The Impact of Crime on Public Transport Demand: Evidence from Six Latin American Capitals *

Santiago De Martini Juan B. González Santiago M. Perez-Vincent

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Abstract

Public urban transportation systems are essential for reducing emissions from private transport and mitigating climate change. However, in regions with high crime rates like Latin America, fear of crime in public transport might limit these efforts. This paper studies the impact of crime on public transport demand across six Latin American capitals. A total of 5,160 participants complete three experiments to quantify the impact of crime on public transport choices and policy preferences. We first estimate the willingness to pay for crime abatement on public transport and find that users place a premium of 51% of current fares on safer transport. The high value users place on safety affects their demand for public transport through two channels. Higher crime rates directly reduce the appeal of public transport, hindering the substitution from private options. Crime also reduces the price elasticity of demand for public transport, making subsidies less effective to increase ridership. Taken together, these results show that crime acts as a negative externality on environmental outcomes by affecting the use of public transportation. In fact, participants don't perceive a trade-off between crime and emissions abatement: we find that higher crime perceptions doesn't crowd out support from green policies. These results show the environmental externalities of crime through public transport demand, and highlight the need to consider safety in transportation policy.

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*Santiago De Martini: Department of Economics, University of Southern California. sd59576@usc.edu.
Juan B. González: Department of Economics, University of Southern California. juanbgon@usc.edu.
Santiago Perez-Vincent: Innovation in Citizen Services Division, Inter American Development Bank. santiagoper@iadb.org .
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1 Introduction

Urban transportation systems are at the forefront of global efforts to combat climate change. Recent estimates suggest greenhouse gas emissions from transport constitute between 14% and 29% of total emissions (Domke et al., 2023; Eurostat, 2020). With the goal of reducing emissions and reducing congestion, governments invest to promote the use of public transport, often subsidizing most of the operational costs of transport systems. However, fear of crime when using public transport can limit these efforts (Ceccato et al., 2022). If crime reduces the appeal of public transport and incentivizes, then it will have an indirect effect on both greenhouse emissions and congestion. In this paper, we evaluate the how crime relates to public transport use and therefore posit a channel between crime abatement and environmental policies that is not usually considered by policymakers.

We provide evidence on several mechanisms through which crime impacts public transport demand. First, we provide experimental evidence on the elasticity of substitution between private and public modes, and show how it relates to crime. Our findings show that for any public transport price, higher crime perceptions will increase the likelihood of choosing a private relative to public transport alternative to complete a trip. Second, crime perceptions might affect how commuters react to changes in public transport fares. If crime in public transport raises, some commuters sufficiently concerned about safety will not change their commute mode in response to lower public transit fares. In other words, crime might reduce price elasticity of demand for public transport, making fare subsidies less effective. This indirect effect of crime makes crime abatement a complement to environmental policies. While previous literature has studied optimal transport subsidies (Almagro et al., 2024; Basso & Silva, 2014; Parry & Small, 2009), and whether crime is a factor in transport mode choice (Delbosc & Currie, 2012; Holmgren, 2007), no study comprehensively studies the relationship between them.

This paper addresses these gaps by studying how crime affects demand for public transport and its price elasticity in Latin America. Latin America offers a prime ground for studying crime externalities. Urban areas in Latin America face high emissions and traffic congestion despite having extensive and heavily subsidized public transport systems, which importantly are perceived as highly unsafe (Ceccato & Loukaitou-Sideris, 2020). We conduct three pre-registered experiments in six Latin American capital cities (Bogotá, Buenos Aires, Ciudad de Mexico - CDMX, Guatemala, Lima, and Santiago de Chile), examining the impact of crime on public transport demand. We first quantify the value commuters place on safety by eliciting the willingness to pay (WTP) for safety in public transportation. In Experiment 1, participants choose between two buses: a control bus with the average crime rate and fare in their city, and a treated bus with either lower or higher crime rates. Information about the following characteristics of each bus is presented: price, crime, CO2 emissions and trip length. We adjust fares of the treated bus to determine the indifference price between the two alternatives, following the Gabor-Granger method (Gabor & Granger, 1964). As the buses are identical in all aspects but safety and price, the difference between the indifference price and the control fare provides an estimate of the WTP for safety. Our estimates show that users are willing to pay a premium equivalent to 51% of the ticket fare for a 20% reduction of crime in public buses, and ask for a compensation of 61% of the ticket fare for a 20% crime increase.

Experiment 2 repeats this contingent valuation design but considering the choice between a taxi and a public bus. In this experiment, we find that, relative to the price that make them indifferent between alternatives, participants require the equivalent of a 27.3% bus fare to be indifferent between alternatives if the crime level of the bus increases by 25%. Finally, we use mouse-tracking to uncover what information users consider most relevant when making a transport decision (Brocas et al., 2014), suggesting that users care most about crime and fare price. Overall, these results offer evidence that commuters do take into account crime when making transportation decisions, and are willing to pay a substantial amount to reduce the crime exposure during their commute.

Having quantified the monetary value of safety when making transport choices, we examine the direct effect of crime on public transport demand. Experiment 2, where participants choose between a standard private taxi and a bus with variable crime rates, allows us to estimate the effect of crime on the probability of choosing public over private transport at current prices. Our analysis shows that participants are 29% more likely (15pp) to choose public transport when crime rates are 25% lower than average, compared to when they are 25% higher. The result that crime has a significant negative effect on the likelihood of choosing public over private transport can be interpreted as a positive externality of crime over emissions. We also explore the indirect effect of crime on mode choice through its interaction with price elasticity. In Experiment 1, we estimate that price elasticity decreases by 0.13 when crime increases by 20%. Consistent with women being more concerned about crime in public transport (Ouali et al., 2020), crime has a higher impact on price elasticity among women (0.16) than among men (0.11). These estimates are robust across public transport use frequency and different levels of crime perceptions. Our results show that crime has an indirect externality over public transport, and that crime abatement complements environmental policies by making fare subsidies more effective in increasing ridership.

Taking crime and environmental policies are complements might seem counterintuitive. Previous literature shows that immediate concerns such as safety might crowd attention and support from environmental concerns affecting policy support (Weber, 2010). Especially for individuals with a zero-sum mindset, higher perceived crime might lead to lower support for pro-environmental policies. Experiment 3 explores the impact of crime perception on the support for different public transport policies. Participants are randomized into reading a real newspaper article about their cities' public transport that either doesn't mention safety, or frames public transport as safe or unsafe. We elicit participants' perceived probability of being victim of a crime on public transport before and after exposure to the news primings. Subsequently, they are asked to allocate a budget among various transport policies, including crime reduction, price cuts, service frequency improvement, and emission reduction. To avoid endogeneity concerns, we instrument crime perceptions with the news-priming random treatment as an instrument. We find no evidence of higher crime perception crowding out support for the pro-environmental policy of reducing emissions. Even when asked to choose among policies in a stringent zero-sum setting, voters don't perceive a trade-off between abating crime and reducing emissions. These results highlight the potential for framing both policies as complements rather than competitors.

Related Literature. This paper builds on the traditional question on travel mode choice (Ben-Akiva & Lerman, 1985; McFadden, 1974). Previous literature has assessed the role of safety in transport mode choice (Börjesson, 2012; Harbering & Schlüter, 2020; Holmgren, 2007). Most of these papers rely on local case studies. For instance, Delbosc and Currie (2012) conduct a household survey in Melbourne and find a positive relation between safety perception and public transport ridership, and Ingvardson and Nielsen (2022) use a travel survey from Copenhagen to show that this relationship is stronger for women, consistent with the findings of Ouali et al. (2020). This literature doesn't consider the impact of crime on price elasticity and subsidy effectiveness. Another strand of the literature studies optimal subsidies to boost public transport ridership and reduce congestion (Almagro et al., 2024; Anderson, 2014; Parry & Small, 2009), but without considering the relation of subsidies to crime perception. Our paper conceptually contributes to this literature by jointly quantifying the impact of crime on public transport demand and its price elasticity, by conducting a large-scale study across six countries. This paper also adds three methodological contributions to the transport choice literature. First, we design an experimental setting where crime perception varies exogenously, avoiding the endogeneity issues the previous literature has faced. Second, we introduce a participatory budget decision as an incentive-compatible mechanism to unveil participants' preferences that is widely used in other fields (Ardanaz et al., 2023; Banerjee et al., 2010; Olken, 2010). Third, we use mouse-tracking tools to study what information participants consider more relevant when making a transport decision (Brocas et al., 2014). Finally, while previous literature has estimated the WTP for crime reduction in the Americas in a general setting (Domínguez & Scartascini, 2024), we estimate it in the context of public transport. Overall, this paper aims to guide policy by offering evidence of the high value crime plays in transport decisions, and highlighting the impact crime has on green transportation policies and emissions.

The paper is structured as follows: Section 2 offers a simple but clarifying conceptual framework of the externalities crime has over public transport. Section 3 details the experimental design, providing a comprehensive overview of the sample and the methodologies employed across the three experiments. Section 4 details the empirical analysis. Section 5 reports the results of each experiment and their implications. Finally, Section 6 offers a discussion of the broader significance of our results for urban transport policy and climate change mitigation, concluding with recommendations for future research and policy directions.

2 Conceptual Framework

We develop a simple framework to illustrate two channels through which crime impacts public transport demand. We consider two perspectives of the problem: the commuter who chooses what mode of transport to use, and an utilitarian government who allocates a budget across different policies.

2.1 Commuter's Perspective

We model the commuter's decision as a simple discrete choice, where agents choose a transport mode among a set of alternatives. We introduce the impact of crime in two ways. On the extensive margin, commuters require a minimum safety level to even consider a transport mode in their decision. Only transport modes with safety levels above the individual threshold are part of the consideration set. On the intensive margin, commuters care about relative crime levels of the transport options they consider.

Let commuter i choose between modes $j \in \mathcal{J}$ to travel from a given origin o to a given destination d. We focus in the set I_{od} of agents that commute from o to d and have to decide which transport mode to use. Thus, agent i chooses the transport mode j that maximizes her utility. Let p_j, s_j, and x_j denote the price, safety level, and 'other' characteristics of mode j. The commuter solves the following problem:

$$\max_{j \in \mathcal{J}} u_{ij}$$

Let the utility of not completing a trip be normalized to 0. We assume that each agent i needs a minimum safety level $\bar{s}_i$ to even consider a transport mode among the alternatives and we assume that the mode utility function follows a random utility model (Ben-Akiva & Lerman, 1985; McFadden, 1974). That is, there is a deterministic component that depend on observable mode characteristics and an additively separable component ε_{ij} that depend on unobserved characteristics that vary at the individual level and have an extreme value type 1 distribution. Formally:

$$u_{ij} = \begin{cases} g(p_j, s_j, x_j) + \varepsilon_{ij} & \text{if } s_j > \bar{s}_i \\ 0 & \text{if } s_j \leq \bar{s}_i \end{cases} \tag{1}$$

Thus, the agent only considers those modes j above the safety threshold $\bar{s}_i$. Define the *consideration set* $\mathcal{C}_i \subseteq \mathcal{J}$ as the set of modes considered by agent i. That is:

$$\mathcal{C}_i = \{j \in \mathcal{J} : s_j > \bar{s}_i\}$$

Then the *conditional* choice probability of mode j among the consideration set will be given by

$$P_{ij|\mathcal{C}_i} = \frac{\exp(g(p_j, s_j, x_j))}{\sum_{k \in \mathcal{C}_i} \exp(g(p_k, s_k, x_k))}$$

We allow for heterogeneity in the safety threshold among commuters, with $F(\bar{s})$ being the distribution of safety thresholds in the population. For simplicity, consider the case where $\mathcal{J} = \{private, public\}$, where *private* correspond to private modes (e.g., taxi or private car) and *public* corresponds to public modes (e.g., bus or train). Given that ϵ_{ij} are random draws across the population, we can map individual probabilities to the aggregate demand for mode P_j. Importantly, if $s_{private} > s_{public}$, the share of the population that chooses *public* modes for a given safety level in public modes s_{public} is:

$$P_{public} = F(s_{public}) \cdot P_{public|\mathcal{J}} \tag{2}$$

Equation (2) captures several mechanisms through which crime affects public transportation demand. First, higher crime rates in public modes can lead to some commuters to not even consider them as an option, reducing overall demand. Second, even among those commuters who would still consider high-crime public modes as an option, crime reduces the share of commuters choosing public transport. Importantly, crime reduce the effectiveness of price subsidies through these two mechanisms. On the extensive margin, price changes will be irrelevant to those commuters that don't consider public transport in their decision. On the intensive margin, commuters who consider public transport will demand lower prices to compensate for higher crime. Therefore, we expect to find higher and more price-elastic demand when public transport is safer.

