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

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July 9, 2024

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.

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1 Introduction

Economists broadly agree that markets work poorly when consumers lack reliable information about product quality (Akerlof, 1970): consumer demand for products falls, markets shrink, and consumer welfare is depressed. Uncertainty about product quality is particularly high in low- and middle-income countries where state capacity is weak and laws that mandate the disclosure of information are difficult to enforce. This has contributed to the proliferation of low-quality products, including medicine (Bennett and Yin, 2018; Björkman Nyqvist et al., 2018), fertilizers (Bold et al., 2017), and grain (Bold et al., 2022). There is some evidence to suggest that providing information to consumers may improve welfare by guiding them toward better choices (Levin, 2001) or incentivizing firms to supply higher quality products (Bai, 2018). Yet the effectiveness of information campaigns likely depends on market structure. This includes perceived quality differences between suppliers, the level of competition these suppliers face (and their incentives to improve), and both customers' and suppliers' expectations of how each side of the market will respond.

In this paper we investigate the extent to which consumer information improves lemon markets, and how this depends on the market dynamics and strategic incentives firms face. We focus on Kenya's informal public transit sector, which is dominated by small firms who compete for market share. Although the sector accounts for just 10% of all motor vehicles circulating in the country, it is responsible for a disproportionate share of traffic deaths. Macharia et al. (2009) find this to be as high as 70%. The problem is not an isolated one: informal transit plays a central role in making traffic fatalities a leading cause of death in many low- and middle-income countries (WHO, 2020). While the industry is perceived to be exceedingly unsafe, passengers lack reliable information that would allow them to distinguish safer options from the rest.

To this end, we run a randomized control trial (RCT) with more than a thousand passengers (i.e. consumers) at one of Kenya's busiest bus terminals. We equip 52 buses across five firms operating on a major route with safety tracking devices. We provide the safety data to bus managers, allowing them to monitor their drivers' safety behavior and improve their safety performance. We also use this data to rate the top safety performer each month based on measures of speed and sharp breaking. The RCT then proceeds in two stages.

In the first stage, we randomly approach passengers and provide them with one of three pamphlets. Crucially, we do not share these pamphlets or discuss them with the companies at the station. Passengers in the 'safety leader' group receive a pamphlet that discusses road safety, and identifies the safest company operating on the route. Passengers in 'salience' group receive a pamphlet that discusses road safety and lists the companies offering their services at this station *without* identifying the safest one. Finally, the control group receives a small pamphlet that only features an ID key.[1] We then monitor which transit company consumers choose. This allows us to see whether the safety information provided in the pamphlets affected passengers' choice.

In the second stage, we erect large signs across the transit station publicizing our tracking efforts (which we refer to as a "public signal/campaign"), and continue to randomly offer passengers one of the three pamphlets detailed above. The public signal informs passengers that firms can potentially improve safety, and lets firms know that passengers may be aware of their safety performance. We continue to monitor consumers' choice of transit company, and whether transit companies improve their safety performance. Passengers' reaction to the safety leader treatment when tracking efforts are publicly revealed identifies how much they value the expected safety difference of the safest bus now that the tracking devices are known to be available. Conversely, how firms react reveals whether the perceived benefits of improving transit quality outweigh the costs to the companies (where the benefits and costs are a function of the cost of improving, the number of competitors, and the quality of services they provide).

We document three key findings. First, we find that the 'safety leader' treatment passengers *do not* respond to the safety information they receive privately before the public signal is in place. The behavior of passengers who receive the pamphlet that identifies the safest bus is the same as those who do not. This suggests that passengers do not perceive there to be large differences between bus companies when it comes to safety, and therefore they have no reason to switch based on this margin (relative to other features of the bus that may be driving their choices).

Second, we find that passengers *do* respond to safety leader information when they receive it with the public signal – the large signs meant that both consumers and transit companies were aware that the other party had access to the information. Consumers who received the pamphlet with information identifying the safest firm

[1]We further cross-randomize the provision of a subsidy to choose the safer bus, which we use for model estimation purposes.

were now more likely to choose it than those who did not receive the information. This suggests that consumers expect some firms to compete on the safety margin and the safest bus company is the one that has meaningfully improved its quality relative to others in the market. Taken together this result demonstrates that the effectiveness of consumer information depends on whether consumers expect firms to respond.

Third, we find that the public campaign improved transit driver safety among the lowest performing companies. On average, we see a 25% drop in speeding alerts, likely contributing to meaningful improvements in road safety. As the effects are concentrated primarily among the two lowest-performing companies, this suggests that consumer information may not affect all companies in the same way.

We develop a game-theoretic model to explain consumer and firm responses. In this environment heterogeneous consumers and firms strategically respond to incentives for safety. When information is public, firms have strategic incentives to improve their quality, and customers have reason to believe that firms are responding to their preferences. 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 in our experiment allow us to distinguish between these equilibria. In either pooling equilibria, differences in safety across firms remain unchanged and therefore consumer demand should not change across firms. The fact that consumers change their behavior when the information campaign becomes public suggests it created a separating equilibrium. By investigating heterogeneous responses to the public signal across firms, we find strong evidence that worse firms catch up to better ones.

There may be other reasons beyond the scope of the model that could explain the results, but we do not find evidence for these alternative explanations. First, passengers may perceive private information to be more trustworthy after the introduction of the public signal. However, in a sub-experiment where we subsidized passengers to choose the safest bus, we found that consumers were equally likely to trust the subsidy offer and switch to the safer bus both before and after the public campaign. This suggests that the public campaign did not affect passengers' trust in our efforts. Second, the public signal may have increased the salience of safety. However, we do not see passengers who receive the 'salience treatment' pamphlet (which makes safety salient) changing their behavior before the public signal. Third, passengers may be subject to an interviewer demand effect after the public signal. However, their stated preferences for safety remain unchanged, which minimizes concerns of interviewer demand effects. Fourth, passengers might worry about the social implications of their choice, but since they receive information privately, their actions are difficult for others to interpret. Fifth, while passengers might coordinate their choice of the safer bus under the public signal, the serial correlation of choices among consecutive passengers remains low and insignificant. Finally, while the safety improvements we observe could be due to mean reversion, our safety index is relatively stable in the three months before and after the introduction of the public signal.

This model provides a foundation for welfare analysis of consumer information in markets with strategic firms. Consumer surplus can be decomposed into a direct effect, where consumers switch to safer firms, and an indirect effect, where some firms provide safer rides, benefiting some consumers who do not switch, an "information externality". We exploit a randomized subsidy for passengers to choose the safest bus to convert these behaviors into dollar values. Additionally, we also estimate consumer welfare under alternative pooling and separating equilibria that did not materialize in our context.

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. Demand for the safest firm 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. Most of the benefit comes from the positive information externality accruing to consumers that do not change their bus choice as companies start to supply safer rides. The change in producer surplus is negative at approximately $3,000 across all firms. The cost of the information provision itself is negligible, suggesting that this intervention is cost effective.

A 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 separating equilibrium, where relatively safe firms further improve their services, welfare would have been substantially higher (approximately \$20,000 per month) than the separating equilibrium that we observe in our setting where relatively unsafe firms improve their safety. This stems from passengers shifting to firms with higher baseline safety. Finally, if all firms had improved by a similar margin (high-pooling equilibrium), welfare benefits would have been approximately \$30,000, more than twice the magnitude of our prevailing catch-up separating equilibrium, although the burden on suppliers would have also been more than twice as large.

This paper makes three primary contributions. First, we contribute to the literature on lemon markets in low-income countries. In high-income countries, inefficiencies in these markets are typically addressed through government regulation and inspection. However, in low-income countries with weak state capacity, fewer solutions have been identified and studied. Bai (2018) shows that providing tamper-proof technologies to firms encourages them to offer higher-quality goods, thereby fostering consumer trust. Björkman Nyqvist et al. (2018) and Bennett and Yin (2018) find that the entry of large firms can encourage other producers to improve their product quality. Our study introduces a novel approach to addressing inefficiencies in lemon markets by combining consumer information with public signals that emphasize the benefits of offering higher-quality products. We demonstrate that such a strategy can prompt firms to respond strategically, leading to overall welfare gains.

