PEDL Research Papers

This research was partly or entirely supported by funding from the research initiative Private Enterprise Development in Low-Income Countries (PEDL), a Foreign, Commonwealth & Development Office (FCDO) funded programme run by the Centre for Economic Policy Research (CEPR).

Information and Strategy in Lemon Markets: Improving Safety in Informal Transit

Gregory Lane ⓡ David Schönholzer ⓡ Erin Kelley*

September 1, 2022

Abstract

Road traffic accidents in poorly regulated public transit is a leading cause of death in low- and middle-income countries. We study how providing information about bus safety to passengers affects the demand and supply of safer public transit. We collect high-frequency measures of safe driving for five firms operating on one of the busiest long-range routes in Kenya, using a newly developed tracking device. We randomize private information to passengers about which firm is the safest choice. We then provide a public signal to both passengers and firms that buses are now being tracked. Treated passengers do not respond to private information at first, but after the introduction of the public signal they substitute strongly towards the safe firm, and some firms provide safer services. We rationalize these effects in a model of heterogeneous firms responding strategically to higher demand for safety due to the public signal. We derive welfare estimates of alternative equilibria, which imply that the welfare effects of information interventions crucially depend on the nature of the market equilibrium.

*Kelley: Development Impact Evaluation Unit, World Bank (erinmkelley@worldbank.org). Lane: Harris School of Public Policy, University of Chicago (laneg@uchicago.edu). Schönholzer: Institute for International Economic Studies, Stockholm University (david.schonholzer@iies.su.se). We thank Jeremy Magruder, Elisabeth Sadoulet, Fiona Burlig, Frederick Manang, Lauren Falcao-Bergquist, Alessandra Peter and audiences at the IIES for helpful feedback. We gratefully acknowledge financial support from the Weiss Fund, CEGA, and T-TRIID. We thank Jeremy Gordon, Boris Maguire, and James Mwangi at EchoMobile for exceptional technical assistance and field management.

1 Introduction

Economists broadly agree that markets work poorly when consumers lack reliable information on the quality of products (Akerlof, 1970). These lemon markets exhibit low demand, limited market size, and depressed consumer welfare. Uncertainty about product quality is particularly high in low- and middle-income countries, resulting in widely documented problems such as subpar medicine (Bennett and Yin, 2018; Björkman Nyqvist et al., 2018), fertilizers (Bold et al., 2017), or grain (Bold et al., 2022). Providing information to consumers may improve welfare by guiding them towards better choices (Levin, 2001) or incentivizing firms to supply higher quality (Bai, 2018), which motivates the widespread use of policies such as restaurant hygiene grades (Jin and Leslie, 2003) or food labeling (Barahona et al., 2020).

We study the role of consumer information in reducing inefficiencies when markets are not perfectly competitive. Firms in low-income countries frequently exert considerable market power (Bergquist and Dinerstein, 2020). But the role of market power for the effectiveness of consumer information is poorly understood: competition may obviate the need for consumer information by reducing inefficiencies (Muthoo and Mutuswami, 2011), but competition may also exacerbate uncertainty about product quality if it breaks down relational contracts (Macchiavello and Morjaria, 2021). When only a small number of firms compete, both equilibria with low-quality provision and with high-quality provision may exist, and consumer information may shift a market from one equilibrium to another.

In this paper, we investigate whether and how consumer information improves lemon markets when firms have market power in the context of Kenya's informal public transit sector. Informal transit plays a central role in making traffic fatalities a leading cause of death in many low- and middle-income countries (WHO, 2020). For example in Kenya, more than 70% of road accidents involve public transit vehicles even though they make up only around 10% of vehicles (Macharia et al., 2009). While the industry as a whole is perceived as exceedingly unsafe, passengers lack reliable information that would allow them to distinguish safer from less safe options. Given that only a small number of firms provide transport services on major routes, the efficacy of consumer information crucially depends on strategic responses by both firms and passengers.

To study these responses, we run a randomized control trial with more than a thousand passengers at one of Kenya's busiest bus terminals in three stages. In the first stage, we equip 52 buses across five firms operating on a major route with safety tracking devices and give managers access to the safety data, allowing them to monitor their buses' safety behavior. In the second stage, we randomize private information to passengers about which firm provides the safest services. This allows us to estimate consumer valuation of baseline differences in safety between firms. In the third stage, we then provide a public signal to both passengers and firms about the provision of safety information. This public signal informs passengers that firms have enhanced capacities to provide safe services, and it informs firms that passengers may learn about their safety performance. The response of passengers receiving private information in the presence of the public signal pins down their valuation of safety improvements they expect firms to undertake due to the tracking devices, while the safety response of firms illuminates their strategic response to the change in the information environment.

In our first contribution, this experiment yields two novel findings on the causal effects of consumer information in lemon markets with strategic firms. First, we find that passengers do not respond to private safety information at baseline, indicating that they deem differences in safety between firms to be small relative to other aspects of consumer choice. But after the introduction of the public signal, consumers substitute strongly towards the safe choice, which suggests that they expect some but not all firms to compete on the safety margin. This finding shows that the effectiveness of consumer information critically depends on consumer expectations about strategic firm responses. Second, and consistent with these passenger expectations, we estimate a substantial improvement in the supply of safety, primarily among the two lowest-performing firms. This supply response led to a 25% drop in speeding alerts, likely contributing to meaningful improvements in road safety. This second finding shows that consumer information can exert positive externalities on firm behavior, but that it may not affect all firms in the same way.

We interpret the changes in demand and supply through the lens of a game-theoretic model in which heterogeneous consumers and firms strategically respond to incentives for safety. We show that three types of equilibria are possible: a pooling equilibrium in which no firm provides safety; a separating equilibrium in which only some firms improve their safety performance; and a pooling equilibrium in which all firms supply safer transport. The demand and supply responses to our experiment allow us to distinguish between these equilibria: in pooling equilibria, comparative advantages in safety across firms remain unchanged and hence there should not be any demand response. It must then be that consumer information induced a separating equilibrium. The model allows us to further distinguish between a separating equilibrium in which worse firms catch up to better firms, or better firms pull away from worse firms. Investigating heterogeneous responses to the public signal across firms, we find strong evidence that it is indeed worse firms catching up to better ones.

We investigate a number of alternative explanations for these effects. Passengers may perceive private information to be more trustworthy after the introduction of the public signal, but they exhibit a similar propensity to respond to a separate treatment requiring trust in information we provide before and after the public signal. The public signal may have increased the salience of safety, but passengers do not respond to placebo information increasing the salience of safety before the public signal. Passengers may be subject to an interviewer demand effect after the public signal, but stated preferences for safety are unchanged. They could also be concerned about the social signal of their choice, but they receive information privately so their actions are hard to interpret by others. Passengers may coordinate on the safe choice under the public signal, but the serial correlation of choices of consecutive passengers remains low and insignificant. Finally, the supply effect may be a statistical artifact due to reversion to the mean, but our safety index exhibits substantial stability in the three months before and after the introduction of the public signal.

In our second contribution, this model provides a foundation for welfare analysis of consumer information in markets with strategic firms. We show that the welfare effect of the intervention can be expressed as a combination of consumer valuations of improved safety and demand shifts across firms. We exploit a randomized subsidy for passengers to choose the safest firm to convert these shifts in behaviors into dollar values. Consumer surplus can be decomposed into a direct effect of information due to the shift of consumers to firms with higher safety provision and an information externality due to the supply response. Importantly, we are able to derive and decompose these welfare expressions not only for the catch-up separating equilibrium that prevails in our market under the public signal but also for alternative pooling and separating equilibria that have not been realized.

We show that three central welfare components can be easily estimated via maximum likelihood in a Logit framework: consumer valuation of baseline safety differences; valuation of safety improvements; and the demand share captured by the safest firm. We estimate that consumer valuation of baseline safety differences is small. In contrast, valuation of safety improvements is moderately large, on the order of 6% of the ticket price. The safest firm's demand increases by 14 percentage points, roughly doubling its market share. Together with estimates on the number of daily passengers, the share of firms that respond to the treatment, the cost of safety improvements per bus, and the cost of the information intervention, we estimate that the monthly welfare effect of our consumer information was around $12,000.

The lion's share of this welfare impact stems from the information externality due to the supply response driving up the consumer surplus. The producer surplus is negative and on the order of about \$3,000 across all firms. The cost of the information provision itself is negligible, suggesting that this intervention is cost effective.

A great strength of our framework is that we can also estimate welfare under counterfactual equilibria. We estimate that the welfare effects of consumer information would have been slightly negative under a low-pooling equilibrium, primarily driven by the cost of the intervention. Under a pull-away separating equilibrium, in which only already relatively safe firms further improve their services, welfare would have been substantially higher than the catch-up separating equilibrium prevailing in our setting (on the order of \$20,000 per month), primarily due to a higher consumer surplus due to passengers shifting to firms with higher baseline safety. Finally, if a high-pooling equilibrium had prevailed in which all firms had improved by a similar margin, welfare benefits would have been around \$30,000, more than twice the magnitude of our prevailing catch-up separating equilibrium, although the burden on producers would have also been more than twice as large.

This paper contributes primarily to the literature on lemon markets in developing countries. High-income countries combat inefficiencies in lemon markets with government regulation and inspection. In low-income countries with weak state capacity fewer solutions have been identified and studied. Bai (2018) finds that supplying tamper-proof technologies to firms induces them to provide higher quality goods as they build consumers' trust. Alternatively, Björkman Nyqvist et al. (2018) and Bennett and Yin (2018) find that large firm entry can spur other producers to improve the quality of the products they supply. Our study provides a new avenue to address lemon market inefficiencies by combining consumer information with public signals raising the perceived returns to higher-quality provision. We demonstrate that such a policy can induce a strategic response among firms that may improve welfare.

Our study also contributes to a small literature on the welfare effects of market regulation by providing product information to consumers. Jin and Leslie (2003) study the introduction of hygiene grades for restaurants in Los Angeles County, finding that service quality improved and demand for high quality increased. Barahona et al. (2020) estimate the demand and supply responses to a warning label mandate on unhealthy foods. Similar to our study, they consider firms with market power whose response may undo or amplify the intended effects of the mandate. We offer the first welfare estimates of consumer information using a randomized trial. Our study is also unique in that we allow for multiple equilibria to exist and we show how to estimate welfare when a market may switch from one equilibrium to another.

Finally, there is growing recognition of the importance of road safety and speed enforcement in particular (Bauernschuster and Rekers, 2022). We contribute to a limited literature on road safety in low- and middle-income countries in economics. Road traffic accidents are an enormous challenge in these countries, burdening economic development and the healthcare sector (Odero et al., 2003; Cervero and Golub, 2007; Raynor and Mirzoev, 2014). Habyarimana and Jack (2011, 2015) use stickers in minibus' to encourage commuters to speak up when drivers engage in dangerous driving. They find this intervention lowers minibuses' average speed on long distance routes in Kenya. Our paper builds on this work by intervening more directly with passengers about minibus safety ratings *before* they board the bus, which has the potential to shift a market to a better equilibrium. Furthermore, we see that providing information to passengers can incentivize bus companies to improve their safety performance, mitigating some of the inefficiencies associated with lemon markets. Importantly, these types of consumer information campaigns may need to be accompanied by public signals that provide incentives on the supply side.

The rest of the paper is organized as follows. Section 2 presents the context and the design of the randomized control trial. Section 3 provides an overview of the data and the econometric framework. Section 4 discusses the experimental results. Section 5 presents the model and Section 6 discusses its welfare implications. Finally, Section 7 concludes.

2 Context and Interventions

2.1 Informal Transit in Kenya

According to the WHO an estimated 1.35 million people are killed annually in road accidents and as many as 50 million individuals are injured worldwide (WHO, 2020). More than 90% of these deaths occur in low and middle-income countries, which have less than 60% of the world's vehicles. In Kenya alone, approximately 3,000 to 13,000 people die each year as a result of reckless driving (WHO, 2015). These road accidents often involve public transportation vehicles. In many low-income countries including Kenya, the public transportation sector is dominated by private minibuses that are notoriously unsafe: drivers often speed, stop suddenly, and perform other dangerous maneuvers in order to collect more passengers and arrive at their destinations more quickly. According to one study, matatus account for 11% of registered vehicles but 70.2% of passenger casualties (Macharia et al., 2009).

One reason why minibus companies undersupply safe rides is that passengers cannot observe how safe a bus is before they board. This information asymmetry between firms and consumers means that each company has less incentive to provide a safe ride as they cannot hope to capture extra revenue by supplying this unobserved quality, even if it is demanded by passengers.[1] This leads to a scenario where there is potentially unmet demand for safety, a scenario that can be thought of as a typical lemons market. This status quo jeopardizes not only the safety of passengers on board, but also other vehicles on the road, and pedestrians.

Given this state of affairs, governments and international institutions are looking for ways to address road safety. This can be challenging in low-income countries where state capacity is weak and regulations are difficult to enact and enforce. Only 28 countries, representing 7% of the world's population, have implemented laws that address all five road risk factors (speed, drunk driving, helmets, seat-belts and child restraints). Less than 35% of low- and middle-income countries have policies in place to protect road users, despite experiencing the highest fatality rates in the world. In Kenya, the government passed the Michuki rules in 2003 requiring that buses install speed limiters, safety belts, and exhibit valid licenses (Michuki, 2003). To date, this limited set of regulations are poorly enforced by the Kenyan police service, which is notoriously corrupt. A survey conducted by Transparency International revealed almost 75% of minibus drivers regularly pay bribes to the police (**?**).

An alternative to government regulation is to empower customers with information. There have been some attempts to do this in Kenya. Ma3 route is a mobile/web/SMS platform in Nairobi that crowd-sources for up to date transportation data, and provides users with information on traffic, matatu directions and driving reports. Similarly, **?** launched the Zusha Road Safety Campaign by placing stickers inside matatus that encourage passengers to speak up against bad driving. In a similar spirit, we implement an experiment in Kenya's public transit industry to directly alleviate information asymmetries between minibus firms and their customers.

We conducted our experiment in one of the largest bus terminals in Kenya, operating near Nairobi's central business district (see Appendix Figure A.2). The terminal offered served between Nairobi and Kisumu, one of the most important and busiest long-distance bus routes in the country. The bus route, like most in Kenya, is dangerous with numerous deadly accidents involving matatus occurring per year. The terminal serves both regular business passengers that transit between Nairobi and Kisumu several times a year, as well

[1] Firms may care about costs from any damages to the vehicle. However we show in a companion paper, Kelley et al. (2022), that these private firm benefits are small and therefore firms have no internal incentive to improve safety.

many passengers who infrequently travel between the two locations.

2.2 Safety Measurement Technology

The intervention required the ability to collect information about the safety of the minibus and supply it in a user-friendly way to different parties. To this end, we developed a new monitoring system for matatus that was considerably cheaper, more flexible and more user-friendly than traditional tracking devices. The physical tracking units were procured from a company in the United States. They featured a GPS and a 3-axis accelerometer for motion sense, tilt and impact detection. The device captured the vehicle's location and forward/backward/lateral/vertical acceleration at 30 second intervals. The device was also calibrated to generate alerts for every instance of vehicle speeding and sharp braking. These safety alerts were calculated by an internal algorithm built into the CalAmp device with threshold parameters as inputs. Further processing of the system data on the server provided additional measures of interest including the total number of kilometers traveled that day, the total time the matatu was running, and a safety index (from aggregating the day's safety alerts).

2.3 Design of Information Experiments

The study location is well suited to the study's requirements. It is a well defined location, with two clear entry points and less congested than other stations in the vicinity, which meant that we could more easily intercept passengers (see Appendix Figure A.2). We worked with five different SACCOS that operated a fleet of minibuses from Nairobi to Kisumu from the terminal. We fit a minimum of six buses per SACCO with our GPS tracking device. After completing the installations of the tracking devices, we collected one month of tracking data for each bus. We then used this information to reliably compare the safety performance of one SACCO relative to another based on the average safety scores of their tracked minibuses.

