	0.13	0.34	160
Driver wage (in USD per day):	6.13	2.27	155
How many trips did this driver complete in the past month?	1.55	5.66	160
Trips			
Distance of trip (km)	284.31	164.10	68
Time spent on trips (hours)	54.26	61.01	68
Average speed, rainy season (km/h)	12.58	9.81	54
Time of trip spent on breaks (hours)	7.96	16.88	40
Percentage of trip spent on breaks (%)	13.36	20.24	40

This table was computed with data collected during baseline interviews. Statistics on managers and trucks were computed using data from manager interviews, and summary statistics on drivers and trips were computed using data from driver interviews. Baseline interviews were collected between August and October 2016, which corresponds to the rainy season. In the case where several managers were interviewed in the same firm, the answers from the oldest manager were retained. All Yes/No questions were coded as Yes=1 and No=0.

Table 2: Balance Table

	Difference	Std. Error
Managers		
How many trucks does the business own?	-3.42	2.27
Is transport the only activity of the business?	0.00	0.10
Is transport the main activity?	0.09	0.08
Is the business officily registered?	0.02	0.08
What is the total number of employees?	-13.37	8.10
Does the business deliver goods outside the country?	-0.12	0.10
Gender of the interviewee (Male=0; Female=1)	-0.01	0.02
Is the manager Liberian?	0.04	0.04
Is the manager a driver?	0.05	0.08
Do you give rules to the drivers in your business?	-0.02	0.03
Does your business hire carboys?	0.12	0.10
How many tires did your business purchased last month?	0.20	1.09
Did the business ever pay for overloading?	0.03	0.09
Has this business ever been a victim of theft?	-0.02	0.10
Trucks		
Did the business import this truck?	0.09	0.10
Was it a second-hand truck when the business acquired it?	0.02	0.07
Amount paid for maintenance in the past month (USD):	76.59	230.22
Price of truck when bought (1k USD)	-4.44	5.40
Drivers		
Is the driver a full time employee of the firm?	0.03	0.07
Did this driver ever have an accident while working for you?	0.04	0.07
Driver wage (in USD per day):	-1.00	0.48
How many trips did this driver complete in the past month?	-0.40	1.24
Trips		
Distance of trip (km)	2.67	49.59
Time spent on trips (hours)	-11.04	18.38
Average speed (km/h)	1.35	3.34
Time of trip spent on breaks (hours)	-7.90	6.64
Percentage of trip spent on breaks (%)	-9.54	7.96

This table was computed with data collected during baseline interviews. Statistics on managers and trucks were computed using data from manager interviews, and summary statistics on drivers and trips were computed using data from driver interviews. Since treatment was randomized at the truck/driver level, the manager and truck data were projected on driver IDs to present balance results. Baseline interviews were collected between August and October 2016, which corresponds to the rainy season. In the case where several managers were interviewed in the same firm, the answers from the oldest manager were retained. All Yes/No questions were coded as Yes=1 and No=0.

Table 3: Effect of Monitoring on Speed

	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: MANAGER INTERVIEWS						
	Instrumental Variable			Reduced Form		
	(1)	(2)	(3)	(4)	(5)	(6)
	Speed (km/h)					
Treatment	12.2*	24.9***	19.8**			
	(7.32)	(8.20)	(7.88)			
Assignment-to-Treatment				3.91*	8.86**	6.86
				(2.35)	(4.25)	(4.18)
Observations	303	303	303	303	303	303
PANEL B: DRIVER INTERVIEWS						
	Instrumental Variable			Reduced Form		
	(1)	(2)	(3)	(4)	(5)	(6)
	Speed (km/h)					
Treatment	10.6*	18.8***	18.5***			
	(5.56)	(4.71)	(4.59)			
Assignment-to-Treatment				5.82*	8.91**	8.90***
				(3.11)	(3.43)	(3.39)
Observations	427	427	427	427	427	427
Season FE	YES	YES	YES	YES	YES	YES
Road FE		YES	YES		YES	YES
Driver FE		YES	YES		YES	YES
Controls			YES			YES

Standard errors are in parentheses and are robust. This table presents coefficients of the regression of speed as calculated by dividing time over distance from trips recorded in managers interviews. Controls include whether the truck came back empty from the trip (back-load), whether there was a technical issue during the trip and whether the truck was accompanied by another truck during the trip.

