Class and the Development of Trust in Police in Latin America
Supporting Information

Tara Slough* Carolina Torreblanca†

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*Assistant Professor, New York University. `taraslough@nyu.edu`
†PhD Candidate, New York University. `carolina.torreblanca@nyu.edu`

Appendix A Survey Data

A1.1 Samples

This section describes the temporal and geographic coverage of the different survey data used in the analyses. Table A1 shows all the included LAPOP country rounds and the year each round was conducted. Table A2 describes the Chilean ELSOC data, including the number of respondents per survey wave and year of survey collection. Table A3 shows the number of survey responses included in each of the two waves from the Medellín, Colombia, survey (Hanson, Kronick, and Slough, 2022). Table A4 reports the number of respondents included in each quarterly wave of the rotating Encuesta Nacional de Seguridad Pública Urbana panel (ENSU), conducted in Mexican cities by the National Institute of Statistics and Geography (INEGI).

Year	**Countries surveyed**
2004	Bolivia, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama.
2005	Colombia
2006	Bolivia, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru
2007	Brazil, Colombia, Uruguay, Venezuela
2008	Argentina, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay, Venezuela
2009	Colombia
2010	Argentina, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay, Venezuela
2011	Colombia
2012	Argentina, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay, Venezuela
2014	Argentina, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay, Venezuela
2016	Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Honduras, Mexico, Nicaragua, Paraguay
2017	Argentina, Bolivia, Brazil, Chile, Guatemala, Jamaica, Panama, Peru, Uruguay
2018	Colombia, Costa Rica, El Salvador, Honduras, Panama
2019	Argentina, Bolivia, Brazil, Chile, Dominican Republic, Ecuador, Guatemala, Jamaica, Mexico, Nicaragua, Paraguay, Peru, Uruguay

Table A1: Table lists all the country-year LAPOP surveys included in the pooled data. All country surveys between 2004 and 2019 were included.

	ELSOC survey wave				
Year	**1**	**2**	**3**	**4**	**5**
2016	2,927				
2017		2,473			
2018			3,748		
2019				2,573	
2020				844	
2021					2,740

Table A2: Number of survey responses included in the Chilean Longitudinal Social Survey (ELSOC) data used in the analysis, per survey wave and year of survey collection.

	Medellín panel survey wave	
Wave	**Year**	**Observations**
Baseline	2018	5,205
Endline	2019	3,644

Table A3: Number of survey responses included in each of the two waves from the representative survey conducted in Medellín, Colombia (Hanson, Kronick, and Slough, 2022), used in the analysis.

The Encuesta Nacional de Seguridad Pública Urbana (ENSU) is a quarterly rolling panel carried out in Mexico by the National Institute of Statistics and Geography (INEGI). It has been conducted since 2013, with a substantial increase in the number of respondents starting in 2017, and is representative at the urban national level. Starting in 2018, respondents are asked about victimization experiences in the second and fourth quarter.

	Mexican rotating panel survey (ENSU)			
	Q1	**Q2**	**Q3**	**Q4**
2017	14,497	15,272	15,303	15,072
2018	15,172	17,548	20,163	18,017
2019	18,113	19,010	22,392	22,158
2020	22,416		22,122	22,283
2021	22,307	22,411	23,356	23,428
2022	23,577	23,688	23,618	24,402
2023	23,778	24,435	24,493	24,064

Table A4: Number of survey responses included in each of the waves from the representative rotating panel survey (ENSU) conducted in Mexican cities that included information about crime victimization, bribe solicitation, feeling of insecurity, and trust in police. Crime victimization and bribe solicitation is asked in Q2 and Q4. Trust in police institutions and feeling of insecurity is asked every round.

A1.2 Survey measures

In Table A5, we report the survey questions and measures employed in the paper and the corresponding data source.

Construct	LAPOP Question	Medellín Panel Question	Chile Panel Question	Mexican Panel Question
Trust in Police	**To what extent do you trust the police?** 7-point Likert scale	**How much do you trust the police?** 4-point Likert scale	**Can you tell me how much confidence you have in the police?** 5-point Likert scale	**How much confidence do you have in the State Police?** 4-point Likert scale
Trust in [other institution]	**To what extent do you trust [other institution]?** 7-point Likert scale	—	—	–
Education	**What was the final year of education that you completed or passed?** 0-18+ years	**What is the highest educational level that you completed?** 11 ranked categories	**What was the highest educational level that you completed or are currently in school for?** 10 ranked categories	**What is the highest educational level that you completed?** 10 ranked categories
Income	**In which of the following ranges does the monthly family income of this household fall, including remittances from abroad and the income of all working adults and children?** 16 ranked categories (depends on local currency)	**In which of the following income ranges does this home's monthly income fall?** 8 ranked categories	**Below is a list of income ranges, could you please indicate which of these ranges you are classified in considering your net income, i.e. your income after taxes, health, welfare or other deductions?** 16 ranked categories	—
Class (subjective)	—	—	**In society, commonly, there are different social groups or classes. People in the upper social class are those with the highest income, the highest level of education and the most valued jobs. People in the lower social class are those with the lowest income, the lowest level of education and the least valued jobs. In between these classes are others. According to your opinion, to which of the following social groups or classes do you belong?** 5 ranked categories	
Class (administrative)	—	Estrato 1-6 (six choices)	—	Estrato 1-4 (four categories)
Preference for *mano dura*	**In order to catch criminals, do you believe that the authorities should always abide by the law or that occasionally they can cross the line?** Yes they can /No they cannot	—	—	—
Crime victimization	**Have you been a victim of any type of crime in the past 12 months? That is, have you been a victim of robbery, burglary, assault, fraud, blackmail, extortion, violent threats or any other type of crime in the past 12 months?** Yes/No answer	**Thinking of the last 6 months, have you or anyone in your home been victims of any of the following crimes? Have any family members, friends, or neighborhood acquaintances? [theft, car robbery, verbal threats or abuse from police, extortion, street fights, family violence, sexual abuse, homicide.]** Yes/No answer	—	**In the last 6 months, have you or anyone in your home have suffered any of the following? [Car theft, burgraly, theft, extortion]** Yes/No answer
Police solicited a bribe	**Has a police officer asked you for a bribe in the last twelve months?** Yes/No answer	—	—	**In the last 6 months, have the police or any other security authority asked implicitly or explicitly for money or presents in order to avoid a traffic ticket or being detained?** Yes/No answer
Views police as corrupt	—	**How strongly do you agree or disagree with the following statement: The police are corrupt.** 5-point Likert scale	—	—
Feels unsafe in neighborhood	**Talking about the place or neighborhood where you live and thinking about the possibility of being the victim of an assault or robbery, do you feel very safe, somewhat safe, somewhat unsafe or very unsafe?** 4-point Likert scale	**In your neighborhood, do you generally feel very safe, relatively safe, relatively unsafe, or very unsafe?** 4-point Likert scale	**How safe or unsafe do you feel in the neighborhood where you live? Very unsafe, unsafe, neither safe nor unsafe, safe, or very safe?** 5-point Likert scale	**Speaking of crime, do you feel safe in the streets you regularly use?** Yes/No answer

Table A5: English translations of relevant survey questions employed in the analyses.

A1.3 Variable recodings and transformations

We transform a number of the variables described in Table A5 in some analyses. We outline the procedures that we use for these transformations, as follows.

Z**-score transformations**:

For a variable X_i, we construct Z-scores using the following formula:

$$X_i^Z = \frac{X_i - \overline{X}_i}{\sqrt{\text{Var}[X_i]}} \tag{1}$$

Decile construction:

We rank respondents by decile of education and socioeconomic status. Since the education and income measures are discrete (as indicated in Table A5), individuals in the same income or education bracket, are in some cases, assigned to different deciles to maintain equal-sized decile bins. To do this, we randomly rank respondents within the same class bracket before partitioning the sample into deciles.

Binary signals of police behavior/security outcomes.

To construct comparable binary signals across the three measures of police behavior/security outcomes, we dichotomize the Likert-measured variable measuring perceptions of safety in a respondent's neighborhood, as follows:

$$\text{Feels unsafe}_i = \begin{cases} 0 & \text{if Likert response } \leq 2 \text{ (very safe or somewhat safe)} \\ 1 & \text{else (somewhat unsafe or very unsafe).} \end{cases} \tag{2}$$

To maintain comparability across the surveys, we dichotomize the Likert-measured variable of "Are the police corrupt?" from the Medellín panel as follows:

$$\text{Police corrupt}_i = \begin{cases} 0 & \text{if Likert response } \leq 3 \text{ (strongly disagree, disagree, neither agree nor disagree)} \\ 1 & \text{else (agree or strongly agree).} \end{cases} \tag{3}$$

Appendix B LAPOP vs. Mexico, Chile, and Medellín Panels

This section compares the correlations between class and trust in police estimated with the LAPOP data to those estimated using the Chile, Mexico, and Medellín panels. Additionally, Table A6 presents results using the longitudinal Chile survey of the estimated association between subjective class and trust in police when individuals change their self-identification to a higher socioeconomic class.

Figure A1 benchmarks the national LAPOP-based correlations between class and trust in the police with the panel-estimated correlations. In the case of Mexico, where panel data includes information about respondents' educational attainment only, the LAPOP and panel correlations are negative and statistically indistinguishable from each other. The results from the Medellín panel show a more muted correlation between class and trust in police than results from the country-wide LAPOP data. Analyses with the Medellín panel data show a negative and statistically significant association between education and trust in police and a very weak, negative, but statistically insignificant correlation between income and trust in police. We note that the LAPOP data aims to be nationally representative. In contrast, the Medellín survey aims to be representative of populous police beats in the city (for details on sampling, see Hanson, Kronick, and Slough, 2022). In the case of the Chile panel, the association between class and trust in police is estimated to be positive, although small in magnitude. This is the only positive and statistically significant correlation we find across all analyses.