Information treatment. Our field team intercepted passengers as they entered the bus terminal area, but before they had an opportunity to purchase a ticket for a specific SACCO. We successfully intercepted approximately 30% of the individuals we approached, resulting in a sample size of 2,415 passengers. We randomly assigned passengers to one of three arms that differed in the amount of information we provided.[2] In the control group, passengers

[2] We created a pre-randomized list with a set of passenger ID's (or "key") and an associated treatment status. The individual keys were included on the pamphlets, which were printed in the same order as the

received a pamphlet with an ID key printed on it, but nothing more. In the salience group, passengers received a pamphlet that contained a message about the safety of the matatu industry, a picture of a matatu after an accident, and a list of the five SACCOs operating from the terminal (see Figure 1). Finally, passengers assigned to the safety information group, received the same pamphlet as the salience group with one notable exception: one of the five SACCOs appeared prominently with the message "Top Safety performer" alongside it. The enumerator carefully explained what this meant and how the title was awarded. Once the pamphlets were assigned, enumerators asked all passengers to report which bus they chose to a second enumerator stationed further down the road where the buses were leaving from. Before passengers left to choose their bus, enumerators tore off the bottom of the pamphlets where the safety information was displayed. This served the purpose of keeping the safety information private from the SACCO managers. Passengers received 50 KES (0.50 USD) for showing their ticket to the second enumerator.

The three information treatment arms were designed to identify two effects. First, comparing the control group to the safety salience group identifies whether priming passengers about matatu safety affects their choice of firm. Second, the comparison of the information group to the salience group will identify the impact of revealing new information about which firm is in fact the safest option on the route. To the extent that passengers use this new information to update their priors about safety, we would expect this treatment to increase the probability that passengers choose the firm marked as "Top Safety performer"

Public signal. Five months into delivering pamphlets and subsidies to passengers we went "public" with our campaign. In particular, we printed two large signs and placed them at the entrance of the bus terminal. The signs read *"Sacco's on Mfangano-Kisumu are now tracked for safety, enjoy the benefits of safer transit, and check out the Top Safety Performer"* (see Figure 2). Everything else about the firm-customer experiments remained the same, and the timing of the treatment was chosen so as to not coincide with other events that could have affected demand or supply. The signs alerted drivers and SACCOs that this information was being delivered publicly to their customer base, which could affect their reputation and ultimately their demand. Before the sign was revealed, we made sure to visit each participating firm and inform them that we would begin to advertise the safety system at the bus station, and explain that passengers would be informed about the top safety performer. We also chose the timing of the public signal so that it did not coincide

randomization lists and provided to the enumerators for distribution. The enumerators were unaware of the process and simply handed out the pamphlets in the same order they were received.

with other seasonal market changes (e.g. major holidays).

Subsidy. In order to provide a benchmark for the magnitude of any effect of the information treatments, we also introduced a sub-experiment where passengers were cross randomized into an additional "subsidy treatment". We selected half of the respondents to receive a 100 KES ($1 USD) subsidy should they purchase a ticket from the Top Safety performer. The other half of the respondents did not receive any additional incentives beyond the 50 KES that they were awarded for completing our surveys. When the subsidies were provided to passengers in the control and safety salience group, enumerators were careful not to tell passengers why this particular bus was being subsidized. The subsidy treatment captures how many passengers are willing to change their choice of bus in response to the subsidy, which we use to assign monetary value to the information treatments.

3 Data and Econometric Framework

We collected data from two different sources. First, we have passengers' survey responses and bus choices collected at the bus terminal area. Second, we have GPS tracker data, which we use to measure driving behavior, and generate the safety ratings detailed above.

Passenger Surveys. We administered a baseline survey to passengers before handing them their assigned pamphlet. This survey collected information about their demographics, their experience riding matatus on this particular route; their preferences for various matatu characteristics including speed, comfort, safety, and style; and their beliefs about which of the five SACCOS was the best along each of these dimensions. After completing the survey, we explained to passengers that the five digit key at the bottom of their pamphlet should be presented to a second enumerator after they purchased their bus ticket in order to claim their 50 KES incentive (note that in in the case of control group the key constituted the entire pamphlet).

Passengers would then purchase their ticket and approach the second enumerator with their key and their ticket receipt. The second enumerator entered both these data points into an "endline survey" and issued the 50 KES reward to all passengers, and an additional 100 KES to those who were in the subsidy treatment and purchased a ticket with the Top Safety performer. The key was recorded to facilitate matching with baseline, and the ticket receipt was entered to record passengers' bus choice. Finally, we asked each passenger whether we could contact them later that day to conduct a travel experience survey. We recorded the phone number of those who agreed, and contacted them via SMS that evening. The survey asked them to rank the overall safety of their journey on a scale from 1 to 5, where 1 was very unsafe and 5 was very safe. We also asked them to flag any specific instances of unsafe driving such as speeding or near accidents.

Tracking data. The monitoring device transmitted high-frequency data on acceleration, braking, speed, and location. In addition to average speed, the tracker subsequently fed the raw data into an algorithm that computed the number of safety events that occurred in a 30-second time frame. These events include speeding and sharp braking, which were recorded if these raw measures exceeded a certain threshold. Threshold were calibrated to the Kenyan road conditions to capture context-appropriate levels of unsafe driving. Finally, we aggregate average speed and our two safety events into a safety index using inverse covariance indexing as in Anderson (2008).

Appendix Figure A.1 shows summary statistics of all safety measures by firm as well as the underlying number of fitted buses and observed bus-days. The number of observed bus-days varies from 339 to 1,191, giving us fairly precise estimates of firm-specific distributions. The distributions of the safety index across the five firms in our study is shown in Figure 3. While there is substantial overlap in these distributions, we can see that safety varies systematically across firms: for example, the average of safety performance in Firm 1 is 0.25 index points higher than of Firm 5, which is associated with a more than 25% drop in the number of speeding and sharp braking alerts per mile driven.

Summary statistics of passengers. Table 2 shows summary statistics of passengers approaching the bus stop. As expected, passengers randomized into control, placebo, and safety information have similar characteristics, state similar preferences over bus characteristics, and are exposed to similar choice sets. Around 86% of passengers take a bus on this route less than once a month, making it difficult for them to learn about systematic differences in safety performance across firms. The majority of passengers names safety as the most important characteristic of their bus choice, underscoring the importance of the issue. Most passengers arrive at the bus terminal at a time when they have the full choice set: on average, they can choose between about 4.3 out of 5 firms with a bus that leaves within 45-90 minutes.[3]

[3]Buses depart when full, but it is difficult to know when this will be. The number of seats already occupied is only a noisy indicator as firms sometimes hire confederates to make a bus seem closer to full (which is when it typically leaves) than it actually may be.

Regression equations. We run the following regression model as our preferred specification to understand the impact of our treatments on passenger bus choices.

$$\begin{aligned} D_i = \alpha &+ \beta_1 \text{Placebo}_i + \beta_2 \text{Safety}_i \\ &+ \beta_3 \text{Placebo}_i \times \text{Public}_{t(i)} + \beta_4 \text{Safety} \times \text{Public}_{t(i)} + \mathbf{X}_i' \gamma + \varepsilon_i \end{aligned} \tag{1}$$

where D_i is an indicator equal to 1 if passenger i selected the safety certified bus and $\mathbf{X}_i$ are controls for individual characteristics and ε_i is an error term.[4] The treatment indicators are Placebo_i for our safety salience treatment and Safety_i for the safety information treatment. Last, $\text{Public}_{t(i)}$ is an indicator equal to one if the interview was conducted on a day after the public signal was activated. To test robustness, we also run specifications without interview timing controls and passenger characteristic controls.

Next, to estimate the effect of the public treatment on firm safety performance, we run the following regression:

$$Y_{m,t} = \alpha_m + \beta \text{Public}_t + \varepsilon_{m,t} \tag{2}$$

where $Y_{m,t}$ is bus m on day t safety outcome, α_m is a bus fixed effect, and Public_t is an indicator that takes the value of one if the public signal has been launched. We cluster standard errors at the bus level.

4 Experimental Results

4.1 Effects of Private Information

We start with the effect of our information and salience treatments on customers before the public signal. Table 3 presents the results from equation 1. Rows 1 and 2 of the table show the effects of the Salience and Information treatments on the probability that a passenger buys a ticket with the bus company that was awarded the Top Safety Performer *before* the public signal. Columns 1-4 show the point estimates on each treatment varying whether fixed effects and passenger controls are included. Across all specifications, we see that there is no detectable effect of either treatment on passenger bus choice. In our preferred specification in column 4, the safety information treatment had a precisely estimated zero impact on the

[4]Specifically, $\mathbf{X}_i$ contains the day of week by time of day when the interview took place (e.g. Monday morning or Wednesday evening), gender, age, education, and travel frequency of the respondent.

probability that the passenger chose the top safety performer.[5]

4.2 Effects of Public Signal

Demand side. After several months of delivering these pamphlets to passengers, we went 'public' with the safety campaign. We placed two large, visible signs at the entrance of the bus terminal indicating that SACCOS on the route were being monitored for safety (see Figure 2). Rows 3 and 4 of Table 3 shows how the effect of both information treatments in the post-public period (days where the public signs were on display) change from the private information period. In all specifications, we see that the public signal increased the the impact of the safety treatment arm meaningfully. In our preferred specification in Column 4, passengers that are informed who the top safety performer is are 10.9 percentage points (nearly 100 percent) more likely to choose that company. This represents an important shift from passengers' reactions to the same information when the signs were not displayed on the street. This result suggests that the signs themselves are changing the way passengers interpret the information we provide about the Top Safety Performer in the pamphlet.

Supply side. The passenger results above suggest that passengers perceive the safety information as conveying more information when the campaign was public. Perhaps this is because passengers now expect that bus companies themselves are engaged in competition along this dimension now that it is an observable characteristic. We investigate whether it is indeed the case that companies improve their safety performance when we publicly provide information to passengers. Table 4 reports the estimates of equation 2 on the three safety components as well as the overall safety index. We see that all measures show meaningful and statistically significant improvements in safety in the public period. Starting with column 1, average speed fell by 1.33 miles per hour, which is a 3 percent reduction. Likewise, column 2 and 3 show that the daily number of high speeding and sharp braking events were reduced by 0.115 (25% decrease) and 0.01 (33%) respectively. Combining all three metrics into a safety index, column 4 shows that the average safety metric improved by 0.164 standard deviations. Figure 4 plots these safety improvements from during the public intervention visually. All four plots show a visually detectable improvement from the pre-period to the

[5] We consider the possibility that firms responded to the provision of private information to passengers, which could have occurred if bus drivers noticed our enumerators and communicated the information to their managers. We test this possible Hawthorne effect using data from our pilot period starting from when buses were being tracked but enumerators were not yet interacting with passengers. We find no changes in the safety performance of buses from this initial period to the private information period.

public treatment period, however the improvement in braking is more gradual than the other metrics.

4.3 Possible Mechanisms for Response to Public Signal

There are many other possible interpretations of the change in the demand and supply response to the public signal. In this section we go through several explanations and discuss their plausibility in explaining the patterns seen in the data.

Credibility. One such possibility that the unveiling of the banners increased the credibility of the safety information provided by the enumerators to passengers. We think this is an unlikely explanation for a few reasons. First, prior to the public signal, we exerted significant effort to make the private safety information as credible as possible. This involved having the enumerators dress professionally, and prominently display ID badges with their photos. Additionally, in our explanation of the research we noted that the project was approved by the NTSA and was funded by American universities. Furthermore, during the private information period, passengers still responded to our subsidy provision with high frequency. This required passengers to change their bus choice trusting that the research team would follow-up through on their promise to provide cash after the ticket was purchased. That around 30% of passengers did so shows that there was at least some degree of trust with the enumerator. For these reasons, we think it unlikely that a change in the credibility of the safety information under the public treatment explains the passenger and firm responses.

Social signaling. Social signaling, where passengers choose the safety certified bus to show others that they care about safety now that this attribute is being advertised, is another potential candidate for the results. However, in the context of the experiment we think that this behavior is not likely to arise. No other passengers observe which treatment provided to the respondent meaning that there is no way for others to know if they received the safety information or not. Additionally, because the majority of passengers also did not receive the safety information, there is no means of publically signaling that you are making the safe choice. Finally, even if passengers could signal to one another, we would expect these pressures to be less strong in a context where almost everyone is a stranger and does not have repeated interactions, and it is not clear that a preference for safety over other attributes (e.g. speed or comfort) would be a socially preferred choice.

Interviewer demand. Passengers may have felt more pressure to "please" the enumerator by choosing the safe bus company under the public signal. This is possible, however, we would also expect that this behavior would be observed in the number of people who report bus safety being the most important attribute they care about when choosing a bus. We check for this and do not observe any change in the proportion of passengers expressing safety as their primary concern.

Passenger salience. The unveiling of the safety banners at the bus stop could have simply increased the salience of safety for both passengers and firms causing them to value it more highly. However, for both passengers and firms, previous aspects of the experiment were already designed to increase safety salience. For the passengers, the safety salience treatment in the private period was design to explicitly increase passengers awareness of safety issues in the matatu industry. If salience alone had the power to change passenger choice, we would expect to see that these passengers were more likely to choose the bus company that they thought was already the safest. However, we do not observe this behavior. For firms, the monitoring app that firms were given access to and trained to use, emphasized the amount of safety information now available to the manager (see Appendix Figure A.1). Therefore, it is unlikely that the public banners increased the salience of safety for firms to a significant degree more.

Coordination. Finally, it is possible that passengers play a coordination game and the safety banner causes them to coordinate on winning firm. However, we think this is an unlikely explanation because of a few factors. First, the size of demand for each firm is difficult for any single passenger to observe. The location where passengers buy tickets is removed from view and it is difficult to know which firm an individual purchased after the transaction. Second, if coordination increased with the public signal we would expect that the serial correlation of passenger ticket purchases increases in the public period. We check for this possibility by regressing passenger bus choice on previous passengers' choice that day in the public period. We find no evidence of autocorrelation, with a point estimate of -0.026 ($t = -0.52$) on the lagged choice of bus.

Market equilibrium. Our preferred explanation for the demand and supply side response to the public signal is that it arises from a competition game being played among firms to capture more demand. In short (for more detail see Section 5 and Appendix A), once firms are aware that safety is now observable by passengers, they can choose to improve along this margin in the hope of attracting more passengers if they are certified as the safest bus. Passengers in turn now understand that some firms may choose to actively improve safety which makes the information signal about the safest bus more powerful (whereas before they did not believe any firms were actively seeking to improve safety and therefore discounted the safety signal).

5 Information Effects and Market Structure

We now present the model in which we describe the public transit market as a static game of monopolistic competition. While a clearly simplified description of the actual market, the model serves several purposes. First, it provides a framework in which to interpret reduced form results from our experimental intervention above. Second, it provide a structure in which we can perform welfare estimation of the intervention and make cost-benefit calculations. Last, the model allows us to consider outcomes under counterfactual equilibria and understand the conditions under which those alternative equilibria are likely to arise.

5.1 Model Setup

In this section we outline a model of strategic interaction between heterogenous firms who are competing for a fixed number of possible customers. The public signal about safety information creates a tournament between firms in which they make choices about whether to improve their own quality (safety) at some fixed cost in order to attract more customers. However, firms will only choose to improve if there is large enough chance that they will win the tournament. For their part, customers anticipate that only some firms may respond to the game by improving quality which in turn determines how strongly they respond to information about which firm is the safest. This leads us to the conclusion that information interventions may affect firms and passengers differently depending on the market structure and the equilibrium that arises as firms compete. Below we give an introduction and intuition about how the basic working of the model. The full model is described in Appendix A.