Second, we contribute to a small body of research at the intersection of market regulation and consumer product information. For instance, Jin and Leslie (2003) examine the introduction of hygiene grades for restaurants in Los Angeles County, finding improvements in service quality and an increase in demand for high-quality establishments. Similarly, Barahona et al. (2020) analyze the effects of a warning label mandate on unhealthy foods, estimating both demand and supply responses. Our study builds on this literature by using a randomized control trial to estimate consumer welfare gains in a low-income country. Moreover, we account for the possibility of multiple market equilibria and demonstrate how to estimate welfare when a market transitions between these different equilibria.

Finally, we contribute to a growing literature on road safety in low- and middle-income countries. Road traffic accidents contribute to a staggering loss of life, and limit economic development (Odero et al., 2003; Cervero and Golub, 2007; Raynor and Mirzoev, 2014). There is emerging literature on the impact of potential solutions. For instance, Habyarimana and Jack (2011, 2015) found that placing stickers in Kenyan minibuses encouraging passengers to report dangerous driving reduces average speeds. Our study expands on this method by directly engaging passengers with minibus safety ratings before they board, potentially moving the market towards a safer equilibrium. Furthermore, we observe that providing information to passengers can motivate bus companies to operate more safety, addressing some of the inefficiencies typical in markets with asymmetric information. Crucially, we show how these consumer information campaigns may benefit from complementary public signals that incentivize improvements from the supply side.

The rest of the paper is organized as follows. Section 2 discusses the context of our study. Section 3 provides an overview of the design of the randomized control trial, 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: 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, which are called *matatus* in Kenya. 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). As a point of comparison, buses in the US account for 1% of registered vehicles and 0.4% of casualties (BTS, 2016).

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 companies have weak incentives to provide safe rides as they cannot hope to capture extra revenue by supplying this unobserved quality, even if it is demanded by passengers.[2] 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.

Governments and international institutions are continuously 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.

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, Habyarimana and Jack (2015) 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 in an effort to improve road safety.

[2] 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.

3 Experimental Design and Data

3.1 Design of Experiment

Study site. 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 provides service between Nairobi and Kisumu, one of the country's most important and busiest long-distance bus routes, which is notoriously unsafe. The terminal serves both regular business passengers that transit between Nairobi and Kisumu several times a year, as well many passengers who infrequently travel between the two locations.

The study location was well suited to the study's requirements. It was 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 companies (commonly referred to as SACCOS) and we fit a minimum of six buses in the SACCO's fleet (of approximately 50 buses) 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 company to another based on sharp breaking and speeding alerts.

Safety measurement technology. The intervention required the ability to collect information about the safety of the minibuses in the sample. Kenya, like most low-income countries, lacks reliable data on safety and road accidents. Hence, we developed a new monitoring system for matatus that can pick up safety behavior with high accuracy. The system was also 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 device with threshold parameters as inputs (which were calibrated to the Kenyan road conditions to capture context-appropriate levels of unsafe driving). 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 on sharp breaking and speeding). This information served two purposes. First, it was conveyed to minibus managers, who could use the information to monitor and address unsafe driving. Second, it was used to assign a Top Safety Performer badge to the company that operated most safely that month.

Information treatments. 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 1,186 passengers during the main study period. We randomly assigned passengers to one of three arms that differed in the amount of information we provided.[3] In the control group, passengers 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 leader 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 discussed with the subject, enumerators asked them to proceed to buying a bus ticket of their choice and to show it to a second enumerator stationed further down the road where the buses were leaving from, which allowed us to measure their actual firm choice. 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 salience group identifies whether priming passen-

[3]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 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.

gers about matatu safety affects their choice of firm. Second, the comparison of the safety treatment group to the salience group identifies 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. Three months into delivering pamphlets 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 experiment 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 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.

Subsidy. We also introduced a sub-experiment where passengers were cross randomized into an additional "subsidy treatment". This helps to assign monetary valuations to the behavior changes we observe in response to the pamphlets, which we also use for model estimation purposes. We selected half of the respondents to receive a 100 KES ($1 USD) subsidy should they purchase a ticket from the company that was awarded the Top Safety performer rating. 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 salience group, enumerators were careful not to tell passengers why this particular bus was being subsidized.

3.2 Data and Descriptive Statistics

Data. We use data from the tracking device to track changes in driving behavior over time by each company. Moreover, we administered a series of passenger surveys to capture changes in passenger behavior. We first 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.

Summary statistics. Table 1 shows summary statistics of passengers approaching the bus stop. As expected, passengers randomized into control, safety salience, and safety leader have similar characteristics, state similar preferences over bus characteristics, and are exposed to similar choice sets. The majority of passengers names safety as the most important characteristic of their bus choice, underscoring the importance of the issue. 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. 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.[4]

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.[5]

[4] 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.

[5] During our main study period, the same firm was deemed the Top Safety Performer throughout, although the gap narrowed.

4 Experimental Results

We run the following regressions as our preferred specification to understand the impact of our treatments on passenger bus choices.

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

where D_i is an indicator equal to 1 if passenger i selected the Top Performing bus company; $\mathbf{X}_i$ are controls for individual characteristics; and ε_i is an error term. 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. The treatment indicators are Salience_i for our safety salience treatment; and SafetyLeader_i for those passengers randomized into learning about the Top Safety Performer. 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.

4.1 Effects of Private Information

We start with the effect of our safety leader and salience treatments on customers before the public signal. Table 2 presents the results from equation 1. Rows 1 and 2 of the table show the impact of being in each group 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 differ in the set of fixed effects and controls that 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 leader treatment had a precisely estimated zero impact on the probability that the passenger chose the top safety performer.[6]

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 2 shows how the effect of our 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 impact of the safety leader arm meaningfully. In our preferred specification in Column 4, passengers that know 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 results indicate that passengers find the safety information in the pamphlet more informative once the campaign is public. This may be because passengers now expect bus companies to compete on safety, as it has become an observable characteristic. Similarly, companies may find it more enticing to improve their safety now that they realize customers know they are being tracked. We investigate whether companies improve their safety after the campaign goes public. Table 3 reports the estimates of equation 2 on the three safety measures we track 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 kilometers 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

[6]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.

reduced by 0.12 (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 visually. All four plots show a visually detectable improvement from the pre-period to the public period, however the improvement in braking is more gradual than the other metrics.

4.3 Possible Mechanisms for Response to Public Signal

Market equilibrium. Our preferred explanation for the demand and supply side response to the public signal is that it results from a competition game among firms to attract more passengers. We provide a full explanation in the model section (Section 5 and Appendix A). To summarize, once firms know that passengers can observe safety, they may choose to improve their safety standards to be certified as the safest bus and attract more passengers. Passengers, in turn, recognize that some firms might actively improve safety, making the safety certification more poweful. Before this, passengers likely did not believe that firms were actively working to improve safety, so they discounted the safety signal.

There are other possible interpretations for the demand and supply response to the public signal. Here, we present these alternatives and explain why we believe they cannot account for the behavior changes we observe in the data.

Credibility. The banners might have increased the credibility of the safety leader treatment, but we believe this explanation is unlikely for a few reasons. First, we provided the pamphlet information in a credible manner: enumerators dressed professionally, displayed laminated ID badges with photos, and explained that the project was approved by the National Transport Safety Authority and funded by reputable international universities. Second, 30% of passengers switched to the safest bus when offered a subsidy (before the public signal), showing they trusted our promise to provide cash after purchasing the ticket. If they trusted us to pay the subsidy, it's likely they also trusted the information about the safest bus.

