Safety First: Crime and the Demand for Public Transportation in Latin America

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Abstract

Public transportation is key to reducing urban pollution and congestion, yet crime may deter its use. We study how crime affects transportation demand, price elasticity, and policy support through a pre-registered survey experiment in six Latin American capital cities. First, we find that commuters are willing to pay a premium of 50% of the current fare to take lower-crime routes, revealing the centrality of safety in modal choice. Second, crime lowers the likelihood of choosing public over private transport, and reduces price sensitivity, weakening the effectiveness of subsidies —especially among women and frequent riders. Third, higher crime perception increases support for safety investments but does not crowd out environmental goals in a budget allocation task. Together, the results show that crime imposes negative externalities by distorting transportation choices, and highlight complementarities between safety and sustainability agendas in urban policy.

Keywords: public transportation, crime, environmental policy, experiments

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1. Introduction

Public transportation is a central tool in the fight against climate change. By shifting commuters away from private vehicles, public transit can reduce emissions, congestion, and energy use. To incentivize commuters to shift to public transportation, public agencies heavily subsidize fares, and more cities are considering making transit completely free (King and Taylor, 2023). But in many high-crime settings, the effectiveness of these policies may be limited if public transportation is perceived as unsafe, which usually is the main concern of riders (Ceccato and Nalla, 2020). When riders fear crime, they may avoid buses and trains regardless of fares, turning instead to private modes. In this way, though safety and environmental goals are often treated as distinct policy agendas, they may in fact be complements. Policy makers recognize the demand for safety improvements in transit systems: across Latin America and other regions, governments have introduced women-only trains, increased policing at transit hubs, and redesigned infrastructure to address crime on public transportation. These interventions suggest that improving safety is seen not only as a social priority, but also as a condition for making green transportation policies work.

Despite of decades of safety policies in public transportation, there is little systematic evidence on how crime shapes demand for public transportation, and how it might constrain the effectiveness of green subsidies. This lack of evidence can be attributed to identification challenges in observational settings. Prices, crime rates, and ridership are jointly determined: transit agencies may adjust fares in response to changing demand, while crime may increase or decrease depending on passenger volume and rider composition. At the same time, individuals' decisions to use public transport depend on both actual crime and their subjective perceptions of risk, which are difficult to observe and often confounded with other unmeasured factors. These endogenous dynamics limit the ability to identify the causal impact of crime. For example, even when safety improvements are implemented, they typically affect entire networks or occur alongside other changes, making it difficult to isolate their effects. Similarly, while surveys show that most transit riders demand safety improvements (Ceccato et al., 2022), there is no evidence of how much are riders willing to pay for those improvements. An experimental approach is needed to overcome these challenges and to disentangle the effects of crime and price on transportation decisions.

This paper provides experimental evidence that commuters put safety first in their transportation choices, with crime reducing demand for public transportation and constraining the effectiveness of green subsidies. We implement a pre-registered[1] online survey experiment with 5,160 participants across six Latin American capital cities: Bogotá, Buenos Aires, Mexico City (CDMX), Guatemala City, Lima, and Santiago. These cities combine high levels of crime with extensive, subsidized public transportation systems, offering a relevant setting to study how crime interacts with transportation policies. The experimental design consists of three parts. In Part 1, participants choose between two public buses that experimentally vary in fare and crime rates, allowing us to estimate how much users are willing to pay to reduce crime exposure during their commute. We use mouse-tracking to reveal which information participants consider for making their transportation choice. In Part 2, participants choose between a public bus and a private taxi under varying levels of crime in public transportation. These two parts allow us to estimate the effect of crime on public transportation demand and its impact on price elasticity. In Part 3, we examine how crime perception affects support for different transportation policies. Participants are randomly assigned to read real news articles that frame public transportation as safe, unsafe, or neutral, and are then asked to do a budget allocation across policies such as fare subsidies, service improvements, emissions abatement, and crime reduction. Across all three parts, the experimental variation in crime allows us to identify the causal effect of crime on transportation choices and policy preferences.

We find that commuters place substantial weight on crime when making transportation decisions, and are willing to pay a large premium for safer public transportation. Using mouse-tracking, we reveal that participants consistently seek out information about crime and price before considering other trip attributes such as emissions or duration, showing that when deciding between transportation modes commuters put safety first. These behavioral patterns are consistent across cities and demographic groups, and have a direct correlate on how users value safety in public transportation. In public-public transportation choices (Part 1), participants are willing to pay a premium equivalent to 51% of the current fare to reduce crime by 20%, and require a 61% discount to tolerate a 20% increase (both $p < 0.001$)[2]. In public-

[1] AEA RCT Registry: AEARCTR-0013745.

[2] In the study countries, the regular ticket fare costs, on average, USD 0.7 at the average

private choices —Part 2, where the alternative is a private taxi— a 50% improvement in safety in public transportation increases the fare at which participants are indifferent between the two options by 27% ($p < 0.001$). These valuations underscore that safety is a key driver of modal decisions.

We next examine how crime affects transportation choice and the responsiveness of demand to price. When choosing between a public bus and a private taxi, we find that lower crime levels in transit increase the likelihood of choosing public transportation by 29% (a 15 percentage point shift; $p < 0.001$). In addition, crime substantially reduces price elasticity. This effect operates primarily at the extensive margin, as higher crime rates nearly double the share of commuters who are unresponsive to price incentives. In other words, many commuters put safety first in their transportation choice, responding less or none at all to price incentives in high-crime settings. Crime therefore weakens the effectiveness of fare subsidies in shifting mode choice. The effect is especially pronounced among women, whose price-elasticity declines by 0.16 versus 0.11 among men, consistent with prior evidence on gendered safety concerns (Ouali et al., 2020). Taken together, these findings suggest that crime not only reduces demand directly but also creates a second-best setting in which traditional price instruments become less effective.

The idea that crime reduction and environmental policies can be complementary may seem counterintuitive, because prior research suggests that immediate concerns, such as safety, can crowd out attention and support for longer-term goals like environmental protection (Weber, 2010; Dechezleprêtre et al., 2025). Part 3 tests whether safety and environmental policies are seen as complements. Participants are randomly assigned to read a news article about public transportation in their city that frames safety as high, low, or is silent on the topic. We measure perceived crime risk before and after the priming, and then ask participants to allocate a fixed budget across four policy areas: crime reduction, fare subsidies, service improvements, and emission abatement. Using the randomized priming as an instrument for crime perception, we find that higher perceived crime increases support for

official exchange rate of September 2024, when the survey took place. Specifically, the prices of an average bus fare in Port of Spain (Trinidad and Tobago), Kingston (Jamaica), Buenos Aires, Santiago, Lima, Bogotá, Guatemala and CDMX are approximately USD 0.45, USD 1.01, USD 0.3, USD 0.77, USD 0.93, USD 0.72, USD 0.65 and USD 0.25, respectively.

safety investments but does not reduce support for emission reduction. Even under a constrained budget, participants do not treat safety and environmental goals as mutually exclusive. These results suggest that crime and climate policies can be framed as complements, and that crime perception need not crowd out support for long-run environmental objectives.

Related Literature. — This paper contributes to the broad literature on travel mode choice initiated by McFadden (1974) and Ben-Akiva and Lerman (1985). While much of this work has focused on how pricing can shift behavior to reduce congestion and pollution (Anderson, 2014; Parry and Small, 2009; Almagro et al., 2024), often through estimates of price elasticity (Davis, 2021), the role of crime in shaping transportation demand has received little empirical attention. Yet in high-crime environments, safety is likely a key determinant of mode choice. This is suggested by case studies and correlational evidence from stated preference surveys: for example, Börjesson (2012) and Holmgren (2007) highlight the role of safety perceptions in transportation choices, while Delbosc and Currie (2012) and Ingvardson and Nielsen (2022) find particularly strong effects among women. However, such studies cannot isolate causal mechanisms. Our experimental design provides causal evidence evidence on how perceived crime affects both demand for public transportation and responsiveness to fare incentives, across six large cities in Latin America.

