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Crime and Erosion of Trust

Evidence for Latin America

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Abstract[*]

Crime has tangible economic costs. It also has less understood and likely sizable intangible costs. In particular, widespread crime has the potential to weaken trust between citizens and institutions, undermine government reform efforts, and become an obstacle to development. Yet, the impact of crime on trust remains relatively unexplored in the literature. This paper analyzes the potential interrelationship between individual victimization and several measures of trust, including trust in formal public institutions and trust in informal private networks. It is based on a representative sample of individuals in 19 countries in Latin America. The empirical strategy is intended to mitigate overt biases and assess sensitivity to hidden biases. The results show that victimization has a substantial negative effect on trust in the local police but no robust effect on informal institutions. Governments may henceforth need to redouble efforts to reduce victimization and the resulting erosion of trust in public institutions.

JEL Codes: D74, D83, H41, I39, K42, O54
Keywords: Crime, Beliefs, Trust, Social

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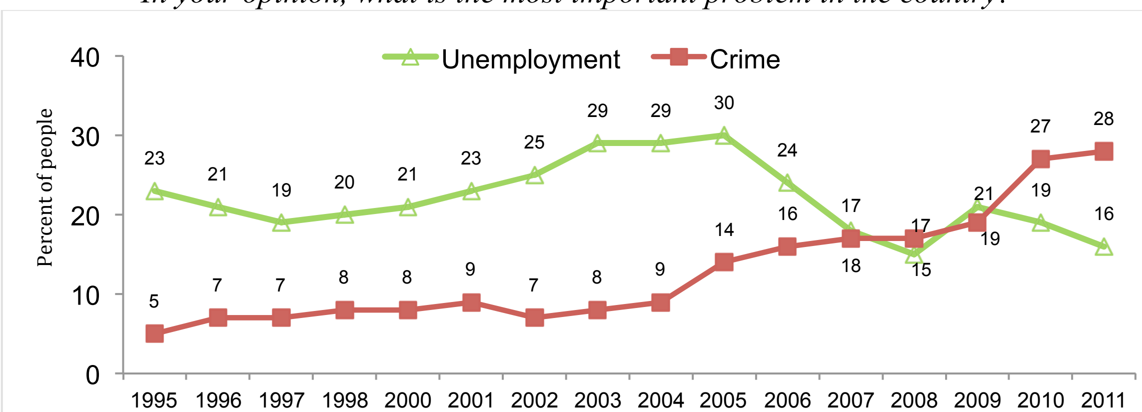
Introduction

Crime is the number one concern of citizens in Latin America. Public opinion polls for 2011 show that nearly 30 percent of respondents cite crime as the most important problem in their country, up from 5 percent in 1995, closing the gap with unemployment for the first time in recent periods (Figure 1). The World Health Organization estimates that the number of homicides committed with firearms in the region is three times the world average. Property crime is also much higher in Latin America than in other regions of the world (Figure 2).

Figure 1. Concern about Crime and Unemployment in Latin America

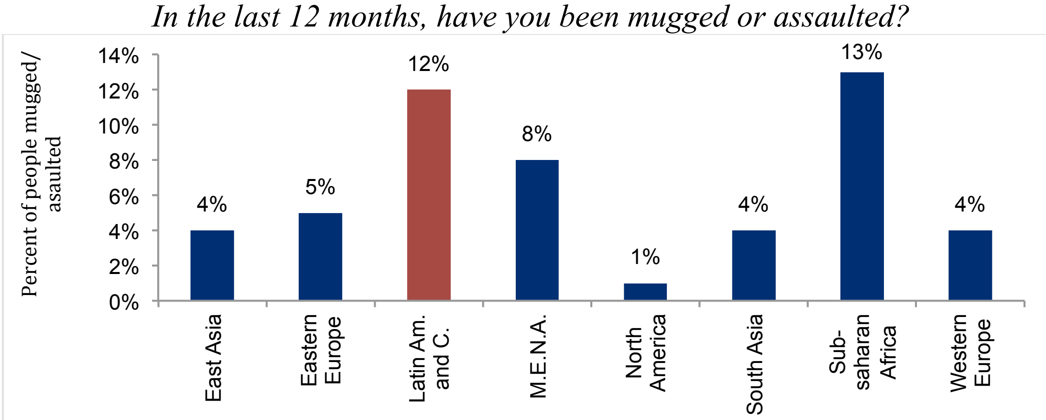
In your opinion, what is the most important problem in the country?



Source: Latinobarómetro (2011).

Figure 2. Crime Rates in Latin America and the Caribbean Compared to Other Regions

In the last 12 months, have you been mugged or assaulted?



Source: Authors' calculations based on Gallup (2007).

Crime has high direct tangible costs, including, for instance, expenditures related to public and private efforts to prevent crime, criminal justice and prison systems, and the value of goods destroyed through criminal activities.[1] But the welfare implications of crime are potentially far deeper. Crime does not only victimize individuals; it can also weaken the fabric of social life by increasing fear, suspicion, and distrust. Trust links ordinary citizens to the institutions intended to represent them. Low trust undermines collaboration and the necessary support to strengthen institutional capacity. The impact of crime on trust can thus perpetuate a vicious cycle of poor cooperation, weak institutions, and reduced economic opportunities. By reducing trust, crime can grind down the foundations of society and become an obstacle to development itself.

In this paper we aim to quantify the relationship between crime and trust in Latin America. In particular, we estimate the effect of individual victimization on different measures of trust in formal and informal institutions. Formal institutions include laws, the constitution, and State organizations, among others. Informal institutions include the behavior and customs of a society. In this paper, we analyze trust in public institutions that deal with crime, such as the police and the judiciary system. We also analyze trust in informal networks, including friends and family (called social networks throughout the paper) and business partners outside the family (called business networks throughout the paper). Finally, the paper discusses the importance of trust for improving the perception of security.

We use propensity score matching (PSM) to isolate the relationship between crime and trust that can be attributed to the experience of victimization. Combined with country fixed effects and other controls, PSM minimizes the *overt bias* in the estimates. Additionally, we quantify the sensitivity of the estimates to *hidden bias*.

Our results suggest that there is a strong negative impact of victimization on trust in the local police. Crime victims have, on average, a 10 percent lower probability of trusting the local police compared to non-victims. This is a sizable effect considering that the average probability of trusting the police in the region is about 50 percent. There is also a negative association

[1] See for instance, Londoño and Guerrero (2000), Soares (2006), and Soares (2010).

between victimization and trust in the judiciary and trust in friends and relatives. However, these results are not significant after controlling for overt biases using PSM. The impact on business networks does not appear to be significant. We also find that victimization is positively correlated with the perception of insecurity and the likelihood that people move out of their cities.

These findings have important implications for public policy. The negative impact of victimization on trust in the local police means that governments must devote even more resources to address the consequences of crime. Policies in the region need to focus on reducing the risks of actual victimization and on rebuilding trust in public institutions.

The next section of this paper briefly presents some related literature. This is followed by our data and empirical strategy, and then a discussion of the results. The final section provides conclusions.

Literature Review

This paper is related to several strands of literature. The literature on the economics of crime emphasizes cost–benefit analysis to understand individual incentives to commit crimes. Significant debate has emerged between authors that consider private incentives versus "the environment" as the main drivers of crime.[2] Both macro (e.g., inequality, poverty, and growth) and micro (e.g., sentence length, policing, and abortion laws) drivers have been subjects of analysis.[3] A more recent strand of literature has grown with the availability of victimization surveys at the micro level. These surveys have allowed researchers to study the socioeconomic determinants of victimization, where the burden of crime on society is the main empirical concern. They have also been used to correct the significant underreporting that is suspected in aggregated official crime data. A third strand of literature has been spurred by the introduction of social capital in empirical

[2] Case and Katz (1991), Glaeser et al. (1996), as well as many others; these studies usually have data on family behavior and peer interactions.

[3] Burdett et al. (2004), Garrett and Ott (2009), Grogger (1998), Raphael and Winter-Ebmer (2001) and Mustard (2010) are examples of the macro perspective, while Corman et al. (1987) and Lochner (2007) focus on the deterrence (policing) hypothesis.

studies. "Bad" social capital has been linked to an overall disruption of society reflected in corruption rates, connections of politicians to illegal activities, and the increased productivity of criminal activities, especially in poor and middle-income countries.[4] Some papers have also established that "good" social capital helps reduce crime.[5]

For the Latin American and Caribbean region, there is growing literature that uses microdata to understand victimization and the impact of crime on wellbeing.[6] Gaviria and Pagés (2002) and Gaviria and Velez (2001) focus on victimization patterns and find that middle- and high-income households are more affected by property crimes. They also establish that high crime rates in the region correlate with drug trafficking and population growth in urban areas, which overload the justice system. Medina and Tamayo (2011) find negative effects of crime (homicide rate by neighborhood) on life satisfaction. Di Tella et al. (2008), who exploit the same database as our study, look at some of the effects of victimization on well-being. In particular, they establish a correlation between being victimized and emotions, such as feeling pain, boredom, and depression. They also find that victimization affects ideological beliefs. Graham and Chaparro (2011) study the effect of victimization on happiness. They propose that people who live in high crime areas may "adapt" and report less impact of crime on happiness than otherwise. They also find a detrimental impact of victimization on health.