Table 4: Effect of Monitoring on Breaks

	Instrumental Variable			Reduced Form		
PANEL A: MANAGER INTERVIEWS						
	(1)	(2)	(3)	(4)	(5)	(6)
	Percentage of Trip Spent on Breaks (%)					
Treatment	4.86	-6.37	-8.63			
	(7.16)	(11.56)	(8.22)			
Assignment-to-Treatment				1.46	-3.48	-3.43
				(2.13)	(4.60)	(5.09)
Observations	205	205	205	205	205	205
PANEL B: DRIVER INTERVIEWS						
	Instrumental Variable			Reduced Form		
	(1)	(2)	(3)	(4)	(5)	(6)
	Percentage of Trip Spent on Breaks (%)					
Treatment	-3.75	-14.0**	-13.7**			
	(5.16)	(5.90)	(5.46)			
Assignment-to-Treatment				-4.13***	-7.05	-6.78
				(1.35)	(4.80)	(4.61)
Observations	337	337	337	337	337	337
Season FE	YES	YES	YES	YES	YES	YES
Road FE		YES	YES		YES	YES
Driver FE		YES	YES		YES	YES
Controls			YES			YES

Standard errors are in parentheses and are robust. This table presents coefficients of the regression of breaks as calculated by dividing the time spent on breaks over total trip time recorded in managers interviews. Controls include whether the truck came back empty from the trip (back-load), whether there was a technical issue during the trip and whether the truck was accompanied by another truck during the trip.

A Appendix

A.1 Sample Recruitment

Two build the most complete sample of trucking firms in Liberia, five different strategies were used.

1. The *Liberian Business Registry* (*LBR*) provided the contact information of 57 firms registered under the freight transport sector. These included different types of firms (not only trucking) such as customs clearing.[49] The list only included businesses that had been registered at one point including businesses that had already closed. Most of the businesses on this list were either closed, not in the trucking business or not reachable.[50]

2. *Building Markets* - an NGO that works with more than 3,000 Liberian businesses - has a publicly available directory of firms by sector, with their contact information.[51]

3. The majority of the firms were recruited directly at the *main transport hubs*. Enumerators were assigned to different areas in Monrovia, and sometimes traveled to other cities.[52] At transport hubs, they either directly talked to managers, or asked drivers for the contact information of their manager.[53]

4. Monrovia has a *Port Trucker Union* that brings together small trucking companies that have access to the port's container unloading area. Contact was made with the transport union and I was invited to a meeting that gathered around 50 drivers and managers. Enumerators had the opportunity to explain the project and took the contact information of interested managers. While this method seemed to be working at first, some of the managers who were

[49] When they register, businesses are asked what sector they are in and LBR never verifies that sector. This leads to businesses being registered under wrong categories.

[50] That I know of, LBR's contact information of businesses is never updated which results in many contact information being obsolete.

[51] Building Market's contact information of firms is regularly updated.

[52] Enumerators were sent to four other cities to recruit firms: Ganta, Saclepea, Saniquellie and Karnplay.

[53] At this point, the drivers were not informed about the GPS trackers. They were told that we were conducting a study on the trucking industry. Enumerators did not report any driver who refused to give out the contact information of the owner of the truck, or other superior.

contacted after the event were skeptical and later refused to answer interviews. According to local informal discussions, it appeared that some firms in that group thought I was working with the government.

5. Lastly, enumerators asked the firms they had recruited for contact information of other firms in their sector. Some firms were able to point us to other firms they knew, but at this point we already had the contact information of most of these firms.

A.2 Randomization Procedure

The randomization of trucks into treatment was done in the following procedure:

1. Each firm was assigned a random share of trucks to be treated, with an average across firms of 2/3 of treated trucks.[54]

2. Within each firm, treated trucks were randomly selected according to the assigned share.

3. If a truck was on the threshold then it was randomly assigned to treatment or control such that the expected value of treated trucks was equal to the randomly assigned share.

This procedure was initially meant to ensure that each company would have a different share of its trucks selected into treatment, and allow heterogeneity estimation of treatment with respect to that share. The procedure was designed and implemented before the end of the recruitment of all firms. Given the number of trucks per firms and the total number of companies in the final sample, I lack statistical power to run such an analysis.

A.3 Econometric specification at the driver level

I apply a fixed effects method in a first stage, and use the fixed-effects of the first stage to run the second stage.

[54]Firms are assigned a random number - the share of treated trucks - according to a normal distribution centered in 2/3 and a standard deviation of 0.1. All firms assigned a number above 1 are assigned the number 1 and all firms assigned a number below 1/3 are assigned 1/3. This random assignment of shares of treated trucks was initially done to investigate the extensive vs. intensive margin of treatment. However, results don't show any significant variation along the intensive margin of treatment, and won't be presented in this paper.

First stage:

$$y_{itr} = \lambda_{it} + \beta_r + X_{itr} + \epsilon$$

Where y_{itr} is the output for driver i at time t on road r,
β_r is a road fixed effect,
X_{itr} are trip controls (the type of goods transported, technical issues during the trip, and whether there were several trucks from the same company on the trip),
and λ_{it} is a driver-period[55] fixed effect

Second stage:

I recover the driver-period fixed effects from the first stage, and use it as the output for the second stage. Now the observations are at the driver level.

$$\hat{\lambda}_{it} = \alpha_i + \gamma_t + \delta T_{it} + \epsilon$$

Where T_{it} is the treatment variable, which takes the value one when the truck of driver i was assigned to treatment at t,
and α_i and γ_t are driver and period fixed effects.

The effect of treatment on speed and breaks using this specification is shown on Tables A.1 and A.2 respectively.