2.2 Government's Perspective

We now focus on the perspective of the government, to show how neglecting the effects of crime on transport demand can lead to underinvestment in safety. Suppose that a government is deciding how to allocate an exogenous income level, W, across L policy areas. The government distributes funds among the different policies $\ell \in L$, including, for instance, safety-related expenditures. We model the government as a *utilitarian social planner*, maximizing the utility of a representative agent. This agent does not derive utility from the investment itself but rather from its outcomes. That is, the agent does not value spending on crime abatement per se, but values the resulting improvements in safety.

Let $\phi^\ell(x_\ell)$ be a function that transforms investment x in area ℓ into outcomes. Define $\phi^\ell_{x_\ell}(\cdot)$ as the derivative of $\phi^\ell(\cdot)$ with respect to x_ℓ. We assume that $\phi^\ell(0) = 0$, $\phi^\ell_{x_\ell}(0) = \infty$, $\phi^\ell_{x_\ell}(x_\ell) > 0$, $\phi^\ell_{x_\ell x_\ell}(x_\ell) < 0$, implying increasing but diminishing returns to investment. Consider the case where the government allocates income W among three objectives: safety (s), environmental quality (e), and all other objectives (o). To maintain tractability, we assume a Cobb-Douglas objective function with weights α_ℓ assigned to each outcome. The government's optimization problem is:

$$\max_{x_s, x_e} \phi^s(x_s)^{\alpha_s} \phi^e(x_e)^{\alpha_e} \phi^o(W - x_s - x_e)^{\alpha_o} \tag{3}$$

The optimality condition implies:

$$\phi^s_{x_s}(x_s) \left(\frac{\alpha_s}{\phi^s(x_s)} \right) = \phi^\ell_{x_\ell}(x_\ell) \left(\frac{\alpha_\ell}{\phi^\ell(x_\ell)} \right), \quad \text{for } \ell \in L \tag{4}$$

Denote the optimal investment levels as $\hat{x}_s$ and $\hat{x}_e$. Now, suppose that safety outcomes also influence environmental quality through transport choices due to the micro-foundations detailed in Section 2.1. To capture this interaction, define a new function that maps investment in environmental quality as $\tilde{\phi}^e(x_e, \phi^s(x_s))$, which simplifies to $\tilde{\phi}^e(x_e, x_s)$. We assume: $\tilde{\phi}^e_{x_s}(x_e, x_s) > 0$; $\tilde{\phi}^e_{x_e}(0, x_s) = \infty$; $\tilde{\phi}^e_{x_s,x_s}(x_e, x_s) < 0$; and $|\tilde{\phi}^e_{x_s,x_e}(x_e, x_s)| = |\tilde{\phi}^e_{x_e,x_s}(x_e, x_s)| < \tau$.[1] This formulation captures a *positive externality* of crime abatement on environmental quality (Pigou, 1920). In this case, the optimality condition adjusts to:

$$\phi^s_{x_s}(x_s)\left(\frac{\alpha_s}{\phi^s(x_s)}\right) + \underbrace{\tilde{\phi}^e_{x_s}(x_e, x_s)\left(\frac{\alpha_e}{\tilde{\phi}^e(x_e, x_s)}\right)}_{>0} = \phi^\ell_{x_\ell}(\cdot)\left(\frac{\alpha_\ell}{\phi^\ell(\cdot)}\right), \quad \text{for } \ell \in L \setminus \{s\} \tag{5}$$

Define the optimal allocation in this case as $\tilde{x}_s$ and $\tilde{x}_e$. Since the second term on the left-hand side is strictly positive, it follows that $\tilde{x}_s > \hat{x}_s$, meaning that a myopic government would underinvest in safety if the impacts of crime on environmental outcomes is not accounted for.

This illustration highlights the importance of recognizing the relationship between crime abatement policies and environmental quality when making budgetary decisions. To our knowledge, this channel has not been explicitly discussed in the literature. Conceptually, this issue can be framed as a *model misspecification problem* (Esponda & Pouzo, 2016), where governments may fail to infer the broader benefits of crime reduction and act as if no relationship exists. If policymakers do not account for this interdependence, they may underinvest in crime abatement. We argue that incorporating this channel into decision-making can improve welfare from a *utilitarian government perspective*, without requiring additional investment—simply by reallocating existing resources more efficiently.

3 Data and Experimental Design

In 2024, we partnered with the firm Offerwise to collect data across six Latin American capital cities: Bogotá, Buenos Aires, Ciudad de Mexico (CDMX), Guatemala, Lima, and Santiago de Chile[2]. Offerwise provides a representative sample of respondents, who were compensated for completing the online experiment[3]. Table A1 presents descriptive statistics for the subject pool. The sample consists of 52.6% males, with an average age of 36.2 years. On average, participants live with 2.9 other people, 96% have at least some secondary school education, and 52% have some university education.

Participants complete three experiments in the same order. The objective of Experiment 1 is to measure willingness to pay (WTP) for crime reduction in public transport. Participants are presented with the characteristics of two bus options (hereinafter, Bus A and Bus B): trip duration, emissions (in grams of CO_2), price, and crime rates. We use a mouse-tracking design to reveal information relevance (Brocas et al., 2014). The attributes are initially hidden behind clickable tags, which participants have to click to reveal the information (see Figure B1). After revealing all attributes, participants select their preferred bus option. We

[1] We introduce the last assumption of small enough cross-derivatives to rule out extreme cases. For example, if $\tilde{\phi}^e_{x_s,x_e}(x_e, x_s)$ is positive and very high, the externality can actually yield a substitution of investment on crime towards environmental policies.

[2] The IRB and preregistration also include the intention of obtaining samples from Jamaica and Trinidad and Tobago, but logistic issues prevented data collection in these countries.

[3] Only participants aged 18 and over were eligible to participate.

record the order in which participants clicked each box as a non-choice measure of the importance they place on each attribute. Since the order in which attributes are displayed on the screen is randomized, deviations from a uniform distribution of look-ups indicate differences in the perceived value of the information.

In Experiment 1, participants are randomly assigned to one of four treatment groups, each exposed to a different crime rate for Bus B (while the crime rate for Bus A is fixed at the average rate for buses in their city). Specifically, the crime rate for Bus B is described as being 'X% (higher/lower) than the average crime rate in bus lines of your city,' where $X \in \{-30\%, -10\%, +10\%, +30\%\}$. Additionally, the price of Bus B also varies by treatment group. While all participants face the same price for Bus A (the standard bus fare in their city), those in the first two groups (-30% and -10%) see a price 50% higher than Bus A, whereas those in the latter two groups (+10% and +30%) see a price 50% lower. If a respondent chooses Bus A (Bus B), they are asked to repeat the choice with the price of Bus B adjusted by 10% (lower or higher, respectively). This process continues until the respondent reverses their initial choice or completes five iterations. The price that makes the respondent indifferent between the two options is calculated as the midpoint between the price at which they switched and the price in the previous iteration. The WTP for safety is then estimated as the difference between this indifference price and the price of Bus A (Gabor & Granger, 1964). This design also allows us to estimate price elasticity of demand for different levels of crime [4].

Experiment 2 follows a similar structure but involves a choice between a bus and a private taxi instead of two buses (see Figure B2). Again, respondents are randomized into four treatment groups. The crime rate for the private taxi is fixed at the average crime rate for taxis in their city, while the crime rate for the bus is described similarly to Bus B in Experiment 1, with $X \in \{-30\%, -20\%, +20\%, +30\%\}$. In this experiment, the initial prices of the alternatives do not vary between groups[5]. If a respondent chooses the bus (private taxi), they are asked to choose again with the bus price adjusted by 20% (higher or lower, respectively). The process is repeated for up to five iterations, with the indifference price calculated in the same manner as in Experiment 1.

In Experiment 3 (see Figure B3), participants are randomized into three groups. The first group (hereinafter, *Dangerous* group) is exposed to a real newspaper headline referring priming the high levels of crime on the public transport system of their city; the second group (hereinafter, *Safe* group) sees a headline priming that public transport in their city is safe; the third group (hereinafter, *Control* group) sees a headline about public transport but unrelated to its safety. Participants are then asked to allocate a hypothetical budget of 120,000 USD across four public transportation policies: increasing bus frequency, cutting fares, reducing crime, and reducing CO2 emissions. To incentivize truthful responses, participants are informed that the study results will be shared with officials from their city's Department of Transportation, potentially influencing real policy decisions. Participatory budgets have been successfully used before to elicit policy preferences (Ardanaz et al.,

[4]Although there is a possibility that participants take prices as a second signal of crime levels, perceiving lower prices might negatively select other riders, this might reduce the informativeness of our crime information and make our estimates a lower bound.

[5]The private taxi price presented corresponds to a 20-minute Uber trip from the city hall on a weekday at 8 PM. The initial bus price is the standard bus fare.

2023; Olken, 2010). We also elicit participants' perceived probability of encountering crime in public transport, both at the beginning of the session (before Experiment 1) and after the news priming in Experiment 3.

4 Empirical Analysis

4.1 Valuation of Crime Reduction in Public Transport

The first goal of Experiment 1 and Experiment 2 is to estimate the willingness to pay for crime reductions in public transport. To this end, we estimate the following model:

$$y_i^* = \alpha + \beta_1 1\{Crime = +10\%\}_i + \beta_2 1\{Crime = -10\%\}_i + \beta_3 1\{Crime = -30\%\}_i + \Phi_c + \mathbf{X}\Delta + \epsilon_i \quad (6)$$

Where $1\{Crime = X\%\}_i$ is an indicator function denoting whether respondent i was exposed to a X% crime variation treatment group. Φ_c correspond to city fixed effects, and in all specifications the vector of control variables ($\mathbf{X}$) are: age, gender and level of education. Note that for Experiment 2, we estimate the same model depicted in Equation (6) but we replace the treatment groups -10% and +10% for -20% and +20%. This specification follows closely that of Domínguez and Scartascini (2024).

We model y_i^* as a latent variable indicating the indifference price between the two transport mode alternatives following Berlinski and Busso (2016). Keep in mind that we do not observe the *real* indifference price, but instead an upper and lower bound, which are the price displayed in the last and the second to last iteration[6]. Each parameter corresponds to the difference in the estimated indifference price between groups, which is our measure of willingness to pay for a crime reduction from +30% (the omitted group variable) to the corresponding crime level denoted by the indicator variable.

The second goal of these experiments is to analyze the effect of crime abatement on environmental outcomes. In particular, we are interested in, first, studying if safety improvements can induce substitution from private to public mode choices and secondly, if lower crime rates increases the effectiveness of subsidies. Therefore, in Experiment 2, we first consider the following specification:

$$1\{ChooseBus_i\} = \alpha + \beta_1 1\{Crime = +20\%\}_i + \beta_2 1\{Crime = -20\%\}_i + \beta_3 1\{Crime = -30\%\}_i + \Phi_c + \mathbf{X}\Delta + \epsilon_i \quad (7)$$

Where $ChooseBus_i$ is an indicator function denoting which is equal to 1 if respondent i chose the public transport over the private taxi on the first decision of the experiment. In this case, the parameters are interpreted as how more (or less) likely is the average respondent to choose the bus over the private taxi, at current prices, for each treatment group (relative to the +30% group).