Specifically, we assume there are J firms competing over a unit interval of passengers. At the beginning of the game, nature draws firm baseline safety quality $\alpha_j \in \{\alpha_L, \alpha_H\}$ where $\alpha_H > \alpha_L$. We denote the probability that baseline safety is high as ϕ. Passengers in turn draw idiosyncratic firm specific preferences ε_{ij}.

With these attributes determined, firms then make a choice about whether to supply high or low quality $\mu_j \in \{\mu_L, \mu_H\}$ where a choice of high quality costs the firm c. This choice, combined with baseline fixed quality, determines the firms overall quality measure $q_j = \alpha_j + \mu_j$. After these choices, firm quality is measured (with some small error to break ties) and the firm with the highest overall quality is determined to be the top safety performer. Passengers then choose which firm to take by selecting the j that maximized their utility given by $U_{ij} = E[q_j|S_j] + \varepsilon_{ij}$. S_j indicates whether the passenger was informed that firm j was the top safety performer, which we call the "winning" firm, as it came out on top of the safety tournament between firms.

Intuitively, firms will choose to supply high quality if the potential passenger demand they capture as the top performing firm times the probability of actually winning, is greater than the cost of supplying high quality. That is, they provide high quality if

$$\underbrace{\Delta D(\theta)}_{\text{Demand effect of winning}} \times \underbrace{\Delta W(\alpha_j, \theta)}_{\text{Win prob. effect of providing safety}} \geq \underbrace{c}_{\text{Cost of providing safety}}$$

where θ indicates the equilibrium of the game, $\Delta D(\theta)$ is the increased demand due to being declared the top safety performer; and $\Delta W(\alpha_j, \theta)$ is the increased probability of winning if the firm provides safer services. Only the increased probability of winning depends on baseline quality α_j as passengers cannot observe baseline quality itself and need to make inferences about the firm's type and quality choice based on the signal S_j we provide.

Passengers choose which bus to take based on the expected firm quality of the winning firm compared to the expected quality of losing firms. Specifically, the additional demand share captured by the winning firm $\Delta D(\theta)$ is proportional to

$$\underbrace{E[q_j|S_j = 1, \theta]}_{\text{Expected firm quality of winning firm}} - \underbrace{E[q_j|S_j = 0, \theta]}_{\text{Expected firm quality of losing firms}}$$

which implies that the larger the gap between these two expected qualities, the larger the demand share captured by the winning firm. This gap could be due to passengers expecting the type of the winning firm to be different, the quality choice to be different, or both. Note that both firm and passenger choices depend on the equilibrium θ, as it determines which strategies are optimal on both the demand side and the supply side of the market.

5.2 Equilibrium without Public Signal

In our first intervention, passengers receive private information S_j that one firm has the highest quality. Because firms are unaware that passengers are receiving this information (and passengers know this), they have no reason to believe that firms have any incentive to adjust their safety choices (μ_j) in response to the private signal. Therefore, there is a unique equilibrium in which passengers interpret this information purely as a signal about fixed attributes of firms (α_j) as opposed to being informative about managerial safety choices of firms. Thus, the model predicts that demand for the safest bus relative to others may change, and the size of this response reflects only how large passengers believe differences between fixed attributes determining safety to be (i.e. $\alpha_H - \alpha_L$). On the supply side, given that firms unaware of the passenger intervention, they do not expect to be able to capture any extra demand by improving safety. Therefore, firms will continue to provide low quality.

5.3 Equilibria with Public Signal

In our second intervention, we provide a public signal about the information intervention, so that (a) firms learn that passengers are receiving safety information, and (b) passengers are aware that firms now have a strategic incentive to improve their quality. For passengers, this now means that the expected quality gap between the winner and losing firms will include both the expected gap in fixed components (α_j), but also the expected gap in quality choice (μ_j). This scenario lead to multiple possible outcomes, which crucially depend on two key parameters: the distribution of the underlying fixed quality attributes determined by ϕ, and the costs of choosing to supply safety, c.

There are three classes of equilibria which arise from this game under the public signal. A low-pooling equilibrium where all firms continue to supply low quality, a high-pooling equilibrium where all firms choose to supply high quality, and separating equilibria where only some firms choose to supply high quality and others do not.

Predictions on the behavior of firms and passengers under each of the equilibria are summarized by Table 1. Each row shows predictions for the type of equilibrium that might arise under either private information (columns 1 and 2) and public signal(columns 3 and 4). A "+" symbol indicates either an increase in demand for the safest bus or an increase in the provision of safety from firms, while a "++" indicates a proportionally larger increase, and a "0" indicates no change from before the intervention. In columns 1 and 2 we show predictions for the private information scenario where there is only one possible equilibrium - low pooling - due to the fact that firms do not yet have the strategic incentive to improve quality. As discussed above, we predict that there will be no supply response from the private information treatment, and a small demand response based on the passengers' perceived difference between the firms' fixed quality attributes α_H and α_L. The larger (smaller) the difference between these parameters, the larger (smaller) the shift in demand for the safety certified bus will be.

Low pooling equilibrium. Columns 3 and 4 of Table 1 cover predictions from the public treatment under all three possible equilibria. If the low pooling equilibrium arises, we would expect the same passenger and firm response as observed in the private information treatment. For firms, despite the possibility of capturing demand by winning the quality competition, if the cost of providing high quality are too large then firms will decide that it is not worth it. Subsequently, passengers will continue to perceive that the difference between the safety certified firm and all the others is due entirely to the fixed quality component, leading to the same demand shift as previously observed in the private treatment.

Separating equilibria. The second row shows predictions for the separating equilibrium where some firms improve their quality while others do not. This split arises due to the initial heterogeneity in fixed firm quality (α_j). These starting difference change the probability of being evaluated as the best firm and subsequently capturing the increase in demand should the firm choose to improve quality.[6] It is possible for either firms with initially high or low quality to choose to improve while the other type does not. Which occurs depends on both the distribution of types (as determined by ϕ) and the cost of improving quality.

Moving to passenger response, in a separating equilibrium passenger demand will shift *more strongly* towards the safety certified firm than was observed in the private information. This results arises because passengers now believe that quality differences across firms arise both from fixed components (α_j) and choice components (μ_j) as some firms are making the effort to improve while others are not. Therefore, the expected quality difference between the safety certified firm and all other firms will be strictly larger than the expected difference in the private information scenario or the pooling equilibrium.[7]

High pooling equilibrium. Last, the third row of Table 1 shows prediction for the high pooling equilibrium where all firms choose to improve quality. On the firm side, all firms now calculate that expected demand benefits out-weigh the costs leading to market wide improvements. For passengers, somewhat counter-intuitively, their demand response towards the safety certified firm is the same as with private information and the low-pooling equi-

[6] A similar prediction would arise if we allowed for heterogeneity in the cost of providing high quality.

[7] We assume that the quality improvements from the choice component μ_j are much larger that the differences in fixed attributes α_j.

librium. This is arises because all firms are choosing to provide high quality (μ_H), which again means that the expected difference between the safety certified firm and all others is due *only* to the fixed quality component. Therefore, while passengers benefit from a better product being supplied by all firms, they are less responsive to safety information than they were in the separating equilibrium.

5.4 Model Interpretation

Market structure. We explore under what market conditions each equilibria could occur under public information. Figure 5 shows which equilibria could exist across the range of two model parameters: ϕ — the probability of a firm having high baseline safety α_H, and c — the cost of providing high quality. Four equilibria are shown, the low and high pooling equilibria, as well as the two separating equilibria which we label "catch-up" — when low baseline quality firms choose to improve and high baseline do not, and "pull-away" when high starting quality firms choose to improve and low starting quality firms do not.

While there are parameter values for which multiple equilibria exist, or none, some broad patterns emerge which determine which outcome is more likely. The high pooling equilibrium is most likely to occur at low cost of quality (which is intuitive) and medium values of ϕ. The low pooling equilibrium is most likely with high costs or low values of ϕ. The pull-away separating equilibrium over-laps substantially with the low and high pooling equilibria, and is possible only for values of ϕ below 0.6. Finally, the catch-up separating equilibrium covers a relatively smaller portion of the parameter space and is only possible for values of ϕ above 0.6.

Interpreting results through model. Using the model framework outlined above, we can return to our empirical results to understand which equilibrium is consistent with our patterns. First, we observe in Table 3 that the passenger response to information with the public signal is much stronger than what we observed when giving private information. This divergence is only consistent with a separating equilibrium where some bus firms improve while other do not. We explore this on the supply side and we do observe heterogenous responses by firms. Figure 6 shows that two out of five firms demonstrate large improvements in their safety performance, which is again consistent with the separating equilibrium.

Model limitations. The focus of this model is on the quality choice. Hence, in order to make the model tractable, we ignore several important features such as prices, attracting new passengers to the market, cost differences across firms, and many other sources of firm heterogeneity. For some factors, we have evidence that these margins are relatively fixed in our context. For example, there is almost zero price heterogeneity across firms, a fact that does not change in the public period (see Appendix Figure A.3). Therefore, we feel comfortable leaving this choice margin out of the model as a matter of practicality. However, other factors could certainly play a role in our setting. That said, including any of these margins would not fundamentally change the basic intuition and predictions of the model proposed here.

6 Welfare Analysis

In this section we combine the reduced form results with the structure of the model to estimate the welfare implications of the public signal treatment as well as counterfactual welfare outcomes under different market equilibria. We consider welfare changes resulting from the public signal treatment accruing to passengers and firms. Note, that there are also likely benefits that accrue to third parties, such as pedestrians or other drivers, however for the purposes of this exercise we ignore these changes. Since our model features multiple equilibria, we first have to determine which equilibrium we are in. This determination consists of two steps: First, given that we see a demand response to private information only after the public signal was introduced, this is only consistent with a separating equilibrium. If it were a pooling equilibrium, all firms would behave the same and there would be no reason for passengers to switch to another firm than the one they would have preferred without private information. Second, we attempt to distinguish between the pull-away equilibrium and the catch-up equilibrium. Figure 6 shows that the two firms with the lowest pre-public safety scores improve the most in the public period while the three highest performing firms improve by a much smaller amount. These patterns of responses are most consistent with a catch-up equilibrium.

In a catch-up separating equilibrium, the welfare effect of private information under the public signal can be written as:

$$\Delta W(\text{CSE}) = N \overbrace{\left[\underbrace{\phi \Delta D(\text{CSE}) \left(\Delta\mu - \Delta\alpha\right)}_{\text{Direct effect}} + \underbrace{(1-\phi)\Delta\mu}_{\text{Externality}} \right]}^{\text{Consumer surplus}} \quad \overbrace{-J(1-\phi)c}^{\text{Producer surplus}} \quad \overbrace{-\tau}^{\text{Info cost}} \tag{3}$$

Starting with passengers, the consumer surplus from the information intervention arises from passengers who now experience higher safety. This occurs in two ways. First, there is a direct channel whereby a proportion of passengers ($\phi\Delta D(\text{CSE})$) switch from a firm that is not exerting effort to provide safety to the winning firm which is, gaining them $\Delta\mu$. However, in the a catch-up equilibrium where only low type firms provide high quality this comes at a cost of $\Delta\alpha$. Second, there is an indirect channel where for some proportion of passengers $(1-\phi)$ who do not switch, the bus they do choose has improved their safety quality as part of the new equilibrium, gaining them $\Delta\mu$ as well.

Next, we consider the producer surplus. Unlike passengers, firms will be worse off in the aftermath of the intervention while one firm will benefit. For the winning firm, they reap the full benefit of increased demand ($\Delta D(\text{CSE})$) minus the cost of suppling high quality c, leaving them with higher profits than before. All other firms which do not win the tournament are left to split the remaining passenger demand ($\frac{1-(\frac{1}{J}+\Delta D(\text{CSE})}{(J-1)}$), leaving them with fewer passengers than before. For the sub-set of losing firms who did chose to improve high quality they additionally lose c. In aggregate however, given that we fix the total size of demand, total producer surplus is simply reduced by the cost of supplying quality multiplied by how many firms choose to do so ($J(1-\phi)c$).

Last, there is the direct cost of the information intervention (τ). The cost of information comes from the cost of collecting the safety outcomes from vehicles and then the cost of dissemination to passengers. Because the marginal cost of data collection is low, these costs are dominated by the labor cost of information dissemination.

6.1 Calibration

As outlined above, the welfare calculation depends on several key values: i) the total number of passengers and the proportion of these that switch to the top safety performer as a result of receiving information, ii) the proportion of buses that improve their quality, iii) the value of safety to passengers, iv) the cost to firms of providing safety, and v.) the cost of the information intervention itself. Below we describe how we estimate these inputs in turn. However, we recognize that these values are in some cases uncertain, therefore we will also show sensitivity of the welfare estimates to ranges of parameter choices.

Demand effect of winning and passenger valuation of safety. The demand effect of being the winning firm and the passenger valuation of safety are estimated simultaneously and reported in Table 5. Table 5 shows the results from a logit specification where we simultaneously estimate the effect of the subsidy offer (which was cross-randomized) and the information treatments (both private and public) on the choice of the safety certified bus. We can then transform the coefficients on the public and private information interventions to estimate the implied value of higher safety for both the fixed component ($\triangle\alpha$) and choice component ($\triangle\mu$).[8] The results of this transformation show that the value of the choice component of safety is worth \$0.58 (se 0.24) per passenger. Similarly, the value of the fixed safety component is actually less than zero at -\$0.14 (se 0.46). However, note that the 95% confidence interval for this value is $[-1.04., 0.76]$, and therefore we assume that the perceived safety benefit is a zero or small positive number.[9] Finally, we also use these values to estimate the extra captured demand that accrues to the winning firm, which we estimate at 0.14 (se 0.06).

Total number of passengers. Given that the valuation of safety is a per passenger estimate, to calculate total welfare we need the estimated number of passengers who use the bus terminal each day. We estimate this by taking the number of passengers that our enumerator team spoke with during the two hour window in which they were operating each day. We estimate that enumerators intercepted approximately 10% of the total number of passengers that entered the bus terminal area in this time, giving an estimated total of 150 passengers per hour. Finally, we scale this by 12, the number of hours in which the bus terminal is active, to give use an estimate of 1,800 passengers per day.

Proportion of high quality firms. We estimate ϕ by examining pre-public safety outcomes across firms. Figure 6 shows that pre-public there are three firms with significantly higher safety provision than the other two firms, so we therefore set $\phi = 0.6$. In the catch-up equilibrium, this means that $(1 - \phi) = 0.4$ of the firms will respond to public signal by improving quality, which is also qualitatively confirmed by Figure 6.

Cost of providing safety for firms. For the cost to firms of providing safety, we take estimates from a companion paper Kelley et al. (2022) which examines the effect on safety outcomes from a direct incentive to the driver to improve their safety performance. Using

[8]Details on this transformation are show in the model appendix. Intuitively, the coefficients on the information treatment reflect the perceived quality gap between the winning and losing firm. This gap in turn reflects the posterior expected quality difference which is a function of fixed model parameters (e.g. ϕ) and the size of the fixed and choice quality differences. This relationship allows us to back out the implied $\triangle\alpha$ and $\triangle\mu$ for the given combination of $beta_2$ and $beta_4$ from Table 5.

[9]Definitionally it does not make sense that customers palce negative value on higher quality. Therefore, we exclude negative numbers from consideration in our estimates of welfare.

results from that paper, we infer that inducing safety improvements in this setting cost firms approximately \$2 per driver per day.

Cost of information intervention. We estimate the cost of the information provision itself from our own project expenses to be approximately \$10 per day.