Our study also contributes to the growing use of survey and choice experiments to measure the valuation of public goods and citizens' preferences over policy trade-offs (see Haaland et al. (2023); Stantcheva (2023) for reviews). In Latin America, Domínguez and Scartascini (2024) use a similar approach to study willingness to pay for public safety, while a broader literature has used participatory budgeting experiments to uncover preferences over public spending (Ardanaz et al., 2023; Banerjee et al., 2010; Olken, 2010). While some question whether experimental preferences translate into real-world behavior, growing evidence suggests these tools yield meaningful predictions (Hainmueller et al., 2015; Dechezleprêtre et al., 2025; Funk, 2016). Our paper extends this approach to the intersection of safety and transportation, showing how citizens respond to crime-related information when making transportation choices and allocating policy budgets. In doing so, we highlight how safety concerns shape not only individual behavior, but also policy priorities.

Finally, we contribute to the literature on policy complementarities and the institutional conditions under which policies are effective. Recent work emphasizes that policy effectiveness often hinges on the presence of complementary interventions, especially in low-capacity states (Gentile Passaro et al., 2024; Muralidharan et al., 2021). In the transportation domain, Bento et al. (2014) show that failing to account for interactions between externalities —such as congestion and emissions— can lead to unintended policy failures. Our findings echo this logic: in high-crime settings, policies like fare subsidies become less effective. In a relevant field experiment, Garlick et al. (2025) offered transportation to work at varying prices to job seekers in Pakistan, and find that price subsidies don't incentivize women unless complemented with safety measures, like women-only buses. By documenting how crime lowers both demand and elasticity, we show that safety concerns may undermine the effectiveness of green transportation subsidies —suggesting that coordinated interventions can improve the effectiveness of environmental policies, a key driver of public support (Dechezleprêtre et al., 2025).

The rest of the paper is structured as follows: Section 2 offers a simple conceptual framework of the externalities crime has over public transportation. Section 3 details the experimental design and the sample recruited. Section 4 details the empirical analysis. Section 5 reports the results of each experiment. Finally, Section 6 offers a discussion of the broader significance of our results for urban transportation and sustainability policies, and Section 7 concludes.

2. Conceptual Framework

We model how crime influences public transportation demand through a simple discrete choice framework that captures both extensive and intensive margin responses. Commuter i chooses between transportation modes $j \in \mathcal{J}$ to commute across a given origin-destination pair, selecting the option that maximizes their utility. Each mode is characterized by a price p_j, a safety level s_j, and other characteristics x_j (e.g., duration, emissions). The utility of choosing mode j is:

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

where $g(\cdot)$ is a deterministic function increasing in s_j and decreasing in p_j, and ε_{ij} is an i.i.d. extreme value Type I error term. Each commuter

i has an idiosyncratic safety threshold $\bar{s}_i$, below which a mode is excluded from their consideration set. Thus, crime determines whether a mode is even considered (extensive margin), and if so, how attractive it is relative to other options (intensive margin).

Let $\mathcal{C}_i = j \in \mathcal{J} : s_j > \bar{s}_i$ denote the set of modes considered by agent i. Conditional on the mode being in the consideration set, the probability that agent i chooses mode j follows the standard logit form:

$$P_{ij|\mathcal{C}_i} = \frac{\exp(g(p_j, s_j, x_j))}{\sum_{k \in \mathcal{C}_i} \exp(g(p_k, s_k, x_k))} \tag{2}$$

To link this to aggregate demand, for simplicity suppose there are two options: a public and a private mode. If $s_{\text{private}} > s_{\text{public}}$, then the share of individuals who consider public transportation is given by $F(s_{\text{public}})$, the cumulative distribution of safety thresholds. Aggregating across commuters:

$$P_{\text{public}} = F(s_{\text{public}}) \cdot P_{\text{public}|\mathcal{C}_i} \tag{3}$$

Equation (3) highlights the two distinct channels through which crime affects public transportation demand. First, as s_{public} declines, fewer commuters include public transportation in their consideration set —an extensive margin effect. Second, even among those who still consider it, lower s_{public} reduces the relative utility of public modes, making them less likely to be chosen —an intensive margin effect. Although both mechanisms result in a negative effect of crime on public transportation demand, the impact on price elasticity is theoretically ambiguous. On the one hand, greater safety expands the number of commuters who consider public transportation as part of their choice set. Therefore, changes in prices will affect a greater number of people, scaling the effect. On the other hand, as public transportation becomes more attractive due to reduced crime, its elasticity of substitution decreases. Ultimately, whether demand becomes more or less elastic with increased safety remains an empirical question that we answer in this experiment.

3. Experimental Design

We implement a pre-registered online experiment composed of three sequential parts, designed to measure (1) willingness to pay for safety in public transportation, (2) how crime impacts public transportation demand, and

(3) whether crime perception shifts support across policy domains. All three parts were completed in fixed order.

In Part 1, participants are shown two public buses (Bus A and Bus B), each described by four attributes: fare, travel time, CO_2 emissions, and crime rate. These attributes are hidden behind clickable labels, and participants must click to reveal each one. We track the order in which attributes are revealed to measure which features respondents prioritize (Brocas et al., 2014), with display order randomized to avoid position effects. Bus A always shows the average fare and crime level in the participant's city. Bus B varies across four treatment arms: the crime level is described as being $X\%$ above or below the city average ($X \in -30, -10, +10, +30$), and its fare starts at either 50% higher (for safer buses) or 50% lower (for more dangerous ones). After the initial choice, we elicit indifference prices using an iterative Gabor-Granger method (Gabor and Granger, 1964), adjusting Bus B's fare by $\pm 10\%$ each round until the respondent switches from her initial choice or reaches five iterations. Keeping variations in price and crime orthogonal to each other rules out participants using price to infer crime rates, which could happen in empirical setting where commuters have limited information about crime and must make their own inferences. This allows us to estimate both willingness to pay for safety and price sensitivity of demand under varying crime levels.

In Part 2, participants choose between a public bus and a private taxi. Bus attributes vary by treatment arm, while taxi attributes remain fixed. The crime rate for the bus is again framed as $X\%$ above or below the city average ($X \in -30, -20, +20, +30$), while the crime rate for the taxi is fixed at the city average. The initial fares are based on local standards: the public bus fare is the city's typical ticket price, and the taxi fare reflects a 20-minute Uber ride from city hall at 8 PM. Respondents who select the bus (or taxi) are asked to repeat the choice with the bus fare increased (or decreased) by 20%, iterating up to five times. Indifference prices are defined as in Part 1. This part allows us to estimate how crime shifts demand away from public transportation and how it moderates the effectiveness of fare subsidies.

To test whether perceived crime influences transportation policy priorities, in Part 3 participants are randomly assigned to view one of three newspaper headlines. The *Dangerous* group sees an article describing a high crime incident on the public transportation in their city; the *Safe* group sees an article framing the system as secure; the *Control* group sees an article about public transportation that makes no mention of safety (see Figure B3). Participants are then asked to allocate a USD 120,000 budget across four policy areas: increasing service frequency, cutting fares, reducing crime, and cutting emissions. We also elicit perceived risk of crime in public transportation once before Part 1 and again after the news priming, enabling us to test whether shifts in perceived safety causally affect policy preferences. 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. This participatory budgeting task follows established methods for eliciting policy preferences (Ardanaz et al., 2023; Olken, 2010), and allows us to test whether higher perceived crime crowds out environmental concerns, as suggested by previous research (González and Sánchez, 2022; Weber, 2010).

Finally, at the end of the study, participants reported the frequency with which they take public transportation, and whether they own a car, as well as some demographic questions. Additionally, participants report the probability of a coss toin landing in heads, which we call *Probability Check* and use as a sanity check for the understanding of probabilities

Table 1: Summary of Survey Experiment Design

Beginning	First crime perception elicitation.
Part 1	Choice between an average and a *treated* bus. Treated bus has a randomized crime rate above or below the city average. We measure the indifference price between the two options.
Part 2	Choice between an average taxi and a *treated* bus. Treated bus has a randomized crime rate above or below the city average. We measure the indifference price between the two options.
Part 3	News headline framing public transit as *Dangerous*, *Safe*, or *Control*. Second crime perception elicitation. Budget allocation across 4 public transportation policies.
End	Public transportation use, car ownership. Basic demographics: age, gender, education, N of household members. Probability check: probability of coin toss landing on heads

Participants and Procedures

The experiment was conducted in September 2024 with 5,160 participants recruited through an online panel provider. Participants were sent a routine invitation email, with no mention of the research topic. Respondents were drawn from six Latin American capitals: Bogotá, Buenos Aires, Mexico City

(CDMX), Guatemala City (Guatemala), Lima, and Santiago de Chile. Table A1 presents descriptive statistics for the subject pool. Our pool, which resides in urban areas and signed up to the online panel, is slightly younger and better educated than representative samples (see Table A2).