A.4 Complementary Theoretical Framework

The framework presented here follows the same structure as the one presented in the core of the text. In addition, it incorporates the more commonly known effect of monitoring—how it can increase the effort provided on monitored. By combining the two effects, it shows that the two effects can co-exist within the same framework.

To do this, I follow the same general framework described in Section 6.1. I then separately explore the two different effects of monitoring: the increase in effort on task 1 and the decrease of effort on task 2. Since the final function F will have to encapsulate these two effects, I denote $F^1(e_1, e_2, m) = \mathbb{E}[f^1(s_{1,}s_2, m)|e_1, e_2]$ the first part of the function F which will explain the first effect, and $F^2(e_1, e_2, m) = \mathbb{E}[f^2(s_{1,}s_2, m)|e_1, e_2]$ the second part which will explain the second effect. Note that the function F_2 mirrors the function F presented in the main text of the paper.

[55]Two periods are defined: before and after the randomization.

Here, the function F is a weighted average of these two effects: $F = \mu F^1 + \lambda F^2$ where μ and λ are the driver's weights on these functions. Section A.4.1 below describes how monitoring can increase effort on monitored tasks, through the function F^1. Section A.4.2 goes through the mechanisms for why effort on non-monitored tasks can decrease with monitoring and how the model can be solved with the two effects. Note that the general framework presented in the Section 6.1 of the paper still holds, in particular Equations (2) and (3).

A.4.1 How monitoring increases effort on monitored tasks

This section explores how monitoring increases effort provided by drivers on monitored tasks. The mechanism explored here is based on the idea that if the driver cares about the signal of effort the manager receives, for example through intrinsic motivation, better measurement of a task will make it easier for him to impress the manager and thus increase his returns to effort on that task.

Suppose the function f^1 can be written as a classic pay-per-performance scheme where performance is based on the manager's belief about the effort provided by the driver.[56]

$$f^1(s_1, s_2, m) = \frac{\mu_1}{\mu}\mathbb{E}[e_1|s_1] + \frac{\mu_2}{\mu}\mathbb{E}[e_2|s_2]$$

Where $\mathbb{E}[e_i|s_i]$ is the manager's belief about the effort on task i given the signal he receive s_i, and μ_i is the weight on that belief.

Suppose the manager has a prior about the distribution of the driver's effort, $e_i \sim \mathcal{N}(e_i^0, (\sigma_i^0)^2)$. By bayesian updating

$$\begin{cases} \mathbb{E}[e_1|s_1] = & \frac{(\sigma_1(m))^2 e_1^0 + (\sigma_1^0)^2 s_1}{(\sigma_1(m))^2 + (\sigma_1^0)^2} \\ \mathbb{E}[e_2|s_2] = & \frac{(\sigma_2)^2 e_2^0 + (\sigma_2^0)^2 s_2}{(\sigma_2)^2 + (\sigma_2^0)^2} \end{cases}$$

The function $F^1(e_1, e_2, m) = \mathbb{E}[f^1(s_1, s_2, m)|e_1, e_2]$ can then be written

[56] Here, I am being agnostic about what motivates the driver to care about the values of signals of effort. The driver may be incentivized by future interactions with the manager, or by pure intrinsic motivation. In theory the driver could also receive an pay-per-performance based on the signal, and the results would be unchanged (the reward would then enter the manager's profit function, which is not the case we solve here).

$$
\begin{aligned}
F^1(e_1, e_2, m) &= \mathbb{E}[f^1(s_1, s_2, m)|e_1, e_2] \\
&= \mathbb{E}[\tfrac{\mu_1}{\mu}\mathbb{E}[e_1|s_1] + \tfrac{\mu_2}{\mu}\mathbb{E}[e_2|s_2]|e_1, e_2] \\
&= \tfrac{\mu_1}{\mu}\left[\tfrac{(\sigma_1(m))^2 e_1^0 + (\sigma_1^0)^2 e_1}{(\sigma_1(m))^2 + (\sigma_1^0)^2}\right] + \tfrac{\mu_2}{\mu}\left[\tfrac{(\sigma_2)^2 e_2^0 + (\sigma_2^0)^2 e_2}{(\sigma_2)^2 + (\sigma_2^0)^2}\right]
\end{aligned}
$$

The marginal effect of an increase in task 1 effort on the function F^1 is then

$$
\frac{\partial F^1}{\partial e_1} = F_1^1 = \frac{\mu_1}{\mu}\frac{(\sigma_1^0)^2}{(\sigma_1(m))^2 + (\sigma_1^0)^2}
$$

And the effect of monitoring on the marginal value of increasing effort on task 1 is

$$
\frac{\partial^2 F^1}{\partial e_1 \partial m} = F_{13}^1 = -2\frac{\sigma_1'(m)\sigma_1(m)(\sigma_1^0)^2}{[(\sigma_1(m))^2 + (\sigma_1^0)^2]^2} > 0
$$

The intuition behind this last inequality is that if the signal s_1 becomes more informative about the real value of effort chosen by the driver, then when the manager updates his belief about effort, he will give the signal a higher relative importance compared to his prior. This means that if the manager decides to monitor the driver, the driver's return to providing effort on the monitored task increase.