6.2 Welfare Estimates and Counterfactuals

Using the above calibration, we then calculate the welfare using Equation 3 above. We do so both for the catch-up equilibrium which we posit best explains this market but also four the three other types of possible equilibria: low-pooling, pull-away, and high-pooling. Figure 7 displays the monthly welfare changes from our intervention broken down into changes in producer surplus, consumer surplus, and information cost. The "CSE" row shows that the estimated monthly welfare gain from our intervention is approximately \$17,500, comprised roughly of a \$20,500 increase in consumer welfare and a \$3,000 decrease in producer welfare.

The other rows of Figure 7 report the expected welfare gain of the other equilibria holding fixed parameter values. As expected, the low-pooling equilibrium is the only outcome in which welfare decreases, as consumers gain little from the safety information when $\triangle\alpha$ is low but the costs of dissemination are fixed. The pull-away equilibrium provides positive welfare gains, but with lower consumer benefit and higher firm costs than the catch-up equilibrium. Note that this result is driven by the relatively low $\triangle\alpha$ and high $\triangle\mu$ and is not true for the majority of the possible parameter space, as we explore below. Finally, the high-pooling equilibrium provides the highest aggregate welfare gain, but involves the highest costs to firms.

6.3 Sensitivity Analysis

Given the uncertainty of many of the values in our calibration, we show how sensitive our welfare calculations are to other choices for the parameters. This process also allows us to i) examine the distribution of welfare changes under all four possible equilibria, ii) examine the likelihood that our intervention would lead to an aggregate welfare loss under each equilibrium.

The sensitivity procedure uses the following steps. First, we simultaneously draw new coefficients from the value of safety estimation reported in Table 5. We draw these coefficients using the full variance-covariance matrix from the regression results, but rejection any draw that assigns a negative value for higher quality. Second, we use this draw to calculate new values for $\Delta\alpha$, $\Delta\mu$, and $\Delta D(\theta)$. Third, we draw from a uniform distribution values for the cost of providing higher quality to firms, c, and the number of daily passengers, N. Using these values we then calculate the resulting total change in welfare based on Equation 3. Last, using the same point estimates, we also calculate the counterfactual welfare changes for the three alternative equilibria.

Figure 8 plots the distribution of welfare estimates derived from the above procedure for the catch-up, pull-away, and high-pooling equilibrium. The low-pooling equilibrium is excluded because it is almost entirely centered around zero. There are a few things to note from figure. First, in contrast to our point estimate calculated above, the catch-up equilibrium provides on average smaller welfare improvements than the pull-away equilibrium (the high-pooling equilibrium nearly always dominates the others). This divergence is driven by the relative size of $\Delta\alpha$ and $\Delta\mu$. When $\Delta\alpha$ is small, passengers who switch their choice to the winning bus (the direct effect) in the catch-up equilibrium receive nearly the same welfare gain as those who switch under the pull-away equilibrium. However, as $\Delta\alpha$ grows relative to $\Delta\mu$, then the welfare gain to compliers in the catch-up falls relative to the gains achieved in the pull-away. The point estimates from our experiment suggest a near zero $\Delta\alpha$, leading to the catch-up equilibrium being preferred to the pull-away. However, this is not generally true, and under the majority of parameters within our confidence intervals the pull-away equilibrium is superior.

Second, Figure 8 shows that the distributions of all equilibria are almost entirely above zero. This is reassuring and suggests that interventions that provide quality information to customers are unlikely to backfire. The scenario in which welfare is most likely to fall is in the low-pooling equilibrium (not shown), as customers only benefit from switching towards low fixed quality firms towards high fixed quality firms. However, the downside of this scenario is also limited because no firms pay the cost c to improve quality, leaving the cost of the intervention itself as the only aggregate loss.

7 Conclusion

In this paper, we present findings from a randomized control trial in which informal transit passengers receive information about bus safety. We make two contributions. First, we show that passengers value this information only when they expect firms to provide safer services in response to a public signal that broadcasts their ability to track buses. In addition to this passenger demand response, we show that firms use their tracking devices to supply safer transit services after the introduction of the public signal. We interpret these findings through the lens of a model with strategic firms and heterogeneous consumers that respond systematically to safety incentives. In our second contribution, we use this model to estimate the welfare effect of the information intervention under the public signal. We can decompose consumer surplus into a direct effect of consumer substitution and an indirect effect that acts as an information externality. The structure of the model also allows us to estimate the welfare effect of counterfactual equilibria that could have emerged after the introduction of the public signal.

What are the implications of these results for optimal policy of an informal transit network? First, as the effect of an information intervention may vary dramatically with the prevailing equilibrium in the informal transit market, it is important to anticipate which firms may respond in what way to consumer information. The equilibrium may vary from station to station, depending on the mix of consumers and firms. Policymakers need to consider which equilibrium will likely emerge as a result of an information campaign to correctly weigh the costs against anticipated benefits. Second, informal transit firms can differ both in their baseline safety and their capacity to improve safety. In settings in which baseline differences are large but the capacity for improvements is small, a policy directly substituting safer services may be more effective than consumer information.

There are a number of important open questions for future research. The effects we demonstrate in this paper are short-run and confined to a local equilibrium. It is interesting to consider how general equilibrium effects across the entire transport network may be affected by consumer information at central bus stations. It may well be that the safety benefits extend beyond treated passengers. The informal transit market as a whole may become safer, which in turn may increase demand, stimulate entry of new firms, and force exit of low-quality firms. Increased competition could in turn drive the industry closer to the first best.

References

Akerlof, George A. (1970): “The Market for ”Lemons”: Quality Uncertainty and the Market Mechanism,” *The Quarterly Journal of Economics*, Vol. 84, pp. 488–500.

Anderson, Michael L. (2008): “Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects,” *Journal of the American Statistical Association*, Vol. 103, pp. pp. 1481–1495.

Bai, Jie (2018): “Melons as Lemons: Asymmetric Information, Consumer Learning and Seller Reputation,” *Working Paper*.

Barahona, Nano, Cristóbal Otero, Sebastián Otero, and Joshua Kim (2020): “Equilibrium Effects of Food Labeling Policies,” *Working Paper*.

Bauernschuster, Stefan and Ramona Rekers (2022): “Speed Limit Enforcement and Road Safety,” *Journal of Public Economics*, Vol. 210, p. 104663.

Bennett, Daniel and Wesley Yin (2018): “The Market for High-Quality Medicine: Retail Chain Entry and Drug Quality in India,” *The Review of Economics and Statistics*, Vol. 101, pp. 76–90.

Bergquist, Lauren Falcao and Michael Dinerstein (2020): “Competition and Entry in Agricultural Markets: Experimental Evidence from Kenya,” *American Economic Review*, Vol. 110, pp. 3705–47.

Björkman Nyqvist, Martina, Jakob Svensson, and David Yanagizawa-Drott, David (2018): “Can Competition Reduce Lemons ? A Randomized Intervention in the Antimalarial Medicine Market in Uganda,” *Working Paper*.

Bold, Tessa, Selene Ghisolfi, Frances Nsonzi, and Jakob Svensson (2022): “Market Access and Quality Upgrading: Evidence from Four Field Experiments,” *American Economic Review*, Vol. 112, pp. 2518–52.

Bold, Tessa, Kayuki C. Kaizzi, Jakob Svensson, and David Yanagizawa-Drott (2017): “Lemon Technologies and Adoption: Measurement, Theory and Evidence from Agricultural Markets in Uganda*,” *The Quarterly Journal of Economics*, Vol. 132, pp. 1055–1100.

Cervero, Robert and Aaron Golub (2007): “Informal transport: A Global Perspective,” *Transport Policy*, Vol. 14, pp. 445 – 457.

Habyarimana, James and William Jack (2011): “Heckle and Chide: Results of a randomized road safety intervention in Kenya,” *Journal of Public Economics*, Vol. 95, pp. 1438 – 1446, Special Issue: International Seminar for Public Economics on Normative Tax Theory.

——— (2015): “Results of a Large-Scale Randomized Behavior Change Intervention on Road Safety in Kenya,” *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 112, pp. E4661–4670.

Jin, Ginger Zhe and Phillip Leslie (2003): “The Effect of Information on Product Quality: Evidence from Restaurant Hygiene Grade Cards,” *The Quarterly Journal of Economics*, Vol. 118, pp. 409–451.

Kelley, Erin, Gregory Lane, and David Schönholzer (2022): “Improving Safety in Kenya’s Public Transit Industry,” *Unpublished Working Paper*.

Levin, Jonathan (2001): “Information and the Market for Lemons,” *The RAND Journal of Economics*, Vol. 32, pp. 657–666.

Macchiavello, Rocco and Ameet Morjaria (2021): “Competition and Relational Contracts in the Rwanda Coffee Chain*,” *The Quarterly Journal of Economics*, Vol. 136, pp. 1089–1143.

Macharia, WM, EK Njeru, F Muli-Musiime, and V Nantulya (2009): “Severe Road Traffic Injuries in Kenya, Quality of Care and Access,” *African Health Sciences*, Vol. 9, pp. 118–124.

Michuki, John (2003): “The Traffic Act.”

Muthoo, Abhinay and Suresh Mutuswami (2011): “Imperfect Competition and Efficiency in Lemons Markets,” *The Economic Journal*, Vol. 121, pp. 580–594.

Odero, Wilson, Meleckidzedeck Khayesi, and P. M. Heda (2003): “Road Traffic Injuries in Kenya: Magnitude, Causes and Status of Intervention,” *Injury Control and Safety Promotion*, Vol. 10, pp. 53–61, PMID: 12772486.

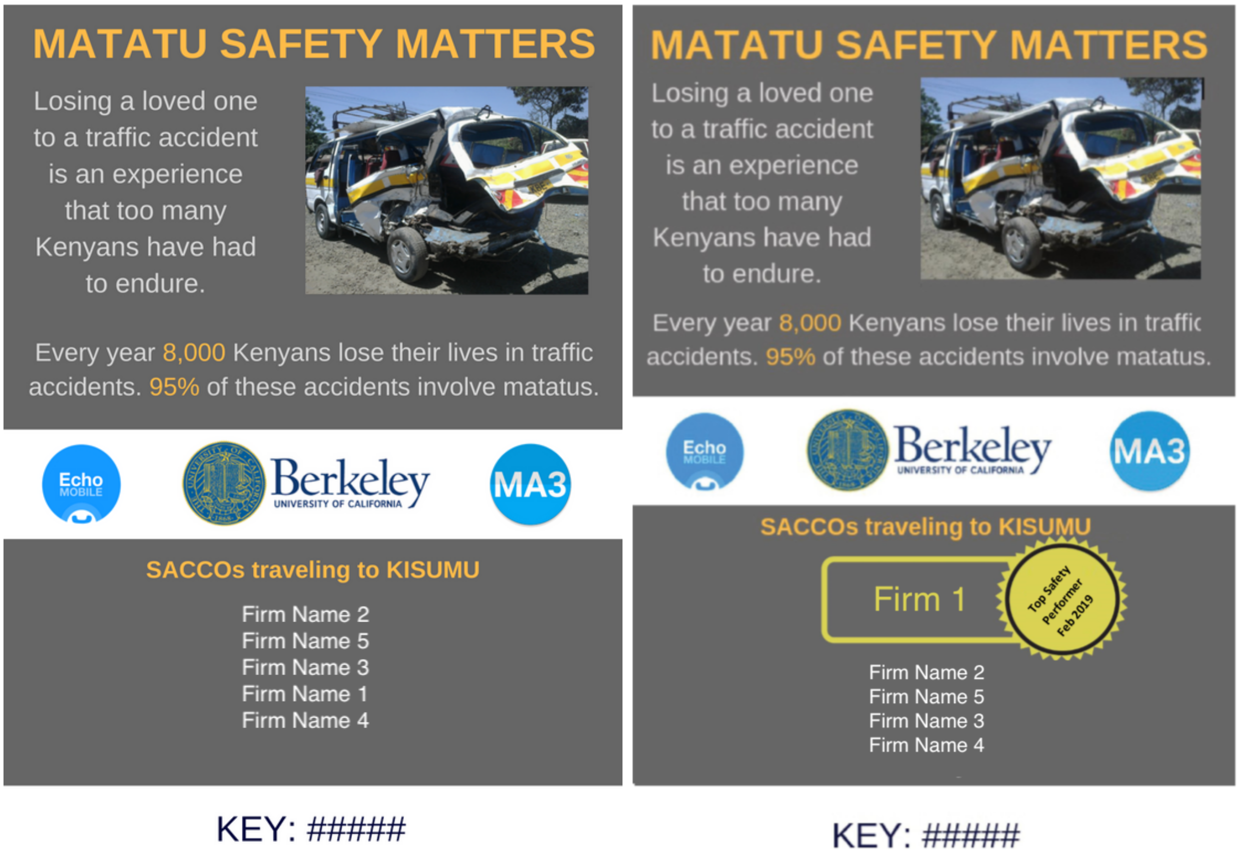
Raynor, Nicolas J. and Tolib Mirzoev (2014): “Understanding Road Safety in Kenya: Views of Matatu Drivers,” *International Health*, Vol. 6, pp. 242–248.

WHO, Geneva (2015): "Global Status Report on Road Safety,"Technical report, World Health Organization, Geneva.

——— (2020): "Road Traffic Injuries: Key Facts," *World Health Organization*.

Figures

Figure 1: Private information: placebo treatment (left) and safety treatment (right)

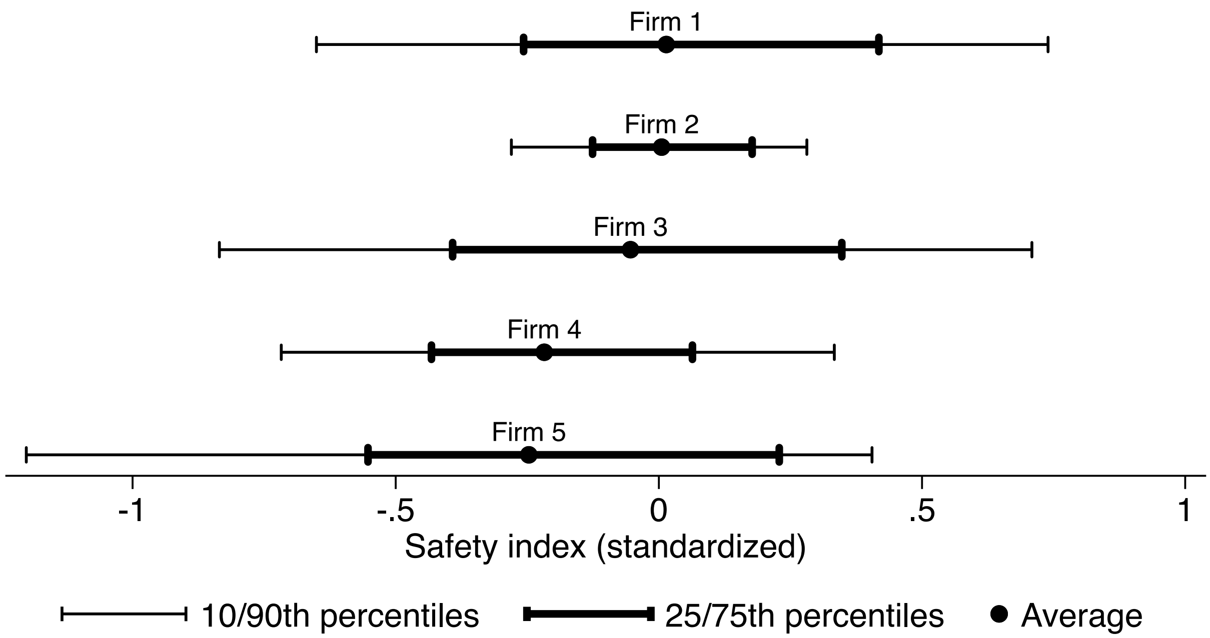


Notes: The pamphlet was distributed to passengers in the safety information group after completion of the baseline survey. Enumerators read the text out loud to each passenger and explained the meaning of the “Safety Certified” designation to ensure understanding. The “KEY: #####” was a randomly generated number that allowed passenger baselines to be matched to their ticket purchase collected by a second enumerator.