Why an Experiment

Despite its simplicity, our design enables us to measure willingness to pay for safety and to isolate the causal effect of crime on public transportation demand, which would be difficult to identify in observational settings. First, prices, demand, and crime levels are endogenously determined in most transit systems. Transportation authorities may adjust prices in response to ridership changes, while crime rates may respond to both prices and demand —for instance, if subsidies generate adverse selection into transit, or if lower ridership reduces crime observability. To address this, we simultaneously vary prices and crime risk while holding constant all other factors, such as service frequency and ridership composition. This design allows us to measure both the willingness to pay for safety and the causal impact of crime on demand. Second, granular data on crime in public transportation is rare, and when available, commuters' risk perceptions often deviate from objective benchmarks (Ceccato et al., 2022). Our design overcomes this challenge by providing participants with an informative signal of crime risk at the bus-line level —information they rarely have access to— and by directly eliciting their risk perceptions. In doing so, we provide evidence on the effects of both objective and perceived risks of crime.

4. Empirical Analysis

4.1. Effect of Crime on Public Transportation Demand

The first goal of Parts 1 and 2 is to estimate participants' willingness to pay (WTP) for crime reduction in public transportation. We model WTP as a latent indifference price y_i^* between the safer and less safe alternative, estimated using:

$$\begin{aligned} y_i^* = &\alpha + \beta_1 1\{Crime = +10\%\}_i + \beta_2 1\{Crime = -10\%\}_i \\ &+ \beta_3 1\{Crime = -30\%\}_i + \Phi_c + \mathbf{X}\Gamma + \epsilon_i \end{aligned} \tag{4}$$

Where $1\{Crime = X\%\}_i$ is an indicator function denoting whether respondent i was exposed to a X% crime variation treatment group. We include city fixed effects Φ_c and controls $\mathbf{X}$ (age, gender, education, and whether the participant was ever a victim of a crime in public transportation) [3] are included correspond to city fixed effects, and in all specifications the vector of control variables ($\mathbf{X}$) are: age, gender, and level of education. The omitted category corresponds to the +30% crime group. Following Domínguez and Scartascini (2024), y_i^* is bounded between the last and second-to-last price shown before participants switched their choice, or the last price shown if they never switched. In Part 2, we adapt this model by replacing the ±10% groups with ±20%.

To analyze the effect of crime on mode choice, we estimate a linear probability model:

$$\begin{aligned} 1\{ChooseBus_i\} =& \alpha + \beta_1 1\{Crime = +20\%\}_i + \beta_2 1\{Crime = -20\%\}_i \\ &+ \beta_3 1\{Crime = -30\%\}_i + \Phi_c + \mathbf{X}\Gamma + \epsilon_i \end{aligned} \tag{5}$$

where the outcome is an indicator for whether participant i chooses the bus over the taxi in their first decision —this is, at current prices, and coefficients are interpreted relative to the +30% group.

Next, we estimate how price sensitivity varies with crime exposure. We group responses by crime and price levels, and estimate a logistic probability model in which the dependent variable is an indicator for choosing the treated alternative:

$$1\{ChooseTreated_i\} = \frac{e^z}{1+e^z} \tag{6}$$

Where

$$z \equiv \beta_0 + \beta_1 Price_i + \beta_2 CrimeLevel_i + \beta_3 Price_i \times CrimeLevel_i + \Phi_c + \mathbf{X}_i\Gamma + \epsilon_i$$

The interaction term β_3 captures how price elasticity varies with crime. We adopt a logistic functional form since it will allow us to capture important nonlinearities of the price-elasticity.

[3]We conduct a randomization balance check in Table A1, which shows the only significant difference between treatment groups is whether the participant has ever been a victim of a crime on public transportation. Consequently, we include this as a control variable in our analysis.

4.2. Crime Perception and Crowding Out

Part 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 environmental perceptions and support for green policies (González and 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 transportation policies: increasing bus frequency, reducing ticket prices, reducing crime, and reducing CO_2 emissions.

Part 3 investigates whether heightened crime perception crowds out support for environmental transportation policies. We first estimate the impact of the article treatment on changes in crime perception:

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 transportation both before Part 1 and after being exposed to the newspaper headline, in line with the literature on belief updating (Cullen and Perez-Truglia, 2022; Andre et al., 2023). We estimate this first stage model:

$$\Delta CrimePerception_i = \alpha + \sum_j \beta_j 1\{Article_i = T_j\} + \Phi_c + \mathbf{X}\Delta + \epsilon_i \qquad (7)$$

where $\Delta CrimePerception_i$ is the difference in perceived probability of being a crime victim before and after the priming.[4] $1\{Article_i = T_j\}$ indicates whether participant i was in treatments $T_j \in \{Dangerous, Safe\}$, while the *Control* group is omitted. We control for the same set of variables as in Equation (4) and use city fixed effects.

After the experimental intervention, subjects were asked to allocate a budget of 120,000 USD across 4 policies. We estimate the following 2SLS

[4] We elicited safety beliefs by asking the question *In an average trip in the public transportation of your city, what do you think is the probability of being victim of a crime?*. We asked this question immediately before and after being exposed to the newspaper headlines.

model:

$$y_i^k = \alpha + \beta_1 \Delta Crime\widehat{Perception}_i + \Phi_c + \mathbf{X}\Delta + \epsilon_i \tag{8}$$

where y_i^k is the share of the budget allocated to policy k $\in$\{frequency, fare, safety, emissions\}, and $\Delta Crime\widehat{Perception}_i$ is the estimated value from Equation (7). The coefficient β_1 captures the causal effect of perceived crime risk on policy preference.

5. Results

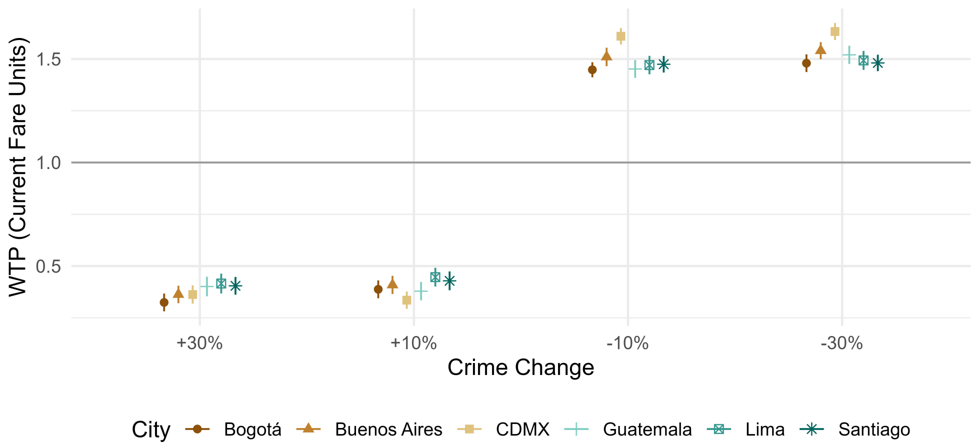
5.1. Valuation of Crime Change in Public Transport

We begin by estimating how much commuters are willing to pay to reduce their exposure to crime. In Part 1, participants choose between two buses that differ in fare and crime levels. Using a price iteration method, we estimate indifference prices across four treatment groups that vary crime levels by ±10% and ±30% relative to the average. Figure 1 shows respondents are willing to pay substantial premiums for crime reductions: reducing crime by 10% increases WTP by 51% of the current fare. Similarly, commuters ask for a 60% fare discount to compensate a 10% increase in crime.

Notably, we observe robust non-linearities: participants respond similarly to +10% and +30% (and to -10% and -30%), but strongly differentiate across the zero threshold. This pattern is consistent with scope insensitivity —a common phenomenon in contingent valuation studies (Diamond and Hausman, 1994), even in valuation by experts (Toma and Bell, 2024)— where respondents treat changes as categorical ("higher" or "lower") rather than continuous. Importantly, this phenomenon is not driven by a misunderstanding of probabilities. We observe similar non-linear WTP patterns among participants who correctly answered to the standard coin-toss question included as a validity check. This suggests the flattening response reflects behavioral attenuation rather than misunderstanding (Enke et al., 2024). Considering these quantitative reasoning limits in valuation tasks, we aggregate treatment groups with lower (higher) than average crime into a single *Lower (Higher) Crime* group in the main text to simplify interpretation.