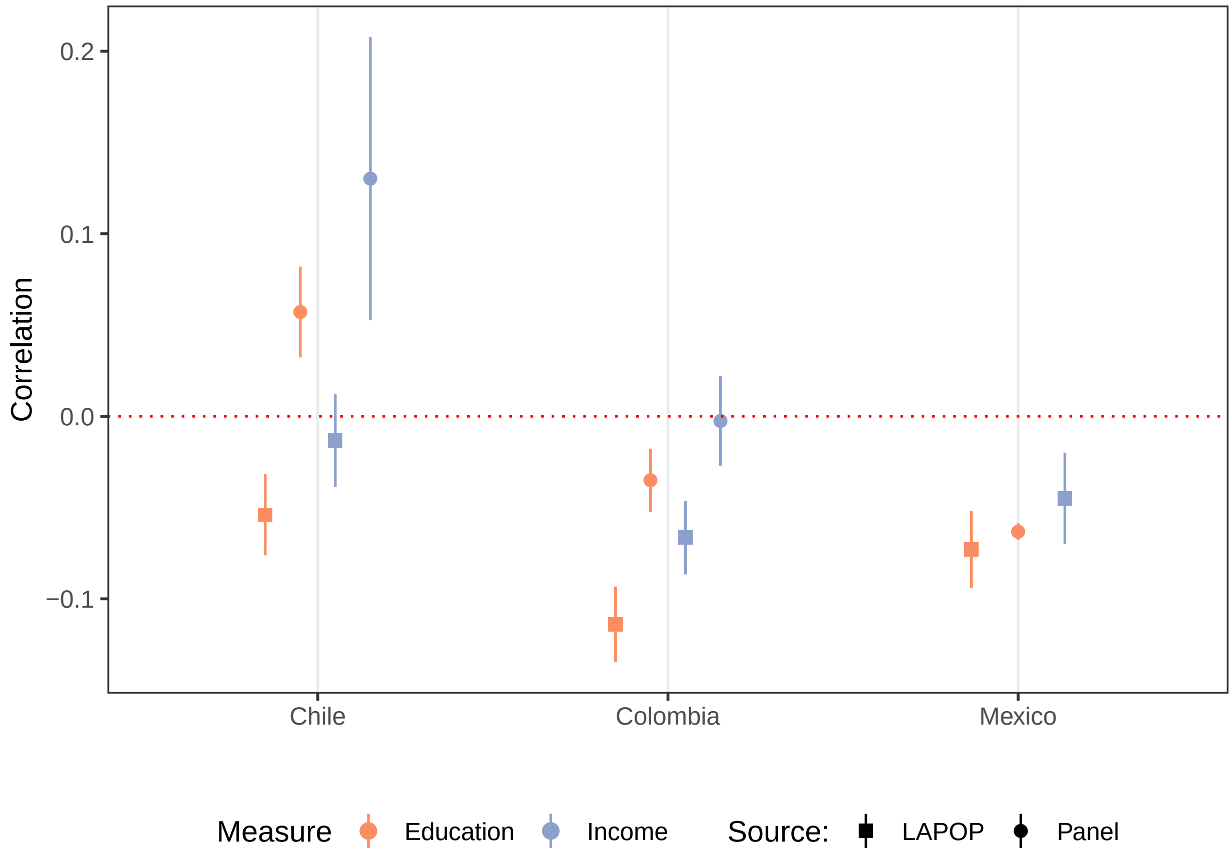


Figure A1: Figure shows the estimated correlation between two measures of class and trust in the police from the Chile ELSOC and Medellín panels, and LAPOP data.

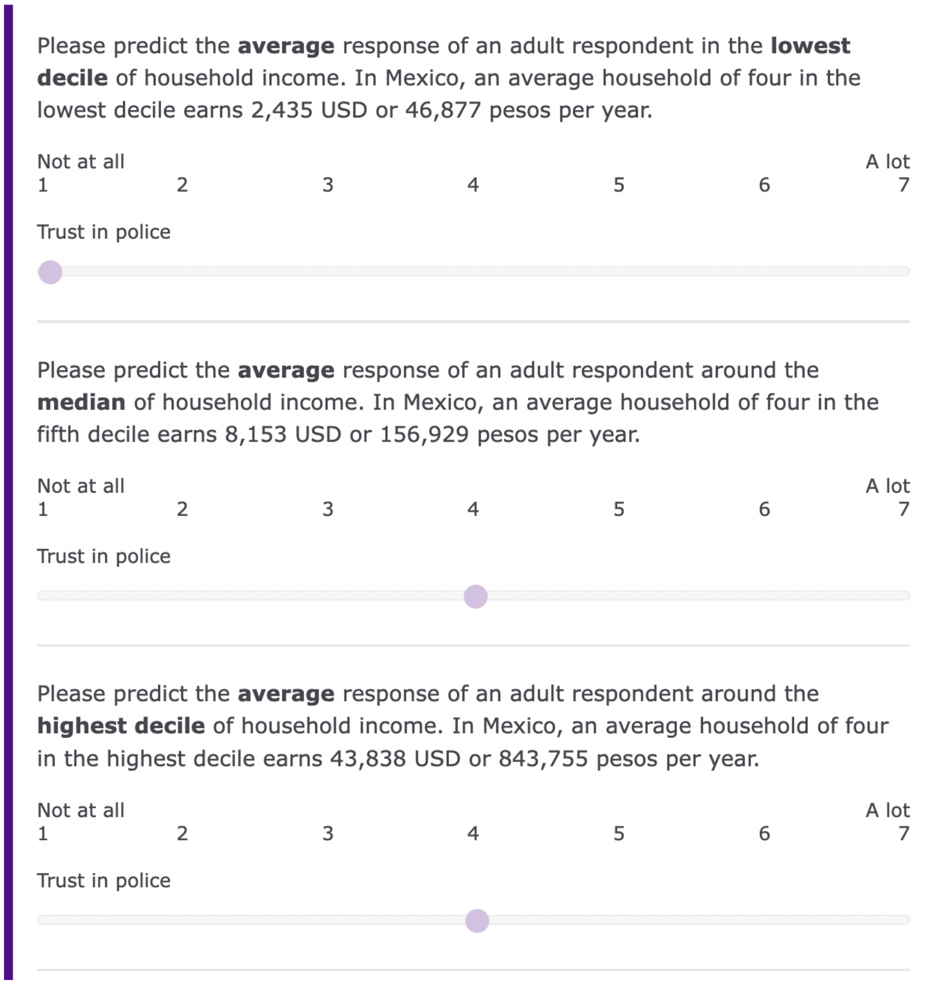
In this paper, we characterize how trust in police varies in social class in Latin America. To that end, we compared trust between individuals of different classes when class is operationalized as education and income. In the following analysis, we report additional estimates using class self-categorization, reported in the ELSOC Chile panel, as the measure of social class. Specifically, we make use of the data's panel structure and analyze the association between *changes* in individuals' self-identification with a class and trust in police. Table A6 shows the estimates of the pooled association (across waves), the average treatment effect (TWFE), and the fixed effects counterfactual estimator proposed by Liu, Wang, and Xu (2022) between trust in the police and identifying with a *higher* class than in the previous survey round. Self-identification with a higher class is associated with higher self-reported trust in police, both between and within individuals, as would be expected if treatment by police improved in class. However, the difference is not statistically significant in any of the three specifications and is small in magnitude.

Quantity	**Estimator**	**Estimate**	**95% CI**
Association	OLS	0.046 (0.032)	[-0.017, 0.109]
ATT	TWFE	0.024 (0.031)	[-0.036, 0.084]
ATT (unit avg.)	FEct (LWX 2022)	0.004 (0.049)	[-.092, 0.049]

Table A6: Table shows the pooled association (across waves), average treatment effect (TWFE), and fixed effects counterfactual estimator proposed by Liu, Wang, and Xu (2022) between trust in the police and identifying with a higher class than in the previous survey round for respondents in the ELSOC Chile panel. Treatment is defined as 1 when respondents changed their answer to the question "According to your opinion, to which of the following social groups or classes do you belong?" to self-identify with a wealthier social group, while respondents who identified with the same social class or a lower social class are coded as 0. Robust standard errors clustered at the primary sampling unit in parentheses.

Appendix C Forecasting Instrument

This section explains in detail the forcasting instrument and data. Figure A2 shows the English version of the web interface used to elicit experts' prior beliefs, while figure A3 shows its Spanish translation. Respondents were asked to predict the mean level of trust in the police for an average adult at the 10th, 50th, and 90th percentiles of household income. We asked experts to provide a forecast for at least one Latin American country or the region as a whole. Figures A2 and A3 show the Mexico-specific prompts.


Please predict the **average** response of an adult respondent in the **lowest decile** of household income. In Mexico, an average household of four in the lowest decile earns 2,435 USD or 46,877 pesos per year.

Not at all ... A lot

1 2 3 4 5 6 7

Trust in police

Please predict the **average** response of an adult respondent around the **median** of household income. In Mexico, an average household of four in the fifth decile earns 8,153 USD or 156,929 pesos per year.