Social signaling. Passengers may have chosen the safety-certified bus to show others that they cared about safety once this attribute was being advertised publicly. However, we believe this behavior is unlikely in the context of our experiment. Other passengers do not observe which treatment was provided to the respondent, so they cannot know if someone received the safety information. Additionally, since the majority of passengers did not receive the safety leader information, there is no way to publicly signal that one is making the safe choice. Finally, even if passengers could signal to each other, we would expect these pressures to be weaker in a context where almost everyone is a stranger and does not have repeated interactions. Moreover, it is not clear that a preference for safety over other attributes, such as speed or comfort, would be considered a socially preferred choice.

Interviewer demand. Passengers might have also felt more pressure to "please" the enumerator by choosing the safe bus company under the public signal. While this is possible, we would expect this behavior to be reflected in the number of people reporting bus safety as the most important attribute when choosing a bus at baseline. However, our checks show no change in the proportion of passengers expressing safety as their primary concern once the public campaign is launched.

Passenger salience. The unveiling of the safety banners might have made passengers and firms value safety more. If salience influenced passenger choice, we would expect passengers who received the safety salience pamphlet (before the public campaign) to have chosen the bus company they believed was the safest, but we did not observe this behavior. Similarly, the tracking data we provided to firms highlighted the available safety information for managers and we do not see changes in their behavior before the campaign went public (see Appendix Figure A.1). Therefore, it is unlikely that the public banners significantly increased the salience of safety for passengers or firms.

Coordination. While the safety banner may have helped passengers coordinate on choosing the winning firm, the demand for each firm is hard for any single passenger to observe, as the ticket purchase locations are out of view, making it difficult to know which firm an individual chose after the transaction. Moreover, if coordination increased due to the public signal, we would expect the serial correlation of passenger ticket purchases to increase during the public period. We tested this by regressing passenger bus choice on the choices of previous passengers that day in the public period. We found no evidence of autocorrelation, with a point estimate of -0.026 (t = -0.52) on the lagged choice of bus.

5 Information Effects and Market Structure

We now present a model describing the public transit market as a static game of monopolistic competition. While this is a simplified representation of the actual market, the model serves several purposes. First, it provides a framework for interpreting the reduced-form results from our experimental intervention. Second, it offers a structure for performing welfare estimations of the intervention and conducting cost-benefit analyses. Finally, the model allows us to explore outcomes under counterfactual equilibria and understand the conditions under which these alternative equilibria are likely to occur.

5.1 Model Setup

We present a model of strategic interaction between heterogeneous firms competing for a fixed number of customers. The public signal about safety information creates a tournament where firms decide whether to improve their quality (safety) at a fixed cost to attract more customers. Firms will only choose to improve if there is a significant chance of winning this tournament. Customers, in turn, anticipate that only some firms will improve their quality, which influences how strongly they respond to information about the safest firm. We conclude that information pamphlets affect firms and passengers differently, depending on the market structure and the resulting equilibrium. Below, we provide an introduction and intuition on the basic workings of the model (presented in full 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 (i.e. α_H) as ϕ. Passengers in turn draw idiosyncratic firm specific preferences ε_{ij}.

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.

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. Baseline quality α_j only affects the probability of winning. The increase in demand that firms would experience from winning is the same regardless of baseline quality because passengers cannot observe it.

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 a monotonically increasing function of

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

which implies that the larger the gap between these two expected qualities, the larger the demand share captured by the winning firm. The reason passengers might expect the winning bus to be safer, is either because of differences in baseline quality, and/or differences in the safety choices made by each set of firms. 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. We turn to this next.

5.2 Equilibrium without Public Signal

Passengers first receive information S_j through a pamphlet 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). 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 firms safety choices. Thus, the model predicts that demand for the safest bus 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 are 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.

Table 4 summarizes the model's predictions regarding the behavior of firms and passengers under each equilibrium. A "+" symbol indicates an increase in the demand for the safest bus or the supply of safety by firms, while a "++" indicates a proportionally larger increase, and a "0" indicates no change. Columns 1 and 2 present the low pooling equilibrium that emerges before the public signal.

5.3 Equilibria with Public Signal

The public signal implemented through the banners ensures that (1) firms become aware that passengers are receiving safety information, and (2) passengers understand 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) (as above without the public signal), but also the expected gap in quality choice (μ_j). Multiple possible equilibria emerge. Which one materializes depends on the proportion of high and low quality buses in the market which are driven by the probability of high-quality firms in the market, ϕ, and the costs of choosing to supply safety, c.

There are three classes of equilibria which arise 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. Columns 3 and 4 of Table 4 present predictions for all three possible equilibria under the public signal.

Low pooling equilibrium. If a low pooling equilibrium arises, we expect to observe the same responses we did absent the public signal. Although firms have the opportunity to capture demand by winning the tournament, they have decided it is not worth it because providing high quality is too costly. Passengers will still believe that the difference between the safest firm and the others is solely due to their fixed quality attributes, leading to the same demand shift as seen absent the public signal.

Separating equilibria. A separating equilibrium where some firms improve their quality while others do not (Table 4, row 2) arises when there is initial heterogeneity in fixed firm quality (α_j). These differences affect the likelihood of being rated as the best firm and capturing the increased demand if the firm chooses to improve quality.[7] It is possible for either initially high-quality or low-quality firms to choose to improve, while the other type does not. Which occurs depends on the proportion of high and low quality buses in the market which is driven by ϕ, and the costs of choosing to supply safety, c (we provide more details below).

Passenger demand will shift more strongly toward the safest firm than it did without the public signal. This happens because passengers now believe that quality differences among firms come from both fixed components (α_j) and choice components (μ_j), with some firms making efforts to improve while others do not. Therefore, the expected quality difference between the safety-certified firm and all other firms will be greater than it was before the public signal, or under the pooling equilibrium.[8]

High pooling equilibrium. In a high pooling equilibrium (Table 4, row 3) all firms choose to improve quality as they estimate that expected demand benefits outweigh the costs. The passenger demand response towards the safety-certified firm is the same as it was before the public signal or under the low pooling equilibrium. Although this seems counterintuitive, it occurs because all firms are providing high quality (μ_H), meaning that the expected difference between the safest firm and the others is only due to the fixed quality component. Therefore, while passengers benefit from all firms supplying a better product, they are less responsive to safety information than they were in the separating equilibrium.

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

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

5.4 Model Interpretation

Market structure. Figure 5 shows which equilibria could exist under the public signal across the range of values for the two relevant model parameters ϕ and c — the proportion of high and low quality buses, and 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 baseline quality firms choose to improve and low baseline quality firms do not.

While some parameter values can lead to multiple or no equilibria, certain broad patterns determine the likelihood of each outcome. The high pooling equilibrium is most likely to occur when the cost of quality is low and medium values of ϕ. The low pooling equilibrium is most likely when the cost of quality is high or ϕ is low. The pull-away separating equilibrium overlaps 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.[9]

Interpreting results through model. We return to our empirical results to understand which equilibrium is consistent with the patterns we predict from the model. Table 2 shows that passengers' response to the pamphlets under the public signal is much stronger than what we observed before the public campaign began. This result is only consistent with a separating equilibrium where some firms improve under the public signal while other do not. We explore this on the supply side and find heterogenous responses by firms. Figure 6 shows that two out of five firms demonstrate large improvements in their safety performance.