Regression estimates shown in Table A3 confirm that participants are willing to pay more than the value of an entire fare (112%) to ride public transportation with lower crime, relative to higher crime. Table A4 shows the results are robust across cities, while Table A5 presents the heterogeneity

Figure 1: Valuation of Crime Change in Public Transportation

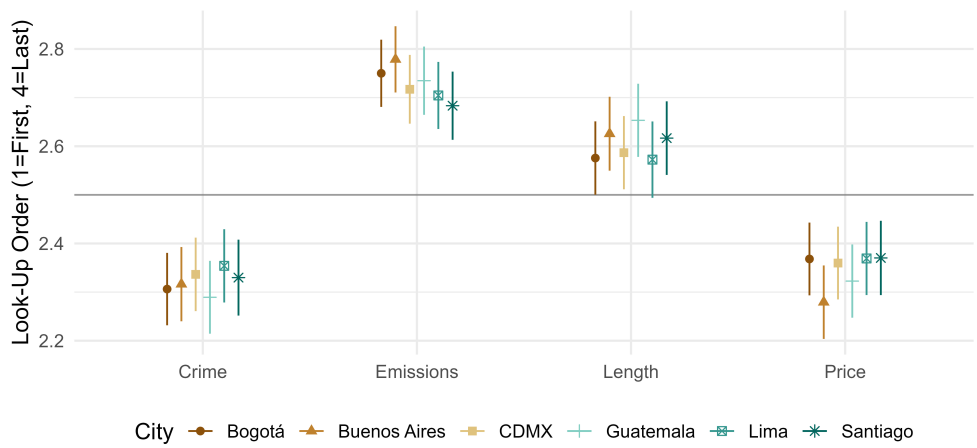


Notes: Willingness to pay (WTP) corresponds to the indifference price between the standard bus option and the treated one, expressed in terms of the current fare price. Error bars correspond to the 95% confidence interval of the mean after controlling for demographic characteristics and whether the participants was victim of a crime in public transportation.

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 participants with higher baseline crime perception to be more willing to pay for crime reductions. We also find higher WTP among women, who are willing to pay 6% ($p < 0.001$) more than males to reduce crime.

Finally, we complement these stated preference estimates with a non-choice measure of attribute relevance, where there is no possible demand effect. Before making a choice, participants click through boxes to reveal information about each transportation option, and previous research shows that most relevant attributes are revealed first (Brocas et al., 2014). Figure 2 shows that safety and price are consistently the first attributes revealed —well below what would be expected from random orderings. This ranking is stable across cities, and significantly predicts WTP: those who consult crime earlier are also willing to pay more for crime reduction (see Table A5). Together, these results show that safety concerns play a central role in transportation choice.

Figure 2: Mouse-tracking results



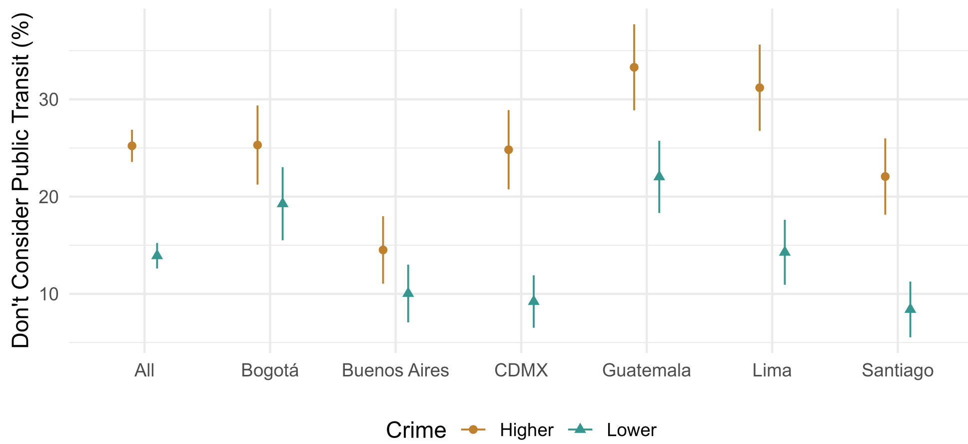
Notes: Look-up order is coded as 1 for the attribute revealed first, and 4 for the attribute revealed last. *Crime* refers to the crime rate in the bus line, *Emissions* to the expected emissions of the bus line, *Length* to the trip length to reach the destination, and *Price* to the bus line fare. Error bars correspond to the 95% confidence interval of the mean after controlling for demographic characteristics and whether the participants was victim of a crime in public transportation.

5.2. Effect of Crime on Public Transportation Demand and Price Elasticity

Part 2 examines how crime influences the substitution between private and public transportation. Participants choose between a bus and a private taxi (e.g., Uber), with initial prices held constant across treatment groups to eliminate anchoring concerns. This setup allows us to study both the extensive margin —whether individuals opt into public transportation at all— and the intensive margin —the fare at which they are indifferent between the two options.

As predicted by the conceptual framework in Section 2, crime affects transportation demand through multiple channels. First, higher crime deters some individuals from considering public options altogether. Figure 3 shows

Figure 3: Share of respondent who don't choose public transportation even when free



Notes: This figure shows the share of respondents who still choose private transportation when the public transportation option in Part 2 is free. Error bars correspond to the 95% confidence interval of the mean after controlling for demographic characteristics.

the share of participants who consistently choose the private taxi, regardless of price, increases from 13.9% to 25.2% when the bus crime rate exceeds the city average ($p < 0.001$). Second, crime reduces the overall appeal of public transportation. Table 2, columns (1)-(4), shows that participants are 15 percentage points more likely (a 29% increase, $p < 0.001$) to initially choose the bus when crime rates are 25% lower than average. These results suggest that safety concerns prompt substitution from public to private modes, with environmental and congestion costs.

Turning to the intensive margin, columns (5)-(8) of Table 2 show that crime significantly shifts the indifference point. Participants require a 27% price discount to choose a bus with 25% higher crime, relative to one with lower crime. Importantly, this pattern is not driven by price anchors, since in Part 2 all participants face the same, local-market starting price.[5] These

[5]We define the private mode market price as the price suggested by a ride-hailing app of a 20 minute ride the city hall of each city at 8PM on a weekday.

results are robust to alternative specifications, to restricting the sample to respondents who correctly answered the coin-toss probability check, and are consistent across cities (Table A7). The exceptions are Buenos Aires and Santiago, where preferences appear less responsive to crime at both margins. We also find that most respondents are willing to pay more than the current fare for the bus, even under high crime, possibly due to large price gaps between public and private options. Table A8 presents treatment heterogeneity, documenting again that women are more responsive to crime in public transportation when making their modal choice. Finally, it's worth noting that most participants consistently choose either private or public transport, despite varying fare price, suggesting strong prior preferences that are not compensated by the small price changes in Part 2.

Table 2: Reduced-form estimates for Part 2

	Chose Bus				WTP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lower Crime	0.149***	0.150***	0.150***	0.171***	0.273***	0.274***	0.273***	0.304***
	(0.014)	(0.013)	(0.013)	(0.015)	(0.021)	(0.021)	(0.021)	(0.025)
Observations	5,161	5,161	5,161	3,789	5,161	5,161	5,161	3,789
Controls	No	No	Yes	Yes	No	No	Yes	Yes
City FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Probability Check	No	No	No	Yes	No	No	No	Yes

Notes: This table presents the results of the estimation of Equation (4) for Part 2. *Lower Crime* is equal to 1 if the participant was assigned to the crime treatment groups with lower crime than average. Columns (1)-(4) correspond to the extensive margin results and columns (5)-(8) to the intensive margin. The vector of control variables considered are age, level of education, and gender. Columns (4) and (8) restrict the sample to participants who correctly answered a standard probability question about a fair coin toss (*Probability Check*). Heteroskedasticity-robust standard errors are considered. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

These results reinforce a key implication: crime makes public transportation less attractive, both by deterring marginal riders and by reducing the willingness to pay among riders. Keeping prices fixed, when public transportation safety decreases, some commuters will stop considering this option, while others who were at the margin will change to other transportation modes. To prevent these marginal commuters from changing to private options, they would need to be compensated with lower fares. Overall, these results provide evidence of two mechanisms through which crime reduces public transportation demand.