Some recent studies that use survey data from Latin America have examined the impact of crime victimization and insecurity on support for democracy. Fernandez and Kuenzi (2010), Cenabou et al. (2011), Paras and Coleman (2006), and Carreras (2011) find that crime victimization negatively affects satisfaction and support for democracy in the region, although not necessarily a change away from democracy.

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[4] "Bad" social capital is related to social capital used within criminal activities to augment their productivity. For example, terrorism and high-profile assassinations tend to scare people away from collaborating with the government to prosecute suspects. The widespread environment of non-cooperation with justice systems increases the business network of criminals by reducing their transaction costs. Rubio (1997) shows that, in Colombia during the 1980s and 1990s, social capital benefited illegal activities, with criminals creating connections and medium-term alliances with rivals to increase the profitability of crime.
[5] See, for example, Buonanno et al. (2009), Cuesta et al. (2007), and Deller and Deller (2010).
[6] See Di Tella et al. (2010) for a volume on the economics of crime in Latin America.

Few studies investigate the relationship between crime victimization and trust in institutions. Bateson (2010), using both original interviews in Guatemala and LAPOP data from 2008, finds that victims of crime exhibit lower levels of confidence in the judicial system and law enforcement compared to non-victims. Malone (2010) concludes that in Central American countries with high crime rates and poor justice institutions, fear of crime in the neighborhood reduces both trust in justice systems and trust in the police. Crime victimization, however, has a negative effect only on trust in the police. Ahmad et al. (2011) suggest that victimization by police corruption and crime victimization negatively affect trust in the national police. In turn, Perez (2003) shows that crime victimization reduces trust in the national civil police in El Salvador, but has no effect in Guatemala.

Our research builds on these results by implementing a more robust econometric approach and by exploring a different set of outcomes related to trust in formal and informal institutions. In particular, this paper is one of the few that controls for overt biases by implementing PSM. Moreover, we perform a host of simulations to assess sensitivity to hidden biases. These techniques allow us to discard a number of results that had been established in other papers and provide support for those results that remain significant after controlling for both overt and hidden biases.

Data and Empirical Strategy

Unfortunately, the data available on crime in Latin America is relatively scarce. Consequently, empirical work faces several methodological challenges, including measurement error, endogeneity, and omitted variable bias. To the extent permitted by the data, this paper aims to resolve some of these problems by employing PSM complemented by sensitivity analyses.

The paper uses a micro database from the World Gallup Survey for 2007. The data is based on a subset of observations for the Latin American region. The countries in our sample are Argentina, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, the Dominican Republic, Ecuador, El Salvador, Guatemala, Guyana, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, and Uruguay.

The survey provides information about individuals' victimization and socioeconomic background. It also includes respondents' attitudes toward politics, democracy, citizen collaboration, law and order, migration, well-being, health, and the environment. It is a cross-country survey with 1,000 respondents per country. The data was collected by randomly choosing telephone numbers or face-to-face visits within the Primary Sample Units. The number of observations in the empirical analysis varies between 9,000 and 17,000, depending on the specification.[7] Table A1 in Appendix A provides definitions of the main variables used in the analysis and Table A2 presents basic summary statistics.

The data contains valuable and novel information about perceptions of trust and insecurity based on a uniform questionnaire. This improves the comparability of data across countries. It also relies on self-reported experiences on victimization that have been found in the literature to be less prone to underreporting bias and measurement error compared to official crime statistics.[8] However, we found two main limitations in the data. It does not follow individuals over time and it does not include a location identifier. These characteristics severely constrain the potential to use external instruments and to control for unobserved fixed effects.

We use two variables for victimization. The first takes the value of 1 if the individual was mugged or assaulted in the past year. The second takes the value of 1 if the individual or a family member had something stolen over the same period. In principle, we expect the first variable to better measure the impact of *direct* victimization. The second variable is therefore primarily used to check the robustness of the results.

We focus on trust as our measure of the strength of institutions given that trust is gaining prominence as an important determinant of development. Trust, cooperative norms, social participation, and associations all fall within the definitions of social capital.[9] Knack and Keefer (1997) conclude that it is trust and civic cooperation—rather than associational activity—that is

[7] To ensure that the results are not being driven by any specific group of countries, we tested whether the coefficients varied by subregions within Latin America. We did not find significant differences across samples. These results are available upon request.
[8] See, for instance, Fajnzylber et al. (2000) and Soares (2006) for a discussion of measurement problems in crime data and the advantages of victimization surveys.
[9] Putnam (1993) defines social capital as features of social organization—such as networks, norms, and trust—that facilitate coordination and cooperation for mutual benefit.

linked to stronger economic performance. More recent literature increasingly emphasizes the role of trust.[10] Consequently, institutional reforms to provide better formal mechanisms for conflict resolution, enforcement of contracts, and access to opportunities acquire even more significance in environments of low interpersonal trust.

In particular, we analyze two indicators of trust in formal public institutions. The indicator variable of trust in the local police takes the value of 1 if the respondent answered positively to the question: "In the city or area where you live, do you have confidence in the local police or not?" The indicator variable of trust in the judiciary system is constructed in a similar fashion. These public institutions are closely linked to crime prevention and their perception is arguably susceptible to victimization. At the same time, low trust in these institutions can undermine incentives to report crimes to the authorities and support public policies to fight crime.

We also look at trust in informal institutions in the private sector, measured as trust in social and business networks. People who belong to such networks trust others who belong to them as well and are more likely to exhibit civic behavior. Victimization has the potential to disrupt this trust. The indicator variable on social networks takes the value of 1 if respondents answered positively to the question: "If you were in trouble, do you have relatives or friends you can count on to help you?" In turn, the indicator variable on business networks is based on the question: "Other than your family members, is there someone you trust enough to make them your partner to start a business?" The analysis of these two measures allows us to test whether victimization has an effect on the economy at the micro level through the business environment as well as through more subtle interpersonal relationships. We finally explore a few other outcomes that could indirectly affect the strength of networks, such as whether the individual is likely to move, recommend the city to a friend or associate as a place to live, or feel satisfied with the city. Table 1 presents key correlations.

[10] See, for instance, Alesina and La Ferrara (2002), Francoise and Zabojnik (2005), and Algan and Cahuc (2010).

Table 1. Correlations of Key Variables

	Mugged	Stolen	Trust in police	Trust in judiciary	Social networks	Business networks	Move away	City getting better
Mugged	1							
Stolen	0.448	1						
Trust in police	-0.110	-0.149	1					
Trust in judiciary	-0.056	-0.078	0.315	1				
Social networks	-0.014	-0.022	0.028	0.037	1			
Business networks	0.008	0.031	0.017	0.034	0.136	1		
Move away	0.072	0.075	-0.055	-0.018	-0.010	0.032	1	
City getting better	-0.062	-0.051	0.134	0.128	0.077	0.057	-0.052	1

Source: Authors' calculations.

Methodology

Our basic econometric specification proposes a relationship between crime victimization and different measures of trust. The baseline equation is:

$$Trust_{ic} = \alpha + \beta\, victimization_{ic} + \delta X_{ic} + \gamma_c + \varepsilon_{ic}$$

where ic denotes individual i in country c, X are individual controls, γ are country fixed effects, and ε_{ic} is the error term. Our baseline results are based on a probit model.

Our main goal is to estimate the parameter β in the equation above, which captures the impact of victimization on trust. The relationship could be positive or negative. Being the victim of a crime can undermine trust in public institutions that deal directly with crime prevention, such as the police and the judiciary. Victimization can also undermine trust in social and business networks by instilling fear. At the same time, however, being the victim of a crime could stimulate associational activity as a community reaction and strengthen rather than undermine social capital. The link between trust and crime is hence complex and multifaceted, and ultimately should be the subject of empirical investigation.

A challenge in the estimation of our equation for trust is potential endogeneity in our victimization variable. Given that we lack exogenous instruments (i.e., most variables that affect

victimization have a direct effect on trust in police) or an experimental design, we use PSM.[11] This technique allows us to compare victimized and non-victimized individuals that are similar in their observable characteristics, so that the only difference that remains between the two subsamples is victimization. We can thus construct a counterfactual scenario to victimization and draw inferences that are less subject to overt biases. Assuming we capture all relevant differences between those who have been victimized and those who have not, PSM yields an unbiased estimate of the impact of victimization on trust.

PSM outperforms OLS or probit estimations because once we control for certain characteristics that might influence the probability of victimization, being mugged is per se a random event at the micro level. For example, two people living in the same area, with the same age, gender, and level of income, have the same likelihood of being mugged when they step out the front door of their own home. This allows us to think of victimization as an exogenous treatment *once we account for all relevant variables*.[12]

We perform the matching in two steps. First we calculate the propensity score, which is the probability of being victimized given a set of observed covariates, for each observation using a probit model. Then we estimate the average treatment effect on the treated (ATT) conditional on the propensity score. Thus, we match each victimized individual with a non-victimized individual with a similar propensity score using common matching methods in the literature.[13]

We also add controls that aim to capture more general aspects of the quality of public institutions, the environment, and personal traits that can affect both the probability of being a victim of crime and trust. The regressions include country fixed effects to control for nationwide policies and characteristics. We also use controls at the individual level related to the perception

[11] For an introduction to propensity score matching, see, for example, Caliendo and Kopeinig (2005), Dehejia and Wahba (2002), and Heinrich et al. (2010).