Second, we estimate how crime affects the price elasticity of demand. Specifically, we study the share of

[6]For those respondents who never switched their decision we consider as the willingness to pay the last price displayed.

respondents who choose the treated alternative (Bus B in Experiment 1, and the bus in Experiment 2) for each given price and crime combination[7]. We use a linear probability model where we interact the price levels with the crime levels to test whether crime affects price elasticity, and include the same battery of controls as in the previous models. Thus, the coefficient of this interaction should be interpreted as by how much the probability (share) of choosing the *treated* choice varies if the price increases by 100%.

4.2 Crime Perception and Crowding Out

Experiment 3 addresses whether crime perception crowds out support for environmental and other policies in the context of the public transportation. Previous research has found that more immediate concerns, like safety, affect climate change perceptions and support for environmental policies (González & Sánchez, 2022; Weber, 2010). In regions with high crime rates such as Latin America, concerns about safety may overshadow considerations for environmental impact or efficiency. To test this hypothesis, we explore whether crime perceptions (elicited before any news priming) are linked to differential support for public transport policies: increasing bus frequency, reducing ticket prices, reducing crime, and reducing CO2 emissions.

To check whether this relation is causal, we vary crime perceptions exogenously by exposing participants to different newspaper headlines. To test whether participants actually change their perceptions after the information provision, we elicit participants' perceived probability of being victim of a crime in public transport both before Experiment 1 and after being exposed to the newspaper headline, in line with the literature on belief updating (Andre et al., 2023; Cullen & Perez-Truglia, 2022). Thus, as a first stage we estimate the following model:

$$\Delta CrimePerception_i = \alpha + \beta_1 1\{Article = Dangerous\} + \beta_2 1\{Article = Safe\} + \Phi_c + \mathbf{X}\Delta + \epsilon_i \tag{8}$$

Here, $\Delta CrimePerception_i$ corresponds to the difference between the reported probability of being victim of a crime reported before and after the experimental intervention; $1\{Article = Dangerous\}_i$ and $1\{Article_i = Safe\}_i$ are two indicator functions that are equal to 1 if the respondent was exposed to the dangerous and the safe headlines, respectively. We control for the same set of variables as in Equation (6) and use city fixed effects.

After the experimental intervention, subjects were asked to allocate a budget of 120,000 USD among 4 policies[8]. To test whether crime perceptions affect policy support, we estimate the following 2SLS model:

$$y_i^k = \alpha + \beta_1 \Delta Crime\widehat{Perception}_i + \Phi_c + \mathbf{X}\Delta + \epsilon_i \tag{9}$$

where y_i^k is the share of the budget that was allocated to policy k. Recall that in this experiment we consider

[7] Note that as when participants switch choices the experiment ends, we don't observe a choice for each price, so we assume choice consistency. This is, if a participant chooses Bus B at some price, we can safely assume they would still choose it at a lower price.

[8] This is a slight variation to what's included in the pre-registration plan and in the IRB file. Originally, participants had to state how much do they agree with the budget being allocated to each policy in a 1-10 scale. We modify this to be a zero-sum game because we consider that this would makes the trade-offs of their decision more salient.

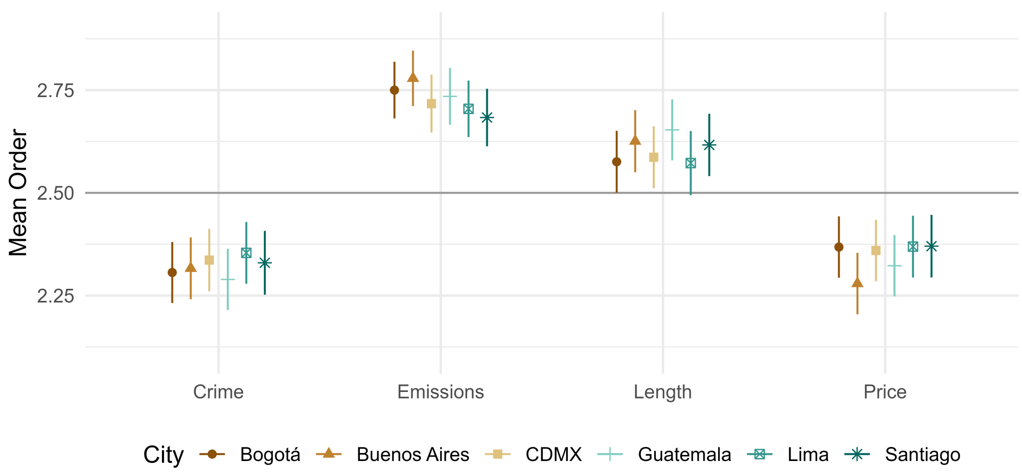
four policies: increasing bus frequency, reducing ticket fares, reducing crime and reducing CO2 emissions. For the sake of simplicity, we normalized the dependent variable to be the share allocated to policy k over the total money allocated. $\Delta \widehat{CrimePerception}_i$ is the fitted value obtained from estimating Equation (8). In this case, β_1 is interpreted as how many percentage points more of the budget are allocated to policy k if crime perception exogenously increases by 1 percentage point.

5 Results

5.1 Valuation of Safety in Public Transport

5.1.1 Non-Choice Data

Figure 1. Mouse-tracking results



Notes: The figure shows the average look-up order for each attribute, where 1 means being clicked first, 4 last. Error bars show the 95% CI. The mean order if the look-ups were random (2.5) is shadowed.

We present the results following the strategy defined in Section 3. Figure 1 presents the average order of clicks for each attribute (i.e., 1 if first, 4 if last). If each attribute had been looked up in random order, the mean order of each attribute would be 2.5. However, it varies by attribute: price and safety are looked up significantly earlier than emissions and trip length (p-value < 0.001), but we do not find a significant difference between the look-up order of the price and safety attributes (p-value $= 0.151$). Participants seek information about price and safety earlier than pollution and trip length, indicating these attributes are more relevant for decision making. The relevance of crime and price is strikingly strikingly robust across countries.

Figure A1 presents further heterogeneity analyses of the results. We find no gender differences in the order of look-ups, which might be a byproduct of women not expecting safety levels to vary across buses. The mean look-up order of the crime attribute is lower among respondents who have been victims of a crime in public transport. This is not surprising since we expect respondents in these group to be more aware of crime risks than their counterparts. Moreover, we find a positive correlation between the age of the respondent and the look-up order of the emissions attribute, consistent with surveys that suggest that young people tend to care more about the environment (Gallup, 2018). Finally, according to our relative relevance measure, participants with higher-educational level tend to prioritize less the information on crime and price and more the length of the trip when deciding between transport modes. Overall, these results robustly show that, when choosing a transport mode, obtaining information about crime is as important as information about price, and these are more important than information about trip duration or emissions.

5.1.2 Choice Data

Experiment 1 estimates the willingness to pay for changes in crime in public transport. To standardize the results across different cities, we normalize prices in terms of current bus fare units. For instance, if the price of Bus B is 20% higher than the current bus fare, we normalize this price as 1.2. We conduct a randomization balance check, which is presented in columns (2)-(4) of Table A1. The table shows that the only significant difference between treatment groups is whether the participant has ever been a victim of a crime on public transport. Consequently, we include this as a control variable in our analysis.

We begin by examining the mean indifference prices between groups. Table A3 shows that, when the alternative is an average bus in their city (Bus B), participants are willing to pay 37.8% of the current bus fare to ride a bus with a +30% crime rate (relative to the average crime rate on bus lines in their city), 39.7% for a bus with a +10% crime rate, 149.4% for one with a -10% crime rate, and 152.5% for one with a -30% crime rate. Notably, the effect is not linear. While participants are willing to pay 1.9% of the current bus fare to lower the crime rate from +30% to +10% (and similarly from -10% to -30%), they are willing to pay 110.1% to lower it from +10% to -10%. Figure A3 shows the similarity of results between variations of the same sign (i.e., between +10% and +30%), is also apparent throughout the entire distribution of responses (CDF of indifference prices).

A potential explanation for this non-linearity is that participants may not understand probabilities, leading them to misinterpret changes in crime rates. To address this, we include a sanity check at the end of the survey, asking participants to report the probability of getting heads in a random coin toss—a standard test in experimental research (Stöckl & Gleissner, 2018). Figure A2 shows that most respondents answered correctly, though there is some variation in the responses. As a robustness check, Table A5 reproduces the analysis but only considering participants who answered the coin toss probability question correctly.[9] The magnitudes of the point estimates are similar in both cases, and the statistical power remains strong. Most importantly, even when considering only respondents who answered the coin toss question correctly, we still find no significant differences between crime treatment groups of the same sign.

This suggests that the observed phenomenon, known as scope insensitivity, is driven by behavioral attenuation (Enke et al., 2024), rather than by a fundamental misunderstanding of probabilities. Scope insensitivity is a phenomenon commonly observed in contingent valuation studies (Diamond & Hausman, 1994), even in

[9]Subjects answered this question using a continuous slider, which introduces some motor noise in the responses. We therefore allow for a 5% error margin.

valuation by experts (Toma & Bell, 2024). In our experiment, participants may interpret crime changes simply as "reductions" or "increases", rendering decisions insensitive to variations in magnitudes away from the zero boundary. Given the lack of significant differences between different magnitudes of positive and negative crime changes, for illustration purposes we decided to aggregate our treatment groups into ±20% instead of ±10% and ±30%. However, the coefficient should be interpreted as the average willingness to pay to reduce crime for +10% or +30% to -10% or -30% (relative to the average crime rate). We present the aggregated results in the text and include the disaggregated results in the Appendix (see Table A4).

Table 1. Reduced-form estimates of Experiment 1

	(1)	(2)	(3)	(4)	(5)	(6)
1(-20% Crime)	1.12***	1.12***	1.12***			
	(0.009)	(0.009)	(0.009)			
Crime % (Continuous)				-0.023***	-0.023***	-0.023***
				(0.0002)	(0.0002)	(0.0002)
Observations	5,161	5,161	5,161	5,161	5,161	5,161
Controls	No	No	Yes	No	No	Yes
City FE	No	Yes	Yes	No	Yes	Yes

Notes: This table presents the results of the estimation of Equation (6) for Experiment 1. $1(Crime = +20\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups +10% or +30%. $1(Crime = -20\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups -10% or -30%. *Crime % (Continuous)* is a continuous variable corresponding to the level of crime rate that the participant was exposed to. The vector of control variables considered are age, level of education, gender and whether the participant reported having being a victim of a crime in public transport. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p < 0.01 , **p < 0.05, *p < 0.1..

Table 1 reports the regression estimates from Equation (6). In our preferred specification, which includes controls and city fixed effects, participants are willing to pay 112% of the bus fare to reduce the crime rate from +20% to -20% (p-value<0.001). Thus, users are willing to pay a premium of more than a bus fare to ride safer public transport. Although the effect is non-linear, for completeness, columns (4)-(6) of Table 1 present the estimates from Equation (6) using crime rates as a continuous variable. Consistent with the results in the discrete specification, we find that participants are willing to pay 2.3% of the current bus fare for a 1% reduction in the crime rate.

Table A6 shows the results by city. We register that the city with the highest willingness to pay for safety is Mexico City, while Lima and Santiago have the lowest. Furthermore, Table A7 presents the heterogeneity of treatment effect by subsamples. In particular, we study whether treatment effects vary by reported crime perceptions, by gender, and by look-up order of the safety attribute. First, we find our results to be robust across different crime perceptions. However, females are willing to pay 6% (p-value<0.001) more than males to reduce crime. Furthermore, those who clicked safety first or second in the attributes look-up display a willingness to pay 5.7% (p=0.002) higher, confirming our mouse-tracking measure indeed captures attribute valuation.