Crime may also alter the responsiveness of ridership to price incentives. Table 3 reports price responsiveness estimates for both parts of the experiment. In Part 1, demand is fairly elastic (–0.7 on average)[6], and crime substantially affects this elasticity. In particular, when crime is higher than average, average responsiveness declines by 0.09 points ($p < 0.001$), implying that price cuts are less effective in boosting ridership in contexts of high insecurity. This aligns with results from the transportation literature (Holmgren, 2007), though our elasticities are somewhat larger, possibly due to the experimental setting and the low baseline fares in our study cities. We find a lower price responsiveness in Part 2 (–0.24 on average), as more than half of respondents never switch transportation modes across the five price iterations. This muted response likely reflects strong modal preferences and substantial baseline price differences between taxis and buses. However, higher crime still significantly limits price responsiveness. The predictions of model (2) of Table 3 implies that making transit completely free would make our average participant choose transit with 88% probability when crime is lower, but only with 77% probability when crime is higher than average. That price responsiveness diminishes with higher crime is consistent with our previous finding that the share of participants who cannot be induced through price to choose the bus almost doubles as crime increases.

Table A9 shows the city-level breakdown, while Table A10 explores heterogeneity by gender, crime perception, car ownership, and frequency of use. Notably, crime has a larger impact on price responsiveness among women in both parts. In particular, we don't find a significant negative effect of crime on price responsiveness among men in Part 2, but we do among women.

[6]To ease the interpretation of the non-linear models presented in Table 3, we calculate the estimate of price responsiveness at the average value of the predictors, according to their empirical distribution among participants. We use this same technique to illustrate further examples, such as the difference in price responsiveness between male and female participants, or the predicted probability of choosing public transportation for our average participant.

Table 3: Price Responsiveness of Demand

	Part 1		Part 2	
	(1)	(2)	(3)	(4)
Price	-3.71***	-3.56***	-1.13***	-1.05***
	(0.050)	(0.058)	(0.021)	(0.025)
Lower Crime	5.43***	5.28***	0.738***	0.802***
	(0.087)	(0.098)	(0.038)	(0.045)
Price × Lower Crime	-0.695***	-0.588***	-0.086***	-0.071**
	(0.074)	(0.084)	(0.031)	(0.036)
Observations	56,771	41,679	56,771	41,679
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Probability Check	No	Yes	No	Yes

Notes: This table presents the results of the price responsiveness estimation. The dependent variable is an indicator variable of whether the respondent chose the 'treated' alternative (Bus B in Part 1 and the bus in Part 2). *Price* is a variable corresponding to the price of the treated alternative in current bus fare (of its city) units. *Lower Crime* is equal to 1 if the participant was assigned to the crime treatment groups with lower crime than average. Columns (1)-(2) correspond to the results of Part 1 and columns (3)-(4) to Part 2. All specifications include control variables and city fixed effects. The vector of control variables considered are age, level of education, and gender. Columns (2) and (4) restrict the sample to participants who correctly answered a standard probability question about a fair coin toss (*Probability Check*). Heteroskedasticity-robust standard errors are considered. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

These results are consistent with previous findings showing that women care more about safety when making transportation choices (Ouali et al., 2020). Similarly, we find higher effects of crime on price responsiveness for participants with a higher crime perception at baseline, and among frequent public transportation users.

5.3. Effect of Crime Perception on Policy Preferences

Part 3 tests whether crime perception crowds out public support for other transportation priorities. Specifically, we study how perceived victimization risk on public transportation —what we call *crime perception*, influences preferences over four types of public investment in a participatory budget task: fare subsidies, service frequency, emissions reduction, and crime prevention.

We implement two strategies. First, we document the correlation between perceived crime risk at baseline —before the news priming— and policy support. Figure A1 reveals no evidence of crowding out. Individuals who at baseline perceive higher crime risk allocate more of the fixed budget to crime prevention and less to other policies, but these latter shifts are not monotonic and not concentrated on one policy. Overall, a higher perceived crime risk at baseline is not linked with a clear crowding-out from environmental policies.

Second, we introduce exogenous variation in crime perception by randomly assigning participants to read one of three real newspaper headlines: a negative (*Dangerous*), neutral (*Control*), or positive (*Safe*) news story about public transportation in their city. The *Dangerous* headline significantly increased perceived crime risk by 3 percentage points, while the *Safe* and *Control* headlines have no detectable effect. This asymmetry may reflect the salience of crime even in stories emphasizing improvements. The first-stage regression confirms instrument relevance, with an F-statistic of 11.75. We use the randomized treatment as an instrument for crime perception and present the two-stage least square estimates in Table 4. A 1 percentage point increase in perceived crime risk leads to a 0.6 percentage point increase in the budget share allocated to crime prevention and a 0.5 point reduction for frequency improvements. These are meaningful shifts: the change in crime perception induced by reading one piece of *Dangerous* news redirects 1.45% of the budget toward crime prevention. We find no significant reallocation away from fare or emissions-related policies, confirming crime perception doesn't crowd out environmental concerns among commuters. Finally, it's worth noting that 97% of participants allocate the full budget despite it not being required, suggesting strong engagement with the task. As a robustness check, Table A11 replicates the analysis using only full-budget respondents, with consistent results.

Taken together, these results highlight that crime and environmental concerns need not be in tension. Policy-makers increasingly frame safety as a precondition for sustainable urban mobility, and our findings suggest that citizens respond in kind: when prompted to prioritize, they do not reallocate

Table 4: Reduced-form estimates of Experiment 3

	Crime (1)	Emissions (2)	Frequency (3)	Price (4)
Change in Crime Perception	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 (8) for Experiment 3. *Change in Crime Perception* is the fitted change in the perceived probability of being a victim of a crime in a public transportation trip as specified in Equation (7). 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, gender, and level of education. Heteroskedasticity-robust standard errors are considered. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

resources away from environmental objectives to address crime. Instead, support for emissions reduction remains stable even as crime perception rises, suggesting the public sees these challenges as complementary. This alignment between institutional framing and public preference strengthens the case for integrated transportation strategies that treat safety improvements as an enabler rather than a competitor of green policy goals.

6. Discussion

This paper provides experimental evidence on how crime affects public transportation demand, price responsiveness, and policy support. Across six Latin American cities, we document three key findings. First, commuters are willing to pay substantial premiums for safer trips. Second, elevated crime rates reduce both the likelihood of choosing public transportation and the price elasticity of demand. Third, higher crime perception reallocates support away from service improvements but does not crowd out support for environmental policies. Together, these results highlight the central role of safety in shaping both individual transportation choices and collective preferences over urban investment.

The impact of crime is not evenly distributed. Women, who perceive significantly higher crime risks in public transportation, respond more strongly to crime variation. Even when controlling for higher baseline crime perception, women display a greater willingness to pay for safety improvements, are more likely to stop considering public transportation altogether, and show a sharper drop in price sensitivity when crime increases (p <0.001 for all outcomes). Frequent public transportation users, who also report higher crime perception, exhibit similar patterns. These findings suggest that crime imposes disproportionate costs on populations that tend to have fewer private alternatives and lower incomes. Given that distributive concerns are a key predictor of support for environmental policies (Dechezleprêtre et al., 2025), improving public transportation safety can promote both equity and environmental goals.

In policy debates, environmental and safety agendas are often framed as distinct or even competing priorities. Our findings suggest they need not be. Safety concerns significantly shape the demand and price responsiveness of public transportation, suggesting that crime abatement can increase the effectiveness of subsidies and other green transit policies. Conversely, these results imply that, in contexts of high crime, over-investing in subsidies may be not be the most effective way to increase ridership. Our results are consistent with previous literature documenting that commuters are less elastic to price changes than to service improvements, and that investments in service can be more effective to increase ridership (King and Taylor, 2023; Chen et al., 2011; Graham et al., 2009).