Not at all ... A lot

1 2 3 4 5 6 7

Trust in police

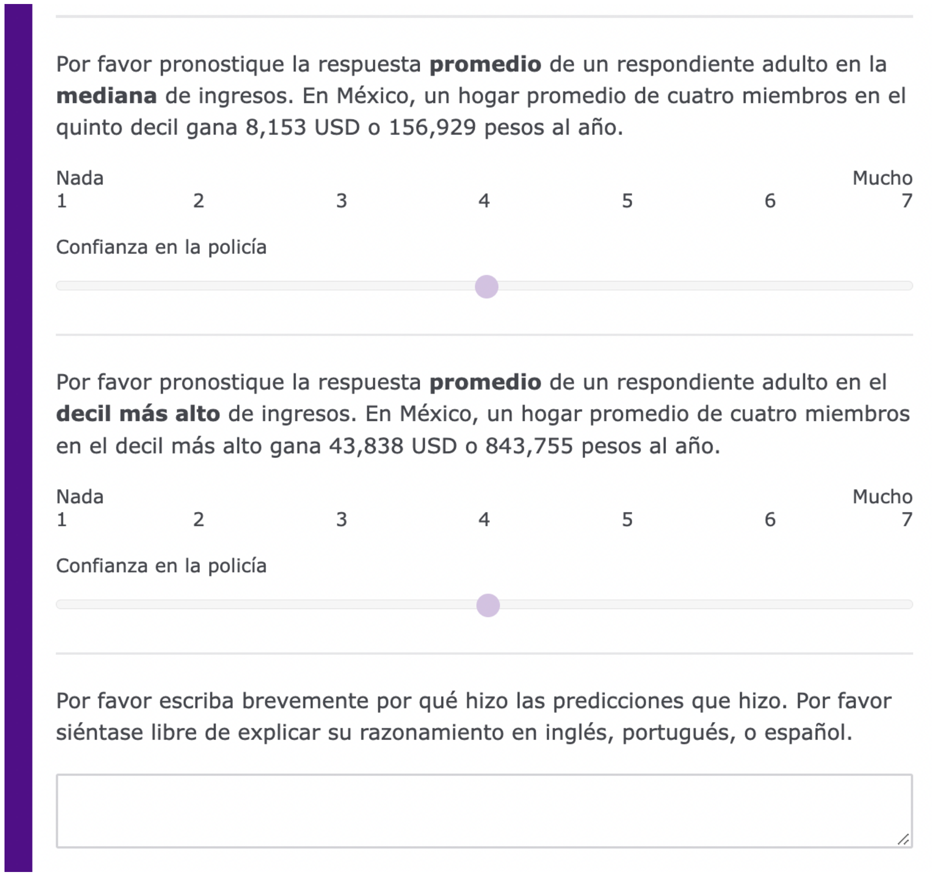
Please predict the **average** response of an adult respondent around the **highest decile** of household income. In Mexico, an average household of four in the highest decile earns 43,838 USD or 843,755 pesos per year.

Not at all ... A lot

1 2 3 4 5 6 7

Trust in police

Figure A2: Screenshot of the web interface used for eliciting experts' priors. As an example, Mexico was selected and Mexico-specific data was provided to contextualized the range of income.



Por favor pronostique la respuesta **promedio** de un respondiente adulto en la **mediana** de ingresos. En México, un hogar promedio de cuatro miembros en el quinto decil gana 8,153 USD o 156,929 pesos al año.

Nada 1	2	3	4	5	6	Mucho 7

Confianza en la policía

Por favor pronostique la respuesta **promedio** de un respondiente adulto en el **decil más alto** de ingresos. En México, un hogar promedio de cuatro miembros en el decil más alto gana 43,838 USD o 843,755 pesos al año.

Nada 1	2	3	4	5	6	Mucho 7

Confianza en la policía

Por favor escriba brevemente por qué hizo las predicciones que hizo. Por favor siéntase libre de explicar su razonamiento en inglés, portugués, o español.

Figure A3: Screenshot shows Spanish-langage verision of the web interface used for eliciting experts' priors. As an example, Mexico was selected and Mexico-specific data was provided to contextualized the range of income.

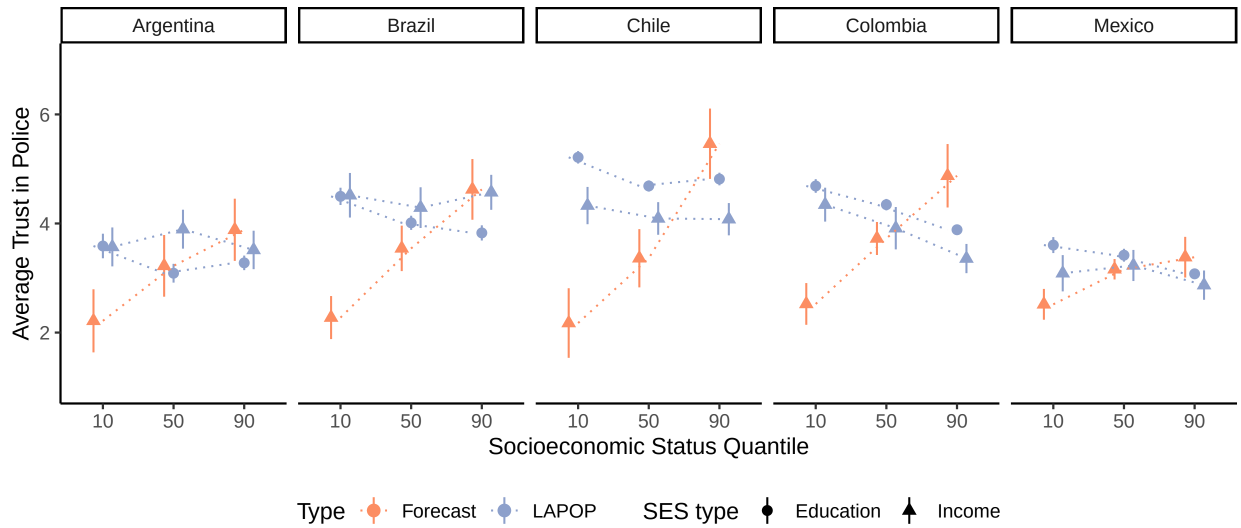


Figure A4: Divergence between average forecasts (in orange) and corresponding survey-based measures (in blue) for the five countries with more than eight survey responses. The figure shows that predictions for the case of Mexico posit a less steep relationship between income and trust in police than for the rest of the countries. Activists, who tend to predict lower scores than other respondents for higher income levels, drive this weaker predicted relationship.

Table A7 shows the number of individual forcasts included in the analysis, disaggregating by type of respondent and country for which the forcast was provided.

Country	Professor	Graduate or Postdoctoral student	Activist	Other	**Total**
Mexico	24	10	10	12	**56**
Brazil	10	6	0	0	**16**
Argentina	8	3	2	0	**13**
Chile	4	3	1	0	**8**
Colombia	4	4	0	1	**8**
Uruguay	7	0	0	0	**7**
Latin America (Regional average)	0	2	1	1	**4**
Guatemala	2	1	0	0	**3**
El Salvador	0	1	0	1	**2**
Ecuador	1	0	0	0	**1**
Honduras	1	0	0	0	**1**
Nicaragua	1	0	0	0	**1**
Peru	0	1	0	0	**1**
	62	**30**	**14**	**15**	**121**

Table A7: Count of survey responses per country and respondent type.

Appendix D Assessing Artifacts of Measurement

A4.1 Rates of missingness

This section describes the country-specific patterns of missingness in the socioeconomic and institutional trust variables used for the analysis. Figure A5 plots the proportion of survey responses with missingness across all survey country-rounds, according to the type of variable.

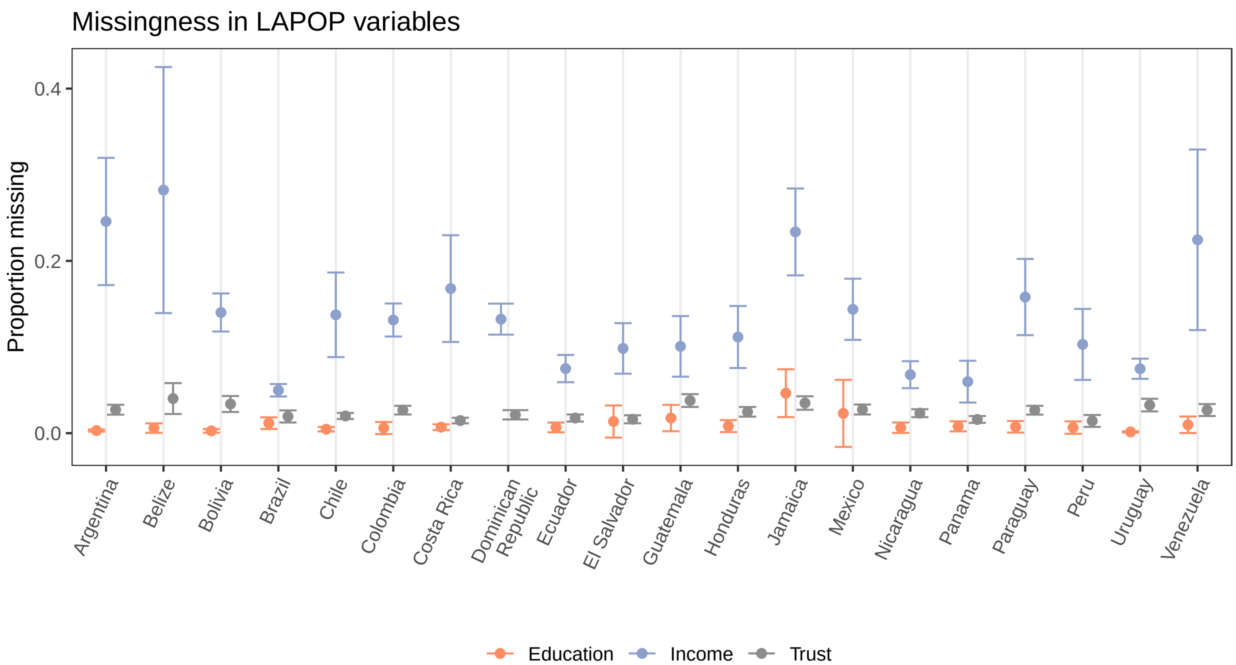


Figure A5: Figure shows the proportion across survey waves (and its 95% confidence interval) of respondents in each country that did not give a valid answer to a question about institutional trust (in blue), their income (in orange), and their educational attainment (in green).

A4.2 Worst-case bounds for missingness

Figure A6 shows the worst-case and best-case bounds for the estimated pooled correlation between trust in police and income or education after accounting for missing responses. For survey respondents who reported either socioeconomic status or trust in police but not both (99.8% of observations with missingness in either), we impute the Z-score value of the non-missing response (and $-1 * Z$-score) as the missing value. Since correlations are bounded between -1 and 1, and both responses are Z-scores, this process guarantees that the missing observation lies on the 45° line, making the estimated correlation the most positive (most negative) possible. The results show that the correlation is negative and of a similar magnitude, even if all missing observations were perfectly and positively correlated. The correlation between trust in police and income, if all missing observations were perfectly and positively correlated, is estimated to be 0.13. That is, the most positive correlation that the data's missingness could conceal is *equal* to the estimated correlation between income and trust in police in the United States.