Since monitoring does not affect task 2's signal quality, there is no effect of monitoring on the marginal value of increasing effort on task 2:

$$
\frac{\partial^2 F^1}{\partial e_2 \partial m} = F_{23}^1 = 0
$$

If this mechanism—that drivers care about the signals of effort received by the manager—is the only one at play (i.e. $F = F^1$) then from (2) and (3)

$$
\frac{\partial e_1}{\partial m} > 0
$$

Monitoring, or in other words reducing the noise on task 1, increases the driver's incentives to provide effort on that task.[57] The effect on task 2 is discussed in the following sections.

[57]Note that depending on how the drivers care about the manager's beliefs (different levels of μ) they will exert different levels of effort at baseline. Highly motivated agents (high μ) will provide a higher level of effort than low motivated agents (low μ).

A.4.2 How monitoring decreases effort on non-monitored tasks

In this section, I explore the mechanisms behind the key empirical finding—how monitoring decreases the effort provided by some drivers on tasks that are not monitored. Each subsection below follows the same mechanisms described in Section 6.2. In each subsection below I suppose that, in addition to the mechanism described above in Section A.4.1, only the mechanism described in that subsection is at play.

Multi-tasking

As in the main text of the paper, suppose the tasks are substitutes in cost: $\frac{\partial cost}{\partial e_1 \partial e_2} > 0$. In addition suppose that $F^2 = 0$ and $F = F^1$.

Following the same logic than in the main text of the paper, from equation (6)

$$\begin{cases} \frac{\partial e_1}{\partial m} > 0 \\ \frac{\partial e_2}{\partial m} < 0 \end{cases}$$

Monitoring increases the effort provided on task 1, and decreases effort provided on task 2, which is the desired effect.

Tit for tat

Mirroring (7) in Section 6.2, let

$$F^2(e_1, e_2, m) = -mC + \gamma(m)\Pi(e_1, e_2)$$

The function F can then be written

$$\begin{aligned} F &= \mu F^1 + \lambda F^2 \\ &= \mu \mathbb{E}[f^1(s_1, s_2, m)|e_1, e_2] + \lambda(-mC + \gamma(m)G(e_1, e_2) - \gamma(m)w) \end{aligned}$$

The effect of monitoring on the marginal value of effort is then

$$\begin{cases} \frac{\partial^2 F}{\partial e_1 \partial m} = F_{13} = \mu F^1_{13} + \lambda F^2_{13} = -\mu r^2 \sigma'(m)\sigma(m)e_1 + \lambda\gamma'(m)G_1(e_1, e_2) \\ \frac{\partial^2 F}{\partial e_2 \partial m} = F_{23} = \mu F^1_{23} + \lambda F^2_{23} = \lambda\gamma'(m)G_2(e_1, e_2) \end{cases}$$

Combining the equations above with Equations (2) and (3), under some assumptions on the shape of the manager's benefit function G, there exists values of λ and μ such that monitoring decreases the effort provided on non-monitored tasks ($\frac{\partial e_2}{\partial m} < 0$) and increases the effort provided on monitored tasks ($\frac{\partial e_1}{\partial m} > 0$).

Signaling Intrinsic Motivation

Let the function f^2 be the manager's belief about the intrinsic motivation of the driver. f^2 takes the following form

$$f^2 = \mathbb{E}[\mu|s_1, s_2, m]$$

Where μ is the weight in front of the function f^1.

The utility of the driver can now be written

$$U = w - cost(e_1, e_2) + \mu\mathbb{E}[\mathbb{E}[\gamma e_1 + \gamma_2 e_2|s_1, s_2]|e_1, e_2] + \lambda\mathbb{E}[\mathbb{E}[\mu|s_1, s_2, m]|e_1, e_2]$$

Where the last term $\lambda_2\mathbb{E}[\mathbb{E}[\lambda_1|s_1, s_2, m]|e_1, e_2]$ is the driver's belief about the manager's belief of his intrinsic motivation, given his effort (e_1, e_2).

Note that this is a slightly different version of the intrinsic motivation framework presented in the main text of the model (see the function F in Equation (8) of the main text for comparison). This is because here the driver values the manager's belief about his effort, while in the version presented in the main text of the paper, the driver values his own effort. This does not change the main insights of the paper.