While policymakers often recognize the relationship between safety and ridership —such as by reinforcing security to boost public transportation use— we show that this complementarity is also acknowledged by commuters. Perceptions of crime do not diminish support for environmental goals, even in a zero-sum budgeting scenario. On the contrary, we find that in contexts of heightened crime perception, individuals tend to prioritize investment in crime-related policies, even at the expense of reducing the budget for policies aimed at increasing service frequency. This highlights the importance of ongoing research into policy preferences. In particular, our findings suggest that safety and environmental concerns may take precedence over frequency —despite the latter being traditionally viewed as one of the most important attributes influencing public transportation demand (Mohring, 1972). These results suggest that framing environmental and safety interventions as complementary could be both effective and politically viable.

7. Conclusion

This study contributes to the debate around policies to increase public transportation ridership and reduce greenhouse emissions by focusing on the critical role of crime. 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 transportation 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 transportation policies. Our mouse-tracking results offer more evidence about the importance of crime in transportation mode choice: participants consider crime as relevant as price and more relevant than other trip attributes when choosing among transportation options.

Second, we provide evidence that crime affects public transportation 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. Conversely, higher crime rates almost doubles the fraction commuters that do not consider public modes at any price. In addition to this direct effect on demand, crime also affects how users react to fare changes. Higher crime rates make demand for public transportation more inelastic, especially among women. Intuitively, if fear of crime is high enough, commuters will be reluctant to use public transportation no matter the price, limiting the effectiveness of current and proposed fare cuts intended to boost public transportation ridership.

Finally, 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 and but increases support for crime-abatement policies.

While our experimental design allows for clean identification of mechanisms, the extent to which these results are generalizable remain an open question. Spanning six Latin American capital, our study finds sizable impacts of crime on public transportation, but it remains a stated-preference experiment. However, prior work on stated-preference and survey experiments show their high external validity for predicting "real-stake" behaviors (Dechezleprêtre et al., 2025; Funk, 2016; Hainmueller et al., 2015). Our results are also consistent across multiple measures —contingent valuation, choice and non-choice data, and participatory budget allocation— reinforcing their robustness. We observe the well-known scope insensitivity common to contingent valuation studies, but even so, the valuations we elicit track closely with other preference and implicit measures. We view these findings as a starting point for future field experimentation that evaluates the effects of improving safety in public transportation.

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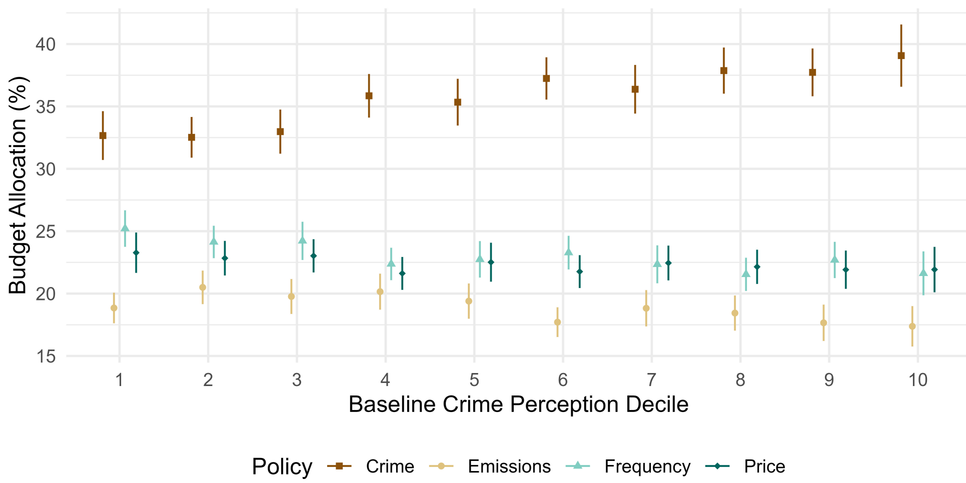
Appendix A. Additional Figures and Tables

Figure A1: Part 3 — Crime perception and policy preferences



Notes: The figure shows the mean budget allocation for each policy, binned by deciles of crime perception, prior to exposure to news. Deciles are calculated separately for each city. Error bars show the 95% CI.

Table A1: Descriptive statistics and balance test

	Summary Stats	Part 1	Part 2	Part 3	
		High Crime	High Crime	Dangerous	Safe
	(1)	(2)	(3)	(4)	(5)
Male (=1)	0.526 (0.499)	-0.008 (0.014)	0.010 (0.014)	0.018 (0.017)	-0.008 (0.017)
Residents in HH	3.905 (1.892)	0.012 (0.053)	-0.024 (0.053)	0.094 (0.066)	0.009 (0.062)
Secondary Schooling	0.218 (0.413)	0.009 (0.011)	-7e-5 (0.011)	0.009 (0.014)	0.018 (0.014)
University Schooling	0.744 (0.437)	-0.016 (0.012)	0.006 (0.012)	-0.007 (0.015)	-0.008 (0.015)
Age	36.222 (13.417)	0.422 (0.374)	-0.015 (0.374)	-0.377 (0.460)	-0.509 (0.452)
Owns Car (=1)	0.433 (0.496)	-0.010 (0.014)	0.022 (0.014)	0.007 (0.017)	-0.003 (0.017)
Freq. PT	4.084 (2.046)	0.100* (0.057)	-0.015 (0.057)	0.051 (0.070)	0.033 (0.069)
Victim (=1)	0.542 (0.498)	0.033** (0.014)	-0.020 (0.014)	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 participant 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. *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 transportation 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. Columns (2) to (5) 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), (3) and (4)-(5) correspond to the treatment groups of Part 1, 2 and 3, respectively. Heteroskedasticity-robust standard errors are considered. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A2: Comparison of Sample and Population

	Bogotá		Buenos Aires		CDMX		Guatemala		Lima		Santiago	
	Experiment	National Survey	Experiment	National Survey	Experiment	National Survey	Experiment	National Survey	Experiment	National Survey	Experiment	National Survey
Age	37.472	38.715	37.991	38.876	35.510	38.050	30.882	36.573	37.711	39.032	37.855	39.111
Male (%)	0.604	0.481	0.495	0.497	0.556	0.461	0.487	0.447	0.607	0.481	0.404	0.505
Parent (%)	0.634	0.712	0.589	0.799	0.603	0.864	0.568	0.872	0.611	0.853	0.619	0.734
HH Size	3.764	3.210	3.496	3.799	4.136	4.446	4.540	4.854	4.523	4.250	4.132	3.560
Years of Education	14.473	11.609	13.328	11.904	14.649	9.587	13.317	6.674	14.909	11.534	14.331	12.604

Notes: This Table presents a comparison of the mean of a set of variables between our sample and the values computed using surveys of the same cities drawn from a nationally representative survey. For each survey we considered only the responses of the cities that match the ones included in our survey and respondents between the age of 18 and 65, which is the criteria that we used to filter candidates in our experiment. To compute the representative means we used the data of the last quarter of 2023 of the following surveys: the Encuesta Permanente de Hogares (EPH) in Argentina, the Encuesta de Caracterización Socioeconómica Nacional (CASEN) in Chile, the Gran Encuesta Integrada de Hogares (GEIH) in Colombia, the Encuesta Nacional de Empleo e Ingresos (ENEI) in Guatemala, the Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH) in Mexico, and the Encuesta Nacional de Hogares (ENAHO) in Peru.