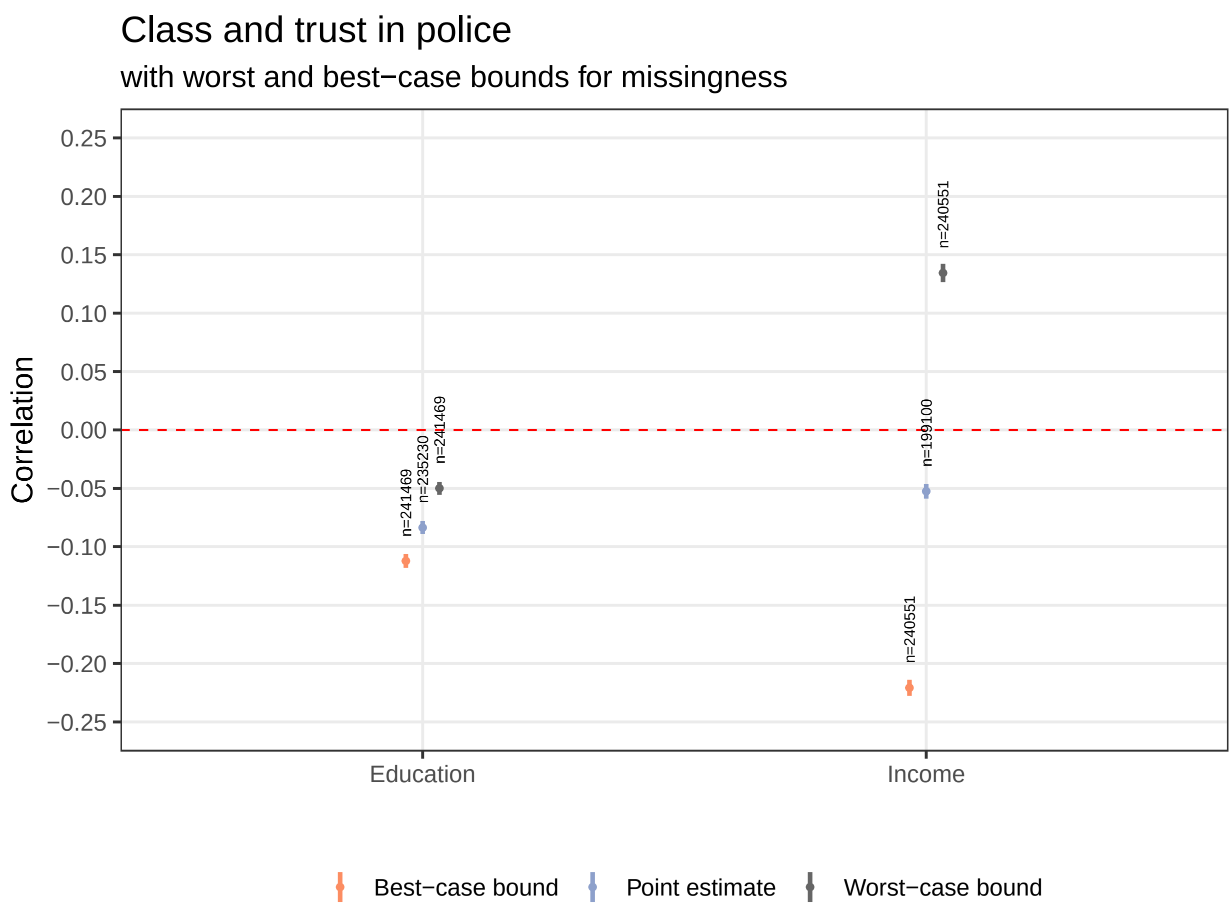


Figure A6: Figure shows the best-case, point estimates, and worst-case bounds for the pooled correlation across LAPOP survey waves between socioeconomic status, operationalized as self-reported education and income, and trust in police. Robust errors arevclustered at the primary sampling unit.

A4.3 Respondent interpretations of trust

This section investigates respondents' conceptions of institutional trust. We conceptualize trust as cognitive and relational. If trust is, in fact, cognitive and relational, if different governments interact with people differently, then changes in the political composition or ideology of the government should affect how individuals expect to be treated by government agents. To test, we analyze changes in reported trust of different institutions under right-wing national governments.

Figure A7 shows the results of estimating the following event study setup:

$$\text{Trust}_{ic} = \alpha + \sum_{s\in[1,3]} \beta_s \text{Right wing}_c + \varepsilon_{ic}$$

where Trust_{ics} is respondent i's self-reported trust in a given authority, standardized within country-years in country c, and Right wing_c is an indicator equal to one if country c's government is headed by a right-wing president at the time of the survey's collection, or zero otherwise. s indexes the number of LAPOP survey waves conducted in each country since the start of the right-wing spell, where $s = 0$ indicates the last survey collected before its start. Robust errors are clustered at the level of the primary-sampling unit.

As figure A7 shows, self-reported trust in certain institutions *is* responsive to the ideological composition of the national government. The onset of right-wing governments significantly increases the correlation between trust in the president and both measures of class, as would be expected if support for right-wing governments was increasing in socioeconomic status. The correlation between trust and class for congress, political parties, and the police also significantly increases with the onset of right-wing spells, albeit by a smaller magnitude. Conversely, there is no significant change in trust in the Supreme Court, the Army, or Elections, as expected of institutions that are more independent of the national government.

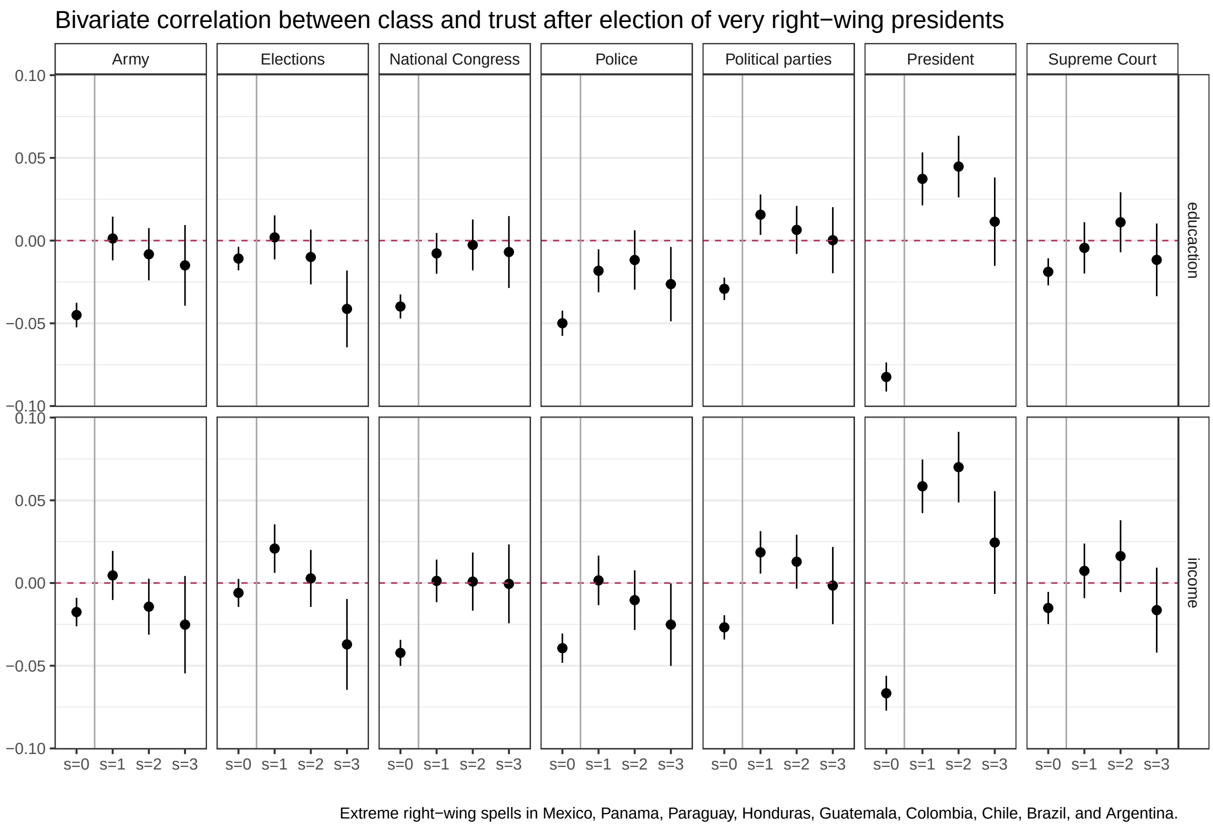


Figure A7: Figure shows the estimated correlation between class and trust in each authority during each survey wave for countries with at least one spell of right-wing presidents. Robust errors clustered at the primary-sampling-unit. The right-wing spells include: Macri in Argentina, Bolsonaro in Brazil, Uribe and Duque in Colombia, Pérez and Morales in Guatemala, Hernández in Honduras, Calderón in Mexico, Martinelli in Panama, and Abodo in Paraguay.

Appendix E Institutional Trust as a Fixed Trait?

If institutional trust were a fixed trait, we would expect a high level of homogeneity in each respondent's ratings of different government institutions. To test for this possibility, Figure A8 plots the pooled and country-specific intra-class correlation between respondent's assesments of trust in the police, congress, the courts, the president, political parties. The intra-class correlation gives the ratio of between-respondent variance to the total variance in trust in these institutions. If the ICC were close to 1, it would suggest limited variance in an individual's assessment of different institutions, suggesting that institutional trust functions as a stable trait or predisposition. Conversely, we can see that the pooled-sample ICC is estimated to be only 0.047 [0.0193, 0.232 95% CI] and all the country-specific ICCs are estimated to be less than .2.