Model limitations. The focus of this model is on quality choice. To make the model manageable, we ignore several important features such as prices, attracting new passengers to the market, cost differences across firms, and various other sources

[9] Pull-away separating equilibria exist when high types are rare (ϕ is low), while catch-up separating equilibria exist when they are common (ϕ is high). The intuition for this result is that if the majority of firms have relatively high baseline safety (ϕ is high), many of them may be complacent, providing an opening for low types to grab some of their market share by improving their services. On the other hand, if the majority of firms have low baseline safety (ϕ is low), the occasional high type may feel the need to pull away from the pack to ensure its dominant market position.

of firm heterogeneity. For some factors, we have evidence that these aspects are relatively fixed in our context. For example, there is almost no price variation across firms, and this remains unchanged during the public period (see Appendix Figure A.3). Therefore, we are comfortable excluding this choice margin from the model for practicality. While other factors could still play a role in our setting, including these margins would not fundamentally change the basic intuition and predictions of the proposed model.

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 and counterfactual welfare outcomes under different market equilibria. We consider welfare changes for passengers and firms resulting from the public signal, acknowledging that there may be additional benefits for third parties, such as pedestrians or other drivers, which we do not consider here. Since our model includes multiple equilibria, we first need to determine which equilibrium we are observing. This involves two steps. First, we observe a demand response to the pamphlets only after the public signal was introduced. This indicates a separating equilibrium because, in a pooling equilibrium, all firms would continue to have the same relative safety as before, and passengers would have no reason to switch firms. Second, we 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 during the public period, while the three highest performing firms improve much less. These response patterns are most consistent with a catch-up equilibrium.

In a catch-up separating equilibrium $\theta = \text{CSE}$, the welfare effect of private information under the public signal can be written as:

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

Starting with passengers, the consumer surplus from the safety leader pamphlet arises because they 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 providing safety efforts to the winning firm that is, gaining them $\Delta\mu$ in quality improvement. However, in a catch-up equilibrium where low-type firms are transitioning to higher quality, the benefits of improved safety are somewhat offset by the lower fixed quality ($\Delta\alpha$) of these firms. Second, for some passengers $(1-\phi)$, the bus they choose has still improved its safety as part of the new equilibrium, gaining them $\Delta\mu$ as well.

Next, we consider the producer surplus. The winning firm benefits from increased demand ($\Delta D(\text{CSE})$) minus the cost of supplying high quality c, resulting in higher profits than before. The remaining firms that do not win the competition share the remaining passenger demand ($\frac{1-(\frac{1}{J}+\Delta D(\text{CSE})}{(J-1)}$), leaving them with fewer passengers than before. The subset of losing firms that chose to improve their quality also incur the cost c. In aggregate, since the total size of demand is fixed, the total producer surplus is reduced by the cost of supplying quality multiplied by the number of firms that choose to improve ($J(1-\phi)c$)).

Finally, there is the direct cost of the information intervention (τ). This includes the expenses associated with collecting safety data from vehicles and disseminating this information to passengers via pamphlets. Since the marginal cost of data collection is low, the overall costs are primarily driven by the labor involved in disseminating the pamphlets.

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. However, we recognize that some of these values are uncertain. Therefore, we will also demonstrate how the welfare estimates vary with different 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 effect of the safety leader treatment (pre and post public signal) on the choice of the safety leader. We can divide the effect of the safety leader treatment by the effect of the subsidy treatment to recover a monetary value for the safety leader treatment. Before the campaign goes public, the effect of the safety leader treatment is a function of the fixed baseline differences between buses ($\Delta\alpha$), the proportion of high quality firms ϕ, and the number of buses in the market. With empirical values for the latter two (discussed below), we can recover a monetary valuation for ($\Delta\alpha$). When the campaign goes public, the effect of the safety leader treatment is also a function of ($\Delta\mu$). Using our estimate for ($\Delta\alpha$), we can then calculate ($\Delta\mu$). The results of this process show that the value of the fixed safety component ($\Delta\alpha$) is very close to zero at -\$0.14 (se 0.46). Note that the 95% confidence interval for this value is $[-1.04., 0.76]$, and therefore we assume for our robustness tests that the perceived safety benefit is between zero and a small positive number.[10] The value of the choice component of safety ($\Delta\mu$) is worth \$0.58 (se 0.24) per passenger. Finally, we also use these values to estimate the extra captured demand share that accrues to the winning firm, which we estimate at 0.14 (se 0.06).

Total number of passengers. To estimate total welfare based on the safety valuation per passenger, we calculate the total number of passengers using the bus terminal daily. This estimate is derived from the passengers our enumerator team engaged with during their two-hour work window. They intercepted approximately 10% of the total passengers entering the bus terminal area, which translates to an estimated 150 passengers per hour. Multiplying this by 12 (the number of active hours at the bus terminal) provides an estimate of 1,800 passengers per day.

Proportion of high quality firms. We estimate ϕ by examining safety outcomes across firms before the public campaign went live. Figure 6 shows that there are three firms with significantly higher safety provision than the other two firms. Therefore, we set $\phi = 0.6$. Since we are in the catch-up equilibrium, this implies that $(1 - \phi) = 0.4$ of the firms will respond to the public signal by improving quality, which is also supported by the qualitative findings in Figure 6.

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

Cost of providing safety for firms. We refer to estimates from a companion paper by Kelley et al. (2022) which examines the impact of directly providing incentives for drivers to improve their safety performance. We find that incentivizing safety improvements in this setting costs firms approximately \$2 per driver per day.

Cost of information intervention. We estimate the cost of providing the information based on our project expenses to be approximately \$10 per day.

6.2 Welfare Estimates and Counterfactuals

Using the calibration described above, we calculate welfare using Equation 3 above. We do so for the catch-up equilibrium ("CSE"), which we believe best represents this market, as well as for three other possible equilibria: low-pooling, pull-away, and high-pooling. Figure 7 illustrates the monthly welfare changes resulting from our intervention, segmented into changes in producer surplus, consumer surplus, and information cost. The "CSE" row indicates that our intervention resulted in an estimated monthly welfare gain of approximately \$17,500. This gain primarily consists 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 $\Delta\alpha$ 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 $\Delta\alpha$ and high $\Delta\mu$ and is not true for the majority of the possible parameter spaces, as we explore below. Finally, the high-pooling equilibrium provides the highest aggregate welfare gain because most consumers benefits (directly or indirectly) from all buses providing safe services, but it also involves the highest costs to firms.

6.3 Sensitivity Analysis

Given the uncertainty surrounding many of our calibration values, we analyze the sensitivity of our welfare calculations to different parameter choices. This analysis allows us to: i) examine the distribution of welfare changes under all four possible equilibria, and ii) evaluate the probability that our intervention might result in an overall 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 reject 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 this 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 this figure. First, in contrast to our point estimate calculated above, the catch-up equilibrium provides smaller welfare improvements on average than the pull-away equilibrium (the high-pooling equilibrium nearly always dominates the others). This divergence is driven by the relative size of $\Delta\alpha$. In a pull-away equilibrium, some consumers are switching from a low fixed quality to high fixed quality bus, whereas in a catch-up equilibrium, some consumers are switching from a high-fixed quality to low fixed quality bus. This means that in general there are more safety gains under a pull away then under a catch up equilibrium. However, when fixed quality differences are relatively low to begin with ($\Delta\alpha$ is small), the gains from the switchers across both equilibrium are similar. The point estimates from our experiment suggest a $\Delta\alpha$ near zero, leading to the catch-up equilibrium being preferred to the pull-away equilibrium. However, this is not generally true, and under the majority of parameters within our confidence set the pull-away equilibrium is superior.

Second, Figure 8 indicates that the distributions across all equilibria are predominantly positive. This is reassuring and suggests that interventions aimed at providing quality information to customers are unlikely to result in negative outcomes as long as some firms respond. 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 under this scenario is also limited because no firms incur c to improve quality, meaning the aggregate loss is solely attributable to the cost of the intervention itself.

7 Conclusion

In this paper, we present findings from a randomized control trial where 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. Additionally, we demonstrate that firms use their tracking devices to supply safer transit services after the introduction of the public signal. We interpret these findings through a model of strategic firms and consumers that systematically respond to safety incentives.