Table A3: Reduced-form estimates of WTP for crime changes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(+10% Crime)	0.019	0.018	0.018	0.026*				
	(0.013)	(0.013)	(0.013)	(0.015)				
1(-10% Crime)	1.12***	1.12***	1.12***	1.15***				
	(0.013)	(0.013)	(0.013)	(0.015)				
1(-30% Crime)	1.15***	1.15***	1.15***	1.18***				
	(0.013)	(0.013)	(0.013)	(0.015)				
1(-20% Crime)					1.12***	1.12***	1.12***	1.15***
					(0.009)	(0.009)	(0.009)	(0.011)
Observations	5,161	5,161	5,161	3,789	5,161	5,161	5,161	3,789
Controls	No	No	Yes	Yes	No	No	Yes	Yes
City FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Probability Check	No	No	No	Yes	No	No	No	Yes

Notes: This table presents the results of the estimation of Equation (4) for Part 1. Columns (1)-(4) show the disaggregated treatment groups, while Columns (5)-(8) show the aggregated groups. $1(Crime = +10\%)$ 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%. *Lower Crime* is equal to 1 if the participant was assigned to the crime treatment groups with lower crime than average. The vector of control variables considered are age, level of education, gender, and whether the participant was a victim of a crime in public transportation. Columns (4) and (8) restrict the sample to participants who correctly answered a standard probability question about a fair coin toss (*Probability Check*). Heteroskedasticity-robust standard errors are considered. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A4: Reduced-form estimates of Part 1 by city

	Bogotá (1)	Buenos Aires (2)	CDMX (3)	Guatemala (4)	Lima (5)	Santiago (6)
Lower 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 (4) for Part 1 by city. *Lower Crime* is equal to 1 if the participant was assigned to the crime treatment groups with lower crime than average.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: Heterogeneity of reduced-form estimates of Part 1

	All	Crime Perception Q4	Female	MT Safety
	(1)	(2)	(3)	(4)
Lower 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 (4) for Part 1 by subsamples. *Lower Crime* is equal to 1 if the participant was assigned to the crime treatment groups with lower crime than average. *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 A6: 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 (4) 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 A7: Reduced-form estimates of Part 2 by city

	Chose Bus						WTP					
	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)
Lower 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 (4) for Part 2, by city. *Lower Crime* is equal to 1 if the participant was assigned to the crime treatment groups with lower crime than average. Columns (1)-(6) correspond to the extensive margin results and columns (7)-(12) 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 A8: Heterogeneity of reduced-form estimates of Part 2

	Chose Bus				WTP			
	All	Crime Perception Q4	Female	Car Owner	All	Crime Perception Q4	Female	Car Owner
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lower Crime	0.150***	0.141***	0.156***	0.150***	0.273***	0.248***	0.278***	0.299***
	(0.013)	(0.025)	(0.019)	(0.021)	(0.021)	(0.040)	(0.031)	(0.034)
Observations	5,161	1,523	2,446	2,234	5,161	1,523	2,446	2,234
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 (4) for Part 2. *Lower Crime* is equal to 1 if the participant was assigned to the crime treatment groups with lower crime than average. *Crime Perception Q4* subsets the sample to participants whose reported probability of being victim of a crime in a bus ride in their city is within the fourth quartile of the reported probability of their city. *Car Owner* subsets the sample to those participants who report owning a car. Columns (1)-(4) correspond to the results of the extensive margin and columns (5)-(8) 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 A9: Price responsiveness results by city

	Part 1						Part 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	-3.78***	-3.89***	-4.00***	-3.45***	-3.47***	-3.90***	-1.25***	-1.25***	-1.07***	-1.12***	-1.07***	-1.15***
	(0.126)	(0.124)	(0.131)	(0.117)	(0.118)	(0.124)	(0.052)	(0.056)	(0.052)	(0.053)	(0.052)	(0.053)
Lower Crime	6.05***	5.60***	6.14***	5.02***	4.56***	6.15***	0.434***	0.348***	1.13***	0.741***	0.977***	0.928***
	(0.221)	(0.220)	(0.219)	(0.205)	(0.200)	(0.244)	(0.089)	(0.104)	(0.099)	(0.087)	(0.091)	(0.101)
Price × Lower Crime	-1.11***	-0.610***	-0.392**	-0.723***	-0.535***	-1.27***	0.032	0.088	-0.221***	-0.089	-0.158**	-0.182**
	(0.189)	(0.185)	(0.185)	(0.174)	(0.172)	(0.200)	(0.075)	(0.080)	(0.078)	(0.074)	(0.075)	(0.080)
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 price responsiveness analysis by city. The dependent variable is an indicator variable of whether the respondent chose the 'treated' alternative (Bus B in Part 1 and the bus in Part 2). *Price* is a variable corresponding to the relative price of the treated alternative in current bus fare (of its city). *Lower Crime* is equal to 1 if the participant was assigned to the crime treatment groups with lower crime than average. Columns (1)-(6) corresponds to the results of Part 1 and columns (7)-(12) to the ones of Part 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 A10: Heterogeneity in price responsiveness

	Part 1					Part 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	-3.69***	-3.56***	-3.57***	-3.81***	-3.44***	-1.11***	-1.07***	-1.03***	-1.19***	-0.936***
	(0.050)	(0.092)	(0.072)	(0.068)	(0.074)	(0.021)	(0.039)	(0.030)	(0.029)	(0.032)
Lower Crime	5.41***	5.47***	5.57***	5.49***	5.45***	0.725***	0.690***	0.862***	0.732***	0.799***
	(0.087)	(0.159)	(0.126)	(0.118)	(0.130)	(0.038)	(0.068)	(0.055)	(0.053)	(0.054)
Price × Lower Crime	-0.692***	-0.746***	-0.770***	-0.785***	-0.605***	-0.087***	-0.117**	-0.189***	-0.163***	-0.131***
	(0.074)	(0.135)	(0.107)	(0.101)	(0.108)	(0.031)	(0.056)	(0.045)	(0.042)	(0.045)
Observations	56,771	16,753	26,906	31,900	24,574	56,771	16,753	26,906	31,900	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 price responsiveness exercise by subsamples. The dependent variable is an indicator variable of whether the respondent chose the 'treated' alternative (Bus B in Part 1 and the bus in Part 2). *Price* is a variable corresponding to the price of the treated alternative in current bus fare (of its city) units. *Lower Crime* is equal to 1 if the participant was assigned to the crime treatment groups with lower crime than average. Columns (1)-(5) corresponds to the results of Part 1 and columns (6)-(10) to the ones of Part 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 transportation 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: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

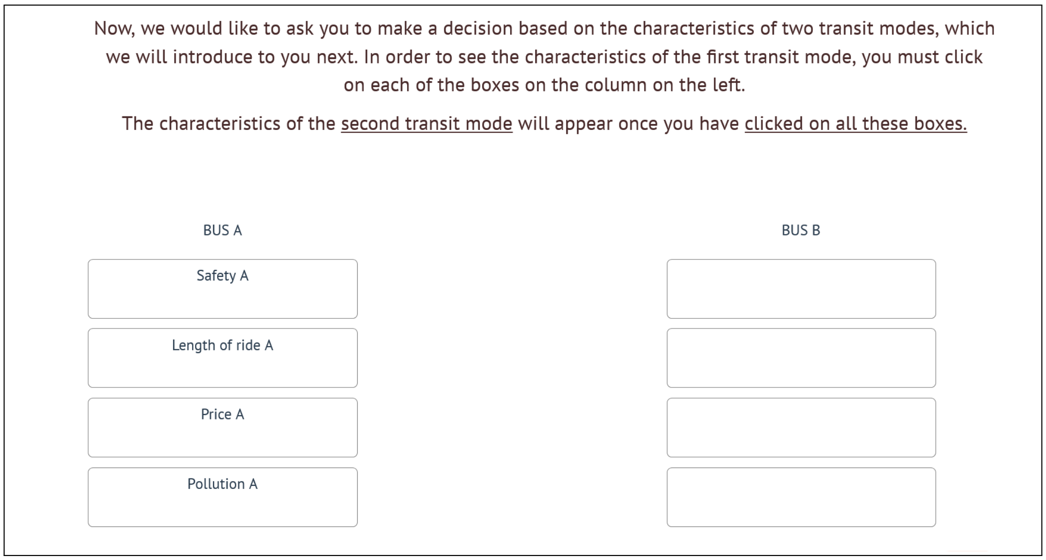
Table A11: 2SLS estimates of Part 3, participants that allocated the totality of the budget