For tractability, suppose that the cost function takes the following form

$$cost(e_{1,}e_2) = \frac{1}{2}k_1 e_1^2 + \frac{1}{2}k_2 e_2^2$$

The manager has priors about e_1 and e_2, observes the signals s_1 and s_2, and updates e_1 and e_2 as in Section A.4.1. From these inferred values of effort, he then infers a belief about the intrinsic motivation of the driver. Following Section A.4.1, the manager's updated beliefs about the efforts e_1 and e_2 are

$$\begin{cases} \mathbb{E}[e_1|s_1] = & \frac{(\sigma_1(m))^2 e_1^0 + (\sigma_1^0)^2 s_1}{(\sigma_1(m))^2 + (\sigma_1^0)^2} \\ \mathbb{E}[e_2|s_2] = & \frac{(\sigma_2)^2 e_2^0 + (\sigma_2^0)^2 s_2}{(\sigma_2)^2 + (\sigma_2^0)^2} \end{cases}$$

And the driver's ex-ante beliefs about the manager's belief are

$$\begin{cases} \mathbb{E}[\mathbb{E}[e_1|s_1]|e_1,e_2] = & \frac{(\sigma_1(m))^2 e_1^0 + (\sigma_1^0)^2 e_1}{(\sigma_1(m))^2 + (\sigma_1^0)^2} \\ \mathbb{E}[\mathbb{E}[e_2|s_2]|e_1,e_2] = & \frac{(\sigma_2)^2 e_2^0 + (\sigma_2^0)^2 e_2}{(\sigma_2)^2 + (\sigma_2^0)^2} \end{cases}$$

The driver's utility can then be written

$$U = w - cost(e_1,e_2) + \mu\gamma_1 \frac{(\sigma_1(m))^2 e_1^0 + (\sigma_1^0)^2 e_1}{(\sigma_1(m))^2 + (\sigma_1^0)^2} + \mu\gamma_2 \frac{(\sigma_2)^2 e_2^0 + (\sigma_2^0)^2 e_2}{(\sigma_2)^2 + (\sigma_2^0)^2} + \lambda R(e_1,e_2,m)$$

Where $R(e_1,e_2,m) = \mathbb{E}[\mathbb{E}[\mu|s_1,s_2,m]|e_1,e_2]$.

The first order conditions of the driver's utility optimization problem are

$$\begin{cases} 0 = & -k_1 e_1 + \mu\gamma_1 \frac{(\sigma_1^0)^2}{(\sigma_1(m))^2 + (\sigma_1^0)^2} + \lambda R_1(e_1,e_2,m) \\ 0 = & -k_2 e_2 + \mu\gamma_2 \frac{(\sigma_2^0)^2}{(\sigma_2)^2 + (\sigma_2^0)^2} + \lambda R_2(e_1,e_2,m) \end{cases} \tag{A.1}$$

From the first order conditions of the driver and Bayesian updating, the manager then infers a guess about the value of μ.[58]

$$R(e_1,e_2,m) = \mathbb{E}[\mathbb{E}[\mu|s_1,s_2,m]|e_1,e_2] = \frac{\frac{(\sigma_1(m))^2+(\sigma_1^0)^2}{(\sigma_1^0)^2}\frac{1}{\gamma_1}(k_1 s_1 - \lambda R_1)\frac{(\sigma_2)^2+(\sigma_2^0)^2}{(\sigma_2^0)^2}\frac{k_2}{\gamma_2}(\sigma_2)^2 + \frac{(\sigma_2)^2+(\sigma_2^0)^2}{(\sigma_2^0)^2}\frac{1}{\gamma_2}(k_2 s_2 - \lambda R_2)\frac{(\sigma_1(m))^2+(\sigma_1^0)^2}{(\sigma_1^0)^2}\frac{k_1}{\gamma_1}(\sigma_1(m))^2}{\frac{(\sigma_2)^2+(\sigma_2^0)^2}{(\sigma_2^0)^2}\frac{k_2}{\gamma_2}(\sigma_2)^2 + \frac{(\sigma_1(m))^2+(\sigma_1^0)^2}{(\sigma_1^0)^2}\frac{k_1}{\gamma_1}(\sigma_1(m))^2} \tag{A.2}$$

Equation A.2 is a simple linear differential equation in R, which can be solved and

$$\begin{cases} R_1(e_1,e_2,m) = & \frac{k_1 \frac{(\sigma_1(m))^2+(\sigma_1^0)^2}{(\sigma_1^0)^2}\frac{1}{\gamma_1}\frac{(\sigma_2)^2+(\sigma_2^0)^2}{(\sigma_2^0)^2}\frac{k_2}{\gamma_2}(\sigma_2)^2}{\frac{(\sigma_2)^2+(\sigma_2^0)^2}{(\sigma_2^0)^2}\frac{k_2}{\gamma_2}(\sigma_2)^2 + \frac{(\sigma_1(m))^2+(\sigma_1^0)^2}{(\sigma_1^0)^2}\frac{k_1}{\gamma_1}(\sigma_1(m))^2} = R_1(m) \\ R_2(e_1,e_2,m) = & \frac{k_2 \frac{(\sigma_2)^2+(\sigma_2^0)^2}{(\sigma_2^0)^2}\frac{1}{\gamma_2}\frac{(\sigma_1(m))^2+(\sigma_1^0)^2}{(\sigma_1^0)^2}\frac{k_1}{\gamma_1}(\sigma_1(m))^2}{\frac{(\sigma_2)^2+(\sigma_2^0)^2}{(\sigma_2^0)^2}\frac{k_2}{\gamma_2}(\sigma_2)^2 + \frac{(\sigma_1(m))^2+(\sigma_1^0)^2}{(\sigma_1^0)^2}\frac{k_1}{\gamma_1}(\sigma_1(m))^2} = R_2(m) \end{cases}$$

[58]Here the manager has no prior on the value of μ. We don't need this assumption to match the empirical findings, but it can be easily incorporated in the model.