[12] In this sense, being mugged is not assigned based on the expected change that individuals might experience in the dependent variable. Our estimation does not suffer from the endogeneity that occurs in the social literature, where the treatment (e.g., subsidy) is based on the expected change in the dependent variable (e.g., consumption), basically because the state wants to “treat” poor individuals to influence their consumption. As such, our setup satisfies the conditional independence assumption. We also checked the overlap assumption and the Stable Unit Treatment Value Assumption.

[13] For a description of different matching methods, see, for example, Caliendo and Kopeinig (2005) and Becker and Ichino (2002).

of widespread corruption in government and the quality of infrastructure. Dummies for urban (vs. rural) location and for the presence of gangs and illicit drug sales in the neighborhood are used as proxies for factors that are likely determinants of both trust and victimization. Finally, we add measures on volunteering and personal and socioeconomic characteristics.

Given the cross-sectional nature of the data, we are unable to control for unobservable fixed effects and thus some hidden bias may remain. While the PSM enables us to control for observed covariates, the matching estimators are not robust to a potential hidden bias. Such a hidden bias may arise if there are unobservable variables that cannot be controlled for in the matching and that simultaneously affect the probability of being victimized and our measures of trust. To address these concerns, we assess the sensitivity of the results to potential unobserved variables. More specifically, our simulations quantify the extent of hidden bias that would need to be present to change the significance of the results.[14] Our empirical strategy thus allows us to test the robustness of our results to both overt and hidden biases.

Results

As a first step, we estimate probit models using four measures of trust: trust in local police, trust in the judicial system, trust in social networks, and trust in business networks. Then we present the results using PSM. For those results that remain significant after the matching process, we perform sensitivity analysis. Finally we look at additional outcomes of interest related to perception of insecurity and incentives to move out of the city.

Probit Results

Tables 2 and 3 focus on public institutions and show that there is a significant negative relationship between victimization and trust in the local police and in the judiciary system. As could be expected, the effect is larger for the local police than for the judiciary, but they are both important in magnitude. The reported marginal effects suggest that victimized individuals have a

[14] For an introduction to sensitivity analysis for matching estimators, see, for example, Rosenbaum (2005) and Ichino et al. (2008).

lower probability of trusting the local police by around 10 percent compared to non-victims. This is a sizable reduction considering the sample probability of trusting the local police is about 50 percent, the lowest rate compared to other regions in the world (Figure 3). The reduction of trust in the judiciary system for victims is about 3 percent compared with a sample probability of 30 percent.

The results further reveal that the infiltration of gangs and drug sales are important factors in increasing the risk of crime. Adding these controls reduces the impact of victimization (from columns (4) to (6) in Tables 2 and 3), signaling positive correlation with our victimization measures. The marginal effects from gangs and drug sales are negative and highly statistically significant for trust in the local police, suggesting they directly reduce trust in public institutions. In the case of trust in the judiciary, the inclusion of drug sales takes away the effect from gangs. Victimization still retains its relevance in size and significance.

Table 2. Marginal Effects After Probit: Victimization and Trust in the Local Police

	In the city or area where you live, do you have confidence in the local police or not?								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Prob(y=1)	0.491	0.491	0.499	0.499	0.495	0.496	0.487	0.487	0.487
Mugged (dummy)	-0.1522***	-0.1522***	-0.1539***	-0.1475***	-0.1197***	-0.1089***	-0.1031***	-0.1068***	
	[0.0113]	[0.0113]	[0.0131]	[0.0134]	[0.0140]	[0.0152]	[0.0158]	[0.0158]	
Stolen (dummy)									-0.1096***
									[0.0130]
Gangs (dummy)					-0.1500***	-0.1021***	-0.0981***	-0.0994***	-0.0918***
					[0.0096]	[0.0121]	[0.0126]	[0.0126]	[0.0127]
Drug sales (dummy)						-0.1304***	-0.1186***	-0.1176***	-0.1165***
						[0.0124]	[0.0129]	[0.0129]	[0.0129]
Age (years)	0.0033***	0.0037***	0.0046***	0.0041***	0.0036**	0.0043***	0.0051***	0.0052***	0.0053***
	[0.0003]	[0.0012]	[0.0014]	[0.0014]	[0.0015]	[0.0016]	[0.0016]	[0.0016]	[0.0016]
Age squared		-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
		[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Education (years)	-0.0067***	-0.0067***	-0.0077***	-0.0063***	-0.0069***	-0.0077***	-0.0069***	-0.0074***	-0.0069***
	[0.0009]	[0.0009]	[0.0011]	[0.0012]	[0.0013]	[0.0014]	[0.0014]	[0.0014]	[0.0014]
HH head (dummy)	0.0105	0.0098	0.0144	0.0166	0.0186	0.0172	0.0143	0.0136	0.0159
	[0.0093]	[0.0095]	[0.0112]	[0.0114]	[0.0118]	[0.0127]	[0.0132]	[0.0133]	[0.0133]
Female (dummy)	-0.0029	-0.0032	-0.0011	0.0035	0.0043	-0.0013	-0.0023	-0.0029	-0.0025
	[0.0085]	[0.0085]	[0.0102]	[0.0103]	[0.0107]	[0.0115]	[0.0119]	[0.0120]	[0.0120]
Have a job (dummy)			-0.0088	0.0041	0.0068	0.0045	0.0127	0.0111	0.0088
			[0.0102]	[0.0104]	[0.0107]	[0.0115]	[0.0120]	[0.0120]	[0.0120]
Log income PPP			0.0050	0.0014	-0.0006	0.0046	0.0011	-0.0002	0.0007
			[0.0047]	[0.0051]	[0.0052]	[0.0056]	[0.0058]	[0.0059]	[0.0059]
Urban (dummy)				-0.0668***	-0.0437***	-0.0279**	-0.0359***	-0.0330***	-0.0326***
				[0.0098]	[0.0103]	[0.0112]	[0.0117]	[0.0117]	[0.0117]
Roads (dummy)							0.1082***	0.1078***	0.1069***
							[0.0106]	[0.0107]	[0.0107]
Corruption (dummy)							-0.0790***	-0.0808***	-0.0784***
							[0.0137]	[0.0137]	[0.0137]
Volunteer (dummy)								0.0557***	0.0562***
								[0.0129]	[0.0129]
Country effects	no	no	no	yes	yes	yes	yes	yes	yes
Observations	16,967	16,967	12,806	12,805	12,098	10,538	9,746	9,709	9,729
P-value for chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

Table 3. Marginal Effects After Probit: Victimization and Trust in the Judicial System

	In your country, do you have confidence in the judicial system and courts?								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Prob(y=1)	0.321	0.320	0.316	0.307	0.306	0.308	0.294	0.293	0.293
Mugged (dummy)	-0.0691***	-0.0697***	-0.0691***	-0.0523***	-0.0437***	-0.0393***	-0.0299**	-0.0326**	
	[0.0104]	[0.0104]	[0.0119]	[0.0125]	[0.0131]	[0.0142]	[0.0146]	[0.0146]	
Stolen (dummy)									-0.0432***
									[0.0120]
Gangs (dummy)					-0.0582***	-0.0207*	-0.0101	-0.0102	-0.0067
					[0.0091]	[0.0115]	[0.0118]	[0.0118]	[0.0119]
Drug sales (dummy)						-0.0923***	-0.0781***	-0.0789***	-0.0794***
						[0.0116]	[0.0119]	[0.0119]	[0.0119]
Age (years)	-0.0000	-0.0050***	-0.0043***	-0.0042***	-0.0046***	-0.0028**	-0.0025*	-0.0025*	-0.0024
	[0.0002]	[0.0011]	[0.0013]	[0.0013]	[0.0013]	[0.0014]	[0.0015]	[0.0015]	[0.0015]
Age squared		0.0001***	0.0000***	0.0000***	0.0001***	0.0000**	0.0000	0.0000	0.0000
		[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Education (years)	-0.0140***	-0.0136***	-0.0162***	-0.0113***	-0.0116***	-0.0120***	-0.0113***	-0.0118***	-0.0116***
	[0.0008]	[0.0008]	[0.0010]	[0.0011]	[0.0012]	[0.0012]	[0.0013]	[0.0013]	[0.0013]
HH head (dummy)	0.0040	0.0128	0.0175*	-0.0023	-0.0014	-0.0080	-0.0101	-0.0123	-0.0111
	[0.0088]	[0.0090]	[0.0105]	[0.0106]	[0.0109]	[0.0117]	[0.0121]	[0.0121]	[0.0121]
Female (dummy)	-0.0032	0.0010	0.0022	0.0008	0.0002	-0.0061	-0.0113	-0.0103	-0.0092
	[0.0080]	[0.0080]	[0.0095]	[0.0096]	[0.0099]	[0.0107]	[0.0110]	[0.0110]	[0.0110]
Have a job (dummy)			-0.0140	-0.0082	-0.0077	-0.0092	-0.0082	-0.0098	-0.0101
			[0.0095]	[0.0096]	[0.0099]	[0.0107]	[0.0110]	[0.0110]	[0.0110]
Log income PPP			0.0110**	-0.0145***	-0.0154***	-0.0130**	-0.0160***	-0.0167***	-0.0166***
			[0.0044]	[0.0047]	[0.0049]	[0.0052]	[0.0054]	[0.0054]	[0.0054]
Urban (dummy)				-0.0638***	-0.0545***	-0.0456***	-0.0534***	-0.0489***	-0.0495***
				[0.0094]	[0.0097]	[0.0105]	[0.0108]	[0.0109]	[0.0108]
Roads (dummy)							0.1102***	0.1091***	0.1090***
							[0.0097]	[0.0097]	[0.0097]
Corruption (dummy)							-0.1488***	-0.1493***	-0.1484***
							[0.0134]	[0.0134]	[0.0134]
Volunteer (dummy)								0.0690***	0.0689***
								[0.0124]	[0.0123]
Country effects	no	no	no	yes	yes	yes	yes	yes	yes
Observations	16,615	16,615	12,610	12,609	11,913	10,384	9,667	9,632	9,651
P-value for chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