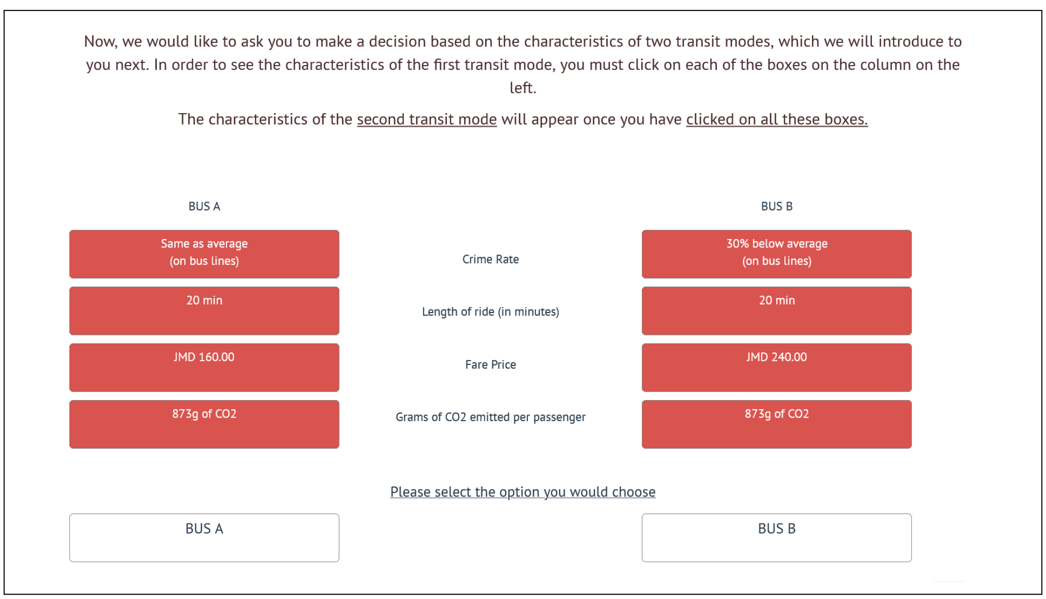
	Crime (1)	Emissions (2)	Frequency (3)	Price (4)
Change in Crime Perception	0.630**	-0.209	-0.566**	0.145
	(0.295)	(0.196)	(0.227)	(0.207)
Observations	4,718	4,718	4,718	4,718
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes

Notes: This table presents the results of the estimation of Equation (8) for Part 3 using the sample of participants who allocated the totality of the available budget. *Change in Crime Perception* is the fitted change in the perceived probability of being a victim of a crime in a public transportation trip as depicted in Equation (7). 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, gender, and level of education. Heteroskedasticity-robust standard errors are considered. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

B. Survey Experiment Overview

Figure B1: Part 1





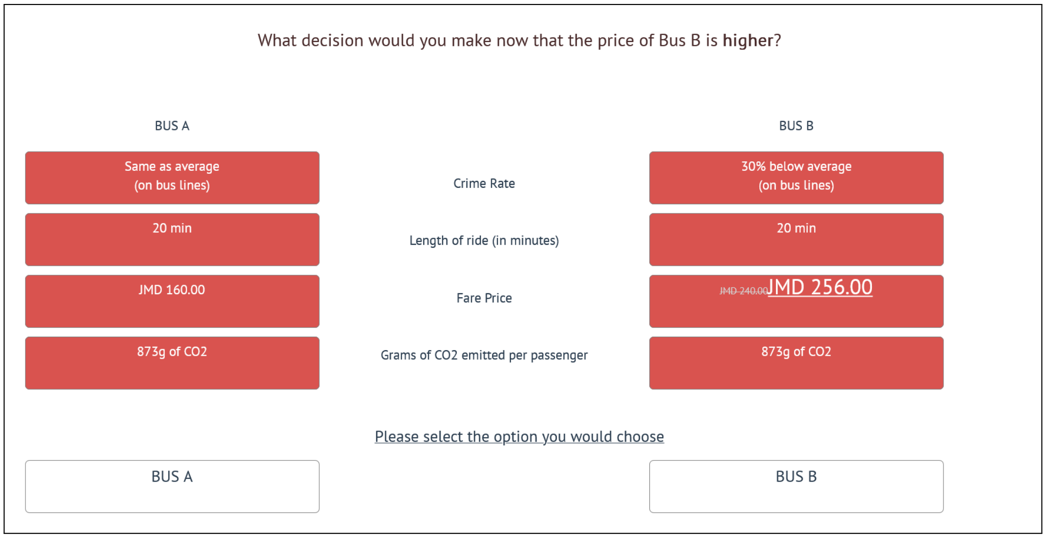

What decision would you make now that the price of Bus B is **higher**?
BUS A
BUS B
Same as average
(on bus lines)
Crime Rate
30% below average
(on bus lines)
20 min
Length of ride (in minutes)
20 min
JMD 160.00
Fare Price
~~JMD 240.00~~ JMD 256.00
873g of CO2
Grams of CO2 emitted per passenger
873g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

Figure B2: Part 2

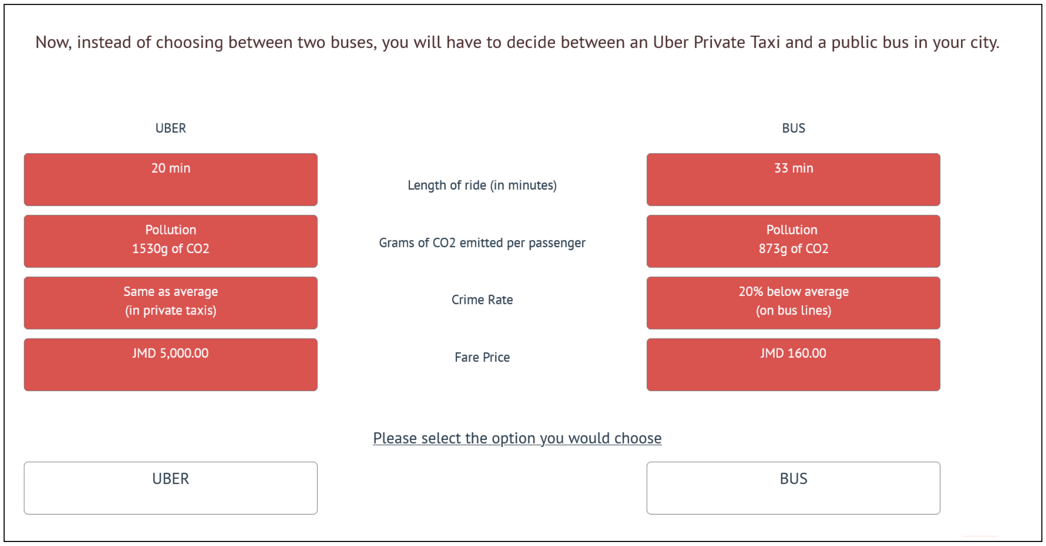


Figure B3: Part 3

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.

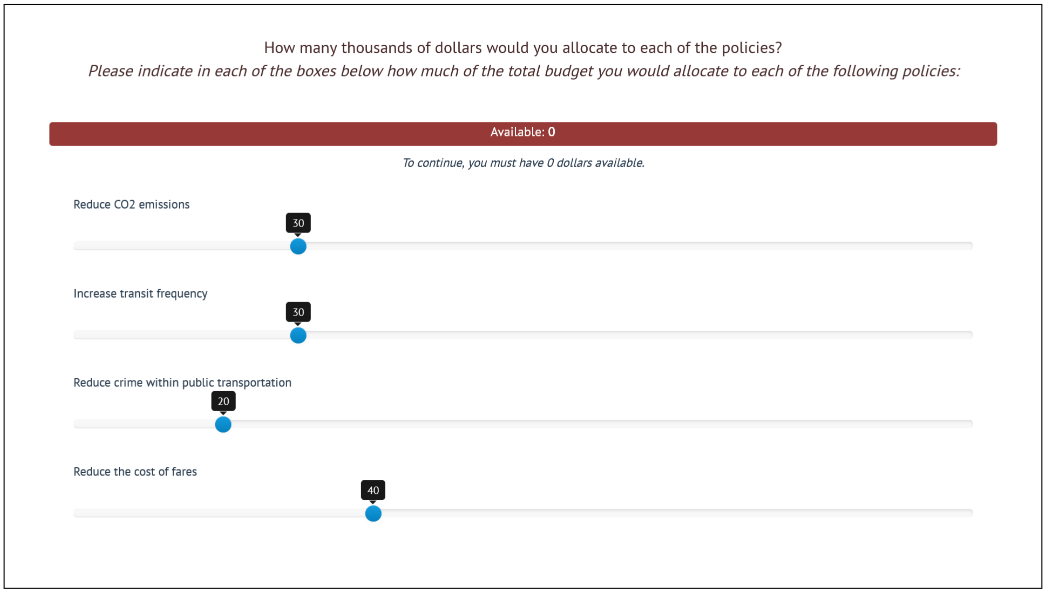
Translation: "Group thefts on buses: the new modality of crime that commuters suffer in the city [of Buenos Aires]. They are groups that board the buses, pretend to not know each other, and then steal cell phones and backpacks before leaving. Palermo and Recoleta, the most affected areas."

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