Where R_1, the marginal effect of an increase in task 1 effort on the manager's belief about intrinsic motivation, is an increasing function of the monitoring decision m, and R_2, the marginal effect of an increase in task 2 effort on the manager's belief about intrinsic motivation, is a decreasing function of the monitoring decision m.

From equation (A.1) above, we know that

$$\begin{cases} e_1 = \mu \frac{\gamma_1}{k_1} \frac{(\sigma_1^0)^2}{(\sigma_1(m))^2 + (\sigma_1^0)^2} + \frac{\lambda}{k_1} R_1(m) \\ e_2 = \mu \frac{\gamma_2}{k_2} \frac{(\sigma_2^0)^2}{(\sigma_2)^2 + (\sigma_2^0)^2} + \frac{\lambda}{k_2} R_2(m) \end{cases}$$

and

$$\begin{cases} \frac{\partial e_1}{\partial m} > 0 \\ \frac{\partial e_2}{\partial m} < 0 \end{cases}$$

A.5 Additional Figures

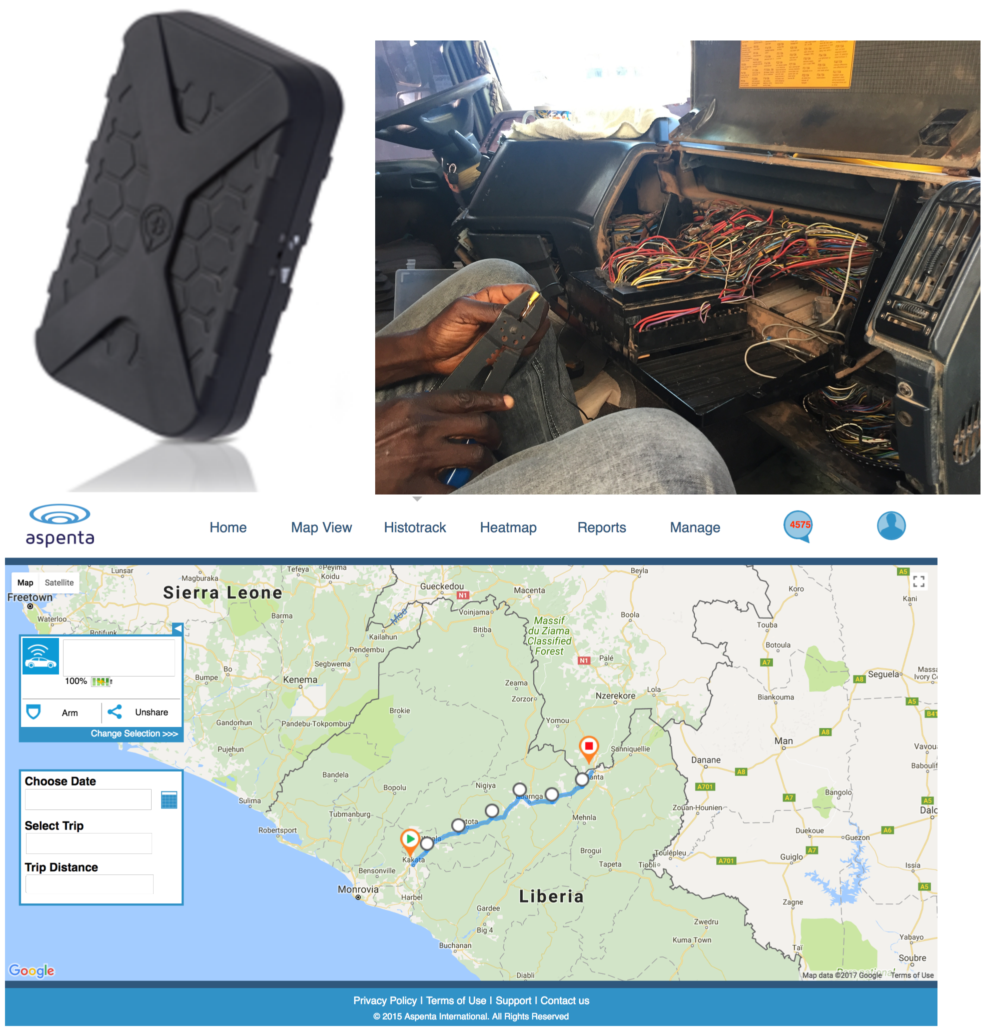
Figure A.1: Liberia's Road Network

Panel A : Map of Liberia's Road Network

Panel B : Picture of Trucks on an Unpaved Road During the Rainy Season

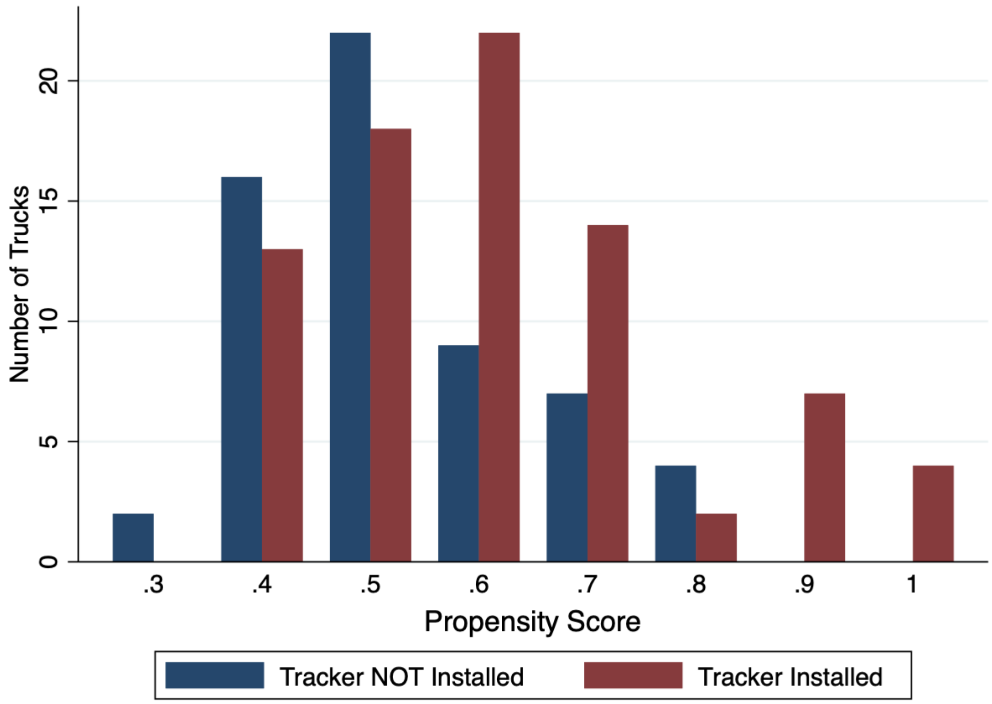
The top panel presents a map of the main road network in Liberia. On the map, the width of roads is proportional to their state, where 0 is a very damaged road and 10 is an all-season paved road. The bottom panel is a picture taken from the media GNN Liberia in 2016. The combination of a poor road network and heavy rains makes travel times very uncertain.

Figure A.2: GPS Tracker and Truck Dashboard



The top-left picture shows a GPS tracker, a small black box of 3 inches by 2. The top-right shows a mechanic installing the tracker on a truck's dashboard. The bottom picture shows an example of what can be seen by the manager when he log into his online account.

Figure A.3: Histogram of the Propensity to be Treated Score