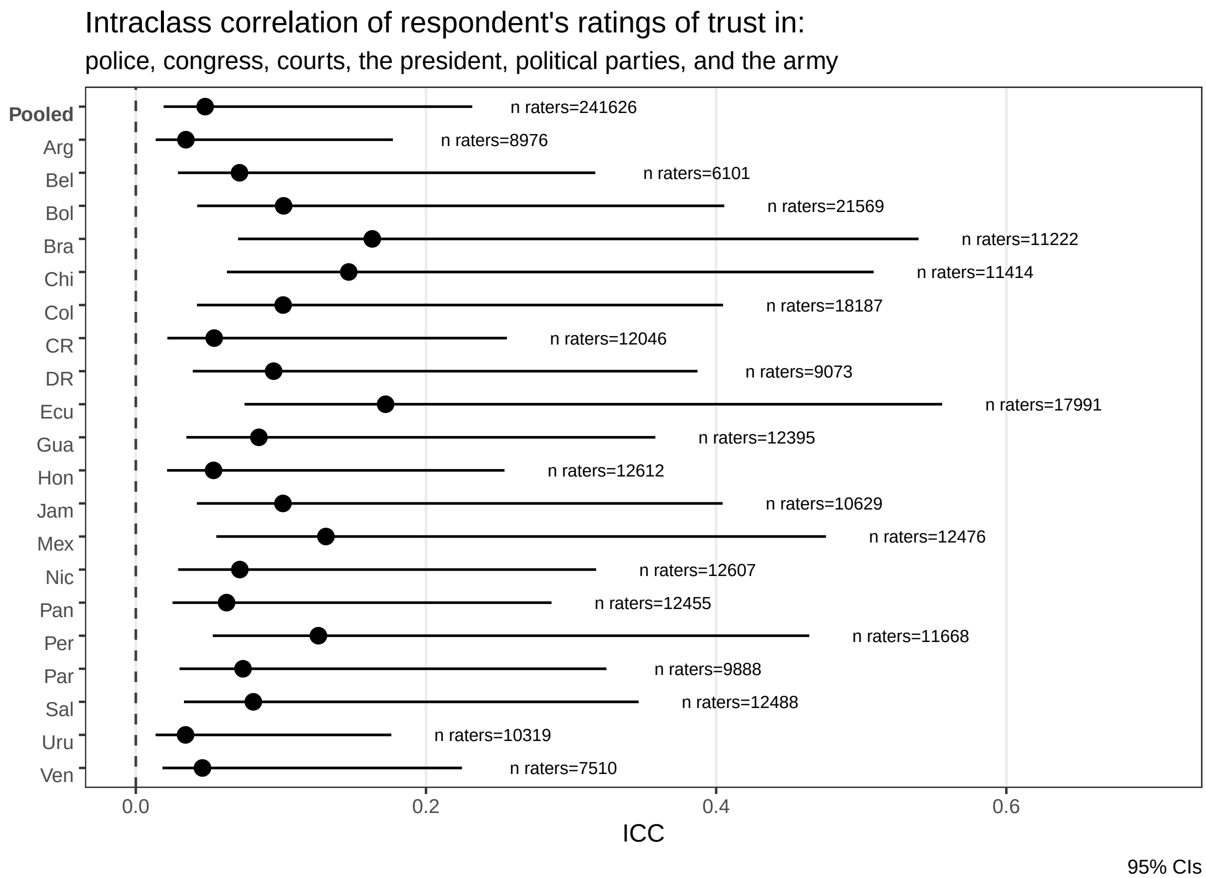


Figure A8: Figure shows the pooled and country-specific intra-class correlations.

Appendix F Updating on Experience with Police

A6.1 Medellín Survey Data

We use three smaller panel surveys, described in Appendix A, and administrative data to gain additional leverage on our account of updating on police trustworthiness. First, one surprising finding in Figure 6 is that high socio-economic status respondents report higher rates of crime victimization than poor respondents. The crime vicitmization survey conducted in Medellín helps to clarify this surprising finding, by examining exposure to different crimes by socioeconomic status. Figure A9 shows that the proportion of respondents that report having experienced theft in the past year, the most commonly reported crime, is increasing in class *estrato*. Thus, the positive gradient of overall victimization and class—seen in the first panel of the top row and Figure 6—is due to the high frequency with which property crimes occur. Conversely, Figure A9 shows that lower-income individuals more commonly report incidences of violence but less frequently perpetrated crimes, like homicide or extortion.

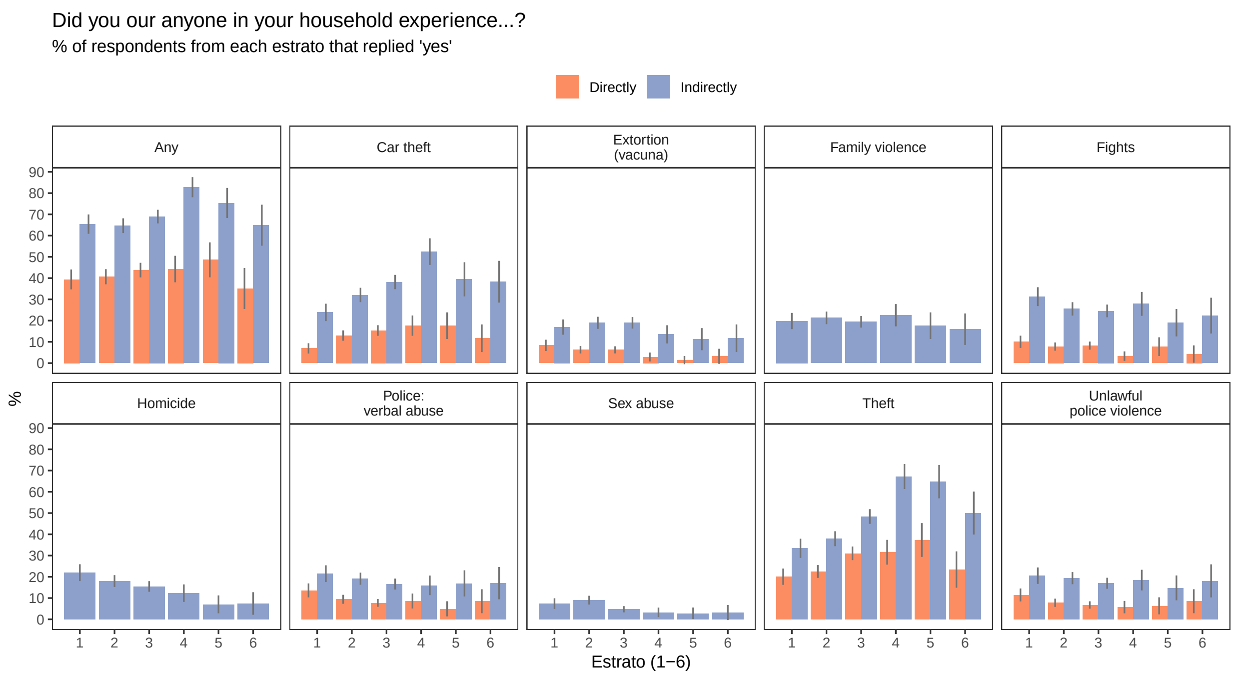


Figure A9: Figure shows the proportion of respondents from the Medellín survey that report direct (in orange) and indirect (in blue) instances of crime happening in their neighborhood in the last 6 months, by administrative class 'estrato'.

A6.2 Administrative Crime Data

Additionally, we examine how the incidence of different crimes, as recorded in geolocated administrative data, covaries in the socioeconomic profile of inhabitants within two Latin American cities: Medellín and Mexico City. While these data measure only crime recorded by city authorities, it is helpful to contrast the association between recorded crime and class with that using self-reported victimization from our survey data.

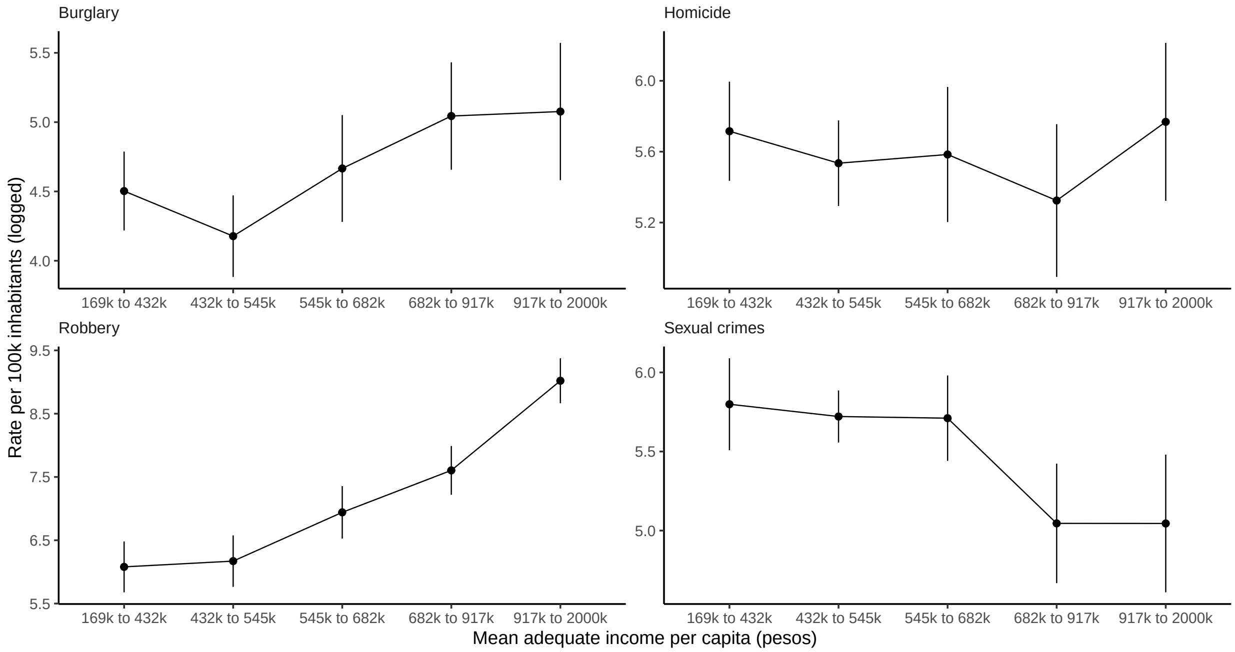


Figure A10: Figure shows the mean crime rate by mean adequate income per capita quantile per police quadrant in the city of Medellín. Crime data comes from official administrative crime statistics for the 2011-2017 period. The mean adequate income per capita comes from the national census.