Table 4. Marginal Effects After Probit: Victimization and Trust in Social and Business Networks

	Social networks				Business networks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prob(y=1)	0.862	0.863	0.867	0.868	0.514	0.521	0.530	0.531
Mugged (dummy)	-0.0242**	-0.0214**	-0.0216*		-0.0077	-0.0178	-0.0242	
	[0.0099]	[0.0109]	[0.0111]		[0.0140]	[0.0155]	[0.0159]	
Stolen (dummy)				-0.0284***				0.0128
				[0.0092]				[0.0131]
Gangs (dummy)		0.0040	0.0026	0.0039		0.0118	0.0084	0.0080
		[0.0084]	[0.0086]	[0.0086]		[0.0123]	[0.0127]	[0.0127]
Drug sales (dummy)		-0.0263***	-0.0247***	-0.0243***		0.0050	0.0077	0.0046
		[0.0087]	[0.0088]	[0.0088]		[0.0126]	[0.0130]	[0.0129]
Age (years)	-0.0090***	-0.0086***	-0.0090***	-0.0090***	-0.0037***	-0.0035**	-0.0037**	-0.0037**
	[0.0010]	[0.0011]	[0.0011]	[0.0011]	[0.0014]	[0.0016]	[0.0016]	[0.0016]
Age squared	0.0001***	0.0001***	0.0001***	0.0001***	0.0000	0.0000	0.0000	0.0000
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Education (years)	0.0046***	0.0050***	0.0048***	0.0048***	0.0115***	0.0113***	0.0103***	0.0103***
	[0.0008]	[0.0009]	[0.0009]	[0.0009]	[0.0012]	[0.0013]	[0.0014]	[0.0014]
HH head (dummy)	-0.0334***	-0.0295***	-0.0276***	-0.0273***	-0.0157	-0.0227*	-0.0265**	-0.0262**
	[0.0077]	[0.0085]	[0.0088]	[0.0087]	[0.0115]	[0.0126]	[0.0131]	[0.0131]
Female (dummy)	-0.0072	-0.0035	-0.0046	-0.0042	-0.0623***	-0.0649***	-0.0648***	-0.0646***
	[0.0070]	[0.0077]	[0.0079]	[0.0079]	[0.0104]	[0.0114]	[0.0118]	[0.0118]
Have a job (dummy)	0.0024	0.0070	0.0062	0.0067	0.0162	0.0181	0.0157	0.0134
	[0.0071]	[0.0077]	[0.0080]	[0.0080]	[0.0104]	[0.0114]	[0.0118]	[0.0118]
Log income PPP	0.0431***	0.0412***	0.0383***	0.0384***	0.0318***	0.0298***	0.0275***	0.0272***
	[0.0034]	[0.0037]	[0.0038]	[0.0038]	[0.0051]	[0.0056]	[0.0058]	[0.0058]
Urban (dummy)	-0.0151**	-0.0081	-0.0059	-0.0050	-0.0203**	-0.0169	-0.0182	-0.0189
	[0.0066]	[0.0075]	[0.0078]	[0.0077]	[0.0100]	[0.0112]	[0.0116]	[0.0116]
Roads (dummy)			0.0137*	0.0131*			0.0329***	0.0327***
			[0.0071]	[0.0071]			[0.0107]	[0.0107]
Corruption (dummy)			-0.0075	-0.0064			0.0142	0.0121
			[0.0089]	[0.0089]			[0.0138]	[0.0138]
Volunteer (dummy)			0.0273***	0.0268***			0.0596***	0.0583***
			[0.0080]	[0.0080]			[0.0127]	[0.0127]
Country effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	13,180	10,775	9,893	9,914	12,724	10,467	9,648	9,667
P-value for chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

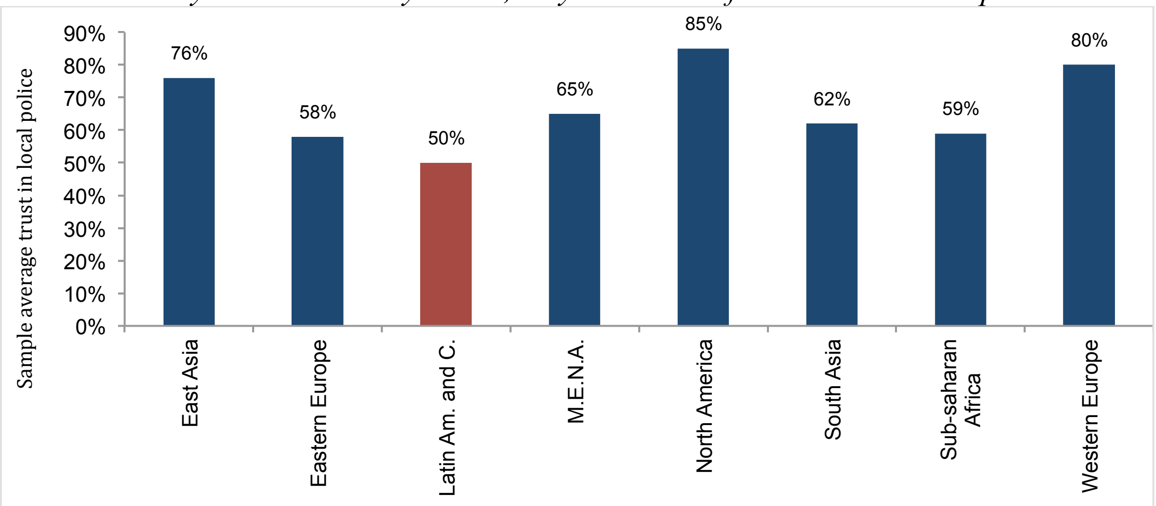
Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations.

Figure 3. Trust in the Local Police in Latin America and the Caribbean Compared to Other Regions

In the city or area where you live, do you have confidence in the local police?



Source: Authors' calculations based on Gallup (2007).

Table 4 presents regressions with trust in social and in business networks as the dependent variable. The correlation of social networks with victimization is negative and significant at the 10 percent level, suggesting that being victimized is associated with a lower probability of counting on a friend or relative in case of trouble. However, the effect is small compared to the sample probability of trusting friends of around 85 percent. Crime victims have, on average, a 2 percent lower probability of trusting friends compared to non-victims. With respect to business networks, the marginal effects of victimization are negative but not statistically significant.

Looking at the other covariates in Tables 2 to 4, the effect of age on trust is mixed. While older age positively affects trust in the local police, it negatively affects trust in the judiciary as well as in social and business networks. Furthermore, individuals with more years of education tend to trust less in the police and the judiciary. In contrast, more education increases trust in friends and in business networks. A similar, yet less pronounced, trend occurs with the income variable, which has no effect on trust in local police, lowers trust in the judiciary, and increases trust in others. Having a job is not statistically significant in any of the regressions. There are no gender differences, except when it comes to trust in business networks, where there is a slightly negative effect for women.

The coefficient on the dummy variable for living in an urban area is highly statistically significant and negative for trust in public institutions but insignificant for trust in others. Trust in public institutions is positively associated with satisfaction with road infrastructure and negatively associated with perceptions of corruption in government. By including infrastructure and corruption variables, we aim to control for the overall satisfaction with public services and quality of public institutions.[15] If not included, the effect of victimization might be overestimated (as in columns (1) to (5)), mainly because the previously omitted variable (quality of institutions) has a direct effect on trust and is correlated to included covariates.

We also find that people who volunteer are on average more likely to trust public institutions and informal networks. Our variable on volunteering aims to control for some inherent individual attitudes that could be correlated with both victimization and trust. For instance, people with more trust in the state who actively participate in the community may have political mechanisms to reduce crime rates at the local level.

Column (9) of Tables 2 and 3, and columns (4) and (8) of Table 4 include the same covariates as the previous column of each table but with having had something stolen as the measure of victimization. The results are very similar. There is a negative and significant effect of having had something stolen on trust in the police, trust in the judiciary, and trust in friends. There is no significant effect of having had something stolen on trust in business networks.