Our second contribution is using this model to estimate the welfare effect of the information intervention under the public signal. We decompose consumer surplus into a direct effect from consumers switching to safer buses, and an indirect effect ("information externality"), as even consumers who do not switch benefit from improved safety services on the route. The model also allows us to estimate the welfare effect of potential counterfactual equilibria that could have emerged after the introduction of the public signal.

What are the implications of these results for optimal policy in an informal transit network? First, the impact of an information intervention can vary significantly depending on the existing equilibrium in the informal transit market, and how different firms might respond to consumer information. Therefore, policymakers must understand which equilibrium currently exists, and anticipate which one is likely to emerge from an information campaign in order to accurately assess the costs and expected benefits. We estimate that the welfare effects of a high pooling equilibrium are highest, followed by a separating equilibrium, and finally a low-pooling equilibrium. Which equilibrium emerges depends on the costs of improving safety, and the proportion of high quality and low quality firms. Second, informal transit firms vary in both their initial safety levels and their ability to enhance safety. In situations where there are substantial initial safety disparities but limited capacity for improvement, policies that directly provide safer services may prove more effective than providing 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 would be interesting to consider how general equilibrium effects across the entire transport network may be affected by consumer information at central bus stations. 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.

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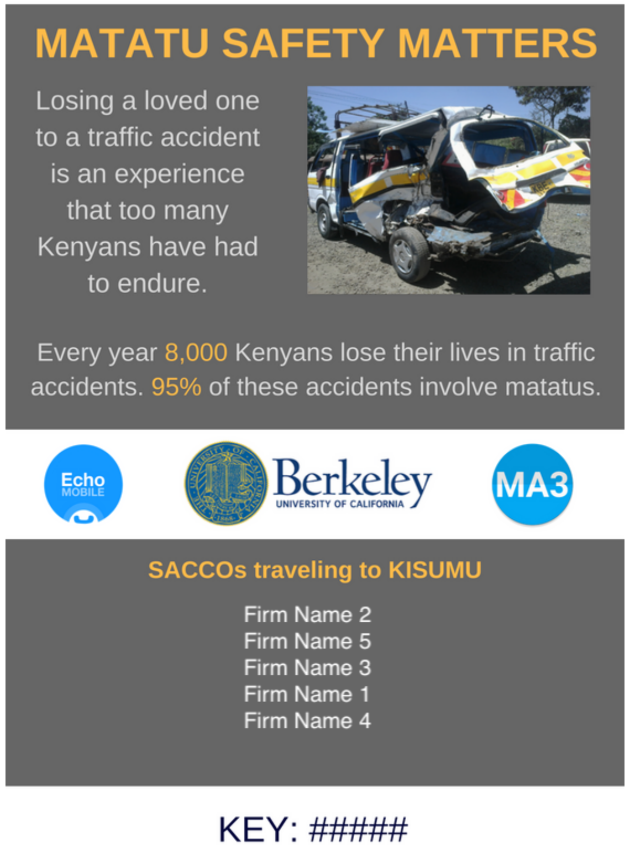
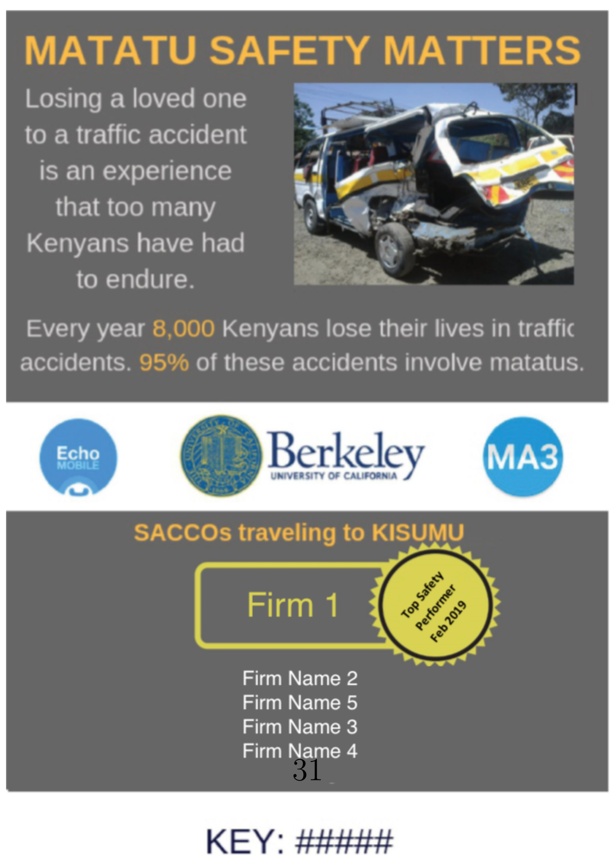
Figures

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



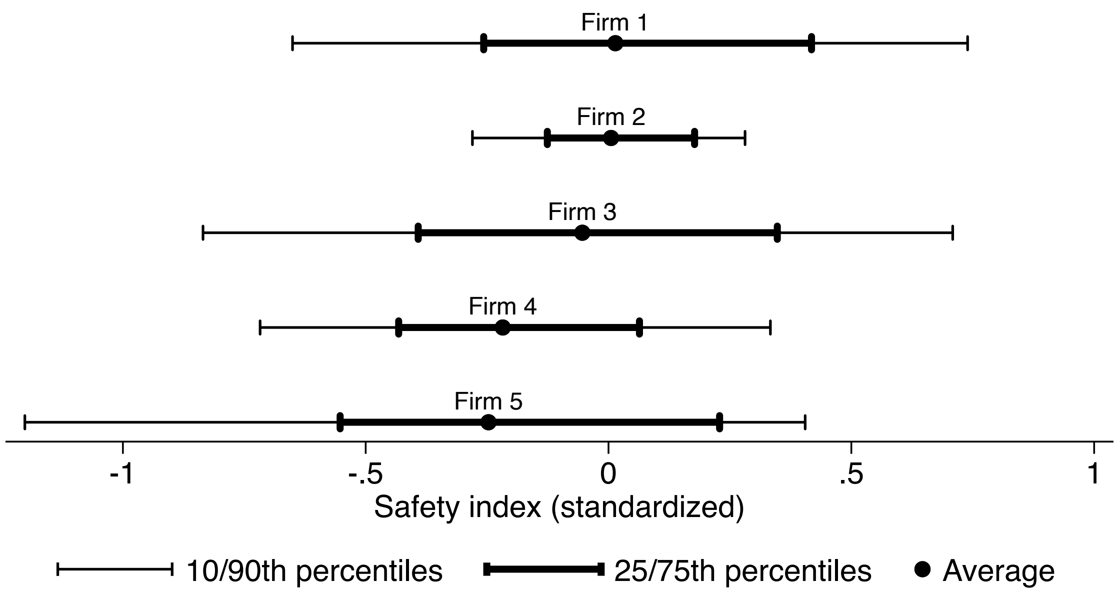


Notes: The pamphlet was distributed to passengers in the safety information group after completion of the baseline survey. Enumerators read the text out loud to each passenger and explained the