5.2 Effect of Crime on Public Transport Demand

The main goal of Experiment 2 is to explore how crime affects the substitution between private and public transport. As detailed in Section 3, Experiment 2 closely follows the design of Experiment 1, but participants now choose between a bus and a private taxi (i.e., Uber). The initial prices of the two options do not vary by treatment group, which eliminates any anchoring effects and allows us to examine both the extensive and intensive margins of decision-making. Following the discrete choice model we present in Section 2.1, the extensive margin captures how crime rates in public transport influence the likelihood of choosing it over a private taxi (i.e., a discrete choice), while the intensive margin measures the price difference required to make respondents indifferent between the two alternatives, given different crime rates.

Table 2. Reduced-form estimates of Experiment 2

	Chose Bus			WTP		
	(1)	(2)	(3)	(4)	(5)	(6)
1(-25% Crime)	0.149***	0.150***	0.150***	0.273***	0.274***	0.273***
	(0.014)	(0.013)	(0.013)	(0.021)	(0.021)	(0.021)
Observations	5,161	5,161	5,161	5,161	5,161	5,161
Controls	No	No	Yes	No	No	Yes
City FE	No	Yes	Yes	No	Yes	Yes

Notes: This table presents the results of the estimation of Equation (6) for Experiment 2. $1(Crime = +25\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups +20% or +30%. $1(Crime = -25\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups -20% or -30%. Columns (1)-(3) correspond to the extensive margin results and columns (4)-(6) to the intensive margin. The vector of control variables considered are age, level of education and gender. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p < 0.01 , **p < 0.05, *p < 0.1..

The simple model presented in Section 2.1 differentiated several effects of crime on public transport demand. First, a higher crime level would increase the share of commuters who not even consider public modes as a viable alternative. Results from Experiment 2 are consistent with this prediction: the fraction of people that would not choose the bus at any price increases from 13.9% to 25.2% when the bus alternative presents a crime level higher than the city average (p-value<0.001). Second, higher crime rates will decrease the appeal of public transportation, leading to a higher share of commuters choosing private options. Columns (1)-(3) in Table 2 show this effect of crime at the extensive margin. [10] Our preferred specification (column (3)) indicates that participants are 15 percentage points (or 29%, p-value<0.001) more likely to initially choose the public option when crime rates are 25% lower than average. This finding suggests that high crime rates in public transport lead people to substitute to private transport, which would result in higher emissions.

Finally, the model predicts that when crime in public transport decreases, commuters preferences would shift towards public options, increasing the fare that would make them indifferent between modes. Columns

[10] As in Experiment 1, we aggregate the results for crime rates of +20% and +30%, and -20% and -30%, to ±25% because we find no significant differences between magnitudes of the same sign.

(4)-(6) present the results for this intensive margin. Our estimates reveal that the bus price making participants indifferent between the two options is 27.3% higher when crime rates are 25% lower than average, compared to when they are 25% higher. Overall, participants are willing to pay up to 27% more for a bus with less crime. These results are robust to only considering the correct respondents of a coin toss question[11] (see Table A9) and are consistent across cities, as shown in Table A10. Moreover, Buenos Aires and Santiago display the least sensitivity to crime rates among the cities studied, both at the intensive and extensive margins[12]. Table A11 shows that treatment effects are robust across other subsamples.

The interpretation of the results is straightforward. Safety is a valuable attribute when deciding between transport modes and therefore agents have a positive willingness to pay to use modes with higher safety levels (all else constant). Therefore, keeping prices fixed, when safety in a given mode decreases, some commuters will stop even considering this transport option, and some others who were at the margin will substitute away from that mode. To prevent this marginal commuters from substituting away from public options, they would need to be compensated with lower fares. Overall, these results provide evidence of two mechanisms through which crime impacts public transport demand, generating a negative externality on emissions.

Experiment 2 rules out any concerns about anchoring effects caused by different starting prices in Experiment 1. Even when the starting price is the same for all treatment groups, we find significant differences between the reported indifference prices for public transport across groups. The pattern mirrors that of Experiment 1: we estimate significant differences between treatment groups of opposite signs but find no effect between groups of the same sign, indicating that the effect is non-linear. Furthermore, Figure A4 illustrates the distributions of indifference prices in both experiments: the mode indifference price is on the extremes of the distribution. This suggests that participants tend to deviate as much as possible from the starting price, which served as the only plausible anchor (0.5 and 1.5 in Experiment 1, and 1 in Experiment 2).

5.3 Effect of Crime on Price Elasticity

Crime might have an indirect effect on public transport demand by affecting price elasticity. If this is the case, the effectiveness of subsidies to promote ridership will depend on crime. Following Domínguez and Scartascini (2024), we estimate a linear probability model using as the dependent variable an indicator of whether the treated alternative was chosen. In Experiment 1, the coefficients reflect the effects of price and crime on the probability of choosing the bus with a different crime rate, when the outside option is an average bus. For Experiment 2, this refers to the probability of choosing the treated bus when the outside option is an average private taxi.

[11] As standard in the experimental literature, when dealing with probabilities is important to test whether participants understand what a probability is. Therefore, as a sanity check, we asked to all of the participants which is the probability that a coin lands on heads if it is tossed randomly.

[12] Also, Table A3 reports the estimates of the indifference prices for each crime treatment group. Interestingly, on average, respondents in all groups are willing to pay a higher bus fare than the current one. A plausible explanation is that, in the context of the cities considered in the experiment, the bus fare is so low (or the private taxi price so high) that commuters are already willing to pay more to avoid taking private transport.

Table 3 presents the estimates of price elasticity for both experiments. In Experiment 1, we find an average elasticity of -0.8 across treatments. However, safety in public transport significantly affects its elasticity. Specifically, when the crime rate is 20% higher than average, elasticity decreases by 0.13 in absolute terms (p-value < 0.001), indicating that higher crime rates make demand more inelastic. In other words, price cuts in contexts of high insecurity are less effective in boosting ridership: elasticity ranges from -0.87 in the -20% crime treatments to -0.73 in the +20% treatments. These estimates, although larger in magnitude than the typical rule of thumb, remain within the range of previous research (Holmgren, 2007). The larger magnitude may be attributed to the experimental nature of the decision-making process and the particular salience of crime. Table A12 details the heterogeneity of these results by city, while Table A13 explores heterogeneity by gender, crime perception, frequency of transport use, and car ownership. Importantly, crime rates have a higher impact on price elasticity for women (0.16) than for men (0.11), and a higher crime perception amplifies the effect of crime.

Table 3. Elasticity main results

	Experiment 1 (1)	Experiment 2 (2)
Price	-0.735***	-0.258***
	(0.007)	(0.004)
1(-20% Crime)	1.06***	
	(0.011)	
Price × 1(-20% Crime)	-0.135***	
	(0.010)	
1(-25% Crime)		0.126***
		(0.007)
Price × 1(-25% Crime)		0.009
		(0.006)
Observations	56,771	56,771
Controls	Yes	Yes
City FE	Yes	Yes

Notes: This table presents the results of the elasticity exercise. The dependent variable is an indicator variable of whether the respondent chose the 'treated' alternative (Bus B in Experiment 1 and the bus in Experiment 2). *Price* is a variable corresponding to the price of the treated alternative in current bus fare (of its city) units. $1(Crime = +20\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment group +20%. $1(Crime = -20\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment group -20%. $1(Crime = -30\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment group -30%. Columns (1) corresponds to the results of Experiment 1 and column (2) of Experiment 2. All specifications include control variables and city fixed effects. The vector of control variables considered are age, level of education and gender. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p < 0.01 , **p < 0.05, *p < 0.1..

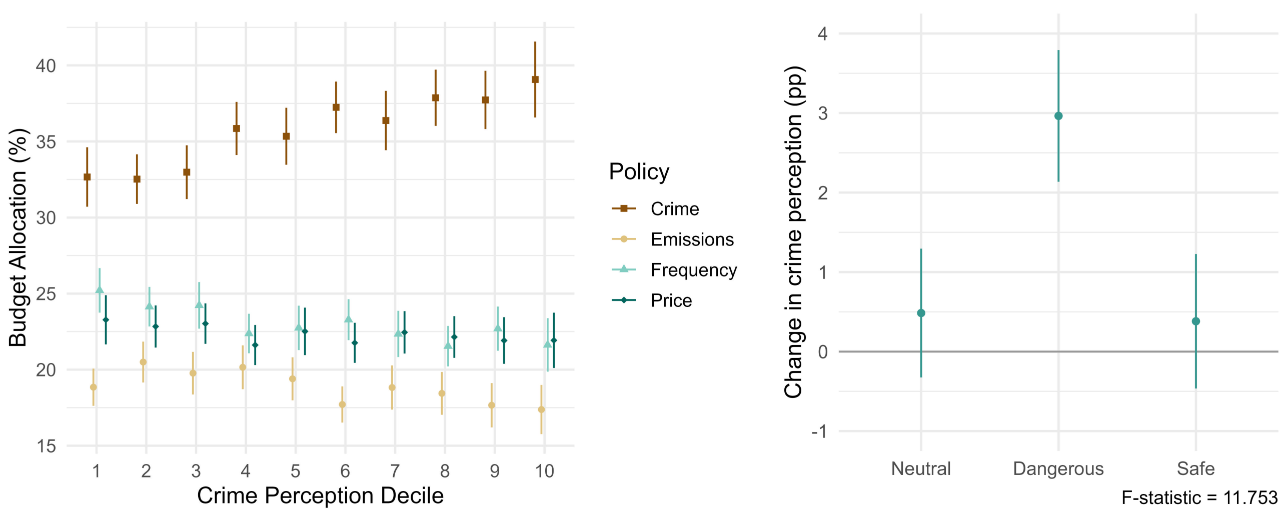
On the other hand, column (2) of Table 3 reports the elasticity estimates for Experiment 2. When the outside option is a private taxi, demand for public transport becomes less elastic than in Experiment 1 (averaging -0.25). In this case, safety does not significantly affect price elasticity. This null result stems from strong personal preferences for either mode of transport or from the substantial price differential between them, as Figure A4 shows that more than half of the respondents consistently stick to one alternative regardless of the price. However, when focusing on these consistent users, we must note that 13.9% of participants can't be incentivized through price to take the bus when crime is lower, but this fraction jumps to more than 25% when crime rates are higher. This is suggestive of crime affecting the price elasticity of those at the tail of the distribution rather than across its entirety. Thus, and given the strong results in Experiment 1, we interpret this null result as a consequence of miscalibration of experimental prices rather than evidence of no relationship between crime and elasticity.

5.4 Effect of Crime Perception on Policy Preferences

The goal of Experiment 3 is to determine whether crime perception crowds support out from other public transport policies. We conduct two analyses to this end. First, we examine the correlation between crime perception (i.e., the perceived probability of being a victim of a crime while using public transport) and transport policy preferences. Second, we introduce exogenous variation in crime perception by priming participants with a real newspaper headline. As described in Section 3, participants were randomized to read one of three headlines ($Dangerous$, $Safe$ and $Control$) about the public transport system in their city. After priming, we again elicit the perceived crime probability and use the change in perceptions induced by the priming as an instrumental variable for our analysis.

Panel (a) of Figure 2 illustrates the correlation between crime perception and policy support. Individuals who perceive a higher likelihood of being a victim of a crime in public transport allocate more of the proposed budget to crime reduction and less to improving frequency, with no significant effect on the allocation to fare subsidies or emission reduction.

Figure 2. Experiment 3



(a) Crime perception and policy support (b) Effect of priming on crime perception

Notes: Panel (a) shows the mean budget allocation for each policy, binned by deciles of crime perception in each city. Error bars show the 95% CI. Panel (b) shows the average effect on crime perception (in percentage points) of the news priming. Error bars show the 95% CI.