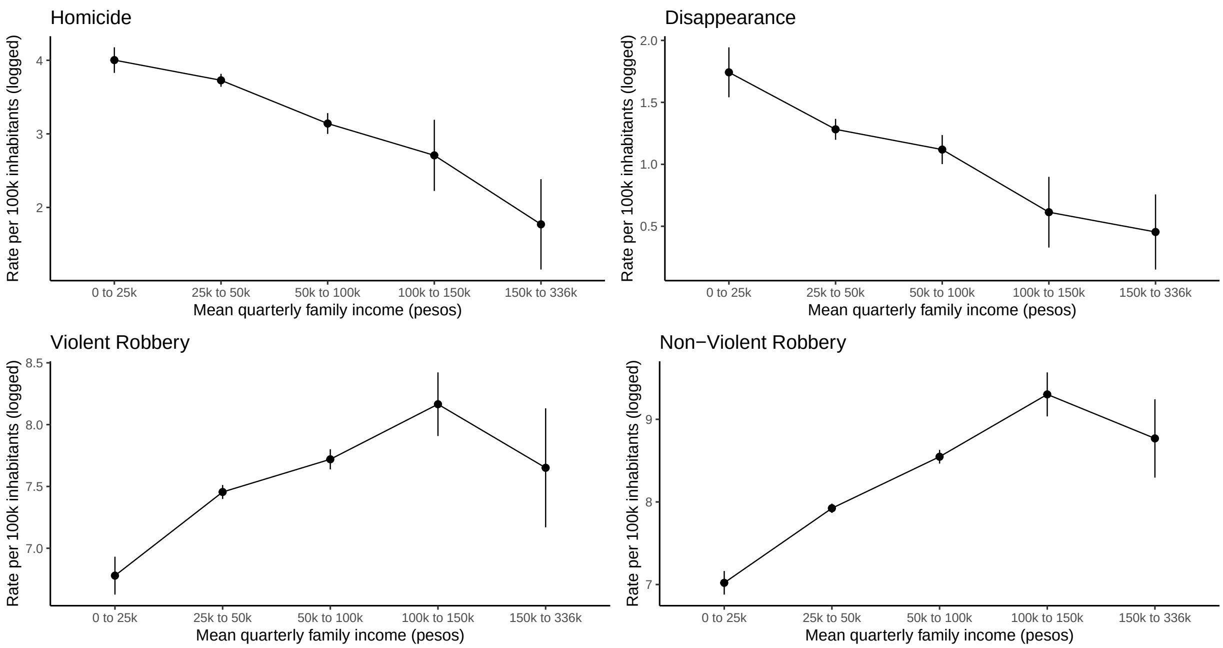


Figure A11: Figure shows the mean crime rate by quarterly income zones in Mexico City. Crime data comes from official administrative crime statistics for the 2015-2022 period. Data on income comes from the 2018 National Survey of Household Income and Expenditure (ENIGH) conducted by the National Institute of Statistics and Geography (INEGI).

Figure A10 plots administrative crime data and shows the mean rate of four crimes in Medellín according to the adequate income per capita of respondents living in each of the 408 police quadrants. Similar to what the survey data shows, the rate of robbery and burglary increases in income while the rate of sexual crimes decreases. Conversely, homicides show either a slightly decreasing or flat gradient. Similarly, figure A11 shows that the homicide and disappearance rate, as per administrative data, decreases in neighborhood income while the robbery rate increases. Administrative data is partly a function of the rate of self-reporting, which can covary in class. However, information on severe crimes like homicides and disappearances is thought to suffer less of self-reporting bias. Thus, results are congruent with lower-income respondents experiencing more severe crimes at higher rates than their higher-income neighbors.

A6.3 Mexico Rotating Panel Data

Last, we leverage the panel structure and large sample size of the Mexican rotating panel survey, ENSU, to examine how three different signals of police trustworthiness affect trust in police at different income levels. We employ a two-way fixed-effect estimator and the fixed-effect counterfactual estimator proposed by Liu, Wang, and Xu (2022) to estimate the ATT of these self-reported signals for each administrative class *estrato*. Figure A12 shows that the estimated ATT of each of the signals on trust is remarkably similar for individuals of different class *estratos*. These results suggest that respondents of different sociodemographic backgrounds are not learning different things from the same signals.

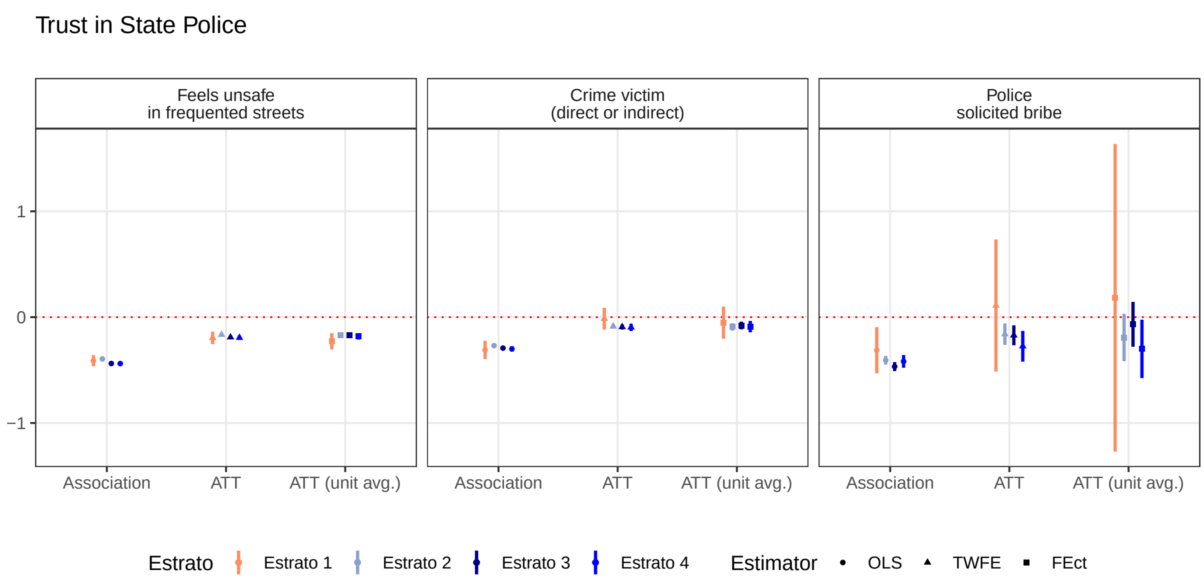


Figure A12: Figure benchmarks the class-specific estimates of pooled associations (across waves) to estimates of the average treatment effect (ATT) on the treated of signals analogous to those in Figure 7 estimated using the Mexico rotating panel ENSU. LWX (2022) indicates the fixed effects counterfactual estimator proposed by Liu, Wang, and Xu (2022). 95% confidence intervals are calculated on standard errors clustered at the primary sampling unit.

A6.4 Feeling of Insecurity

For some analyses, we conceptualize the feeling of insecurity as a perceived signal of police trustworthiness on which citizens update, since part of police officers' job is preventing crime and, in so doing, inspiring a feeling of security. However, how feeling "safe" correlates with the objective level of violence in a geography—or whether such feeling tracks objective measures of "successful" policing— is less clear. Table A8 shows the correlation between self-reported feeling of insecurity in respondents' neighborhoods and municipal-level homicides for respondents living in Brazil, Colombia, and Mexico. The measure of feeling of insecurity comes from all LAPOP survey waves (see Table A5), while municipal-level homicide data come from each country's official administrative records. Feeling unsafe is positively related to the intensity of homicidal violence in all countries and using all transformations of the measure of homicides, as we would expect if feeling of insecurity increased in the actual level of perpetrated violence. The correlation is strongest in Brazil but positive and statistically significant at the 95% level for Colombia and Mexico as well.

'Feels unsafe'	Brazil	Colombia	Mexico
Rate per 100k	0.15 (0.02)	0.05 (0.02)	0.04 (0.02)
Total homicides	0.10 (0.02)	0.15 (0.02)	0.07 (0.02)
Rate per 100k (logged)	0.14 (0.02)	0.09 (0.02)	0.08 (0.02)
Rate per 100k (pooled quantile)	0.16 (0.02)	0.04 (0.02)	0.09 (0.02)
Rate per 100k (year quantile)	0.15 (0.02)	0.04 (0.02)	0.07 (0.02)

Table A8: Table shows the correlation between self-reported feeling of insecurity in respondents' neighborhood and homicides (measured at the municipal-level) for respondents living in Brazil, Colombia, and Mexico. In each country's column, the first row shows the country-specific correlation when the intensity of homicidies is operationalizes as rate per 100k municipal inhabitants, the second shows the correlation with the total number of homicides, the third with the logged rate per 100k municipal inhabitants, the fourth when violence is operationalizes as the municipal quantile of the overall number of homicides in the entire period, and the fifth when the quantile is constructed using the total number of homicides perpetrated there that year. Robust standard errors in parenthesis.

Although we use panel surveys to estimate the ATTs of different signals of police trustworthiness, it is helpful to see how associations estimated with these data relate to those estimated from the LAPOP sample. In Figure A13, we plot the association between feeling unsafe in the neighborhood, crime victimization, and bribe solicitation, and standardized measures of trust in police. The first and second panels show that the association between feeling unsafe and crime victimization is slightly more negative when using the Medellín panel than the Colombia-wide LAPOP data. The former, but not the latter is also true when using the Mexico panel, which also shows a similar association for bribe solicitation using the two measures. As for Chile, the LAPOP and panel-based estimates of the association between feeling unsafe and trust in police are similar.