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

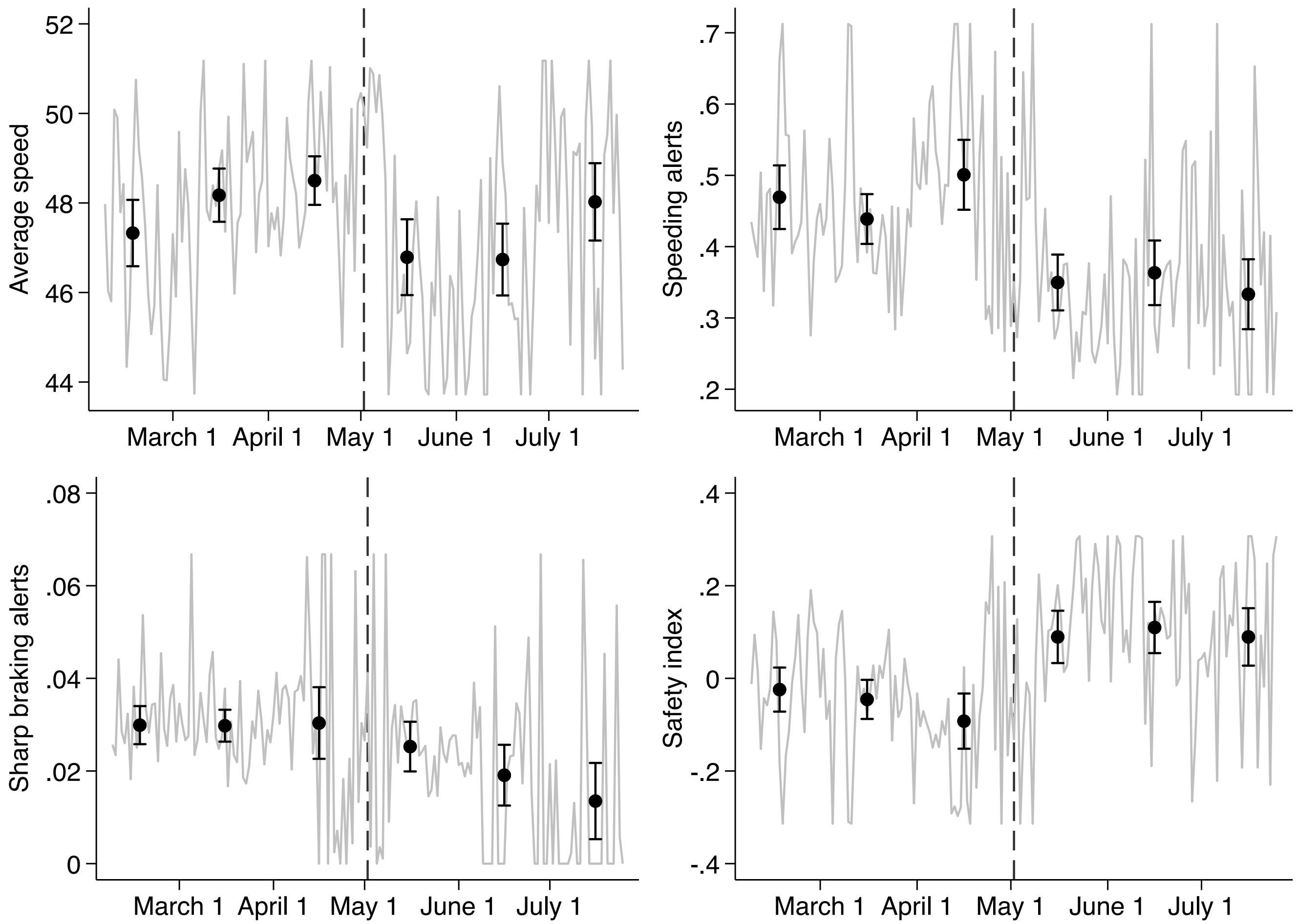
Notes: These banners were placed at both entries to the bus station from which the five firms in our study depart. The banner reads: "SACCOs on Mfangano-Kisumu [the route in our study] are now tracked for safety. Enjoy the benefits of safer transit, and check out the Top Safety Performer."

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



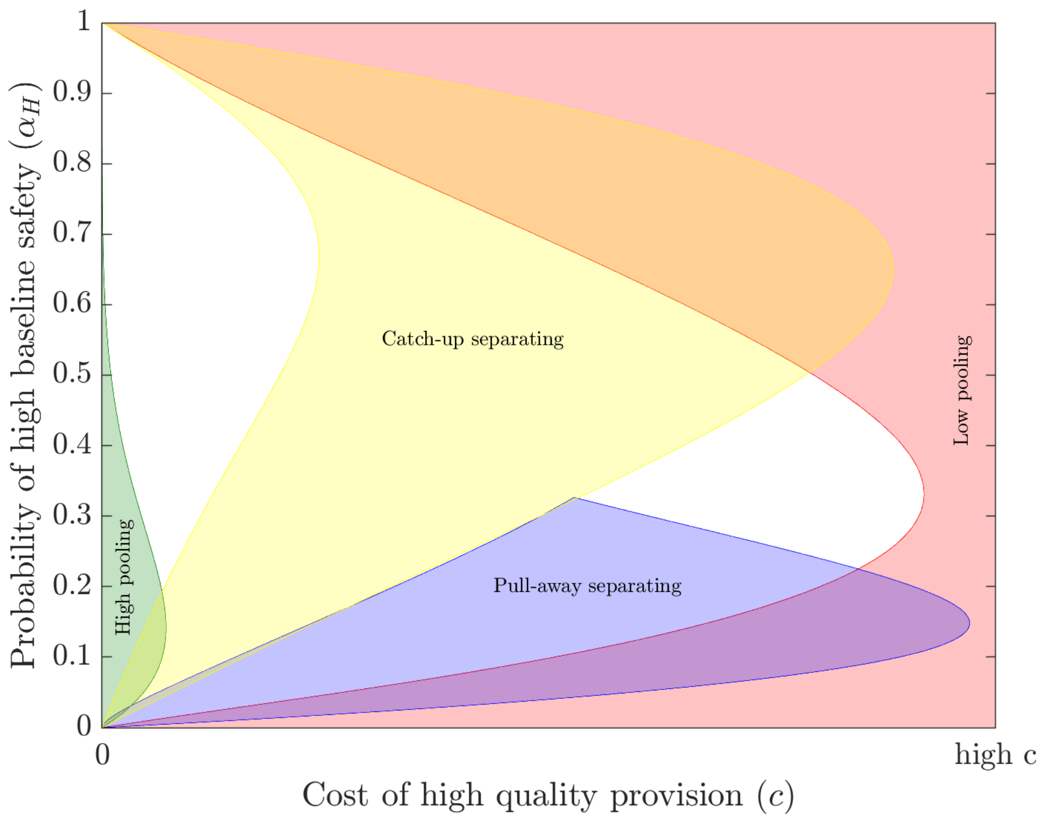
Notes: Averages and intervals ranging from the 10th to the 90th percentile and the 25th to the 75th percentile (in bold), respectively, of the distribution of the safety index by firm. The safety index is computed as the inverse covariance index as in Anderson (2008) using average speed, speeding alerts, 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



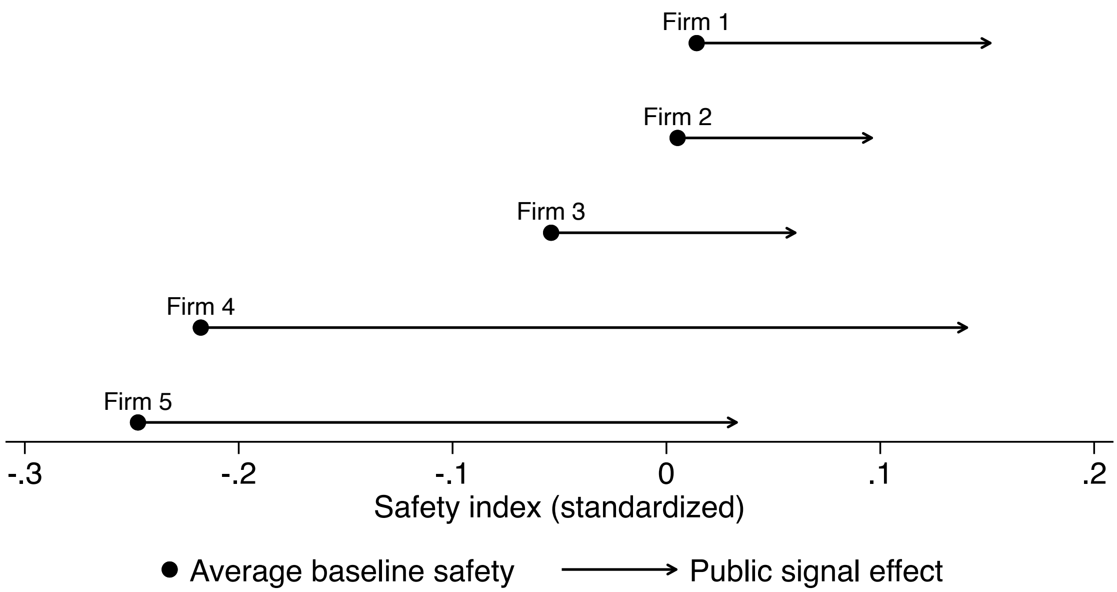
Notes: Time series of average speed, speeding alerts, sharp braking alerts, and the safety index three months before to three months after the introduction of the public signal. The gray line shows daily averages, whereas the black dots show monthly averages with 90% confidence intervals computed from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