To test whether this link is causal, we use news priming to induce exogenous variation in crime perception. First, we assess the effectiveness of our instrument in modifying respondents' crime perceptions. Panel (b) in Figure 2 shows that while the *Dangerous* treatment effectively changes participants' perceptions as expected, the *Safe* and *Neutral* treatments do not. The failure of the *Safe* treatment to improve safety perception might be due to the saliency of crime throughout the experiment, and that crime is still mentioned even when news focus on safety. Moreover, the regression-equivalent of the figure reports an F-statistic of 11.75, meeting the standard rule of thumb for testing the relevance of instruments in the literature.

Table 4. Reduced-form estimates of Experiment 3

	Crime (1)	Emissions (2)	Frequency (3)	Price (4)
Change in CP	0.579**	-0.257	-0.499**	0.177
	(0.294)	(0.200)	(0.217)	(0.206)
Observations	4,850	4,850	4,850	4,850
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes

Notes: This table presents the results of the estimation of Equation (9) for Experiment 3. *Change in CP* is the fitted change in the perceived probability of being a victim of a crime in a public transport trip as specified in Equation (8). The dependent variable is the share of the total budget allocated to each policy. All specifications include control variables and city fixed effects. The vector of control variables considered are age, level of education and gender. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p < 0.01 , **p < 0.05, *p < 0.1..

The change in crime perception impacts public transport policy preferences. We report the estimates of Equation (9) in Table 4. Specifically, starting from a budget of 120,000 USD, a 1pp increase in crime perception raises the allocation to crime reduction policies by 0.6pp ($720) and reduces the allocation to frequency improvement by 0.5pp. It is worth noting that we did not require participants to use the entire available budget to test their attention and engagement. A strikingly high 97.3% of the sample allocates the entire budget, suggesting they feel engaged with the allocation. As a robustness check, we re-estimated our key regressions considering only those participants who used the whole budget. Table A14 shows that these results are consistent with those from the full sample.

This set of findings demonstrates that higher crime perception leads citizens to prioritize crime reduction policies at the expense of efficiency improvements, but there is no crowding-out from green policies. We find particularly valuable two aspects of these results. First, our results shed light on the complementarities between the types of transport policies considered. In particular, participants don't perceive a trade-off between environmental and crime abatement policies even in a stringent zero-sum setting. Secondly, the point estimates of columns (1)-(4) of Table 4 correspond to the semi-elasticity of budget allocation with respect to safety perception. Thus, column (1) suggests that a 1% increase in crime perception would increase the budget allocation to safety measure by 0.58%; highlighting how important safety is among participants' preferences.

6 Conclusion

This study contributes to the debate on the policy levers to increase public transport ridership and reduce greenhouse emissions by focusing on the critical role of crime and crime perceptions. Through three pre-registered experiments in six Latin American capital cities, our work highlights three takeaways for policy makers.

First, crime is a determinant factor in transport modal choice. We quantify users valuation of crime reductions in public transport, estimating that users are willing to pay a premium of 51% of current bus fares to ride safer transport. This valuation offers a tangible measure of the value that users place on safety, which can be incorporated into cost-benefit analyses of public transport policies. Our mouse-tracking results offer more evidence about the importance of crime in transport mode choice: participants consider crime as relevant as price and more relevant than other trip attributes when choosing among transport options. Overall, our results show participants place a substantial value on safety in their public transport systems.

Second, we provide evidence that crime affects public transport demand through two channels: by changing the appeal of public transport, and by changing the price elasticity of demand. Participants are 29% more likely to choose public over private transportation at current prices when the public option is 25% safer than average. Thus, reducing crime in public transport can boost the substitution from private to public transport and reduce emissions. In addition to this direct effect on demand, crime also affects how users react to fare changes. Higher crime rates make demand for public transport more inelastic, especially among women. Intuitively, if fear of crime is high enough, commuters will be reluctant to use public transport no matter the price. This indirect effect of crime can limit the effectiveness of current and proposed subsidies to boost public transport ridership. Taken together, these direct and indirect effects imply that higher crime rates can limit the efforts to reduce greenhouse emissions. As long as these effects are not taken into account by policy, crime will continue to have a negative externality on environmental outcomes.

While crime abatement and environmental policies might often be perceived as unrelated or even opposed given their positioning among political platforms, if crime has a negative externality on emissions, crime and environmental policies can be levered together for joint goals. We test whether participants perceive a trade-off between environmental and crime-reducing policies, in which case higher crime perceptions could crowd out support for green policies. By experimentally inducing an exogenous change in crime perceptions, our results show that crime perceptions do not crowd out support for green policies. Even in a stringent zero-sum setting, participants don't perceive a trade-off between the abatement of crime and emissions.

The evidence presented in this paper highlights the critical role of actual and perceived crime in shaping public transport demand and policy preferences. Our findings suggest that the success of initiatives aimed at increasing public transport usage —an essential component of climate change mitigation strategies— may hinge on addressing safety concerns in tandem with other measures such as fare subsidies and service improvements. In the context of Latin American cities, where crime is a pervasive issue, the implications are particularly stark: without substantial investments in safety, policies with the goal of reducing private vehicle use and its associated emissions may remain ineffective. Future research should continue to explore the intricate dynamics between crime, safety perception, and transport demand, with an eye toward informing more effective urban and environmental policies.

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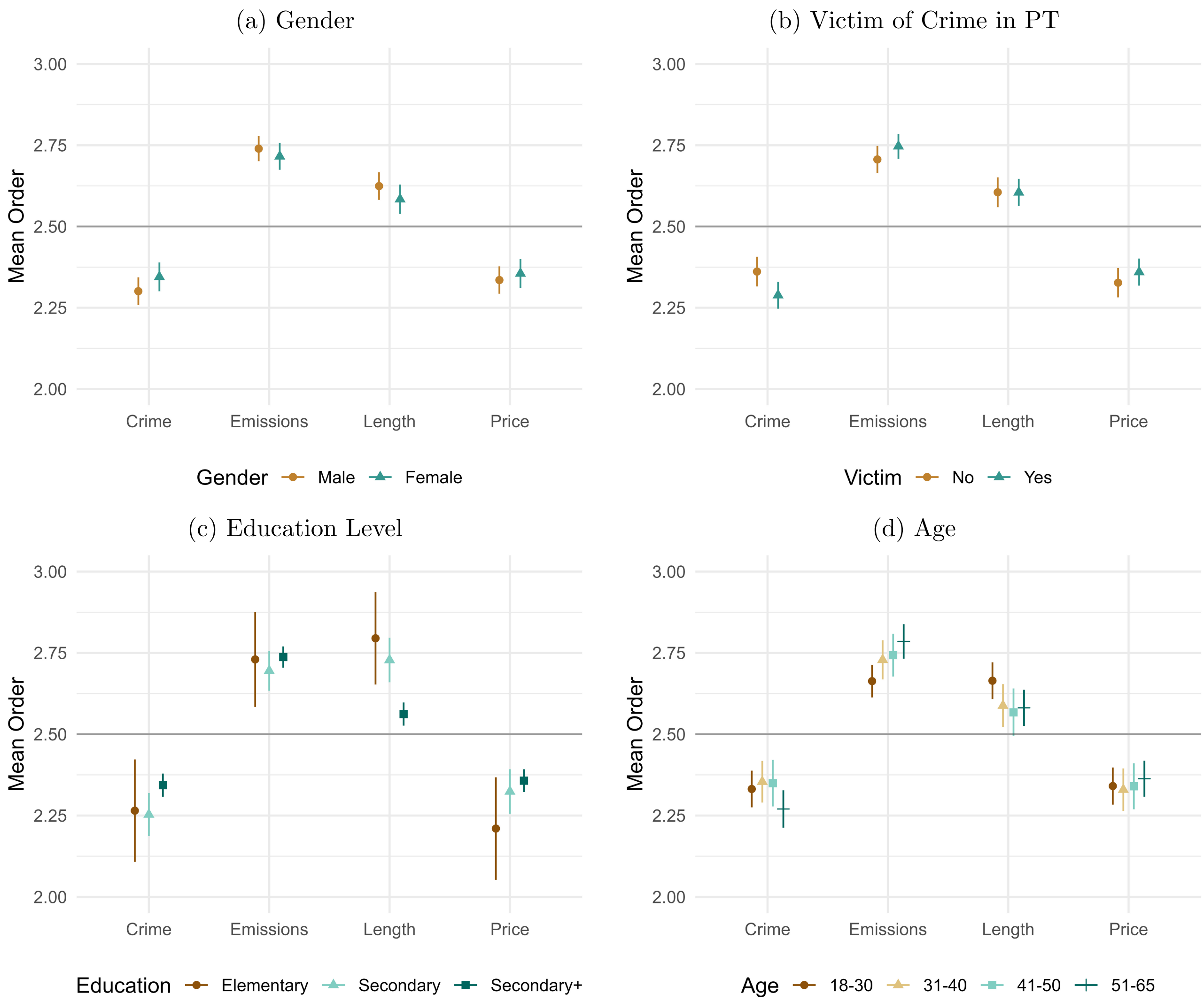
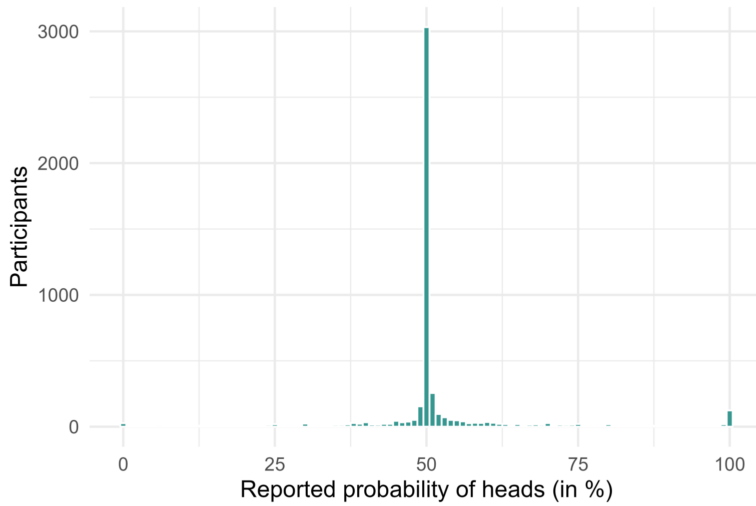
Appendix Tables and Figures

Figure A1. Heterogeneity in mouse-tracking results



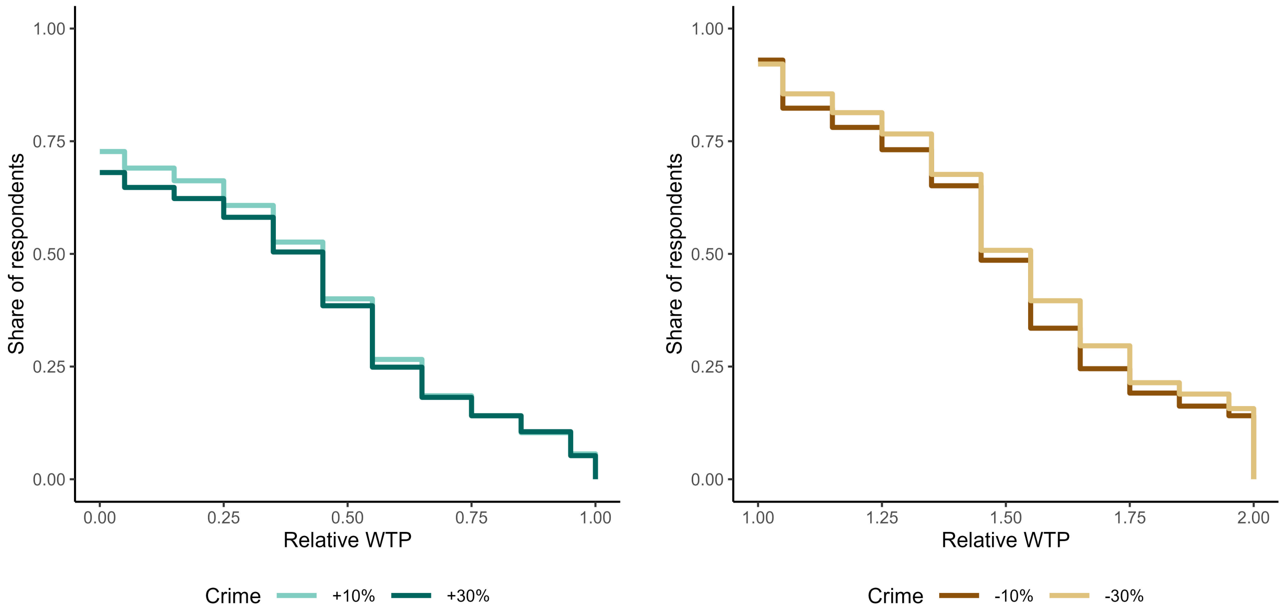
Notes: This figure shows the mean and standard errors of the order of look-up of each attribute. The mean order is depicted by a point and the 95% CI interval by the bars around it. Panel (a) groups the estimates by gender; Panel (b) differentiates the results between respondents who were victims of a crime in the public transport in the past; ; Panel (c) differentiates the results by education level; Panel (d) differentiates the results by age range. The education levels considered are *Elementary* (maximum education level is either complete or incomplete elementary schooling), *Secondary* (maximum education level is either complete or incomplete secondary schooling) and *More than Secondary* (maximum education level is more than complete secondary schooling).