The graph presents two histograms of the "propensity to be treated" score for drivers of the treatment group. The drivers who had a GPS tracker are more likely to have a high propensity to be treated, drivers who did not are more likely to have a low propensity to be treated.

A.6 Additional Tables

Table A.1: Effect of Monitoring on Speed Fixed Effects

	Instrumental Variable			Reduced Form		
PANEL A: MANAGER INTERVIEWS						
	(1)	(2)	(3)	(4)	(5)	(6)
	Speed (km/h)					
Treatment	2.89	44.1***	29.9*			
	(7.71)	(16.18)	(15.66)			
Assignment-to-Treatment				1.03	16.7	11.3
				(2.77)	(11.37)	(11.21)
Observations	203	119	119	203	119	119
PANEL B: DRIVER INTERVIEWS						
	Instrumental Variable			Reduced Form		
	(1)	(2)	(3)	(4)	(5)	(6)
	Speed (km/h)					
Treatment	10.5**	15.2***	14.5***			
	(4.99)	(3.51)	(3.44)			
Assignment-to-Treatment				6.54**	9.02*	8.66*
				(3.23)	(4.51)	(4.44)
Observations	240	159	159	240	159	159
Season FE	YES	YES	YES	YES	YES	YES
Road FE		YES	YES		YES	YES
Driver FE		YES	YES		YES	YES
Controls			YES			YES

Standard errors are in parentheses and are robust. This table presents coefficients of the regression of speed as calculated by dividing time over distance from trips recorded in managers interviews. This specification is at the driver level, with each observation being a driver-round observation. Since driver fixed effects require to observe drivers at least once before and once after the treatment, adding these fixed effects reduces the number of observations. Controls include whether the truck came back empty from the trip (backload), whether there was a technical issue during the trip and whether the truck was accompanied by another truck during the trip.