Figure 5: Equilibria in public signal game



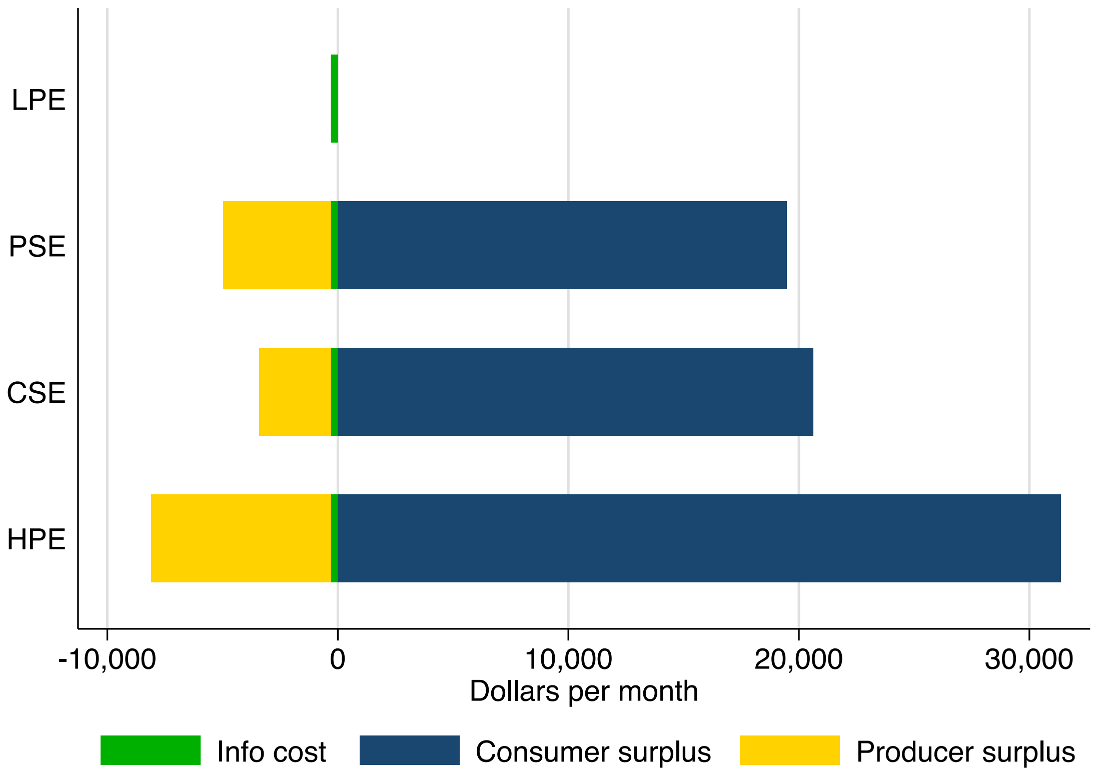
Notes: Equilibrium existence under various parameter values for the cost of safety provision c and the probability of high-quality firms $\phi = \Pr(\alpha_j = \alpha_H)$. The red area shows (c, ϕ)-combinations for which a low-pooling equilibrium exists; the blue and yellow areas for pull-away and catch-up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

Figure 6: Public signal effect by firm



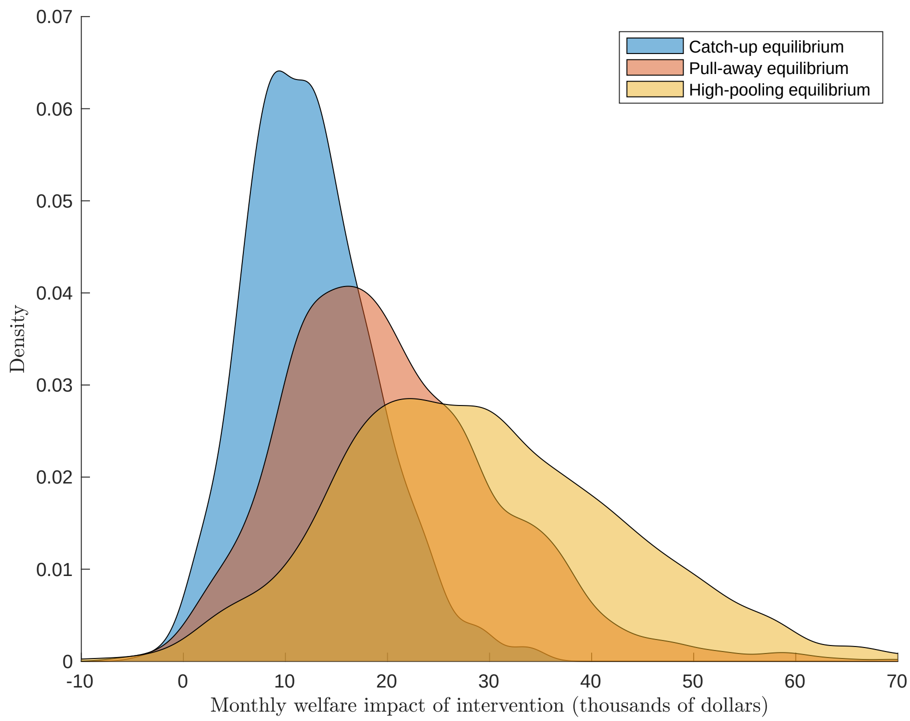
Notes: Average safety by firm before the public signal (black markers) and improvement in safety after the public signal (arrows).

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: 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 2: 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 3: 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 4: 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 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 $\times$ Public signal (β_3)	-0.192
	(0.263)
Safety information $\times$ 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 (0.6) [0, 2.14]	15.66 (6.34) [4.97, 29.93]	25.17 (10.91) [7.77, 50.02]	37.32 (14.7) [12.21, 69.54]
Producer surplus	0 (0) [0, 0]	-3.08 (1.07) [-5.33, -1.39]	-4.63 (1.61) [-8, -2.08]	-7.71 (2.68) [-13.34, -3.47]
Total welfare	0.25 (0.6) [-0.15, 1.99]	12.43 (6.2) [1.7, 25.76]	20.4 (10.71) [2.96, 44.69]	29.46 (14.34) [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.[11]

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.[12] 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.

[11]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.

[12]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).

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 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: $\mu_H - \mu_L > \alpha_H - \alpha_L$.[13]

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

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

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 $S_j = 1[q_j = \max_{k=1,\ldots,J} q_k + \xi_k]$ 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.* $\xi_j \sim U[-\sigma, \sigma]$ 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.[14]

[13] 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.

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

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.