Figure A2. Histogram of reported probabilities of a coin landing on heads



Notes: This figure shows the distribution of the reported probability of a random coin toss landing heads by our sample of respondents.

Figure A3. Distribution of relative WTP for safety in public transport, Expt. 1., by treatment

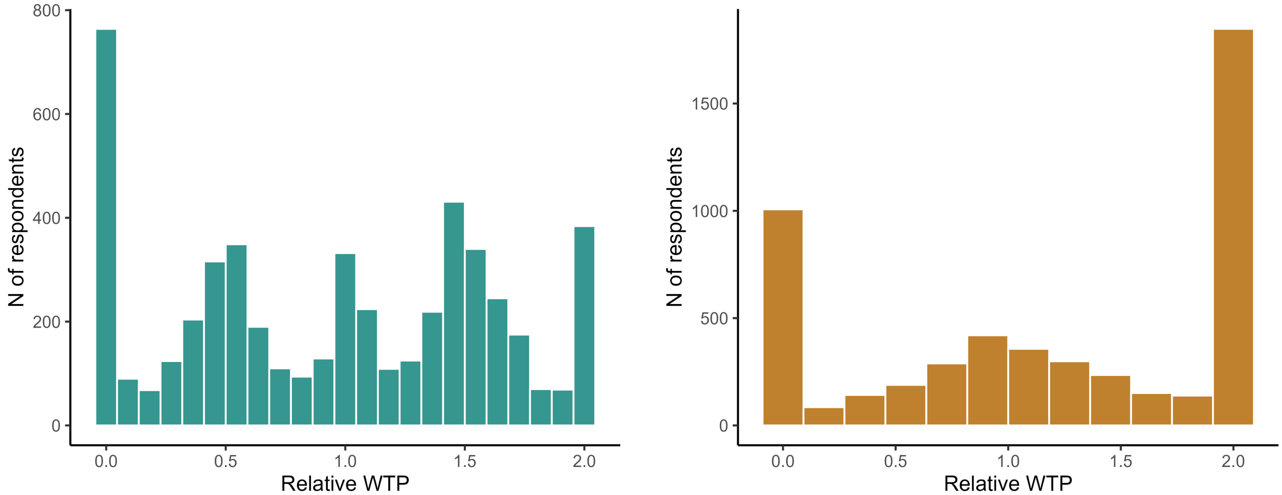


(a) Positive variation in crime

(b) Negative variation in crime

Notes: This figure shows elasticity with respect to price for each treatment group. Each line corresponds to the share of participants who would choose the Bus B in Experiment 1 at each price, in current bus fare units (of their city). Panel (a) corresponds to the results of the +10% and +30% treatment groups and Panel (b) to the -10% and -30% treatment groups.

Figure A4. Distribution of relative WTP for safety in public transport



(a) Experiment 1

(b) Experiment 2

Notes: This figure shows the indifference price distribution reported in each experiment. Panel (a) correspond to the results of Experiment 1 and Panel (b) correspond to the results of Experiment 2.

Table A1. Descriptive statistics and balance test

	Summary Stats	Balance Table							
		Experiment 1			Experiment 2			Experiment 3	
		+10%	-10%	-30%	+20%	-20%	-30%	Dangerous	Safe
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Male (=1)	0.526 (0.499)	0.008 (0.020)	-0.006 (0.020)	-0.001 (0.020)	0.015 (0.020)	0.038. (0.020)	0.033. (0.020)	0.018 (0.017)	-0.008 (0.017)
Residents in HH	3.905 (1.892)	-0.108 (0.076)	-0.068 (0.075)	-0.014 (0.075)	-0.019 (0.076)	0.011 (0.074)	0.041 (0.076)	0.094 (0.066)	0.009 (0.062)
Secondary Schooling	0.218 (0.413)	0.0010 (0.016)	0.014 (0.016)	0.005 (0.016)	0.005 (0.016)	0.004 (0.016)	0.009 (0.016)	0.009 (0.014)	0.018 (0.014)
University Schooling	0.744 (0.437)	0.004 (0.017)	-0.018 (0.017)	-0.010 (0.017)	0.002 (0.017)	-0.006 (0.017)	-0.017 (0.017)	-0.007 (0.015)	-0.008 (0.015)
Age	36.222 (13.417)	0.683 (0.525)	0.609 (0.526)	0.918. (0.522)	0.398 (0.532)	0.256 (0.525)	0.676 (0.533)	-0.377 (0.460)	-0.509 (0.452)
Ideology (Right)	5.794 (2.168)	-0.041 (0.086)	0.031 (0.085)	0.088 (0.085)	-0.035 (0.087)	-0.141. (0.086)	0.164. (0.086)	-0.052 (0.074)	0.037 (0.073)
Trust in Police	4.583 (3.04)	0.053 (0.120)	-0.008 (0.119)	0.006 (0.120)	-0.003 (0.122)	0.052 (0.119)	0.201. (0.121)	-0.201. (0.104)	0.070 (0.103)
Owns Car (=1)	0.433 (0.496)	0.025 (0.019)	-0.005 (0.019)	0.010 (0.019)	0.011 (0.020)	0.010 (0.019)	-0.023 (0.019)	0.007 (0.017)	-0.003 (0.017)
Freq. PT	4.084 (2.046)	0.026 (0.081)	0.112 (0.080)	0.115 (0.080)	-0.005 (0.081)	-0.100 (0.081)	-0.076 (0.081)	0.051 (0.070)	0.033 (0.069)
Victim (=1)	0.542 (0.498)	0.038. (0.020)	0.052** (0.019)	0.051** (0.020)	-0.010 (0.020)	-0.033. (0.019)	-0.004 (0.020)	0.023 (0.017)	0.011 (0.017)

Notes: This table presents summary statistics of a given set of covariates and the results of the randomization balance test. *Male(=1)* corresponds to an indicator variable equal to 1 if the observation is male. *Residents in HH* corresponds to the number of people living in the same house as the respondent. *Secondary* and *University Schooling* are two indicator variables equal to 1 if the participant has some Secondary or University Schooling, respectively. *Age* corresponds to the age of the respondent. Ideology is a variable that can take values from 0 to 10, the closer to 0 (10) the closer the respondent identifies to a left- (right-) line of thought, politically. *Trust in Police* is a variable that can take values from 0 to 10, the highest the value the more trust the participant has in the police. *Owns Car (=1)* is an indicator variable equal to 1 if the respondent owns a car. *Freq. PT* corresponds to the number of days that the respondent used the public transport in the last 7 days. *Victim (=1)* is an indicator variable equal to 1 if the respondent has ever been victim of a crime in the public transportation. Column (2) presents the mean of each variable with the standard deviation in parenthesis.

Columns (2) to (8) report the coefficients and standard errors for a regression of each variable on each treatment group in the corresponding experiment including city fixed effects (the results from each row come from an independent regression). Columns (2)-(4) correspond to the treatment groups of Experiment 1. Columns (5)-(7) correspond to the treatment groups of Experiment 2. Columns (8)-(9) correspond to the treatment groups of Experiment 3. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p $<$ 0.01 , **p $<$ 0.05, *p $<$ 0.1..

Table A2. Summary statistics of mouse-tracking

	Crime	Emissions	Length	Price
Mean Order	2.32	2.73	2.61	2.34
95% CI	(2.29, 2.35)	(2.7, 2.76)	(2.57, 2.64)	(2.31, 2.38)

Notes: This table presents the mean and 95% CI of the order in which each attribute was clicked in Experiment 1. The variable goes from 1 (if it was clicked first) to 4 (if it was clicked last).

Table A3. Mean willingness to pay for transport by crime rate, as fraction of current bus fare

	Experiment 1	Experiment 2
+30%	0.38	1.04
	(0.36, 0.4)	(1, 1.09)
+10% (+20%)	0.4	1.04
	(0.38, 0.42)	(0.99, 1.08)
-10% (-20%)	1.49	1.32
	(1.48, 1.51)	(1.28, 1.36)
-30%	1.53	1.3
	(1.51, 1.54)	(1.26, 1.34)

Notes: This table presents the mean and 95% CI of the indifference price between 'treated' and 'non-treated' alternative by treatment group in each experiment, in current bus fare terms. The 'treated' alternative is Bus B in Experiment 1 and the bus in Experiment 2. Each row corresponds to a different treatment group. Note that second and third row correspond to a 10% variation in the crime rate for Experiment 1 and 20% for Experiment 2.

Table A4. Reduced-form estimates of Experiment 1, disaggregated

	(1)	(2)	(3)	(4)	(5)	(6)
1(+10% Crime)	0.019	0.018	0.018			
	(0.013)	(0.013)	(0.013)			
1(-10% Crime)	1.12***	1.12***	1.12***			
	(0.013)	(0.013)	(0.013)			
1(-30% Crime)	1.15***	1.15***	1.15***			
	(0.013)	(0.013)	(0.013)			
Crime % (Continuous)				-0.023***	-0.023***	-0.023***
				(0.0002)	(0.0002)	(0.0002)
Observations	5,161	5,161	5,161	5,161	5,161	5,161
Controls	No	No	Yes	No	No	Yes
City FE	No	Yes	Yes	No	Yes	Yes

Notes: This table presents the results of the estimation of Equation (6) for Experiment 1. $1(Crime = +10\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment group +10%. $1(Crime = -10\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment group -10%. $1(Crime = -30\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment group -30%. *Crime % (Continuous)* is a continuous variable corresponding to the level of crime rate that the participant was exposed to. The vector of control variables considered are age, level of education and gender. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p < 0.01 , **p < 0.05, *p < 0.1..

Table A5. Reduced-form estimates of Experiment 1, only correct respondents to coin question

	(1)	(2)	(3)	(4)	(5)	(6)
1(+10% Crime)	0.028*	0.026*	0.026*			
	(0.015)	(0.015)	(0.015)			
1(-10% Crime)	1.15***	1.15***	1.15***			
	(0.015)	(0.015)	(0.015)			
1(-30% Crime)	1.18***	1.18***	1.18***			
	(0.015)	(0.015)	(0.015)			
Crime % (Continuous)				-0.023***	-0.023***	-0.023***
				(0.0003)	(0.0003)	(0.0003)
Observations	3,789	3,789	3,789	3,789	3,789	3,789
Controls	No	No	Yes	No	No	Yes
City FE	No	Yes	Yes	No	Yes	Yes

Notes: This table presents the results of the estimation of Equation (6) for Experiment 1. $1(Crime = +10\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment group +10%. $1(Crime = -10\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment group -10%. $1(Crime = -30\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment group -30%. *Crime % (Continuous)* is a continuous variable corresponding to the level of crime rate that the participant was exposed to. The vector of control variables considered are age, level of education and gender. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p < 0.01 , **p < 0.05, *p < 0.1..