Figure 2: Public signal: banners announcing tracking and safety "tournament"

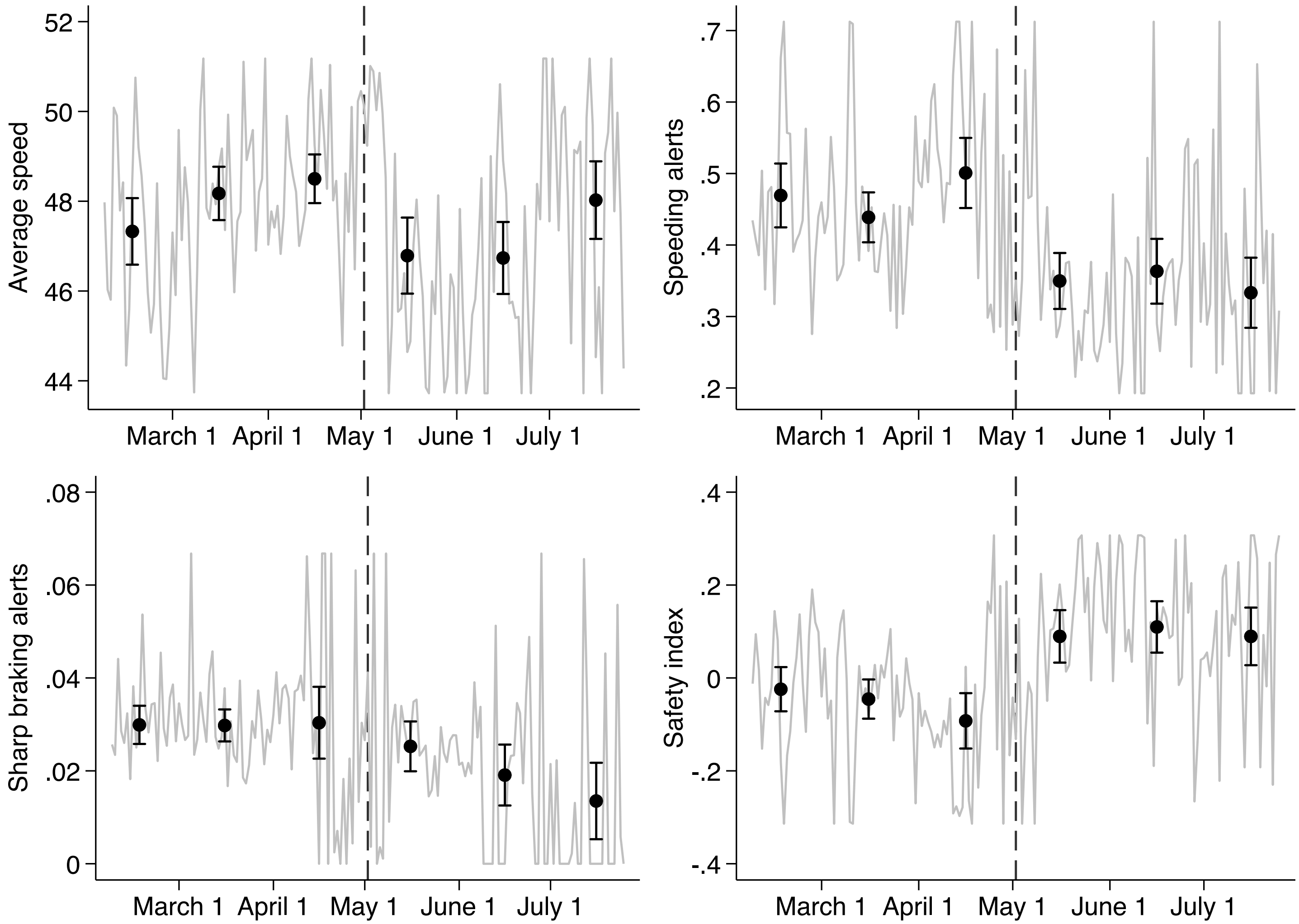
Notes: These banners were placed at both entries to the bus station from which the five firms in our study depart. The banner reads: "SACCOs on Mfangano-Kisumu [the route in our study] are now tracked for safety. Enjoy the benefits of safer transit, and check out the Top Safety Performer."

Figure 3: Distribution of baseline safety by firm across bus-days



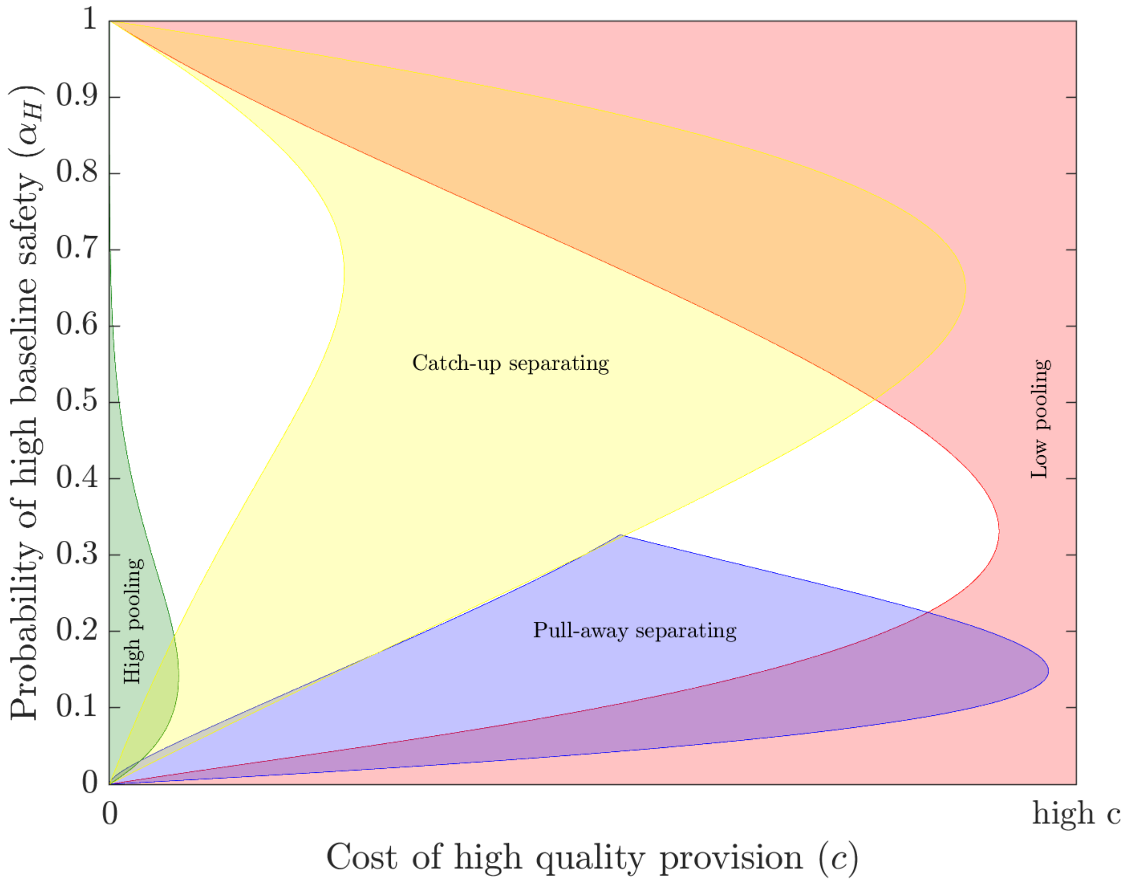
Notes: Averages and intervals ranging from the 10th to the 90th percentile and the 25th to the 75th percentile (in bold), respectively, of the distribution of the safety index by firm. The safety index is computed as the inverse covariance index as in Anderson (2008) using average speed, speeding alerts, and sharp braking alerts. Firms are sorted from 1 (highest safety index at baseline) to 5 (lowest safety at baseline).

Figure 4: Safety supply response after public signal



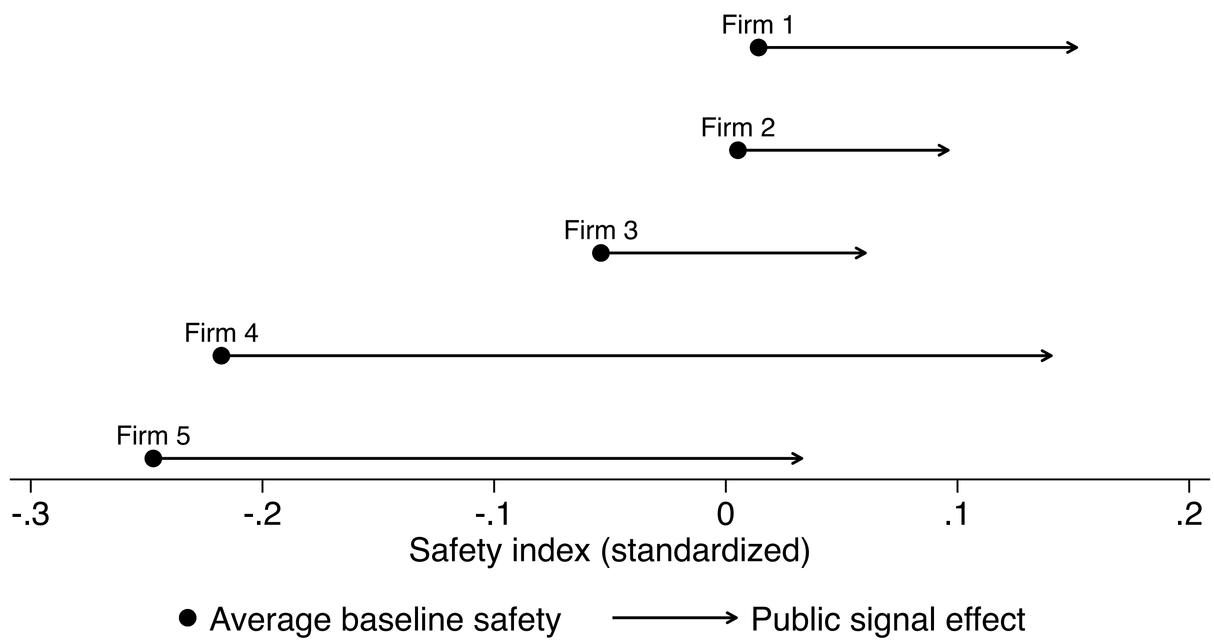
Notes: Time series of average speed, speeding alerts, sharp braking alerts, and the safety index three months before to three months after the introduction of the public signal. The gray line shows daily averages, whereas the black dots show monthly averages with 90% confidence intervals computed from robust standard errors.

Figure 5: Equilibria in public signal game



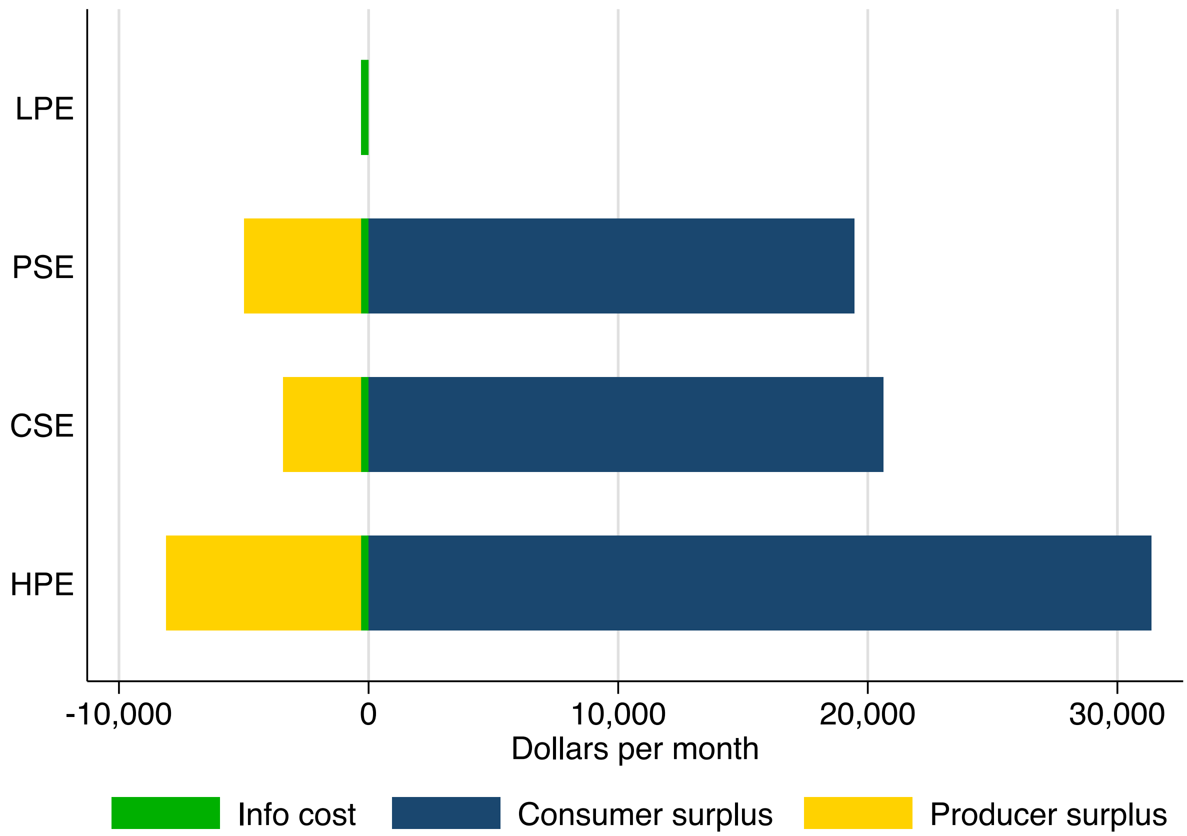
Notes: Equilibrium existence under various parameter values for the cost of safety provision c and the probability of high-quality firms $\phi = \Pr(\alpha_j = \alpha_H)$. The red area shows (c, ϕ)-combinations for which a low-pooling equilibrium exists; the blue and yellow areas for pull-away and catch-up separating equilibria, respectively; and the green area for high-pooling equilibria.

Figure 6: Public signal effect by firm



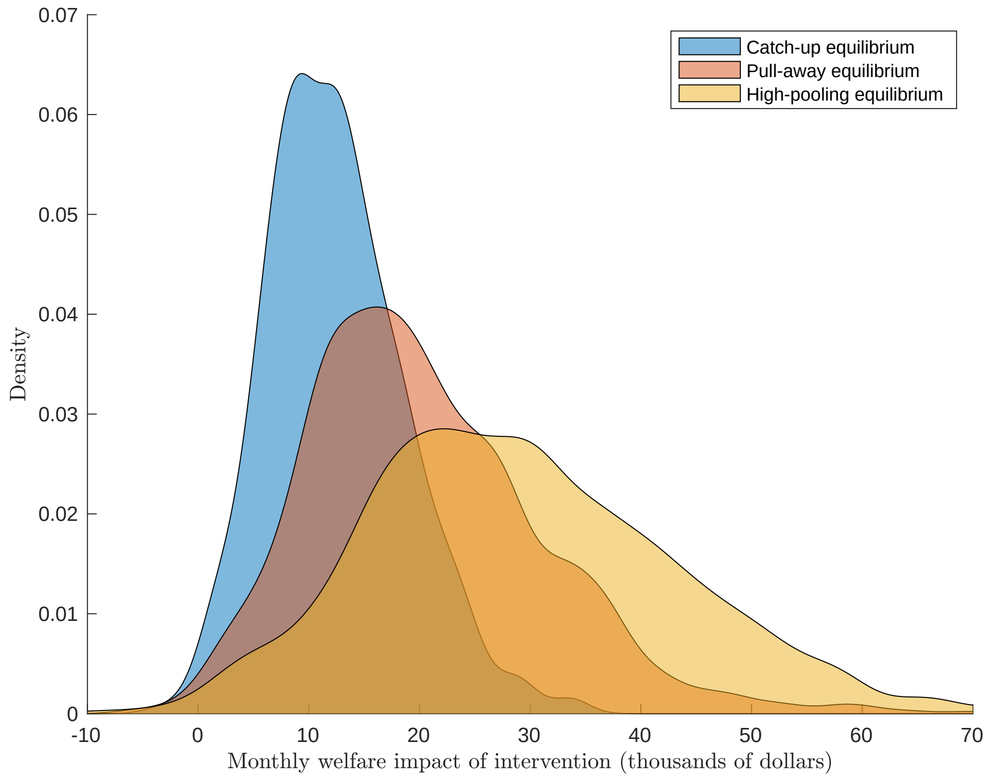
Notes: Average safety by firm before the public signal (black markers) and improvement in safety after the public signal (arrows).