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

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

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:

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

high quality, if any bus chose high quality at all.

whereby passengers update their expecation of firm j's safety: the winner's expected quality type becomes $E\left[\alpha_j | S_j = 1\right] = (1-\phi)^J \alpha_L + \left[1 - (1-\phi)^J\right] \alpha_H$. The probability $(1-\phi)^J$ 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 if it didn't win. Define

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

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 $D\left(\alpha_j, \mu_j\right)$ 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:

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

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.[15]

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.*

[15]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

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, 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 $\theta \in \{\text{LPE}, \text{PSE}, \text{HPE}, \text{CSE}\}$. 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:

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

where $W(\alpha_j, \mu_j, \theta) = \Pr(S_j = 1 | \alpha_j, \mu_j, \theta)$ is the probability of being the winner; $D_s(\theta) = \Pr(j = \arg\max_k U_{ik} | S_j = s, \theta)$ is demand with winner status s; and $\Delta D(\theta) = D_1(\theta) - D_0(\theta)$ 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:

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

where $\Delta W(\alpha_j, \theta) = W(\alpha_j, \mu_H, \theta) - W(\alpha_j, \mu_L, \theta)$ 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 $\Delta W(\alpha_j, \theta)$ and $\Delta D(\theta)$ for each α_j and θ, starting with $\Delta W(\alpha_j, \theta)$. 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

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

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

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

Hence all we need to do is to characterize the expected quality $E[q_j | S_j, \theta]$. 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 con-

changes in idiosyncratic preferences without violating their model.

sider three cases: pooling equilibria and the two separating equilibria. For *pooling equilibria*, we have the following expected qualities for winners and non-winners.

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

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:

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

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:

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

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

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

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. □

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

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

Reduced form to structural.

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

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:

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

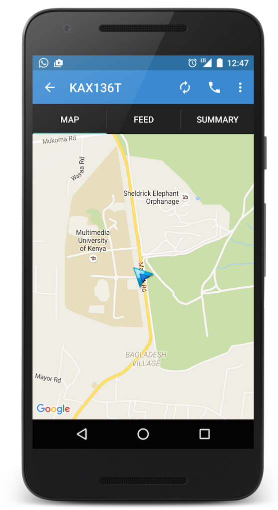
B.3 Welfare

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

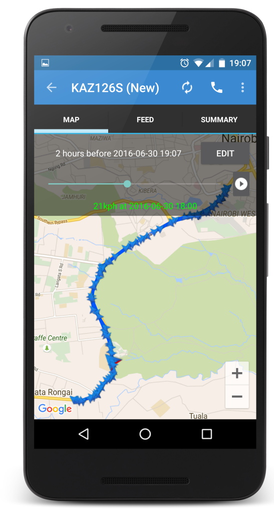
- Producer surplus:
  - LPE: 0
  - HPE: $-Jc$
  - PSE: $-J\phi c$
  - CSE: $-J(1-\phi)c$
- Consumer surplus
  - LPE: $N\,(1-\phi)\,\Delta D(\text{PE})\Delta\alpha$
  - HPE: $N\,\{(1-\phi)\,\Delta D(\text{PE})\Delta\alpha + \Delta\mu\}$
  - PSE: $N\,\{(1-\phi)\,\Delta D(\text{PSE})\Delta\alpha + [\phi + (1-\phi)\,\Delta D]\,\Delta\mu\}$
  - CSE: $N\,\{\phi\Delta D(\text{CSE})\,(\Delta\mu - \Delta\alpha) + (1-\phi)\,\Delta\mu\}$
- 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: $N\,\{(1-\phi)\,\Delta D(\text{PE})\Delta\alpha + \Delta\mu\} - Jc - \tau$
  - PSE: $N\,\{(1-\phi)\,\Delta D(\text{PSE})\,[\Delta\alpha + \Delta\mu] + \phi\Delta\mu\} - J\phi c - \tau$
  - CSE: $N\,\{\phi\Delta D(\text{CSE})\,(\Delta\mu - \Delta\alpha) + (1-\phi)\,\Delta\mu\} - J(1-\phi)c - \tau$

C Appendix Figures

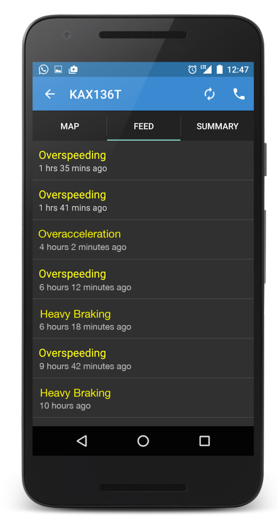
Figure A.1: Mobile app “SmartMatatu” tracking bus safety



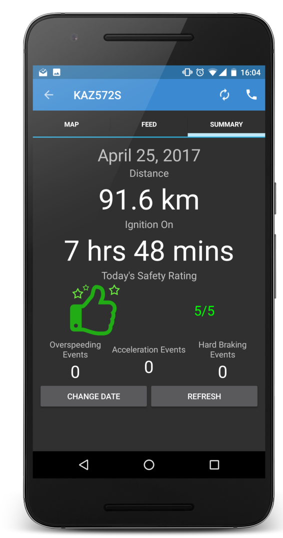
(a) Map Viewer



(b) Historical Map Viewer



(c) Safety Feed

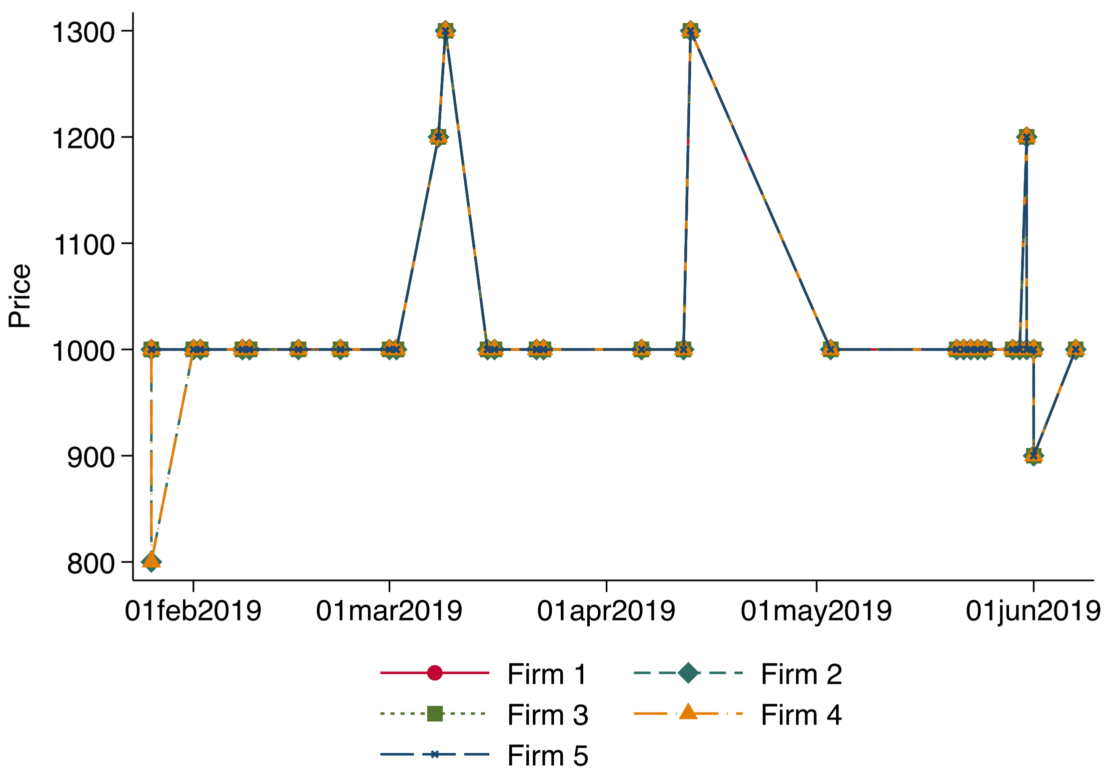


(d) Productivity and Safety Summary

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

			Safety index components			
	Buses	Bus-days	Avg. speed	Speeding	Sharp braking	Safety index
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.