Table A6. Reduced-form estimates of Experiment 1 by city

	Bogotá (1)	Buenos Aires (2)	CDMX (3)	Guatemala (4)	Lima (5)	Santiago (6)
1(-20% Crime)	1.11***	1.14***	1.27***	1.09***	1.05***	1.06***
	(0.021)	(0.022)	(0.021)	(0.023)	(0.023)	(0.022)
Observations	872	863	859	871	856	840
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the estimation of Equation (6) for Experiment 1 by city. $1(Crime = +20\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups +10% or +30%. $1(Crime = -20\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups -10% or -30%. The vector of control variables considered are age, level of education and gender. The vector of control variables considered are age, level of education and gender. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p < 0.01 , **p < 0.05, *p < 0.1..

Table A7. Heterogeneity of reduced-form estimates of Experiment 1

	All (1)	Crime Perception Q4 (2)	Female (3)	MT Safety (4)
1(-20% Crime)	1.12***	1.15***	1.15***	1.15***
	(0.009)	(0.017)	(0.013)	(0.012)
Observations	5,161	1,523	2,446	2,982
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes

Notes: This table presents the heterogeneity in the estimation of Equation (6) for Experiment 1 by subsamples. $1(Crime = +20\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups +10% or +30%. $1(Crime = -20\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups -10% or -30%. *Crime Perception Q4* is an indicator variable equal to 1 if the participant's reported perceived probability of being victim of a crime in a trip by bus in their city is within the fourth quartile of the reported probability of their city. *MT Safety* is an indicator variable equal to 1 if the participant clicked the crime attribute first or second in Experiment 1. All specifications include control variables and city fixed effects. The vector of control variables considered are age, level of education and gender. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p < 0.01 , **p < 0.05, *p < 0.1..

Table A8. Reduced-form estimates of Experiment 2, disaggregated

	Chose Bus			WTP		
	(1)	(2)	(3)	(4)	(5)	(6)
1(+20% Crime)	-0.009	-0.004	-0.004	-0.007	0.001	0.002
	(0.020)	(0.019)	(0.019)	(0.032)	(0.031)	(0.031)
1(-20% Crime)	0.155***	0.159***	0.159***	0.279***	0.286***	0.285***
	(0.019)	(0.019)	(0.019)	(0.031)	(0.030)	(0.030)
1(-30% Crime)	0.135***	0.138***	0.138***	0.260***	0.264***	0.265***
	(0.019)	(0.019)	(0.019)	(0.030)	(0.030)	(0.030)
Observations	5,161	5,161	5,161	5,161	5,161	5,161
Controls	No	No	Yes	No	No	Yes
City FE	No	Yes	Yes	No	Yes	Yes

Notes: This table presents the results of the estimation of Equation (6) for Experiment 2. $1(Crime = +20\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment group +20%. $1(Crime = -20\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment group -20%. $1(Crime = -30\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment group -30%. Columns (1)-(3) correspond to the extensive margin results and columns (4)-(6) to the extensive margin. The vector of control variables considered are age, level of education and gender. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p < 0.01 , **p < 0.05, *p < 0.1..

Table A9. Reduced-form estimates of Experiment 2, only correct respondents to the coin toss question

	Chose Bus			WTP		
	(1)	(2)	(3)	(4)	(5)	(6)
1(-25% Crime)	0.168***	0.169***	0.171***	0.302***	0.302***	0.304***
	(0.015)	(0.015)	(0.015)	(0.025)	(0.025)	(0.025)
Observations	3,789	3,789	3,789	3,789	3,789	3,789
Controls	No	No	Yes	No	No	Yes
City FE	No	Yes	Yes	No	Yes	Yes

Notes: This table presents the results of the estimation of Equation (6) for Experiment 2 considering only participants who answered correctly what is the probability of a random coin toss landing heads (with 5% margin of error). $1(Crime = +25\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups +20% or +30%. $1(Crime = -25\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups -20% or -30%. Columns (1)-(3) correspond to the extensive margin results and columns (4)-(6) to the extensive margin. The vector of control variables considered are age, level of education and gender. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p $<$ 0.01 , **p $<$ 0.05, *p $<$ 0.1..

Table A10. Reduced-form estimates of Experiment 2 by city

	Chose Bus						WTP					
	Bogotá	Buenos Aires	CDMX	Guatemala	Lima	Santiago	Bogotá	Buenos Aires	CDMX	Guatemala	Lima	Santiago
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1(-25% Crime)	0.205***	0.172***	0.356***	0.290***	0.351***	0.292***	0.143***	0.086***	0.181***	0.177***	0.185***	0.142***
	(0.052)	(0.050)	(0.051)	(0.053)	(0.054)	(0.051)	(0.034)	(0.032)	(0.032)	(0.034)	(0.034)	(0.032)
Observations	872	863	859	871	856	840	872	863	859	871	856	840
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the estimation of Equation (6) for Experiment 2 by city. $1(Crime = +25\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups +20% or +30%. $1(Crime = -25\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups -20% or -30%. Columns (1)-(3) correspond to the extensive margin results and columns (4)-(6) to the extensive margin. All specifications include control variables: age, level of education and gender. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p < 0.01 , **p < 0.05, *p < 0.1..

Table A11. Heterogeneity of reduced-form estimates of Experiment 2

	Chose Bus				WTP			
	All	Crime Perception Q4	Female	MT Safety	All	Crime Perception Q4	Female	MT Safety
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(-25% Crime)	0.149***	0.140***	0.155***	0.133***	0.272***	0.245***	0.277***	0.250***
	(0.013)	(0.025)	(0.019)	(0.018)	(0.021)	(0.040)	(0.031)	(0.028)
Observations	5,161	1,523	2,446	2,982	5,161	1,523	2,446	2,982
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the estimation of Equation (6) for Experiment 2 by city. $1(Crime = +25\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups +20% or +30%. $1(Crime = -25\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups -20% or -30%. *Crime Perception Q4* is an indicator variable equal to 1 if the participant's reported perceived probability of being victim of a crime in a trip by bus in their city is within the fourth quartile of the reported probability of their city. *MT Safety* is an indicator variable equal to 1 if the participant clicked the crime attribute first or second in Experiment 1. Columns (1)-(3) correspond to the results of the extensive margin and columns (4)-(6) to the ones of the extensive margin. All specifications include control variables and city fixed effects. The vector of control variables considered are age, level of education and gender. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p $<$ 0.01 , **p $<$ 0.05, *p $<$ 0.1..

Table A12. Elasticity results by city

	Experiment 1						Experiment 2					
	Bogotá (1)	Buenos Aires (2)	CDMX (3)	Guatemala (4)	Lima (5)	Santiago (6)	Bogotá (7)	Buenos Aires (8)	CDMX (9)	Guatemala (10)	Lima (11)	Santiago (12)
Price	-0.718***	-0.755***	-0.740***	-0.702***	-0.722***	-0.777***	-0.282***	-0.262***	-0.243***	-0.256***	-0.243***	-0.259***
	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)
1(-20% Crime)	1.14***	1.09***	1.12***	1.00***	0.921***	1.11***						
	(0.027)	(0.028)	(0.027)	(0.029)	(0.029)	(0.028)						
Price × 1(-20% Crime)	-0.206***	-0.125***	-0.072***	-0.139***	-0.095***	-0.178***						
	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)	(0.024)						
1(-25% Crime)							0.088***	0.037**	0.168***	0.154***	0.187***	0.135***
							(0.017)	(0.015)	(0.015)	(0.017)	(0.017)	(0.015)
Price × 1(-25% Crime)							0.012	0.049***	0.009	-0.013	-0.013	0.010
							(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	9,592	9,493	9,449	9,581	9,416	9,240	9,592	9,493	9,449	9,581	9,416	9,240
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the elasticity exercise by city. The dependent variable is an indicator variable of whether the respondent chose the 'treated' alternative (Bus B in Experiment 1 and the bus in Experiment 2). *Price* is a variable corresponding to the relative price of the treated alternative in current bus fare (of its city). $1(Crime = +25\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups +20% or +30%. $1(Crime = -25\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups -20% or -30%. Columns (1)-(6) corresponds to the results of Experiment 1 and columns (7)-(12) to the ones of Experiment 2. All specifications include control variables and city fixed effects. The vector of control variables considered are age, level of education and gender. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p < 0.01 , **p < 0.05, *p < 0.1..

Table A13. Elasticity main results, heterogeneity by sumbsamples

	Experiment 1					Experiment 2				
	All	Crime P. Q4	Female	Frequent PT	Car Owner	All	Crime P. Q4	Female	Frequent PT	Car Owner
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Price	-0.735***	-0.707***	-0.705***	-0.768***	-0.672***	-0.258***	-0.248***	-0.241***	-0.269***	-0.221***
	(0.007)	(0.014)	(0.011)	(0.012)	(0.011)	(0.004)	(0.008)	(0.006)	(0.007)	(0.007)
1(-20% Crime)	1.06***	1.08***	1.10***	1.03***	1.08***					
	(0.011)	(0.021)	(0.017)	(0.019)	(0.018)					
Price × 1(-20% Crime)	-0.135***	-0.151***	-0.159***	-0.128***	-0.138***					
	(0.010)	(0.019)	(0.015)	(0.016)	(0.016)					
1(-25% Crime)						0.126***	0.128***	0.148***	0.091***	0.161***
						(0.007)	(0.012)	(0.010)	(0.010)	(0.011)
Price × 1(-25% Crime)						0.009	-0.007	-0.010	-0.005	-0.012
						(0.006)	(0.011)	(0.009)	(0.009)	(0.009)
Observations	56,771	16,753	26,906	20,999	24,574	56,771	16,753	26,906	20,999	24,574
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the elasticity exercise by subsamples. The dependent variable is an indicator variable of whether the respondent chose the 'treated' alternative (Bus B in Experiment 1 and the bus in Experiment 2). *Price* is a variable corresponding to the price of the treated alternative in current bus fare (of its city) units. $1(Crime = +20\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups +10% or +30% in Experiment 1. $1(Crime = -20\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups -10% or -30% in Experiment 1. $1(Crime = +25\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups +20% or +30% in Experiment 2. $1(Crime = -25\%)$ is an indicator variable equal to 1 if the participant was assigned to the crime treatment groups -20% or -30% in Experiment 2. Columns (1)-(6) corresponds to the results of Experiment 1 and columns (7)-(12) to the ones of Experiment 2. Columns (1) and (6) consider the whole sample. Columns (2) and (7) consider respondents whose perceived probability of being victim of a crime in a bus trip is in the 4th quartile of their city. Columns (3) and (8) consider only respondents who identify themselves as females. Columns (4) and (9) consider the respondents whose reported days that they used the public transport in their city last week is above the median answer of their city. Column (5) and (10) report the results for participants who own a car. All specifications include control variables and city fixed effects. The vector of control variables considered are age, level of education and gender (except for the female subsample). Heteroskedasticity-robust standard errors are considered. Significance levels: ***p < 0.01 , **p < 0.05, *p < 0.1..