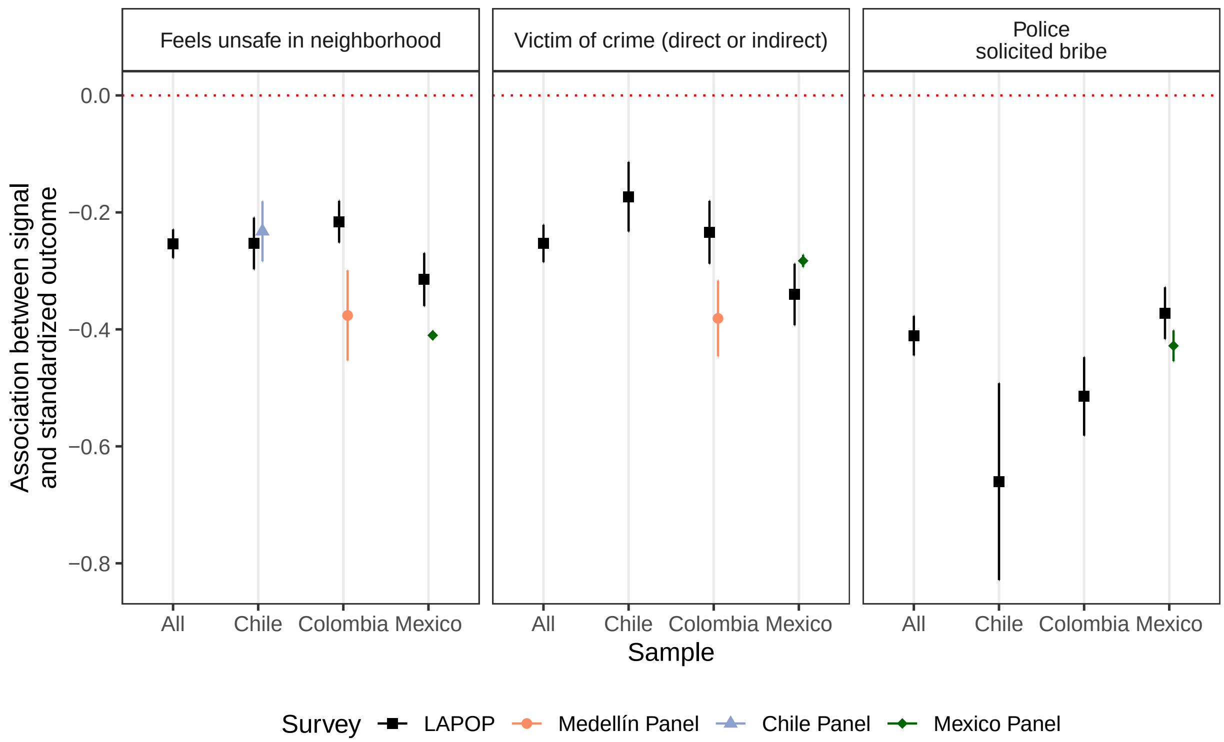


Figure A13: Figure shows the association between three signals of police trustworthiness and a standardized measure of trust in police when estimated using the data from LAPOP (black), the Medellín panel (orange), the Chile panel (blue), and the Mexico panel (green). Robust standard errors clustered at the primary sampling unit.

Appendix G Beliefs versus Preferences

We have argued that trust should be characterized as a belief. As such, the evolution of trust could be subject to motivated reasoning. If this were the case, a respondent who prefers a policy that necessitates active police involvement may be motivated to hold more positive views of the police, thereby generating higher levels of trust in police (all else equal). To gauge if respondents' trust in police depends on their prior preferences over policing practices or policy, we characterize the relationship between socioeconomic status, self-described support for tough-on-crime or *mano dura* policing, and trust in police. A motivated-reasoning or inference process of updating on police trustworthiness should lead to pro-*mano dura* individuals having higher trust in police. Given the generally negative correlations between socioeconomic status and trust in police reported in Figure 1, this should translate to the poor holding more favorable views of *mano dura* policies.

Conversely, the left panel in Figure A14 shows a close-to-zero and *positive* correlation between income and support for tough-on-crime policing across most countries. Additionally, the right panel in Figure A14 shows the predicted level of trust in police by class decile as a function of respondents' self-reported support for 'mano dura.' The black line plots the expected level of trust in police for respondents in each decile, and the blue line plots the conditional expectation for respondents in that decile who support 'mano dura.' In contrast, the orange line plots the conditional expectation for respondents in that decile who are *unsupportive* of 'mano dura.' As we can see, the expected level of trust for individuals supportive of *mano dura* is lower than for individuals unsupportive of the measure across all income levels. Additionally, trust for both groups decreases at a similar rate. The results show the opposite empirical pattern we would expect to find if trust is largely driven by individuals' preferences, discounting the possibility of a motivated-reasoning explanation of our results.

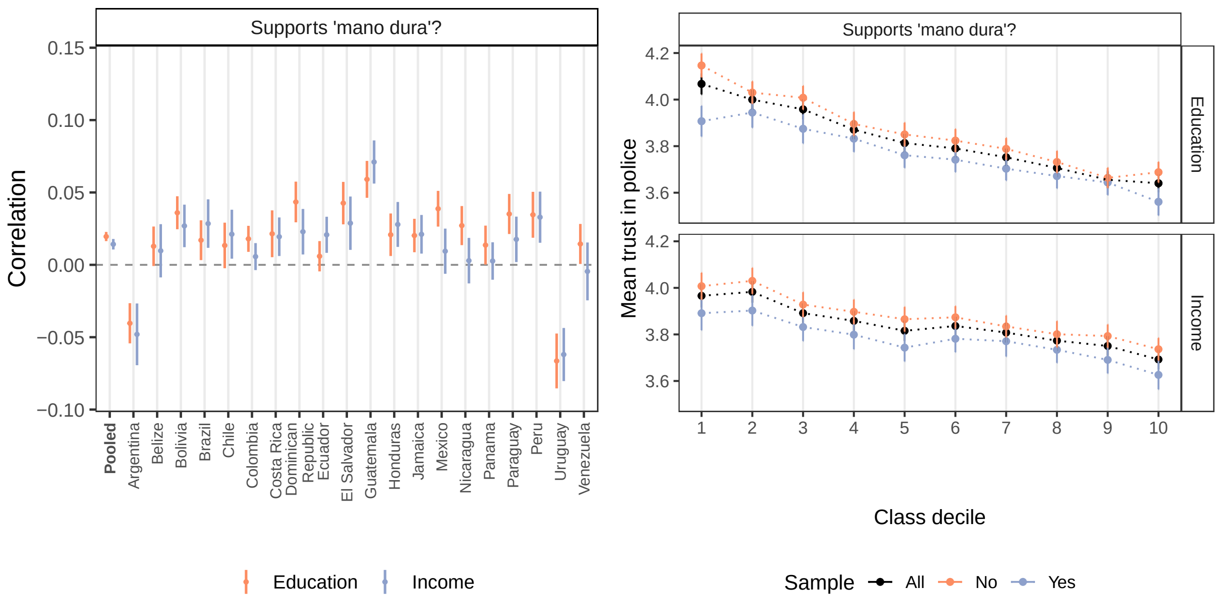


Figure A14: The left panel shows the estimated correlation between income (orange), education (blue), and support for tough-on-crime or *mano dura* policing. The right panel shows the predicted level of trust in police for the pooled sample, by class decile, as a function of support for *mano dura* (yes in blue/no in orange).

Appendix H Framework for the Evolution of Trust in Police

We propose a simple theoretical framework to organize and synthesize these empirical results. Our framework builds on our conception of trust as cognitive. It seeks to illuminate how disparities in trust might emerge (or fail to emerge) within the course of citizen-police agent interactions. Ultimately, we are interested in characterizing citizen learning about police trustworthiness. Our measure of trust in police operationalizes citizen beliefs about the trustworthiness of the police, which we will refer to as μ_t, where t indexes time. Police agents are of type $\theta \in \{0, 1\}$, where $\theta = 1$ indicates trustworthy and $\theta = 0$ indicates non-trustworthy. We think of citizen beliefs as a subjective assessment of the pool of police agents, e.g., $\mu_t = \Pr(\theta = 1)$. As the share of trustworthy agents in the police increases, a citizen trusts the police more.

Citizens learn about police trustworthiness by observing police behavior or security outcomes. We denote a citizen's prior belief about the trustworthiness of the police as μ_{t-1}, which has an analogous interpretation to μ_t. At a given time, t, police choose an action $S_t \in \{0, 1\}$. Without loss of generality, we think of $S_t = 1$ as an action that harms the citizen's welfare (e.g., solicitation of a bribe or failure to prevent a crime). A trustworthy police agent chooses the action that harms the citizen, $S_t = 1$, with probability $\Pr(S_t = 1|\theta = 1) = \sigma_1 \in (0, 1)$, whereas the non-trustworthy police agent chooses $S_t = 1$ with probability, $\Pr(S_t = 1|\theta = 0) = \sigma_0 \in (\sigma_1, 1)$. We will assume that non-trustworthy police agents are more likely to take the action that harms the citizen, $\sigma_0 > \sigma_1$. A citizen who observes S_t can update according to Bayes' rule as follows:

$$\mu_t = \begin{cases} \frac{\mu_{t-1}\sigma_1}{\mu_{t-1}\sigma_1 + (1-\mu_{t-1})\sigma_0} & \text{if } S_t = 1 \\ \frac{\mu_{t-1}(1-\sigma_1)}{\mu_{t-1}(1-\sigma_1) + (1-\mu_{t-1})(1-\sigma_0)} & \text{if } S_t = 0. \end{cases}$$

The assumption of Bayesian updating is (directionally) consistent with our findings in Figure 6 for all socioeconomic strata when we examine how levels of trust vary as a function of crime victimization, bribe solicitation, and feelings of safety.