Table A.2: Effect of Monitoring on Break Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: MANAGER INTERVIEWS						
	Instrumental Variable			Reduced Form		
	Percentage of Trip Spent on Breaks (%)					
Treatment	7.91	-18.6*	-15.1			
	(7.49)	(9.51)	(9.37)			
Assignment-to-Treatment				2.79	-7.03	-5.71
				(2.59)	(6.75)	(6.67)
Observations	142	119	119	142	119	119
PANEL B: DRIVER INTERVIEWS						
	Instrumental Variable			Reduced Form		
	(1)	(2)	(3)	(4)	(5)	(6)
	Percentage of Trip Spent on Breaks (%)					
Treatment	-5.61	-14.7***	-13.2***			
	(6.30)	(4.24)	(4.80)			
Assignment-to-Treatment				-3.59	-8.72*	-7.85
				(4.01)	(5.13)	(6.05)
Observations	204	159	159	204	159	159
Season FE	YES	YES	YES	YES	YES	YES
Road FE		YES	YES		YES	YES
Driver FE		YES	YES		YES	YES
Controls			YES			YES

Standard errors are in parentheses and are robust. This table presents coefficients of the regression of breaks as calculated by dividing the time spent on breaks over total trip time recorded in managers interviews. This specification is at the driver level, with each observation being a driver-round observation. Since driver fixed effects require to observe drivers at least once before and once after the treatment, adding these fixed effects reduces the number of observations. Controls include whether the truck came back empty from the trip (back-load), whether there was a technical issue during the trip and whether the truck was accompanied by another truck during the trip.

Table A.3: Effect of Monitoring on Breaks, Per Type of Break

	Instrumental Variable			Reduced Form		
	(1)	(2)	(3)	(4)	(5)	(6)
	Percentage of Trip Spent on Breaks (%)					
	Mud Stop	Delivery	Personal Break	Mud Stop	Delivery	Personal Break
Treatment	-3.65	-0.63	-9.47**			
	(4.17)	(2.31)	(4.23)			
Assignment-to-Treatment				-1.80	-0.31	-4.67
				(3.49)	(1.91)	(3.67)
Observations	337	337	337	337	337	337
Season FE	YES	YES	YES	YES	YES	YES
Road FE	YES	YES	YES	YES	YES	YES
Driver FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

Standard errors are in parentheses and are robust. This table presents coefficients of the regression of breaks as calculated by dividing the time spent on each type of breaks over total trip time recorded in drivers interviews. This specification is at the trip level. Controls include whether the truck came back empty from the trip (back-load), whether there was a technical issue during the trip and whether the truck was accompanied by another truck during the trip.

Table A.4: Effect of Monitoring on Technical Issues, Accidents and Maintenance Costs

	(1)	(2)	(3)
	Technical Issues	Accidents	Maintenance Costs
treated	0.096	0.025	6.20
	(0.09)	(0.08)	(78.30)
Observations	285	285	228
Season FE	YES	YES	YES
Road FE	YES	YES	YES
Driver FE	YES	YES	YES
Controls	YES	YES	YES

Standard errors are in parentheses and are robust. This table presents coefficients of the regression of technical issues, accidents and maintenance costs as estimated by managers. This specification is at the driver level, with each variable being the average for each driver per round of interview. Controls include whether the truck came back empty from the trip (back-load), whether there was a technical issue during the trip and whether the truck was accompanied by another truck during the trip.

Table A.5: Baseline Comparisons by Treatment Take-Up

	Difference	Std. Error
Speed driver fixed effects (km/h)	-3.352	5.772
Breaks driver fixed effetcs (% of trip)	3.096	12.697
Does the driver use the truck for personal reasons?	0.172	0.109
Does the driver carry unauthorized passengers or goods?	0.154	0.117
Does the driver infringe any of the rules?	0.235	0.105
Number of accidents the driver had in the past year	0.301	0.157
You have a good relation with the driver	-0.372	0.291

Baseline comparisons between drivers who were in the treatment group and received a GPS tracker on their truck, and driver who were also in the treatment group and did not receive a GPS tracker on their truck. Results are based on manager interviews. Speed and Break are estimated as a driver fixed effect, with season and road fixed effects, as well as controls. To the sentence "You have a good relationship with the driver", the manager was asked to select a score between 0 (disagree) and 10 (agree).

Table A.6: Effect of Monitoring on Driver Effort by Propensity to be Treated

	(1)	(2)	(3)
	Overall Rules	Observable Rules	Non-Observable Rules
Treatment x Low Propensity Drivers	0.39**	0.19	0.37**
	(0.19)	(0.24)	(0.17)
Treatment x High Propensity Drivers	-0.38	-0.35*	-0.41*
	(0.25)	(0.20)	(0.25)
Observations	275	275	275

Standard errors are in parentheses and are robust. This table presents the heterogeneity estimation of the effect of monitoring. The outputs are based on drivers' answer to the question "Have you infringed a rule set out by your manager in the past month?", referring to each rule in particular. Column (1) include any rule, Column (2) includes rules that can be observed with the GPS tracker, Column (3) includes rules that are not easily observed with a GPS tracker. The table present Local Average Treatment Effects, where treatment is instrumented by assignment-to-treatment.