Figure 7: Welfare comparison across equilibria



Notes: Welfare estimates under the four equilibria, decomposed into consumer surplus (blue); producer surplus (yellow), which is negative; and the cost of information provision (gree), which is also negative. The four equilibria are the low-pooling equilibrium (LPE), the pull-away separating equilibrium (PSE), the catch-up separating equilibrium (CSE), and the high-pooling equilibrium (HPE).

Figure 8: Welfare comparison across equilibria



Notes: Simulated sensitivity of welfare estimates using 1,000 draws from the covariance matrix of estimated reduced-form coefficients as well as calibrated uncertainty in the number of passengers and the costs of safety provision. Three of the four equilibria are shown here: the catch-up separating equilibrium (CSE), the pull-away separating equilibrium (PSE), and the high-pooling equilibrium (HPE). Not shown is the low-pooling equilibrium (LPE), whose estimates are distributed tightly around zero.

Tables

Table 1: Equilibrium-dependent effects of information on public transit safety

	Private information (PI)		PI & Public signal	
	(1)	(2)	(3)	(4)
Equilibrium	Demand	Supply	Demand	Supply
Low pooling	+	0	+	0
Separating			++	+
High pooling			+	++

Notes: This table summarizes the predictions of the effect of private information (PI) with (columns 1-2) or without (columns 3-4) a public signal on the demand and supply of informal transit safety. Each row corresponds to predictions under a different prevailing equilibrium in the local transit market. Columns for "demand" and "supply" indicate predictions for the demand effect and supply effect, respectively. A "0" indicates no change in demand or supply; "+" indicates a small increase in demand or supply, whereas a "++" indicates a large increase in demand or supply.

Table 2: Summary statistics of passengers across treatments

	Means by treatment group			p-value	p-value
	Control	Placebo	Safety	difference	difference
	(1)	(2)	(3)	(3)−(1)	(3)−(2)
Passenger characteristics					
Age	29.90	29.15	29.44	0.158	0.390
Sex (male)	0.50	0.56	0.54	0.079	0.283
Education index	3.97	4.07	3.98	0.159	0.916
Estimated yearly travel frequency	9.28	9.41	9.14	0.872	0.871
Travel less than once a month	0.86	0.87	0.86	0.810	0.782
Stated preferences					
Rank safety most important	0.56	0.55	0.52	0.664	0.188
Rank comfort most important	0.16	0.18	0.16	0.407	0.880
Rank price most important	0.16	0.15	0.15	0.606	0.651
Rank travel time most important	0.11	0.12	0.17	0.787	0.010
Choice characteristics					
Firms with waiting bus (out of 5)	4.21	4.32	4.32	0.066	0.076
At least three firms with waiting bus	0.95	0.96	0.96	0.241	0.241
Average time to departure	67.01	65.41	65.22	0.417	0.360
Shortest time to departure across firms	45.88	45.05	45.50	0.589	0.804
Longest time to departure across firms	94.07	92.78	93.35	0.674	0.815
Total observations	506	473	449		
p-value of F-test: joint test of orthogonality				0.612	0.281
Pre-public signal observations	282	244	254		
p-value of F-test: joint test of orthogonality				0.870	0.182
Post-public signal N	224	229	195		
p-value of F-test: joint test of orthogonality				0.540	0.948

Notes: Summary statistics for each treatment group (columns 1-3, representing control group, placebo information group, and safety information group, respectively) and p-value of difference between safety information and control group, (3)–(1); and between safety information and placebo information group, (3)–(2). The education index ranges from 1 (lowest) to 5 (highest). Sum of stated preference shares may not add to one due to rounding.

Table 3: Passenger information and public signal: effect on choosing safe firm

	Passenger chose safety-certified bus			
	(1)	(2)	(3)	(4)
Placebo information	0.035	0.035	0.030	0.031
	(0.036)	(0.036)	(0.036)	(0.036)
Safety information	-0.001	-0.003	-0.004	-0.006
	(0.035)	(0.035)	(0.035)	(0.035)
Placebo information × Public signal	-0.057	-0.053	-0.053	-0.050
	(0.046)	(0.049)	(0.047)	(0.049)
Safety information × Public signal	0.101**	0.113**	0.104**	0.115**
	(0.051)	(0.054)	(0.051)	(0.054)
Mean of dependent variable	0.115	0.115	0.115	0.115
p-value of test: Placebo + Placebo × Public = 0	0.586	0.690	0.579	0.673
p-value of test: Safety + Safety × Public = 0	0.035	0.028	0.035	0.029
Timing-of-interview controls		•		•
Passenger controls			•	•
N	1,186	1,186	1,186	1,186

Notes: OLS regression results. The outcome is an indicator for buying a ticket for the safest bus company as measured by the tracking devices. "Placebo information" is an indicator for receiving a pamphlet that increases the salience of safety in the industry. "Safety information" is an indicator for receiving a pamphlet that indicates which SACCO was awarded the "Top safety performer". "Public signal" is an indicator for having been interviewed after the public signal was introduced. Timing-of-interview controls include day-of-the-week interacted with an indicator for afternoon (as opposed to morning). Passenger controls include sex, age bin, an indicator some college or professional education, and frequency of traveling on the route. Robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Public signal: effect on safety provision of firms

	Safety index components			Safety index	
	(1) Avg. speed	(2) Speeding	(3) Sharp braking	(4)	(5)
Public signal	-1.328**	-0.115***	-0.010**	0.164***	
	(0.537)	(0.031)	(0.004)	(0.037)	
Public signal × Firm 1					0.137**
					(0.061)
Public signal × Firm 2					0.091*
					(0.047)
Public signal × Firm 3					0.114*
					(0.058)
Public signal × Firm 4					0.358**
					(0.144)
Public signal × Firm 5					0.280***
					(0.091)
Mean pre-public	48.120	0.470	0.030	-0.070	-0.070
p-value of test: Firm 1-3 = Firm 4-5					0.028
Matatu FE	•	•	•	•	•
Controls	•	•	•	•	•
N	5,159	5,159	5,159	5,159	5,159

Notes: OLS regression results. "Public" is an indicator for the safety rating system being advertised at the bus terminal. All regressions have controls for kilometers driven, hours driven, being a "safety certified" bus, include fixed effects for buses and idle days. The hypothesis test conducted in the second row of the model statistics is that the average of coefficients on Public × Firm j for $j \in \{1, 2, 3\}$ is equal to the average of coefficients for $j \in \{4, 5\}$. Standard errors are clustered by bus. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Logit estimates for welfare estimation

	Parameter estimates
Subsidy (β_0)	1.606***
	(0.150)
Placebo information (β_1)	0.104
	(0.188)
Safety information (β_2)	-0.059
	(0.193)
Placebo information × Public signal (β_3)	-0.192
	(0.263)
Safety information × Public signal (β_4)	0.609**
	(0.252)
Value of high-type firm ($\Delta\alpha$)	-0.142
	(0.463)
Value of firm safety behavior ($\Delta\mu$)	0.581**
	(0.242)
Demand effect of winning (ΔD)	0.144**
	(0.068)
N	1,186

Notes: Logit estimation of reduced-form coefficients and structural parameters for welfare estimation. The structural parameters $\Delta\alpha$, $\Delta\mu$, and ΔD are functions of the reduced-form coefficients β_0 to β_4 as described in Appendix B. The outcome is an indicator for buying a ticket for the safest bus company as measured by the tracking devices. "Subsidy" is an indicator for receiving a 100 Ksh discount to take the safest bus. "Placebo information" is an indicator for receiving a pamphlet that increases the salience of safety in the industry. "Safety information" is an indicator for receiving a pamphlet that indicates which SACCO was awarded the "Top safety performer". "Public signal" is an indicator for having been interviewed after the public signal was introduced. Robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Monthly welfare effects of intervention (thousands of dollars)

	Equilibrium			
	LPE	CSE	PSE	HPE
Consumer surplus	0.4	15.66	25.17	37.32
	(0.6)	(6.34)	(10.91)	(14.7)
	[0, 2.14]	[4.97, 29.93]	[7.77, 50.02]	[12.21, 69.54]
Producer surplus	0	-3.08	-4.63	-7.71
	(0)	(1.07)	(1.61)	(2.68)
	[0, 0]	[-5.33, -1.39]	[-8, -2.08]	[-13.34, -3.47]
Total welfare	0.25	12.43	20.4	29.46
	(0.6)	(6.2)	(10.71)	(14.34)
	[-0.15, 1.99]	[1.7, 25.76]	[2.96, 44.69]	[4.26, 59.57]

Notes: Means of simulated welfare sensitivity estimates. Standard errors in parentheses and 90% confidence intervals in square brackets. The columns correspond to the four equilibria: the low-pooling equilibrium (LPE), the catch-up separating equilibrium (CSE), the pull-away separating equilibrium (PSE), and the high-pooling equilibrium (HPE). The CSE highlighted in gray is the equilibrium likely to prevail in our market. All four total welfare estimates include the cost of information provision.

Online Appendix for

Information and Competition in Lemon Markets: Improving Safety in Informal Transit

Erin Kelley, Gregory Lane, and David Schönholzer

Contents

A Model

Overview. We model the market for long-range public transport services as a static game of monopolistic competition between firms with private information. $J \geq 2$ firms compete over a unit interval of passengers (i.e. consumers) by deciding whether or not to invest into bus safety. Passengers have idiosyncratic preferences ε_{ij} for firms and choose the firm whose characteristics (including perceived safety) appeals most to them. To focus on the subject of competition on the safety margin, prices are fixed at unity. In many low-income contexts, firms exhibit collusive behavior that limits price competition (Bergquist and Dinerstein, 2020). Empirically, we show in Appendix Figure A.3 that prices are almost perfectly cointegrated with almost no price dispersion across firms on any given day.[10]

The safety of a firm q_j is determined by two components: a safety type $\alpha_j \in \{\alpha_L, \alpha_H\}$, and a safety choice $\mu_j \in \{\mu_L, \mu_H\}$. Firms are either high type (α_H) or low type (α_L), drawn randomly at the beginning of the game. This type represents slow-moving safety characteristics of the firm, such as the condition of the firm's bus stock or the amount of experience of the firm's drivers. In contrast, the safety choice represents more flexible, managerial aspects of safety, such as instructing drivers not to drive above some speed or to take specific routes. These managerial choices become possible after buses are fitted with our tracking devices. Enforcing safety measures, $\mu_j = \mu_H$, comes at a publicly known cost c, representing the incentive cost for drivers to slow down or the effort cost to monitor the drivers.[11] Since price is normalized to unity, this cost is relative to the uniform choice price.

We begin by describing the structure of the game and how our information interventions affect it. We then focus on firms' incentives to provide safety in different information environments: first, the baseline environment, then with provision of private safety information to passengers, and finally with the public signal about the information environment.

Timing of game and baseline information sets. The game consists of three stages:

1. **Stage 1: Drawing heterogeneity**. *Nature* draws a type $\alpha_j \in \{\alpha_L, \alpha_H\}$ for each firm, which is privately known to each firm, with independent probability $\phi = \Pr(\alpha_j = \alpha_H) \in (0, 1)$. Nature also draws i.i.d. preferences ε_{ij} from an Extreme Value Type I random

[10] If firms were to compete both on the safety and the price margin, this likely weaken the extent of safety competition while leaving our qualitative results intact, assuming that price elasticities are finite.

[11] In theory, safety measures may also be beneficial to the firm, such as by lowering repair costs and reputational damage. In our context, these savings are small and firms do not use this technology to independently improve safety, as we show in a companion paper (Kelley et al. 2021).

variable for the unit interval of passengers, with ε_{ij} privately known to passengers only.

2. **Stage 2: Supply side**. Knowing their own type, the probability of any firm being high type ϕ, and the distribution F of idiosyncratic passenger preferences, *firms* then choose safety $\mu_j \in \{\mu_L, \mu_H\}$ for their bus services. Together with their type, a firm's safety is then given by $q_j = \alpha_j + \mu_j$. We assume that safety choice is more important than type: $\mu_H - \mu_L > \alpha_H - \alpha_L$.[12]

3. **Stage 3: Demand side**. Using their knowledge on ϕ and c, *passengers* form expectations over the quality of firms. They then choose firm based on their idiosyncratic preferences for firms ε_{ij} so as to maximize their utility given by

$$U_{ij} = E\left[q_j\right] + \varepsilon_{ij},$$

where the expectation is taken over the distributions of α_j and ε_{ij}.

Information interventions. We conduct two information interventions:

1. *Private information to passengers about safest firm.* We use information on tracked buses to measure safety q_j of each firm and construct a signal $S_j = 1\left[q_j = \max_{k=1,\dots,J} q_k + \xi_k\right]$ for each bus revealing to passengers which firm is the best safety performer. In the absence of the public signal described below, firms are unaware of the fact that passengers receive this information. We refer to the best safety performer as the *winner*. $\xi_j \sim U\left[-\sigma, \sigma\right]$ with $\sigma < (\alpha_L + \mu_H) - (\alpha_H + \mu_L)$ captures quality measurement error and is independent of α_j and ε_{ij}, which serves as a tie-breaker to guarantee that there is always exactly one winner.[13]

2. *Public signal that buses are being tracked.* We publicly inform both firms and passengers that buses are being tracked and hence managerial safety measures are available to firms. This contrasts with the private information environment in that firms are aware that passengers are receiving the safety information and passengers learn that firms have this information.

[12]If we were to drop this assumption, the conditions for equilibria in the public information game would change slightly but our qualitative conclusions would be similar.

[13]The restriction on the size of the noise, σ, guarantees that the winner is always a firm that chose high

Equilibrium notion. We are interested in pure-strategy Nash equilibria. These are trivial in the baseline and private signal environment but turn out to be rich under the public information intervention.

A.1 Baseline Environment

In the baseline environment, passengers cannot tell whether a firm has enforced safety measures or not. Consequently, enforcing safety measures at a cost is a dominated strategy for all firms, and so they all choose $\mu_j = \mu_L$. Passengers thus expect the safety of choice j to be

$$E\left[q_j\right] = \left(1-\phi\right)\alpha_L + \phi\alpha_H + \mu_L.$$

Hence, the only Nash equilibrium is for all firms to forgo the use of safety measures, and passengers decide between firms solely on the basis of their idiosyncratic preferences for them, as they expect them all to have the same level of safety. This baseline environment functions like a Lemon market, since passengers lack information about bus quality and firms thus have no incentive to provide it.