Propensity Score Matching Results

As a first step in PSM, we estimate the propensity score using a probit model. The results are shown in Table 5. All observations are on support (Figure 4). Several variables are significantly associated with victimization. Younger age, being male, living in an urban area, the perceived presence of gangs and drug sales, dissatisfaction with roads, government corruption, and volunteering are significantly and positively associated with victimization. The variables that have the strongest association with victimization are living in an urban area and the presence of gangs, with the presence of drug sales following in magnitude.

[15] In addition to satisfaction with roads and perceptions of government corruption, we explored other specifications, including variables measuring satisfaction with public transportation, the educational system, and the availability of quality health care. We included indices of all these variables based on principal component analysis and on simple sums of the binary variables. Since all measures gave similar results, we only report satisfaction with roads and perceptions of corruption.

Table 5. Probit Estimates of the Propensity to Be Mugged

Dependent variable: mugged	Coefficient	Standard error
Age (years)	-0.0094*	[0.0053]
Age squared	0.0001	[0.0001]
Education (years)	0.0069	[0.0045]
HH head (dummy)	0.0174	[0.0423]
Female (dummy)	-0.0817**	[0.0376]
Have a job (dummy)	0.0421	[0.0379]
Log income PPP	0.0223	[0.0192]
Urban (dummy)	0.3746***	[0.0390]
Gangs (dummy)	0.3377***	[0.0405]
Drug sales (dummy)	0.1630***	[0.0412]
Roads (dummy)	-0.1357***	[0.0342]
Corruption (dummy)	0.1015**	[0.0461]
Volunteer (dummy)	0.1013**	[0.0401]
Constant	-1.6290***	[0.2552]
Country effects	yes	
Observations	9,966	
Log likelihood	-3533.8238	

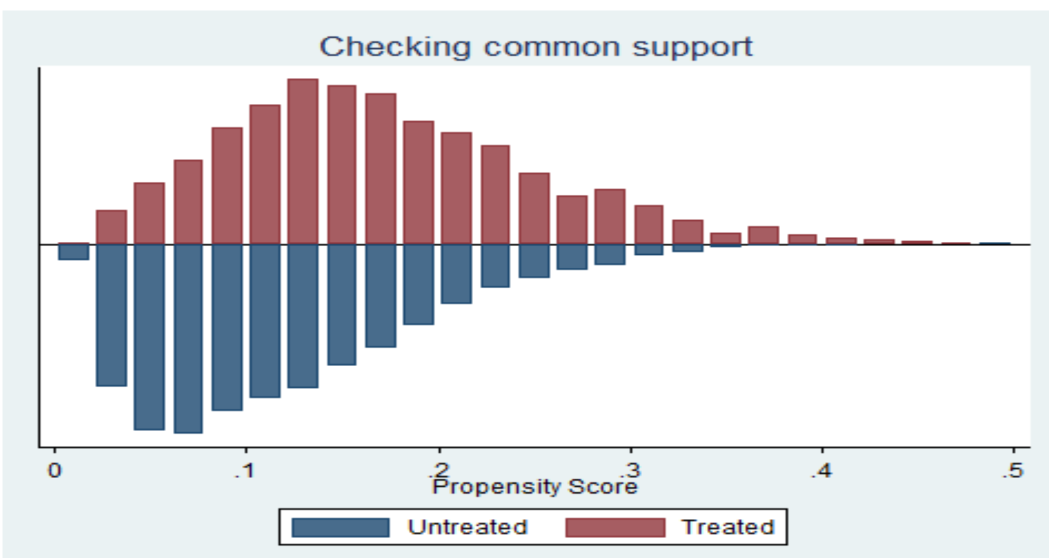
*** p<0.01, ** p<0.05, * p<0.1

Region of common support: [0.0192, 0.4777]

Propensity score: Mean 0.127, Standard Deviation 0 .0750

Source: Authors' calculations.

Figure 4. Common Support of Overlap Region



Source: Authors' calculations.

To compute the average treatment effect on the treated (ATT) in the second step of the PSM, we chose different matching algorithms, namely nearest neighbor matching, nearest neighbor matching without replacement, 50 nearest neighbor matching, and radius matching. Table 6 shows that the matching was successful in reducing the mean standardized bias (last two columns) from around 10 percent to around 3 percent or below in all cases.[16]

In the regression with local police as the dependent variable, the results are in line with the results from the probit models and thus confirm their robustness. Individuals that have been mugged are on average roughly 10 percent less likely to exhibit trust in the local police. These results are highly statistically significant. For both trust in the judiciary and trust in social networks, the impact of victimization is not robust to the matching. There is a statistically significant effect for only two of the four matching methods.[17] For trust in business networks, the PSM results confirm the results obtained from the probit estimations: there is generally no significant effect of victimization on trust in business networks.

Table A3 in Appendix A shows the differences in means before and after matching for the 50 nearest neighbor matching with trust in the police as the outcome variable. The table reveals that matching successfully balances the distributions of the covariates in the victimized and non-victimized subsamples. The standardized bias is successfully reduced, from a mean of 9.8 before the matching to a mean of 0.7 after the matching (last two rows of Table A3). Furthermore, the t-test on the hypothesis that the mean value of each variable is the same for the two subsamples cannot be rejected for any of the variables after the matching.

In sum, the results of the PSM show that the effect of victimization on trust in the judiciary and trust in social networks is negative but small and at most significant at the 10 percent level. The results further confirm that there is no effect of victimization on trust in business networks. Finally, the results give confidence that there is indeed a large and highly

[16] The standardized bias for each covariate X is defined as the difference of sample means in the treated and matched control subsamples as a percentage of the square root of the average of sample variances in both groups. A bias reduction to below 3 percent or 5 percent is usually seen as sufficient (Caliendo and Kopeinig, 2005).

[17] This result is in line with Malone (2010), who finds that victimization in Central American countries affects trust in the police but not trust in the judiciary.

statistically significant effect of victimization on trust in the local police. This seems intuitive, since the local police are most directly involved with handling crime and hence being victimized can undermine trust in this public institution.

Table 6. Propensity Score Matching Results: Average Treatment Effects on the Treated (ATT)

Outcome: trust variable	Matching algorithm	ATT		Standard error	Bias before matching	Bias after matching
Police	NN (nearest neighbor)	-0.1219	***	0.0212	9.847	2.981
	NN without replacement	-0.1082	***	0.0196	9.847	1.929
	50 nearest neighbors	-0.1046	***	0.0152	9.847	0.717
	Radius	-0.0993	***	0.0151	9.847	0.782
Judiciary	NN (nearest neighbor)	-0.0301		0.0194	9.947	2.895
	NN without replacement	-0.0252		0.0178	9.947	2.032
	50 nearest neighbors	-0.0272	*	0.0140	9.947	0.736
	Radius	-0.0268	*	0.0139	9.947	0.742
Friends	NN (nearest neighbor)	-0.0199		0.0156	9.874	2.969
	NN without replacement	-0.0136		0.0147	9.874	1.878
	50 nearest neighbors	-0.0222	*	0.0116	9.874	0.645
	Radius	-0.0226	*	0.0116	9.874	0.685
Business	NN (nearest neighbor)	-0.0341		0.0216	9.940	3.004
	NN without replacement	-0.0365	*	0.0201	9.940	2.003
	50 nearest neighbors	-0.0246		0.0158	9.940	0.765
	Radius	-0.0233		0.0157	9.940	0.794

Source: Authors' calculations.

Sensitivity Analyses

While the matching appears to successfully balance the distribution of covariates between the victimized and non-victimized subsamples, PSM only controls for observable covariates and can thus only eliminate overt biases. The concern that there is some hidden bias, caused by an unobservable variable that influences our results, remains.

To address this concern, we implement two types of sensitivity analysis. We do so only for the estimations that use trust in the local police as the outcome variable, since only these results are robust after matching. While it is impossible to prove that a hidden bias is present or

absent, a sensitivity analysis yields insights into how much hidden bias would need to be present to invalidate the results obtained from the matching analysis.

Table 7. Sensitivity to Unobserved Biases (Rosenbaum Bounds)

Trust in the local police		
Gamma Γ	p_mh+	p_mh-
1	< 0.0001	< 0.0001
1.05	< 0.0001	< 0.0001
1.1	< 0.0001	< 0.0001
1.15	< 0.0001	0.0001
1.2	< 0.0001	0.0007
1.25	< 0.0001	0.0033
1.3	< 0.0001	0.0125
1.35	< 0.0001	0.0373
1.4	< 0.0001	0.0900
1.45	< 0.0001	0.1802
1.5	< 0.0001	0.3075

Γ : odds of differential assignment due to unobserved factors

p_mh+ : significance level (assumption: overestimation of treatment effect)

p_mh- : significance level (assumption: underestimation of treatment effect)

Source: Authors' calculations.

