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Patterns of crime victimization in Latin American cities

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Abstract

In this paper, we draw a profile of the victims of crime in Latin America. We show that the typical victims of property crime in Latin America come from rich and middle class households and tend to live in larger and faster growing cities. On the whole, our results indicate that urban crime in Latin America is, to an important extent, a reflection of the inability of many cities in the region to keep up with the increasing demands for public safety brought about by a hasty and disorderly urbanization process. © 2002 Elsevier Science B.V. All rights reserved.

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1. Introduction

Crime has become a staple feature of many cities in Latin America. As any casual observer would immediately notice, muggings, burglaries, carjackings and even homicides occur with alarming frequency in many urban centers throughout this region. But despite the sense of urgency brought about by rising crime levels, few studies have attempted to explore the magnitude and causes of urban crime in Latin America.[1]

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[1] See Bourguignon (1999), Fajnzylber et al. (1998) and Londoño et al. (in press) for previous attempts to uncover the causes in Latin America.

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Lack of reliable data has been the most important impediment to research on the evolution and nature of crime in developing countries in general and Latin American countries in particular. Official crime statistics are often incomplete and suffer from serious problems of under-reporting. Victimization surveys, the alternative to official records, are either unavailable or incomplete. Comparable cross-country data are even more difficult to come by; which is why most cross-country studies on the determinants of crime and violence have focused exclusively on homicide rates.

In this paper, we use an unusual data set to study the patterns of crime victimization in Latin America. Our main source of data is the Latinobarometer, a public opinion survey covering more than 50,000 households in 17 Latin American countries. This survey, although not specifically designed to study crime, provides a uniquely data set of comparable cross-country information on criminal victimization.

Our approach is more descriptive than analytical. We first lay out some empirical regularities and only then offer some interpretations, which reflects not so much our methodological preferences as the constraints imposed by our data. Our analysis focuses mainly on how the relative socioeconomic status of an individual, the population size of her city of residence, and the city's recent population growth affects the probability of being a victim of crime. We find that this probability increases with socioeconomic status, city size, and urban growth.

We argue that the positive connection between socioeconomic status and the probability of victimization may be driven by both the difficulties of the relatively wealthy in protecting themselves against street crime and the tendency of burglars and kidnappers to target wealthy victims. Little can be said, however, about the distribution of the crime burden across social classes because we do not observe household investments in crime avoidance.

We cannot provide a definitive interpretation of the positive connection between city size and crime. Two different hypotheses are consistent with our empirical results: (i) the probability of arresting a criminal is lower in larger cities (either because there are diseconomies of scale in the production of arrests or because larger cities invest relatively less in law enforcement), and (ii) larger cities harbor a greater proportion of crime-prone individuals. We are able to reject the also plausible hypothesis that larger cities have more crime because they present wealthier victims.

We also reject the hypothesis that the association between city growth and crime is driven by the characteristics of the victims. Thus, we do not find evidence that the higher levels of crime present in faster growing cities are due to an excess of rich or poor people in these areas (perhaps attracted by higher opportunities in the city or lower opportunities in rural areas). Instead, we find that the levels of confidence in the police and the judiciary are lower in faster growing cities and that lower levels of confidence in the police are in turn associated with higher victimization rates. These results suggest that urban growth increases victimization by lowering the effectiveness (and hence the reputation) of law enforcement institutions. On the whole, our results indicate that urban crime in Latin America is, to an important extent, a consequence of the inability of many cities in the region to keep up with the increasing demands for public safety brought about by a hasty and disorderly urbanization process.

The rest of this paper is organized as follows. Section 2 describes the data. Section 3 presents the empirical methodology. Sections 4, 5 and 6 examine the link between crime and socioeconomic status, city size and urban growth, respectively. Finally, Section 7 draws some general conclusions.

2. Victimization data for Latin America

In this paper, we use the Latinobarometer to study the patterns of crime victimization in Latin America. The Latinobarometer is a public opinion survey covering 17 Latin American countries.[2] This survey has been regularly conducted every year since 1996. Each year, 1500 individuals have been interviewed in each country. Although there have been some adjustments to the survey questions and answer formats, many questions have remained the same and are comparable over time. The sampling method varies slightly from country to country as implementation is contracted out to national polling firms. Quotas were included in most cases to ensure representation across gender, socioeconomic status, and age. Here, we combine the data sets of 1996, 1997 and 1998 in order to get larger samples.

The survey is restricted to urban populations. We use sample weights to correct the oversampling of richer households.[3] The weights were created so that that the distribution of individuals across education groups in the sample matched the actual distribution of the urban population in the country in question. All results below are weighted, but they do not differ substantially from the unweighted ones.

Although the Latinobarometer is not a victimization survey (its emphasis is on political attitudes and social values), all rounds of the survey have included a question about crime victimization at the household level.[4] The Latinobarometer also contains detailed information about the demographic characteristics of both the respondent and the head of the household, as well as information about trust in the police, the judicial system and other public institutions.

Fig. 1 shows the average victimization rates for all the countries included in the survey. The levels of victimization are staggering. In five countries (Ecuador,

[2] In 1996, the Latinobarometer also include Spain. Unless otherwise mentioned, Spain was not included in our analysis.

[3] This is a common problem in large opinion surveys. For example, both the World Values Survey and Eurobarometer also oversample individuals form higher socioeconomic groups.