A.2 Private Signal

In this intervention, passengers receive a private signal that (a) firms can enforce safety measures and (b) about which firm provides the safest services, but firms are unaware of this information passengers receive. Hence, firms continue to operate as if enforcing safety measures was a dominated strategy. As passengers know that firms have no incentive to enforce safety measures, passengers interpret private information about the winner to reflect entirely the variation in firm safety type:

$$E\left[q_j|S_j\right] = E\left[\alpha_j|S_j\right] + \mu_L$$

whereby passengers update their expecation of firm j's safety: the winner's expected quality type becomes $E\left[\alpha_j|S_j=1\right] = \left(1-\phi\right)^J\alpha_L + \left[1-\left(1-\phi\right)^J\right]\alpha_H$. The probability $\left(1-\phi\right)^J$ accounts for the possibility that none of the firms are high types, and hence the winner would be selected purely due to measurement error from among the low types. In all other cases, the winner is guaranteed to be a high type. In contrast, the expected quality of non-winners is $E\left[\alpha_j|S_j=0\right] < E\left[\alpha_j\right]$, reflecting that it is more likely that the firm is low quality

quality, if any bus chose high quality at all.

if it didn't win. Define

$$D(\alpha_j, \mu_j | S_j) = \Pr\left(j = \arg\max_{k=1,\ldots,J} U_{ik} | S_j\right)$$

to be the demand share of a firm of type α_j and safety choice μ_j, conditional on whether the firm is the winner; and let $D(\alpha_j, \mu_j)$ be the corresponding unconditional demand share. Relative to the baseline environment, the winner may now receive a passive demand boost from the intervention, no matter what type the winner is:

$$D(\alpha_j, \mu_L | S_j = 1) > D(\alpha_j, \mu_L).$$

This holds because the private signal boosts the expected quality of the winner, although entirely due to the winner being more likely a high type, rather than the winner choosing high quality. If the difference between types is small, then so is the demand boost from private information.[14]

A.3 Public Information Game

The public information intervention (a) informs firms that passengers know about the capacity to enforce safety measures, and (b) passengers are aware that firms receive this information. As a result, several new equilibria are possible, which we summarize in the following proposition.

Proposition 1. *(*Nash equilibria in the public information game*). Consider the safety provision game with public information. There are four Nash equilibria in pure strategies:*

1. Low Pooling (LPE)*: all firms choose μ_L.*
2. High Pooling (HPE)*: all firms choose μ_H.*
3. Pull-away Separating (PSE)*: high-type firms choose μ_H and low-type firms μ_L.*
4. Catch-up Separating (CSE)*: high-type firms choose μ_L and low-type firms μ_H.*

Proof. We proceed in three steps. In the first step, we characterize the decision rule for a firm to provide high quality and how it may depend on the equilibrium. In the second step,

[14]Firms are unlikely to be able to infer the change in the information environment in the short term due to the presence of ε_{ij}. That is, they may associate any changes in demand shares with changes in idiosyncratic preferences without violating their model.

we show for each candidate equilibrium what values the decision rule takes on. Finally, in the third step, we show that there are no profitable deviations from each candidate equilibrium for some parameter values.

Step 1. Note that any equilibrium requires all firms of a given type to choose the same quality level. If not, there would be a profitable deviation for at least one firm. The four equilibria stated in the Proposition are thus the only candidate equilibria. We denote them by $\theta \in \{\mathrm{LPE}, \mathrm{PSE}, \mathrm{HPE}, \mathrm{CSE}\}$. By the law of total probability, the demand of firm j of type α_j and choice μ_j in equilibrium θ is given by:

$$
\begin{aligned}
D\left(\alpha_j, \mu_j, \theta\right) &= \Pr\left(j = \arg\max_k U_{ik} | \theta\right) \\
&= D_0\left(\theta\right) + W\left(\alpha_j, \mu_j, \theta\right) \Delta D\left(\theta\right)
\end{aligned}
$$

where $W\left(\alpha_j, \mu_j, \theta\right) = \Pr\left(S_j = 1 | \alpha_j, \mu_j, \theta\right)$ is the probability of being the winner; $D_s\left(\theta\right) = \Pr\left(j = \arg\max_k U_{ik} | S_j = s, \theta\right)$ is demand with winner status s; and $\Delta D\left(\theta\right) = D_1\left(\theta\right) - D_0\left(\theta\right)$ is the demand premium winners receive over non-winners. Notice that we make the demand function an explicit function of the equilibrium state θ because how passengers update their safety expectation (and hence their demand) after receiving a signal will be dependent on the equilibrium.

The firm provides high quality if profit by doing so is higher than if not:

$$
\begin{aligned}
D\left(\alpha_j, \mu_H, \theta\right) - c &\geq D\left(\alpha_j, \mu_L, \theta\right) \\
\Delta W\left(\alpha_j, \theta\right) \Delta D\left(\theta\right) &\geq c
\end{aligned}
$$

where $\Delta W\left(\alpha_j, \theta\right) = W\left(\alpha_j, \mu_H, \theta\right) - W\left(\alpha_j, \mu_L, \theta\right)$ is the increase in the probability of being a winner by choosing high quality. This means the increase in winning probability times the increase in demand have to be greater than the cost of providing high quality for a firm to choose to do so.

Step 2. We now work out $\Delta W\left(\alpha_j, \theta\right)$ and $\Delta D\left(\theta\right)$ for each α_j and θ, starting with $\Delta W\left(\alpha_j, \theta\right)$. In each case, the value corresponds to the increase in probability of being the winner when choosing high over low quality. Letting

$$B_H(J,\phi) = \frac{1}{J}\sum_{j=1}^{J}\binom{J}{j}\phi^{j-1}(1-\phi)^{J-j}$$
$$B_L(J,\phi) = \frac{1}{J}\sum_{j=1}^{J}\binom{J}{j}\phi^{J-j}(1-\phi)^{j-1},$$

these can be written as

$$\Delta W\left(\alpha_j, \text{LPE}\right) = \begin{cases} 1-\frac{(1-\phi)^{J-1}}{J} & \text{if } \alpha_j = \alpha_L \\ 1-B_H(J,\phi) & \text{if } \alpha_j = \alpha_H \end{cases}$$
$$\Delta W\left(\alpha_j, \text{PSE}\right) = \begin{cases} (1-\phi)^{J-1}-\frac{(1-\phi)^{J-1}}{J} & \text{if } \alpha_j = \alpha_L \\ B_H(J,\phi)-(1-\phi)^{J-1} & \text{if } \alpha_j = \alpha_H \end{cases}$$
$$\Delta W\left(\alpha_j, \text{HPE}\right) = \begin{cases} \frac{(1-\phi)^{J-1}}{J}-0 & \text{if } \alpha_j = \alpha_L \\ B_H(J,\phi)-0 & \text{if } \alpha_j = \alpha_H \end{cases}$$
$$\Delta W\left(\alpha_j, \text{CSE}\right) = \begin{cases} B_L(J,\phi)-0 & \text{if } \alpha_j = \alpha_L \\ 1-\frac{\phi^{J-1}}{J} & \text{if } \alpha_j = \alpha_H \end{cases}$$

These probabilities are straightforward other than the $B_H(J,\phi)$ and $B_L(J,\phi)$, which capture the probability of winning among "competing" firms, which are usually other high-type firms, except in RE, where it is other low-type firms (since only low types play μ_H in RE).

Turning to $\Delta D\left(\theta\right)$, note that since ε_{ij} is Extreme Value Type I we can write

$$\Delta D\left(\theta\right) = \frac{\exp E\left[q_j|S_j=1,\theta\right]-\exp E\left[q_j|S_j=0,\theta\right]}{\sum_{k=1}^{J}\exp E\left[q_k|S_k\right]}.$$

Hence all we need to do is to characterize the expected quality $E\left[q_j|S_j,\theta\right]$. The expected qualities for different equilibria below show that $\Delta D(\text{LPE}) = \Delta D(\text{HPE})$. That is, for the demand premium of providing high quality, we only need to consider three cases: pooling equilibria and the two separating equilibria. For *pooling equilibria*, we have the following expected qualities for winners and non-winners.

$$\begin{aligned}
E\left[q_j|S_j=1,\theta\right] &= (1-\phi)^J \alpha_L + \left[1-(1-\phi)^J\right]\alpha_H + \mu_j \\
E\left[q_j|S_j=0,\theta\right] &= (1-\phi)^J \alpha_L \\
&\qquad + \sum_{j=1}^{J} \binom{J}{j} (1-\phi)^{J-j} \phi^j \left[\frac{J-j}{J-1}\alpha_L + \frac{j-1}{J-1}\alpha_H\right] + \mu_j
\end{aligned}$$

with $\theta = \text{LPE}$ if $\mu_j = \mu_L$ and $\theta = \text{HPE}$ if $\mu_j = \mu_H$. The combinatorial component in the expected quality of non-winners reflects the probability that any non-winner may still be a high type, depending on the realized number of low and high types. Since the probability weight on α_H in $E\left[q_j|S_j=1,\theta\right]$ is greater than the corresponding weight in $E\left[q_j|S_j=0,\theta\right]$, it holds that $\Delta D(\theta) > 0$ for pooling equilibria.

In the case of the *pull-away separating equilibrium*, we have:

$$\begin{aligned}
E\left[q_j|S_j=1,\text{PSE}\right] &= (1-\phi)^J \alpha_L + \left[1-(1-\phi)^J\right](\alpha_H + \Delta\mu) + \mu_L \\
E\left[q_j|S_j=0,\text{PSE}\right] &= (1-\phi)^J \alpha_L \\
&\qquad + \sum_{j=1}^{J} \binom{J}{j} (1-\phi)^{J-j} \phi^j \left[\frac{J-j}{J-1}\alpha_L + \frac{j-1}{J-1}(\alpha_H + \Delta\mu)\right] + \mu_L,
\end{aligned}$$

which are identical to the expected qualities of pooling equilibria, except that α_H gets replaced by $\alpha_H + \Delta\mu$ – that is, expecting a firm to be high type implies that it will also provide high quality, further bumping up its expected quality. A similar argument as for pooling equilibria shows that again $\Delta D\,(\text{SE}) > 0$.

Finally, for the *catch-up separating equilibrium*, we arrive at similar expressions as with the separating equilibrium:

$$\begin{aligned}
E\left[q_j|S_j=1,\text{CSE}\right] &= \phi^J \alpha_H + \left[1-\phi^J\right](\alpha_L + \Delta\mu) + \mu_L \\
E\left[q_j|S_j=0,\text{CSE}\right] &= \phi^J \alpha_H \\
&\qquad + \sum_{j=1}^{J} \binom{J}{j} (1-\phi)^{j} \phi^{J-j} \left[\frac{J-j}{J-1}\alpha_H + \frac{j-1}{J-1}(\alpha_L + \Delta\mu)\right] + \mu_L,
\end{aligned}$$

except that the safety choice premium accrues to low types instead of high types. Note that plugging in the expected qualities for PSE and CSE into the expression for $\Delta D(\theta)$ above confirms that they result in the same demand premium. Hence, the expressions for SE imply

$\Delta D\,(\text{RE}) > 0$.

Step 3. We now show that there are no profitable deviations from each of the four equililbria for some values of ϕ and c, meaning we check that $\Delta W\,(\alpha_j, \theta)\,\Delta D\,(\theta) \geq c$ holds for all firm types providing high quality and $\Delta W\,(\alpha_j, \theta)\,\Delta D\,(\theta) < c$ for firm types playing low quality. Beginning with the LPE, we require that

$$\alpha_j = \alpha_L : \left[1 - \frac{(1-\phi)^{J-1}}{J}\right] \Delta D\,(\text{LPE}) < c$$
$$\alpha_j = \alpha_H : \left[1 - B_H(J, \phi)\right] \Delta D\,(\text{LPE}) < c.$$

The bound for high types is tighter, hence it is sufficient to show that this inequality holds. Both the term in square brackets and $\Delta D\,(\text{LPE})$ are finite whereas c is unbounded, hence there exists a c for which the inequality is satisfied.

For the HPE, we need

$$\alpha_j = \alpha_L : \frac{(1-\phi)^{J-1}}{J} \Delta D\,(\text{HPE}) \geq c$$
$$\alpha_j = \alpha_H : B_H(J, \phi) \Delta D\,(\text{HPE}) \geq c.$$

If $\phi < 1$ and $c \to 0$, both inequalities are satisfied.

Turning to the PSE, we require that

$$\alpha_j = \alpha_L : \left[(1-\phi)^{J-1} - \frac{(1-\phi)^{J-1}}{J}\right] \Delta D\,(\text{PSE}) < c$$
$$\alpha_j = \alpha_H : \left[B_H(J, \phi) - (1-\phi)^{J-1}\right] \Delta D\,(\text{PSE}) \geq c,$$

which amounts to showing

$$B_H(J, \phi) - (1-\phi)^{J-1} > (1-\phi)^{J-1} - \frac{(1-\phi)^{J-1}}{J}$$

for some ϕ. Taking the limit of $\phi \to 0$, we get $1/J > 0$, which is always satisfied since J is positive and finite.

Finally, for the CSE, we require

$$
\begin{aligned}
\alpha_j = \alpha_L : & B_L(J, \phi) \Delta D \,(\text{CSE}) \geq c \\
\alpha_j = \alpha_H : & \left[1 - \frac{\phi^{J-1}}{J}\right] \Delta D \,(\text{CSE}) < c,
\end{aligned}
$$

which amounts to

$$
1 - \frac{\phi^{J-1}}{J} < B_L(J, \phi)
$$

which holds if $\phi \to 1$. To summarize, these comparisons show that all four equilibria are possible under certain parameter values. $\square$

B Welfare Estimation

In this section we show the link between the reduced form estimates of how passenger choice changes in response to information and our underlying structural parameters $\Delta\alpha$, $\Delta\mu$, and $\Delta D(\theta)$. For simplicity, we set $\alpha_L = \mu_L = 0$ throughout and hence $\alpha_H = \Delta\alpha$ and $\mu_H = \Delta\mu$

B.1 Expected Firm Qualities

B.1.1 Pre-Public

In the pre-public period, when all firms choose μ_L, we define the expected quality from the customer's perspective of the winning firm as $\bar{\alpha}_H$, and the expected quality of all losing firms as $\bar{\alpha}_L$. The expression for these values are:

$$\bar{\alpha}_H \equiv E\left[\alpha_j | S_j = 1\right] = \left[1 - (1-\phi)^J\right] \Delta\alpha$$
$$\bar{\alpha}_L \equiv E\left[\alpha_j | S_j = 0\right] = \left[\phi^J + \sum_{j=1}^{J} \binom{J}{j} (1-\phi)^j \phi^{J-j} \left(\frac{J-j}{J-1}\right)\right] \Delta\alpha$$

Reduced form to structural. The coefficient on private information from the logit estimation, β_1, of passenger choice will capture difference between these values

$$\beta_1 = \bar{\alpha}_H - \bar{\alpha}_L = \left[1 - (1-\phi)^J - \phi^J - \sum_{j=1}^{J} \binom{J}{j} (1-\phi)^j \phi^{J-j} \left(\frac{J-j}{J-1}\right)\right] \Delta\alpha$$

and rewriting:

$$\Delta\alpha = \frac{\beta_1}{\left[1 - (1-\phi)^J - \phi^J - \sum_{j=1}^{J} \binom{J}{j} (1-\phi)^j \phi^{J-j} \left(\frac{J-j}{J-1}\right)\right]}$$

Therefore, for a given J and ϕ, we can use $\hat{\beta}_1$ to estimate $\hat{\Delta\alpha}$.

B.1.2 Post-Public

Similarly, in the public, for each equilibrium we can define the expected quality of the winning and losing firms. We can then use these expressions to derive a mapping the coefficient on public information from the logit estimation, β_2, to $\Delta\mu$, using the value of $\Delta\alpha$ found in the pre-public stage.