Table 7 shows the results of the sensitivity analysis on hidden bias based on the bounding approach proposed by Rosenbaum (2002).[18] Γ is defined in terms of the odds of receiving treatment and equals 1 for randomized experiments. In an observational study, Γ may be larger than 1 and the victimized and non-victimized subsamples may differ in their odds of receiving treatment by that factor. The bigger Γ gets, the further the study differs from an experimental setup and the wider the range of possible p-values because of the uncertainty caused by potential hidden bias. Looking at a conventional p-value of 0.05, Table 7 shows that the critical level of gamma, at which our conclusion of a negative effect of victimization on trust in the local police may be questioned, lies between 1.35 and 1.40. This implies that, if we fail to account for an unobserved variable associated with a 35 percent increase in the odds of victimization and if that

[18] The analysis is based on nearest neighbor matching without replacement. For an intuitive explanation of the methodology, see Rosenbaum (2005).

variable had a strong relationship with the outcome variable (trust), then the significance level for the coefficient on victimization after adjusting for the unobserved variable lies somewhere between 0.000 and 0.0373 (see Table 7). In other words, our results would still be valid even in the presence of an unobserved variable that is both strongly related to trust in the police and Γ = 1.35 times more common among victimized individuals. Therefore, moderate hidden biases cannot explain the observed association between victimization and trust in the local police.

To investigate which potential variables might be strongly correlated to trust in the local police and 40 percent more common among victims compared to the non-victims (and thus invalidate our results), we look at the literature on the sources of trust in institutions. Devos et al. (2002) find that the level of trust in institutions depends on value priorities, such as openness to change or preservation of traditional practices. The authors further find that differences in these value priorities are the reason why religious and right-wing people exhibit more trust in institutions than non-religious and left-wing individuals. Since we have no data on value priorities, we investigate differences in religious affiliation and political affiliation. Table A4 in Appendix A reveals that there are no statistically significant differences in political orientation or religious affiliation among victims and non-victims. Hence, these variables are unlikely sources of hidden bias.

Another paper that investigates the origins of political trust is Mishler and Rose (2001). By analyzing political trust in post-communist societies, the authors find strong support for theories emphasizing that trust in institutions is correlated to individual evaluations of institutions' performance. This implies that satisfaction with public services may be a potential source of hidden bias. Additionally, personality traits that influence individual evaluations of institutions' performance might be a source of hidden bias.

Therefore, we identify satisfaction with public services and inherent personality traits as variables that might invalidate our results. For example, it is possible that an individual is inherently anxious or depressed and exhibits behavior that makes him or her more likely to be victimized. If, at the same time, this individual is less likely to trust the local police because of his or her anxiety or depression, this is an unobserved variable that may invalidate our results. A high satisfaction with public services such as infrastructure may be associated with a lower probability of being victimized, since good infrastructure contributes to better citizen security. If,

at the same time, individuals that are satisfied with public services are more likely to trust the police, this might be a source of hidden bias. To address these concerns, we implement another type of sensitivity analysis (Table 8).[19] The goal is to simulate the distribution of an unobserved variable that might generate the problems detailed above.

In this sensitivity analysis, which is based on Nannicini (2007), we assume that the conditional independence assumption (CIA: outcome in case of no treatment is independent of treatment assignment) no longer holds, but holds given the covariates and an additional, unobserved binary variable u. We choose the four parameters p_{ij}[20] and can thus describe the distribution of the confounding factor u that we simulate. The simulated u is then treated as all the other covariates. We repeat the matching estimation 100 times and estimate a simulated value of the ATT. We are thus able to calculate an estimate of the ATT, which is robust to a specific kind of hidden bias (i.e., a hidden bias specified by the four parameters p_{ij}). As the baseline ATT, we use the estimate from the single nearest neighbor matching, which has a coefficient of -12.1 percent. We simulate confounders that behave like the covariates included in the matching. To address the concerns mentioned above, we also simulate confounding variables that approximate feelings, mobility, and satisfaction with public services.

Table 8 shows that the inclusion of the confounding factors leads to a reduction of the effect of victimization on trust in the police of 2 to 4 percentage points compared to the baseline estimate of -12.1 percent. While this is quite a large reduction, in all of the cases with simulated confounders, the effect of victimization remains sizable and highly statistically significant. This indicates that our results on trust in the local police are robust to potential hidden biases caused by variables similar to the ones included in the matching, as well as variables approximating feelings, mobility, and satisfaction with public services.

[19] For a detailed explanation of the methodology, see Ichino et al. (2008).
[20] See Table 8 for a definition of p_{ij}.

Table 8. Sensitivity Analysis Using Simulated Confounding Variables

	Fraction U = 1 by treatment/outcome							
Trust in the local police	p11	p10	p01	p00	Outcome effect Γ	Selection effect Λ	ATT	SE
No confounder	-	-	-	-	-	-	-0.121 ***	0.021
Neutral confounder	0.50	0.50	0.50	0.50	1.007	1.016	-0.097 ***	0.026
HH head	0.48	0.43	0.47	0.40	1.307	1.066	-0.101 ***	0.025
Female	0.51	0.51	0.56	0.57	0.989	0.808	-0.098 ***	0.025
Have a job	0.44	0.44	0.39	0.41	0.933	1.184	-0.099 ***	0.026
Urban	0.71	0.76	0.56	0.63	0.736	1.967	-0.090 ***	0.026
Gangs	0.53	0.70	0.37	0.53	0.513	2.105	-0.072 ***	0.027
Drug sales	0.47	0.65	0.35	0.52	0.492	1.779	-0.075 ***	0.025
Roads	0.61	0.46	0.64	0.50	1.810	0.836	-0.091 ***	0.026
Corruption	0.79	0.87	0.75	0.84	0.577	1.294	-0.093 ***	0.027
Volunteer	0.27	0.21	0.22	0.19	1.167	1.201	-0.100 ***	0.025
More days like yesterday	0.79	0.69	0.82	0.75	1.539	0.773	-0.095 ***	0.026
Smiled yesterday	0.82	0.76	0.84	0.81	1.268	0.794	-0.095 ***	0.026
Worry yesterday	0.38	0.50	0.36	0.41	0.797	1.346	-0.095 ***	0.026
Sadness yesterday	0.25	0.33	0.21	0.26	0.792	1.430	-0.095 ***	0.026
Depression yesterday	0.19	0.20	0.13	0.15	0.849	1.446	-0.096 ***	0.025
Anxiety	0.18	0.26	0.16	0.20	0.767	1.425	-0.091 ***	0.026
Mobility	0.12	0.10	0.11	0.09	1.247	1.150	-0.097 ***	0.026
Satisfied with public transportation	0.67	0.53	0.74	0.58	2.003	0.752	-0.087 ***	0.026
Satisfied with educational system	0.76	0.55	0.79	0.63	2.254	0.721	-0.086 ***	0.026

pij = Pr(U = 1 | T = i, Y = j), with i, j = {0,1}
Based on nearest neighbor matching
100 iterations
Γ = outcome effect (effect of U on the untreated outcome, controlling for observable covariates)
Λ = selection effect (effect of U on assignment to treatment, controlling for observable covariates)
Both Γ and Λ are odds ratios from logit estimations.
***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively

Source: Authors' calculations

The two confounding factors that most reduce the impact of victimization on trust are the presence of gangs and drug sales. In line with the results obtained from the probit estimations, the sensitivity analysis confirms that the perception of the presence of gangs and drug sales has an effect on trust in the local police, independent from victimization. This can be interpreted as follows. If there exists a variable that has a similar distribution and effect as the variables perception of gangs and perception of drug sales, and if we control for them in the matching, the coefficient of victimization would be reduced from −12.1 percent to approximately −8 percent.

In sum, this sensitivity analysis indicates that our results are robust to a number of potential hidden biases, including those caused by personality traits and institutional performance. The impact of victimization on trust in the local police remains sizable and statistically significant. This is in line with the sensitivity analysis based on the Rosenbaum bounds. We can thus conclude that the effect of victimization on trust in the local police is not highly sensitive to hidden bias and that it is unlikely that a hidden bias exists that is both 40 percent more common among victims and a strong predictor of trust.

Additional Results

Table 9 explores other variables that could be affected by victimization. We find that victimization is positively correlated to the probability of moving away from the city, potentially disrupting existing networks. It is also negatively related to the probability of recommending the city to a relative or associate, potentially weakening future networks. Moreover, victimization generally contributes to dissatisfaction in the city and perceptions of the city getting worse as a place to live.

Our final exploration deals with the relationship between trust, victimization, and the perception of security (Table 10). We estimate a probit model where the dependent variable takes the value of 1 if the respondent indicates she feels safe walking alone at night in the neighborhood. We include as controls victimization and our measures of trust, as well as individual and environment characteristics. Victims of a crime have a lower probability of feeling safe of around 20 percent compared to non-victims. This is a sizable effect considering the sample probability of feeling safe is about 47 percent. Our results also suggest that, controlling for victimization, lack of trust in public institutions and informal networks has a compounding negative effect on the perception of security. The impact is particularly large in the case of trust in the police, even surpassing the direct effect of victimization. These results suggest that, to increase citizens' perception of security, the objective phenomenon of crime clearly matters. Yet, the efficacy of formal and informal institutions in promoting trust in the state and in others can be as relevant as crime itself, and the erosion of trust is as important as victimization in determining feelings of insecurity.