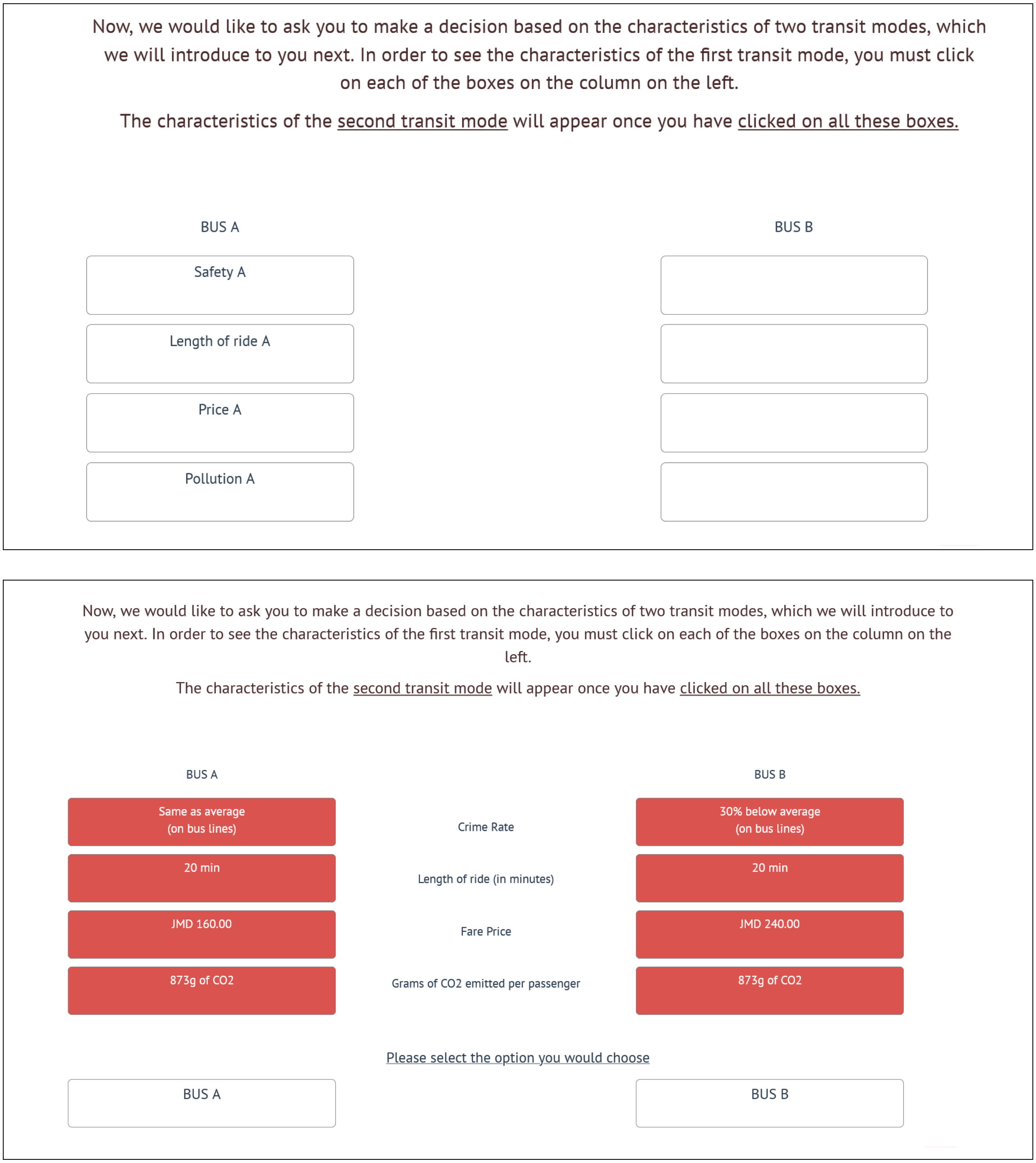
Table A14. 2SLS estimates of Experiment 3, participants that allocated the totality of the budget

	Crime (1)	Emissions (2)	Frequency (3)	Price (4)
Change in CP	0.630**	-0.209	-0.566**	0.145
	(0.295)	(0.196)	(0.227)	(0.207)
Observations	4,718	4,718	4,718	4,718
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes

Notes: This table presents the results of the estimation of Equation (9) for Experiment 3 using the sample of participants who allocated the totality of the available budget. *Change in CP* is the fitted change in the perceived probability of being a victim of a crime in a public transport trip as depicted in Equation (8). The dependent variable is the share over the total budget allocated that was allocated to the policy detailed in each column. All specifications include control variables and city fixed effects. The vector of control variables considered are age, level of education and gender. Heteroskedasticity-robust standard errors are considered. Significance levels: ***p $<$ 0.01 , **p $<$ 0.05, *p $<$ 0.1..

B. Online Experiment

Figure B1. Experiment 1



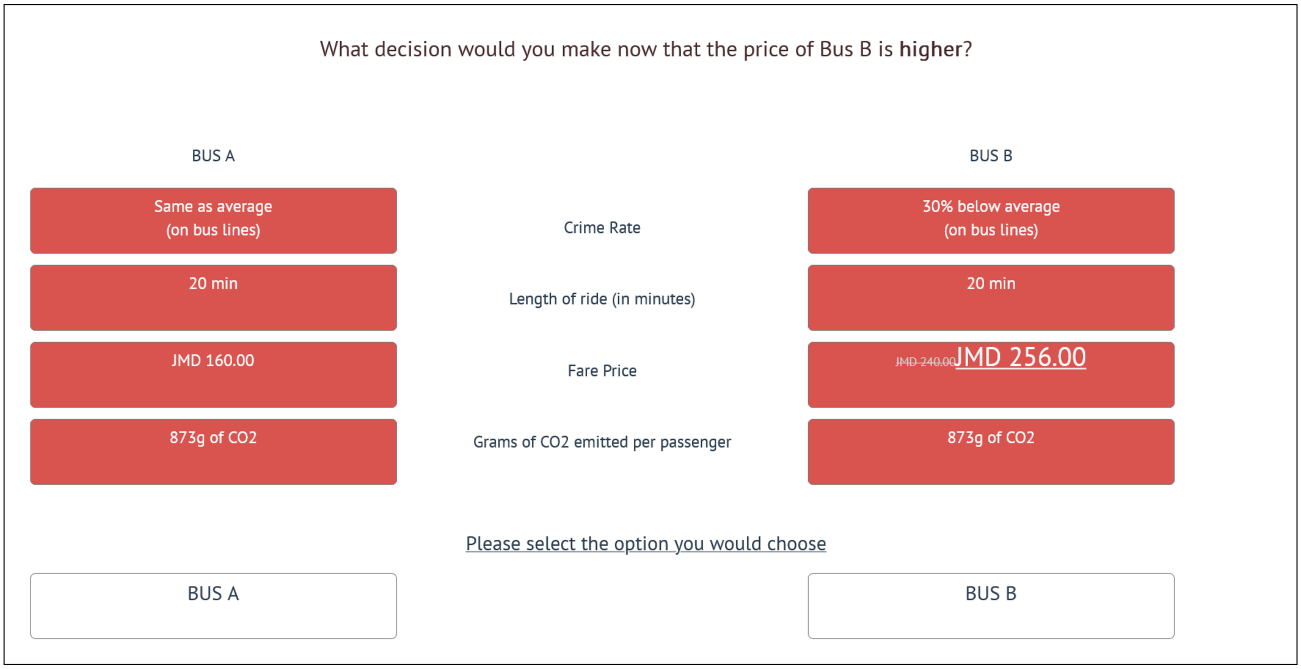

What decision would you make now that the price of Bus B is **higher**?
BUS A
BUS B
Same as average (on bus lines)
Crime Rate
30% below average (on bus lines)
20 min
Length of ride (in minutes)
20 min
JMD 160.00
Fare Price
~~JMD 240.00~~ JMD 256.00
873g of CO2
Grams of CO2 emitted per passenger
873g of CO2
Please select the option you would choose
BUS A
BUS B

Figure B2. Experiment 2

Now, instead of choosing between two buses, you will have to decide between an Uber Private Taxi and a public bus in your city.

UBER		BUS
20 min	Length of ride (in minutes)	33 min
Pollution 1530g of CO2	Grams of CO2 emitted per passenger	Pollution 873g of CO2
Same as average (in private taxis)	Crime Rate	20% below average (on bus lines)
JMD 5,000.00	Fare Price	JMD 160.00

Please select the option you would choose

UBER

BUS

Figure B3. Experiment 3

Robos en manada en colectivos: la nueva modalidad que sufren los pasajeros en la Ciudad

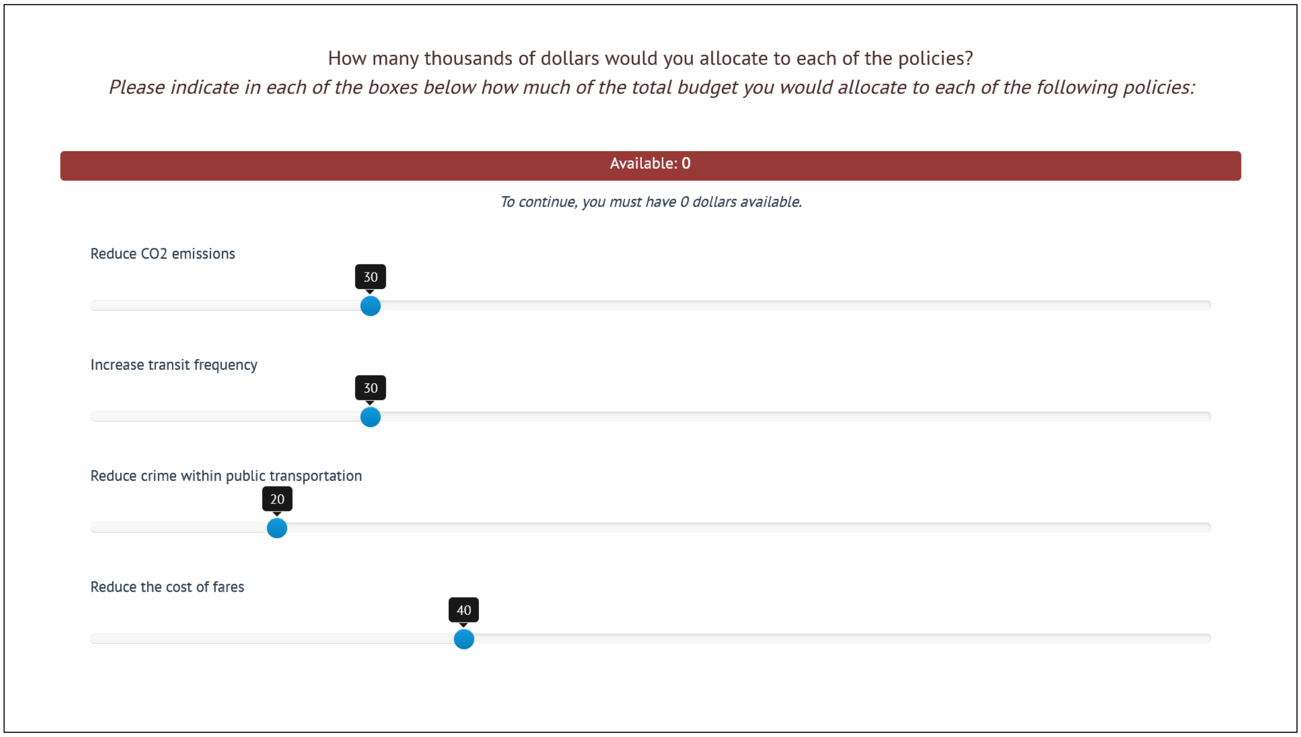
Son grupos que suben a los micros, fingen no conocerse y antes de bajar arrebatan celulares y mochilas. Palermo y Recoleta, las zonas más afectadas.

Imagine that Buenos Aires' government is debating how to spend a **US$120,000** budget to improve public transit.
Please keep in mind that the money spent on one area cannot be spent on another area.

You will be asked about how you think these funds should be used.
The results of this study will be presented to the agency in charge of public transit in your city. Your answer may **influence** the government's choices in your city, so it is in your best interest to be honest and careful in your answers.

From 0% to 100%, in which 0% means *impossible* and 100% means *most certainly*.

During your average commuting, how likely would you say you are to be a victim of crime while using public transit in your city?


How many thousands of dollars would you allocate to each of the policies?
Please indicate in each of the boxes below how much of the total budget you would allocate to each of the following policies:
Available: 0
To continue, you must have 0 dollars available.
Reduce CO2 emissions
30
Increase transit frequency
30
Reduce crime within public transportation
20
Reduce the cost of fares
40