Pooled Equilibria

$$\bar{q}_H(\theta) \equiv E\left[q_j | S_j = 1, \theta\right] = \left[1 - (1-\phi)^J\right] \Delta\alpha + \mu_j$$
$$\bar{q}_L(\theta) \equiv E\left[q_j | S_j = 0, \theta\right] = \left[\sum_{j=1}^{J} \binom{J}{j} (1-\phi)^{J-j} \phi^j \left(\frac{j-1}{J-1}\right)\right] \Delta\alpha + \mu_j$$

with $\mu_j = 0$ if $\theta = \text{LPE}$ and $\mu_j = \Delta\mu$ if $\theta = \text{HPE}$

Reduced form to structural.

$$\begin{aligned}\beta_2 &= \bar{q}_H(\theta) - \bar{q}_L(\theta) \\ &= \left[1 - (1-\phi)^J - \sum_{j=1}^{J} \binom{J}{j} (1-\phi)^{J-j} \phi^j \left(\frac{j-1}{J-1}\right)\right] \Delta\alpha\end{aligned}$$

Pull-Away Separating Equilibrium

$$\bar{q}_H(\text{PSE}) \equiv E\left[q_j | S_j = 1, \text{PSE}\right] = \left[1 - (1-\phi)^J\right] (\Delta\alpha + \Delta\mu)$$
$$\bar{q}_L(\text{PSE}) \equiv E\left[q_j | S_j = 0, \text{PSE}\right] = \left[\sum_{j=1}^{J} \binom{J}{j} (1-\phi)^{J-j} \phi^j \left(\frac{j-1}{J-1}\right)\right] (\Delta\alpha + \Delta\mu)$$

Reduced form to structural.

$$\begin{aligned}\beta_2 &= \bar{q}_H(\text{PSE}) - \bar{q}_L(\text{PSE}) \\ &= \left[1 - (1-\phi)^J - \sum_{j=1}^{J} \binom{J}{j} (1-\phi)^{J-j} \phi^j \left(\frac{j-1}{J-1}\right)\right] (\Delta\alpha + \Delta\mu)\end{aligned}$$

Catch-Up Separating Equilibrium

$$
\begin{aligned}
\bar{q}_H(\text{CSE}) \equiv E\left[q_j|S_j=1,\text{CSE}\right] &= \phi^J\Delta\alpha + \left[1-\phi^J\right]\Delta\mu \\
\bar{q}_L(\text{CSE}) \equiv E\left[q_j|S_j=0,\text{CSE}\right] &= \phi^J\Delta\alpha + \sum_{j=1}^{J}\binom{J}{j}(1-\phi)^j\phi^{J-j}\left[\frac{J-j}{J-1}\Delta\alpha + \frac{j-1}{J-1}\Delta\mu\right] \\
&= \left[\phi^J + \sum_{j=1}^{J}\binom{J}{j}(1-\phi)^j\phi^{J-j}\left(\frac{J-j}{J-1}\right)\right]\Delta\alpha \\
&\quad + \left[\sum_{j=1}^{J}\binom{J}{j}(1-\phi)^j\phi^{J-j}\left(\frac{j-1}{J-1}\right)\right]\Delta\mu
\end{aligned}
$$

Reduced form to structural.

$$
\begin{aligned}
\beta_2 &= \bar{q}_H(\text{CSE}) - \bar{q}_L(\text{CSE}) \\
&= \left[\left(1-\phi^J\right) - \sum_{j=1}^{J}\binom{J}{j}(1-\phi)^j\phi^{J-j}\left(\frac{j-1}{J-1}\right)\right]\Delta\mu - \left[\sum_{j=1}^{J}\binom{J}{j}(1-\phi)^j\phi^{J-j}\left(\frac{J-j}{J-1}\right)\right]\Delta\alpha
\end{aligned}
$$

and rewriting:

$$
\begin{aligned}
\Delta\mu &= \frac{\beta_2 + \left[\sum_{j=1}^{J}\binom{J}{j}(1-\phi)^j\phi^{J-j}\left(\frac{J-j}{J-1}\right)\right]\Delta\alpha}{1-\phi^J-\sum_{j=1}^{J}\binom{J}{j}(1-\phi)^j\phi^{J-j}\left(\frac{j-1}{J-1}\right)} \\
&= \frac{\beta_2 + \frac{\left[\sum_{j=1}^{J}\binom{J}{j}(1-\phi)^j\phi^{J-j}\left(\frac{J-j}{J-1}\right)\right]}{\left[1-(1-\phi)^J-\phi^J-\sum_{j=1}^{J}\binom{J}{j}(1-\phi)^j\phi^{J-j}\left(\frac{J-j}{J-1}\right)\right]}\beta_1}{1-\phi^J-\sum_{j=1}^{J}\binom{J}{j}(1-\phi)^j\phi^{J-j}\left(\frac{j-1}{J-1}\right)}
\end{aligned}
$$

B.2 Demand Effects

Finally, we can use the estimates of $\bar{q}_H(\theta)$ and $\exp\bar{q}_L$ to derive the expected demand shift towards the winning firm, $\Delta D(\theta)$ using the logic of the logit estimator:

$$
\Delta D(\theta) = \frac{\exp\bar{q}_H(\theta) - \exp\bar{q}_L(\theta)}{\exp\bar{q}_H(\theta) + (J-1)\exp\bar{q}_L(\theta)}
$$

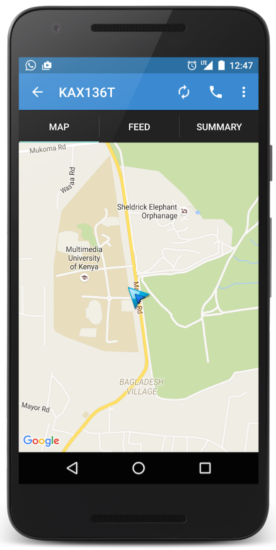
B.3 Welfare

Here we simply summarize the welfare changes to producers, consumers, planners, and their total for each of the possible equilibria:

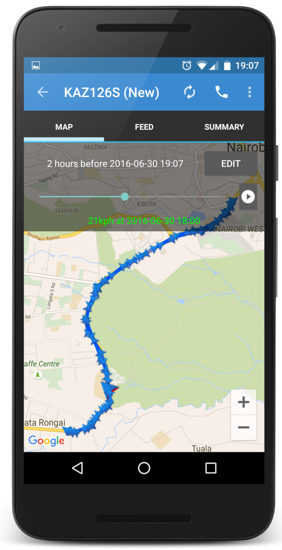
- Producer surplus:
  - LPE: 0
  - HPE: $-Jc$
  - PSE: $-J\phi c$
  - CSE: $-J(1-\phi)c$
- Consumer surplus
  - LPE: $N\,(1-\phi)\,\Delta D(\text{PE})\Delta\alpha$
  - HPE: $N\left\{(1-\phi)\,\Delta D(\text{PE})\Delta\alpha + \Delta\mu\right\}$
  - PSE: $N\left\{(1-\phi)\,\Delta D(\text{PSE})\Delta\alpha + \left[\phi + (1-\phi)\,\Delta D\right]\Delta\mu\right\}$
  - CSE: $N\left\{\phi\Delta D(\text{CSE})\,(\Delta\mu - \Delta\alpha) + (1-\phi)\,\Delta\mu\right\}$
- Planner cost: τ
- Welfare effect = change in producer surplus + change in consumer surplus
  - LPE: $N\,(1-\phi)\,\Delta D(\text{PE})\Delta\alpha - \tau$
  - HPE: $N\left\{(1-\phi)\,\Delta D(\text{PE})\Delta\alpha + \Delta\mu\right\} - Jc - \tau$
  - PSE: $N\left\{(1-\phi)\,\Delta D(\text{PSE})\left[\Delta\alpha + \Delta\mu\right] + \phi\Delta\mu\right\} - J\phi c - \tau$
  - CSE: $N\left\{\phi\Delta D(\text{CSE})\,(\Delta\mu - \Delta\alpha) + (1-\phi)\,\Delta\mu\right\} - J(1-\phi)c - \tau$

C Appendix Figures

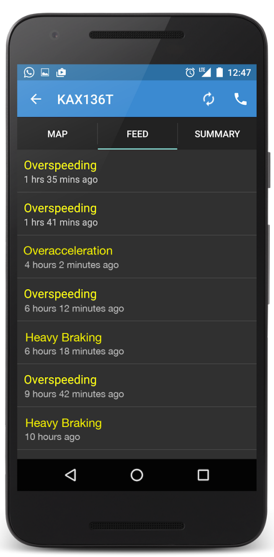
Figure A.1: Mobile app "SmartMatatu" tracking bus safety



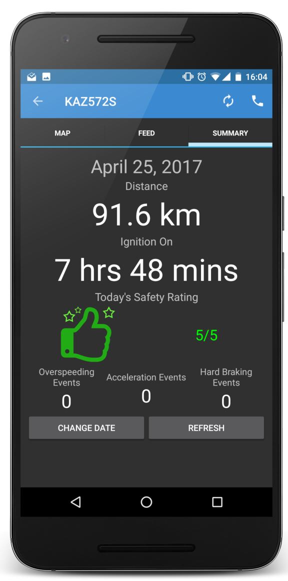
(a) Map Viewer



(b) Historical Map Viewer



(c) Safety Feed

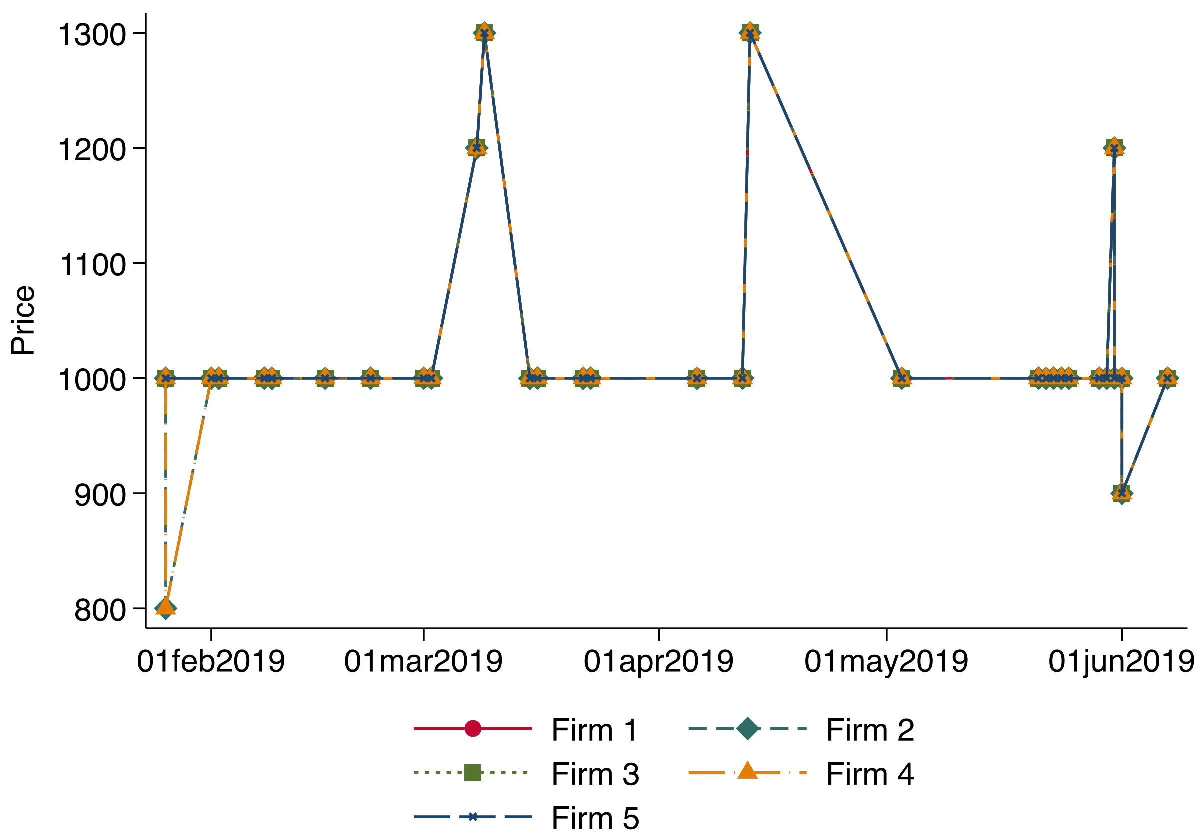


(d) Productivity and Safety Summary

Figure A.2: Study site: Nairobi-Kisumu bus stage in downtown Nairobi

Notes: Satellite image of the bus station (Mfangano Road) from which the buses of the five firms in our study depart to Kisumu. The blue stars indicate the northern and southern entrance to Mfangano Road where our baseline enumerators and the banners after the introduction of the public signal were located. Ticket offices for all five firms are located in between the blue stars. The red star indicates the location of our endline enumerators, to whom passengers showed the ticket they purchased in exchange for the participation incentive.

Figure A.3: Ticket Prices by Firm



Notes: Ticket prices for the trip from Mfangano Road to Kisumu over our study period in Kenyan Shilling.

D Appendix Tables

Table A.1: Four safety outcomes at baseline

	Buses	Bus-days	Safety index components			Safety index
			Avg. speed	Speeding	Sharp braking	
Firm 1	14	664	46.619	0.478	0.027	0.014
			(0.291)	(0.019)	(0.004)	(0.027)
Firm 2	7	536	51.997	0.200	0.013	0.005
			(0.197)	(0.015)	(0.001)	(0.013)
Firm 3	18	1,191	46.751	0.524	0.035	-0.054
			(0.224)	(0.017)	(0.002)	(0.018)
Firm 4	4	345	47.705	0.565	0.056	-0.218
			(0.321)	(0.021)	(0.006)	(0.032)
Firm 5	9	339	50.145	0.628	0.034	-0.247
			(0.395)	(0.037)	(0.005)	(0.040)

Notes: Means and standard error of average speed, speeding alerts, sharp braking alerts, and the safety index by firm. "Buses" is the number of buses of a given firm fitted with our tracking device; "bus-days" is the number of days on which the tracking device was active by firm across the whole study period.

Table A.2: OLS estimates of subsidy and information

	Passenger chose safety-certified bus			
	(1)	(2)	(3)	(4)
Subsidy	0.296***	0.297***	0.297***	0.297***
	(0.024)	(0.024)	(0.024)	(0.024)
Placebo information	0.027	0.027	0.024	0.025
	(0.033)	(0.033)	(0.033)	(0.033)
Safety information	-0.003	-0.006	-0.005	-0.007
	(0.032)	(0.033)	(0.032)	(0.033)
Placebo information × Public signal	-0.038	-0.031	-0.035	-0.029
	(0.044)	(0.047)	(0.044)	(0.047)
Safety information × Public signal	0.108**	0.124**	0.111**	0.126**
	(0.047)	(0.051)	(0.047)	(0.051)
Mean of dependent variable	0.11	0.11	0.11	0.11
Timing-of-interview controls		•		•
Passenger Controls			•	•
N	1,215	1,215	1,215	1,215

Notes: OLS regression estimates of coefficients in Table 5. The outcome is an indicator for buying a ticket for the safest bus company as measured by the tracking devices. "Subsidy" is an indicator for receiving a 100 Ksh discount to take the safest bus. "Placebo information" is an indicator for receiving a pamphlet that increases the salience of safety in the industry. "Safety information" is an indicator for receiving a pamphlet that indicates which SACCO was awarded the "Top safety performer". "Public signal" is an indicator for having been interviewed after the public signal was introduced. Timing-of-interview controls include day-of-the-week interacted with an indicator for afternoon (as opposed to morning). Passenger controls include sex, age bin, an indicator some college or professional education, and frequency of traveling on the route. Robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.