Table 9. Victimization and Other Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Move away	Move away	Recommend city	Recommend city	Satisfied with city	Satisfied with city	Area/city getting better	Area/city getting better
Prob(y=1)	0.198	0.198	0.788	0.788	0.851	0.851	0.559	0.559
Mugged	0.0668***		-0.0673***		-0.0481***		-0.0556***	
	[0.0130]		[0.0129]		[0.0114]		[0.0152]	
Stolen		0.0387***		-0.0631***		-0.0498***		-0.0440***
		[0.0103]		[0.0106]		[0.0094]		[0.0126]
Gangs	0.0349***	0.0356***	-0.0800***	-0.0783***	-0.0722***	-0.0694***	-0.0571***	-0.0556***
	[0.0084]	[0.0084]	[0.0085]	[0.0085]	[0.0075]	[0.0075]	[0.0105]	[0.0105]
Trust in police	-0.0151*	-0.0162**	0.0842***	0.0825***	0.0831***	0.0813***	0.1164***	0.1180***
	[0.0083]	[0.0083]	[0.0083]	[0.0083]	[0.0073]	[0.0073]	[0.0102]	[0.0102]
Social networks	-0.0292**	-0.0290**	0.0668***	0.0647***	0.0797***	0.0766***	0.0750***	0.0752***
	[0.0121]	[0.0121]	[0.0123]	[0.0123]	[0.0116]	[0.0115]	[0.0143]	[0.0143]
Country effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	10,425	10,450	10,706	10,730	10,634	10,659	10,657	10,683

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Regressions include controls for age, age squared, years of education, household head, gender, income, employment, urban location, individual perceptions of corruption, satisfaction with roads, and negativism.

Persistent negativism is defined as: "Once again imagine a ladder with steps numbered from zero at the bottom to ten at the top. Suppose the top of the ladder represents the best possible situation for (country x) and the bottom represents the worst possible situation. What is the number of the step on which you think (country x) stood about five years ago?". From this variable, we subtract the same question posed for how the person felt at the time of the interview. A positive value of this difference means that the person thinks the country is worse than five years ago. We interpret this as being negative, since LAC countries were emerging from the 1999-2001 crisis in the previous five years and were experiencing economic growth in 2007.

Source: Authors' calculations.

Table 10. Victimization, Trust, and Perception of Security

	Do you feel safe walking alone at night in the city or area where you live?						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prob(y=1)	0.472	0.472	0.476	0.474	0.473	0.476	0.474
Mugged	-0.2200***	-0.1762***	-0.1850***	-0.1891***			
	[0.0132]	[0.0152]	[0.0149]	[0.0147]			
Stolen					-0.1568***	-0.1723***	-0.1737***
					[0.0127]	[0.0124]	[0.0123]
Gangs		-0.2301***	-0.2511***	-0.2518***	-0.2254***	-0.2446***	-0.2454***
		[0.0104]	[0.0102]	[0.0101]	[0.0105]	[0.0102]	[0.0101]
Social networks		0.0348**	0.0410***		0.0299**	0.0361**	
		[0.0149]	[0.0147]		[0.0148]	[0.0146]	
Trust in police		0.2773***			0.2753***		
		[0.0102]			[0.0102]		
Trust in judiciary			0.1192***			0.1150***	
			[0.0117]			[0.0117]	
Business networks				0.0316***			0.0369***
				[0.0105]			[0.0105]
Country effects	no	yes	yes	yes	yes	yes	yes
Observations	11,543	10,628	10,536	10,636	10,654	10,559	10,660

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Regressions include controls for age, age squared, years of education, household head, gender, income, employment, urban location, individual perceptions of corruption, satisfaction with roads, and negativism.

Persistent negativism is defined as: "Once again imagine a ladder with steps numbered from zero at the bottom to ten at the top. Suppose the top of the ladder represents the best possible situation for (country x) and the bottom represents the worst possible situation. What is the number of the step on which you think (country x) stood about five years ago?". From this variable, we subtract the same question posed for how the person felt at the time of the interview. A positive value of this difference means that the person thinks the country is worse than five years ago. We interpret this as being negative, since LAC countries were emerging from the 1999-2001 crisis in the previous five years and were experiencing economic growth in 2007.

Source: Authors' calculations.

Conclusion

This paper explores the relationship between individual experiences of victimization and trust in formal and informal institutions in a sample of 19 Latin American countries. We used propensity score matching combined with country dummies, neighborhood traits, and individual controls to minimize the overt bias in the estimates. We complemented the matching with a sensitivity analysis that asked how sensitive the results were to the potential presence of hidden bias. By employing a more robust econometric approach and by analyzing a complete set of trust outcomes, this paper has contributed to the scarce literature on the relationship between crime and trust in formal and informal institutions.

Our results show that victims of crime are less likely to trust the local police. The probability of trusting the local police is roughly 10 percent lower among victims, a significant reduction from already low levels of trust in the local police in the region. The results are robust to the inclusion of additional control variables, to matching, and to moderate hidden biases. Our results further show that the impact of victimization on trust in the judiciary and trust in social and business networks are marginal at best.

We also found a significant correlation between crime and behaviors that may undermine institutional effort, such as moving away from the city and not recommending the city to others. Victimization was also positively and significantly correlated to fear of crime. These additional results suggest that crime increases the distance between citizens and public institutions.

Reducing crime and its spillover effects on social welfare are core challenges in the policy agenda of Latin America today. Our results suggest that in environments of low trust, governments must work even harder to address the consequences of crime. Public programs to fight crime will not be as effective in the eyes of citizens, and collaboration to report crime and work with the police will be lower. In addition, governments will have to spend more money to improve the perception of public institutions, adding further burden to the already high costs of crime in the region. Policies in the region clearly need to focus on reducing risks of victimization, as well as on rebuilding trust in public institutions.

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Appendix A: Tables

Table A1. Definition of Variables

Variables	Description
Dependent variables	
Trust in local police	1 if respondent has confidence in the local police, 0 otherwise
Trust in judicial system	1 if respondent has confidence in the judicial system and courts, 0 otherwise
Trust in social networks	1 if respondent has friends to count on when in trouble, 0 otherwise
Trust in business networks	1 if respondent has someone other than family members to trust enough to make them a business partner, 0 otherwise
Independent variables	
Stolen	1 if respondent has had money or property stolen in the last 12 months, 0 otherwise
Mugged	1 if respondent has been assaulted or mugged in the last 12 months, 0 otherwise
Gangs	1 if respondent indicates that there are gangs in the area, 0 otherwise
Drug sales	1 if respondent indicates that there is illicit drug trafficking or drug sales in the area, 0 otherwise
Age	Age in years
Age squared	The square of age in years
Education	Years of education (0, 7, 12, and 15 years for having no education, complete primary school, high school, or tertiary education, respectively)
HH head	1 if respondent is the head of the household, 0 otherwise
Female	1 if respondent if female, 0 otherwise
Have a job	1 if respondent currently has a job or work (either paid or unpaid), 0 otherwise
Log income PPP	Log of monthly per capita income, PPP
Urban	1 if respondent lives in an urban area, 0 otherwise
Roads	1 if respondent is satisfied with the roads and highways in the area, 0 otherwise
Corruption	1 if respondent indicates that corruption in the government is widespread, 0 otherwise
Volunteer	1 if respondent has volunteered in the past month, 0 otherwise

Table A2. Summary Statistics

Mean and standard deviation (below)