To think about citizen beliefs in the aggregate, we consider two additional features. The first, institutional quality, π, is the share of trustworthy agents among the police. Since citizens will generally hold heterogeneous beliefs about police trustworthiness—as in our data—given the updating process above, it is useful to parameterize the (objective) pool of agents. We will define $\pi = \Pr(\theta = 1)$. One direct consequence of this parameterization holds that:

$$\Pr(S_t = 1) = \pi\sigma_1 + (1 - \pi)\sigma_0 \qquad \text{and} \qquad \Pr(S_t = 0) = \pi(1 - \sigma_1) + (1 - \pi)(1 - \sigma_0)$$

The second additional feature, citizen attention, introduces a behavioral element to our model. With probability $\gamma \in (0, 1]$, citizens observe police behavior or security outcomes. With complementary probability, they remain oblivious and do not update, such that $\mu_{t-1} = \mu_t$. Collectively, we can then express the expectation of police trusworthiness in time t, μ_t, as follows:

$$\begin{aligned} E[\mu_t] = \gamma\Big(& \overbrace{(\sigma_0 + \pi(\sigma_1 - \sigma_0))}^{\Pr(S_t=1)} \overbrace{\frac{\mu_{t-1}\sigma_1}{\mu_{t-1}\sigma_1 + (1 - \mu_{t-1})\sigma_0}}^{\mu_t|S_t=1} + \\ & \underbrace{(1 - \sigma_0 - \pi(\sigma_1 - \sigma_0))}_{\Pr(S_t=0)} \underbrace{\frac{\mu_{t-1}(1 - \sigma_1)}{\mu_{t-1}(1 - \sigma_1) + (1 - \mu_{t-1})(1 - \sigma_0)}}_{\mu_t|S_t=0} \Big) + (1 - \gamma)\mu_{t-1} \end{aligned} \tag{4}$$

Parameter(s)	Source of variation	Description
μ_0	Differences in (initial) beliefs	*Ex-ante* beliefs about the police emerging from early socialization.
$\|t\|$	Different histories of observation	Number of periods of updating on police quality, likely proxied by age.
σ_0, σ_1	Different likelihoods of poor police treatment of citizens or poor security outcomes.	Police may be biased toward some citizens over others. Bias may be a result of police tastes or institutional incentives for abuse/poor service in some communities but not others.
π	Different pools of police agents.	Better (more trustworthy) officers may select into or be assigned to some jurisdictions than others. Alternatively, changes in police compensation or selection may lead to different pools of police over time.
γ	Different levels of attentiveness to police behavior	Some citizens may be more observant than others due to cognitive load

Table A9: Sources of variation in trust in police.

To the extent that our goal is to understand systematic *variation* in trust in police, this framework broadens the set of explanations for this variation, as discussed in Table A9. To understand how trust varies in social class, suppose that one or more of these parameters varies in social class. Placing the conventional wisdom—poor service/outcomes begets distrust—in the context of our framework shows where this account is underspecified. First, we do not know whether variation in service quality comes from variation in the likelihood of police treatment and security outcomes (σ_1 or σ_0), contact with different pools of police agents (π), or both. Second, we identify other sources of variation in trust that could covary with socioeconomic status and drive the weak, negative correlation between socioeconomic status and trust in police that we have documented. Importantly, these features fall within our conception of institutional trust rather than the alternative accounts we have provided evidence against.
The updating process we describe in (4) has some notable features. First, it is useful to note that $\lim_{t\to\infty} E[\mu_t] = \pi$. Yet, individual beliefs (μ_t) will not generally converge to π. Second, it is also useful to examine Var$[\mu_t]$, but whether variance increases or decreases in t is ambiguous. Within the LAPOP repeated cross-sectional data or the (relatively) short panels from Medellín and Chile, our ability to track individual updating over long histories (sufficiently large $|t|$) is limited. Given that we only have surveys of adults, these survey data do not offer a persuasive measure of μ_0. Nevertheless, as long as citizens (sometimes) see signals of police quality, μ_0 (so long as it is not 0 or 1) should play little role in characterizing trust in a cross-section of citizens.

To examine variation in $|t|$, we compare trust in police as a function of respondent age. Trust in police is increasing in age (Figure A15). This observation posits an alternate explanation for the main finding, that trust is decreasing (weakly) in social class, given compositional differences between rich and poor respondents. In our sample, the young are both better educated, slightly more affluent (income is maximized at middle age), and less trusting of the police. Figure A15 suggests that while these compositional differences may strengthen our finding of a negative correlation between socioeconomic status and income, they alone cannot account for the negative correlation we observe. This is evident from the very similar negative gradients of income on trust within each age bracket.

Given the observation of a signal—a poor security outcome or mistreatment by police—different citizens could emerge with different beliefs because (a) they had different priors; or (b) they update via different likelihoods (σ_1 and σ_0). To the extent that a posterior today (in t) serves as a prior tomorrow (in $t + 1$), our main finding is that average beliefs in police trustworthiness decrease slightly as income increases. Yet, when we compare the beliefs of citizens exposed to the adverse signal ($S_t = 1$) vs. those that were not exposed ($S_t = 0$) in Figure 6, there exists a high degree of stability in the extent of updating (the difference between the orange and blue lines) across all deciles of socioeconomic status. Nevertheless, because the rich have (slightly) lower priors about police trustworthiness, we should expect them to update slightly less on the basis of a "bad" signal when all citizens share the same likelihoods. Table A10 reveals that, for both measures of social class, this is the case for crime victimization and bribe solicitation, though these differences are small in magnitude as we might expect for such small differences in prior beliefs.[1] The data we observe are broadly consistent with Bayesian updating in the model and do not point to different likelihoods or differential ability to update as a source of the pattern of beliefs that we observe. This is an important observation in light of debates about education, cognitive sophistication, and the ability to update.

The final sources of variation in trust in police deal with the probability that citizens encounter or observe a given signal of police trustworthiness. Table A9 suggests two possible sources of this variation: the share of trustworthy vs. non-trustworthy police agents that citizens encounter (π) or the probability that citizens detect signals of police behavior (γ). In our conceptualization, the former is institutional, and the latter is behavioral. On the one hand, the sorting of police officers into police precincts, either by police commanders or officers themselves, could lead some populations to greater exposure to untrustworthy or abusive officers. If this varied in citizen social class, these differences in rates at which bad signals ($S_t = 1$) emerge could lead to variation in the frequency of downward updating. Importantly, this can occur even if all police agents (of a given type) treat citizens equally, e.g., without bias.[2]

A8.1 Supplementary analysis

This section provide supplementary analyses supporting our discussion of our framework for the construction of trust in police. Figure A15 shows that trust in police is decreasing in class, both operationalized as income and education, across all age groups, discounting the possibility that systematic differences in the age of individuals of different income groups explain the negative relationship between the variables.

[1] For the "feeling unsafe" signal, point estimates on the interaction between class and the signal are negative and significant, but small in magnitude.

[2] In our model, equal treatment is equivalent to non-class specific likelihoods (σ_1 and σ_0).

	Trust in police (standardized)					
	(1)	(2)	(3)	(4)	(5)	(6)
Victimized in past year (binary)	-0.245***	-0.255***				
	(0.007)	(0.007)				
Feels unsafe in neighborhood (binary)			-0.238***	-0.238***		
			(0.005)	(0.005)		
Bribe solicited (binary)					-0.371***	-0.372***
					(0.008)	(0.008)
Education (Z-score)	-0.083***		-0.081***		-0.072***	
	(0.003)		(0.003)		(0.003)	
Income (Z-score)		-0.056***		-0.051***		-0.041***
		(0.004)		(0.004)		(0.003)
Victimized × Education	0.022***					
	(0.007)					
Victimized × Income		0.018*				
		(0.007)				
Feels unsafe × Education			-0.010*			
			(0.005)			
Feels unsafe × Income				-0.012*		
				(0.005)		
Bribe solicited × Education					0.008	
					(0.007)	
Bribe solicited × Income						0.005
						(0.007)
Observations	154,180	130,510	235,291	199,160	233,142	197,420
Mean DV (signal = 0)	0.050	0.055	0.098	0.100	0.039	0.043

$^{+}p < 0.1, ^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

Table A10: Differential updating on signals by socioeconomic status proxy. Standard errors are clustered at the level of the primary sampling unit.

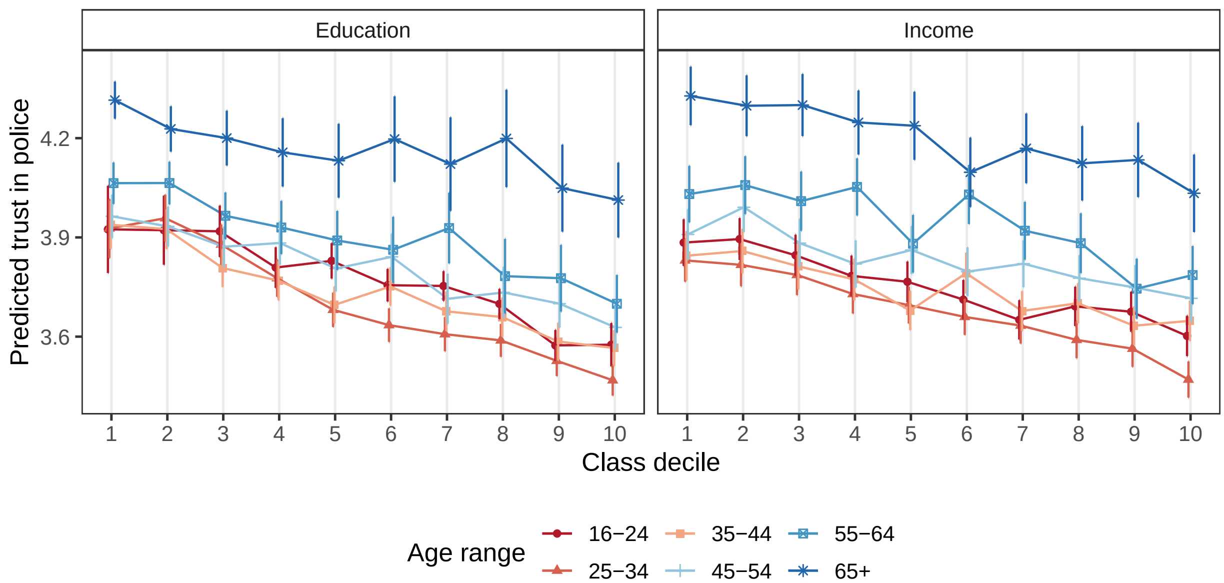


Figure A15: Trust in police as a function of age and class. 95% confidence intervals constructed on standard errors clustered at the primary sampling unit level.

Supplementary Appendix: References

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