	Trust in police	Trust in judiciary	Trust in social networks	Trust in business networks	Safe walking	Mugged	Stolen	Age	Education	HH head	Female	Have a job	Log income PPP	Urban	Gangs	Drug sales	Roads	Corruption	Volunteer
Argentina	0.447	0.284	0.844	0.566	0.444	0.118	0.229	40.429	8.840	0.429	0.585	0.476	5.636	0.816	0.615	0.594	0.451	0.878	0.124
	0.498	0.452	0.363	0.496	0.497	0.322	0.420	17.412	3.728	0.496	0.493	0.500	0.885	0.388	0.487	0.492	0.498	0.327	0.330
Belize	0.442	0.346	0.923	0.615	0.500	0.115	0.135	31.596	8.500	0.404	0.519	0.596	6.216	0.365	0.615	0.558	0.308	0.808	0.231
	0.502	0.480	0.269	0.491	0.505	0.323	0.345	10.509	3.589	0.495	0.505	0.495	0.764	0.486	0.491	0.502	0.466	0.398	0.425
Bolivia	0.353	0.287	0.768	0.507	0.450	0.147	0.296	37.028	7.945	0.512	0.538	0.569	4.652	0.495	0.573	0.294	0.562	0.763	0.249
	0.478	0.453	0.423	0.501	0.498	0.354	0.457	15.583	5.677	0.500	0.499	0.496	1.105	0.501	0.495	0.456	0.497	0.426	0.433
Brazil	0.454	0.390	0.855	0.486	0.377	0.095	0.189	39.648	7.666	0.484	0.535	0.536	5.325	0.738	0.478	0.609	0.574	0.715	0.181
	0.498	0.488	0.352	0.500	0.485	0.293	0.392	16.554	4.526	0.500	0.499	0.499	0.957	0.440	0.500	0.488	0.495	0.452	0.386
Chile	0.536	0.225	0.796	0.505	0.366	0.156	0.234	45.132	10.277	0.443	0.569	0.414	5.348	0.615	0.527	0.517	0.737	0.692	0.172
	0.499	0.418	0.404	0.500	0.482	0.364	0.424	17.904	3.767	0.497	0.496	0.493	0.904	0.487	0.500	0.500	0.441	0.462	0.378
Colombia	0.581	0.401	0.898	0.600	0.532	0.124	0.253	38.228	11.140	0.403	0.627	0.358	5.476	0.498	0.430	0.428	0.504	0.855	0.215
	0.494	0.491	0.303	0.490	0.499	0.329	0.435	15.489	2.768	0.491	0.484	0.480	1.108	0.500	0.496	0.495	0.500	0.353	0.411
Costa Rica	0.479	0.439	0.934	0.705	0.505	0.162	0.222	38.148	7.888	0.545	0.453	0.501	5.700	0.627	0.469	0.711	0.533	0.814	0.228
	0.500	0.497	0.248	0.457	0.500	0.369	0.416	15.585	4.278	0.498	0.498	0.500	0.934	0.484	0.500	0.454	0.499	0.389	0.420
Dom. Republic	0.454	0.342	0.835	0.589	0.475	0.080	0.198	38.479	9.686	0.580	0.542	0.426	5.086	0.568	0.411	0.608	0.506	0.755	0.361
	0.498	0.475	0.371	0.493	0.500	0.272	0.399	16.327	3.844	0.494	0.499	0.495	1.155	0.496	0.493	0.489	0.500	0.430	0.481
Ecuador	0.475	0.172	0.829	0.500	0.442	0.155	0.264	38.519	9.205	0.389	0.595	0.465	4.816	0.592	0.409	0.376	0.604	0.785	0.165
	0.500	0.378	0.376	0.500	0.497	0.362	0.441	16.368	3.930	0.488	0.491	0.499	0.905	0.492	0.492	0.485	0.489	0.411	0.371
El Salvador	0.551	0.302	0.775	0.451	0.503	0.191	0.217	36.531	6.805	0.477	0.487	0.320	4.729	0.501	0.247	0.183	0.662	0.813	0.187
	0.498	0.460	0.418	0.498	0.500	0.394	0.413	15.379	5.052	0.500	0.500	0.467	0.974	0.501	0.432	0.387	0.474	0.390	0.390
Guatemala	0.398	0.318	0.882	0.439	0.533	0.159	0.253	35.211	7.862	0.488	0.453	0.377	4.855	0.651	0.457	0.332	0.654	0.834	0.329
	0.490	0.467	0.323	0.497	0.500	0.366	0.435	16.201	4.881	0.501	0.499	0.486	0.880	0.478	0.499	0.472	0.477	0.373	0.471
Guyana	0.515	0.596	0.818	0.162	0.606	0.061	0.222	36.101	10.141	0.535	0.444	0.596	5.728	0.414	0.485	0.626	0.788	0.788	0.313
	0.502	0.493	0.388	0.370	0.491	0.240	0.418	14.761	3.623	0.501	0.499	0.493	0.709	0.495	0.502	0.486	0.411	0.411	0.466
Honduras	0.560	0.375	0.810	0.519	0.615	0.183	0.156	35.120	5.788	0.462	0.500	0.332	4.960	0.447	0.183	0.245	0.505	0.822	0.356
	0.497	0.485	0.393	0.500	0.487	0.387	0.364	15.730	4.461	0.499	0.501	0.471	0.894	0.498	0.387	0.431	0.501	0.383	0.479
Mexico	0.507	0.362	0.886	0.533	0.554	0.105	0.158	36.506	8.665	0.407	0.502	0.491	4.942	0.626	0.536	0.469	0.589	0.810	0.116
	0.500	0.481	0.318	0.499	0.497	0.306	0.365	14.387	3.529	0.492	0.500	0.500	1.051	0.484	0.499	0.499	0.492	0.393	0.320
Nicaragua	0.544	0.396	0.877	0.598	0.527	0.147	0.197	33.017	6.977	0.405	0.453	0.443	4.979	0.546	0.415	0.368	0.547	0.819	0.248
	0.498	0.489	0.328	0.491	0.500	0.354	0.398	14.334	5.015	0.491	0.498	0.497	0.974	0.498	0.493	0.482	0.498	0.385	0.432
Panama	0.526	0.247	0.938	0.538	0.546	0.103	0.147	36.901	9.760	0.447	0.478	0.430	5.041	0.707	0.469	0.560	0.452	0.954	0.238
	0.500	0.432	0.242	0.499	0.498	0.304	0.354	15.348	3.602	0.498	0.500	0.496	0.930	0.456	0.499	0.497	0.498	0.209	0.426
Paraguay	0.475	0.175	0.860	0.574	0.421	0.100	0.179	38.437	9.506	0.395	0.616	0.448	4.922	0.501	0.499	0.379	0.475	0.936	0.311
	0.500	0.380	0.348	0.495	0.494	0.301	0.383	16.705	3.407	0.489	0.487	0.498	1.037	0.500	0.500	0.486	0.500	0.245	0.464
Peru	0.361	0.135	0.798	0.497	0.517	0.112	0.226	37.134	10.547	0.406	0.562	0.395	4.641	0.672	0.440	0.344	0.477	0.930	0.246
	0.481	0.342	0.402	0.500	0.500	0.316	0.418	15.908	4.383	0.492	0.497	0.489	1.038	0.470	0.497	0.476	0.500	0.256	0.431
Uruguay	0.524	0.560	0.857	0.399	0.458	0.121	0.253	44.128	10.033	0.527	0.597	0.465	5.649	0.960	0.678	0.707	0.758	0.564	0.106
	0.500	0.497	0.351	0.491	0.499	0.327	0.435	18.175	3.714	0.500	0.491	0.500	0.955	0.197	0.468	0.456	0.429	0.497	0.309
Total	0.487	0.312	0.850	0.532	0.485	0.131	0.213	37.980	8.786	0.452	0.535	0.443	5.103	0.609	0.458	0.454	0.559	0.814	0.223
	0.500	0.463	0.357	0.499	0.500	0.337	0.409	16.223	4.403	0.498	0.499	0.497	1.040	0.488	0.498	0.498	0.496	0.389	0.416

Note: Sample that is not missing for any of the variables.

Source: Authors' calculations.

Table A3. Covariate Balancing: Differences in Means Before and After Matching

Variable	Sample	Mean: Treated	Mean: Control	%bias	% reduct bias	t-test: t	t-test: p>t
Age	Unmatched	36.6	38.5	-11.7		-3.79	0
	Matched	36.6	36.8	-1.2	89.8	-0.3	0.763
Age squared	Unmatched	1596.7	1754.7	-11		-3.53	0
	Matched	1596.7	1611.3	-1	90.8	-0.26	0.795
Education	Unmatched	9.2	8.6	12.4		4.03	0
	Matched	9.2	9.1	1	91.8	0.25	0.799
HH head	Unmatched	0.453	0.455	-0.4		-0.15	0.883
	Matched	0.453	0.462	-1.9	-312.7	-0.46	0.645
Female	Unmatched	0.497	0.543	-9.2		-3.04	0.002
	Matched	0.497	0.498	-0.1	99.2	-0.02	0.985
Have a job	Unmatched	0.471	0.434	7.3		2.41	0.016
	Matched	0.471	0.471	-0.2	97.6	-0.04	0.965
Log income PPP	Unmatched	5.212	5.079	13.1		4.2	0
	Matched	5.212	5.202	1	92.3	0.26	0.797
Urban	Unmatched	0.756	0.586	36.8		11.53	0
	Matched	0.756	0.759	-0.6	98.3	-0.17	0.864
Gangs	Unmatched	0.630	0.432	40.3		13.14	0
	Matched	0.630	0.629	0.1	99.9	0.01	0.989
Drug sales	Unmatched	0.589	0.434	31.4		10.31	0
	Matched	0.589	0.583	1.3	95.9	0.32	0.75
Roads	Unmatched	0.512	0.568	-11.2		-3.7	0
	Matched	0.512	0.516	-0.9	92.3	-0.21	0.831
Corruption	Unmatched	0.851	0.808	11.3		3.57	0
	Matched	0.851	0.849	0.5	95.4	0.13	0.893
Volunteer	Unmatched	0.247	0.216	7.4		2.47	0.013
	Matched	0.247	0.245	0.5	93.5	0.12	0.907
Total	Unmatched			9.8			
	Matched			0.7			

Note: 50 nearest neighbors for trust in the police, with matching on countries.

Source: Authors' calculations.

Table A4. Two-Sample t-Test of Equality of Means Between Mugged and Non-mugged Individuals

	Non-victims	S.E.	Victims	S.E.	Difference
Political orientation					
More socialist than capitalist (dummy)	0.69	0.005	0.69	0.012	0.01
Religious affiliation					
Religion important (dummy)	0.79	0.003	0.79	0.008	0.00
Christian (dummy)	0.86	0.002	0.86	0.007	0.00

Source: Authors' calculations.