[4] The exact wording of the question is, “Have you or any member of your family been assaulted, robbed of victimized in any way during the past twelve months?”

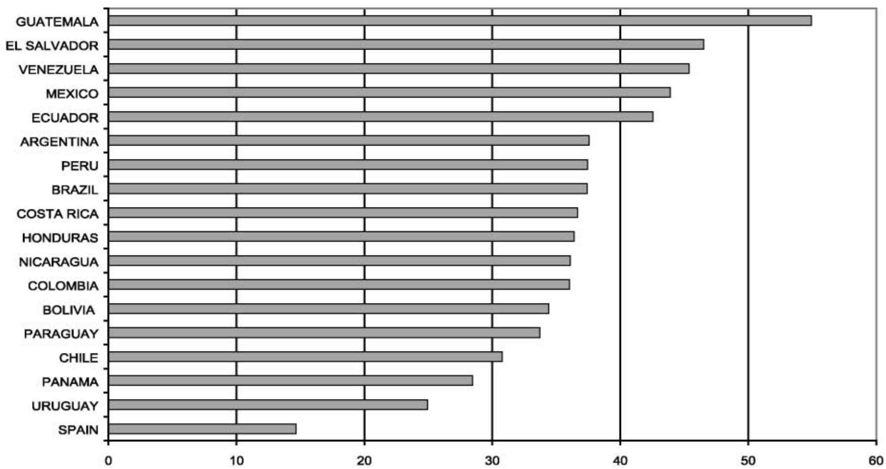

Fig. 1. Victimization rates by country.

Mexico Venezuela, El Salvador and Guatemala) more than 40% of the urban households experienced at least one episode of victimization during the year previous to the survey. In Guatemala, at least one person in every two households was victimized. Spain, the only industrialized country included in the survey, has the lowest victimization rates in the sample, and Uruguay, Panama and Chile exhibit the lowest victimization rates in Latin America.

A serious shortcoming of the Latinobarometer is the absence of information about the type of victimization. We will assume here that the victimization data obtained from this survey correspond mainly to property crimes; an assumption justified by the fact that property crimes usually represent the bulk of all criminal offenses.[5] Another shortcoming of the Latinobarometer is the absence of data on household income. All rounds of the survey have included, however, two sets of questions related to the socioeconomic status of the households. The first set includes questions about ownership of durable goods (respondents were asked if any member of the household owns a car, a computer, a television, a washing machine, and so on). The second set includes questions about housing characteristics (respondents were asked if their place of residence has access to potable water, sewage, electricity and so on).

In this paper, we use this information to rank households according to their socioeconomic status. The procedure entails three main steps. First, we use Principal Components to compute a weighted average of the relevant household

[5] See, for example, Londoño et al. (in press).

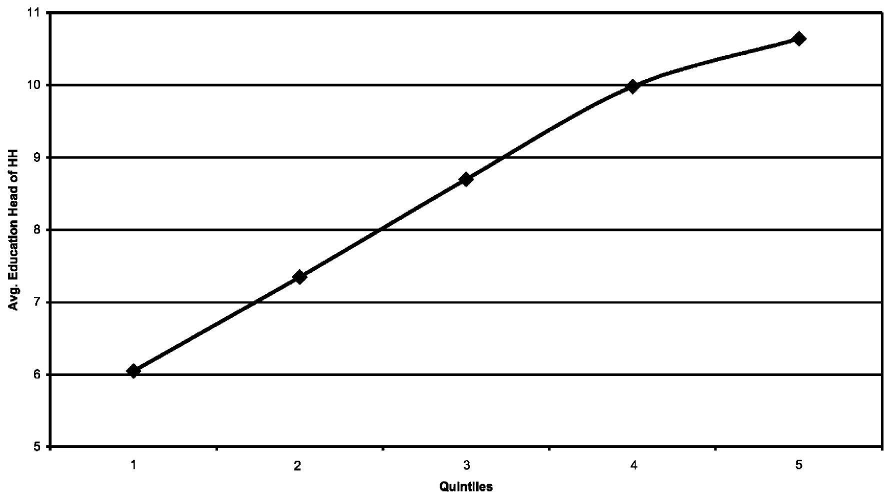

Fig. 2. Material wealth and education of the head.

attributes, then we rank all households on the basis of this average and, finally, we use the corresponding ranking to compute quintiles of socioeconomic status.[6] Fig. 2 shows the average years of education of the household head by quintiles of socioeconomic status. As expected, this variable increases steadily across quintiles, lending credence to our use of household possessions to approximate socioeconomic status.

In order to more carefully examine the positive link between crime and city-size mentioned in Section 1, we also use a victimization module included in the *Encuesta Nacional de Calidad de Vida* of Colombia. This survey is representative of urban areas of the country and includes 5623 households. All questions in the survey were administered only to the heads of household, and thus refer to incidents affecting either the respondent or any member of his household. Unlike the Latinobarometer, this survey contains information on property crimes as well as other crimes such as homicides, assaults (including rape) and kidnappings. Only serious incidents were reported, which explain the low victimization rates obtained (the national average is below 13%).

[6] Principal Components are often used to approximate socioeconomic status in the absence of reliable income data. Filmer and Pritchett (1998) show that durable goods and housing attributes are observed with much more precision than consumption expenditures, and that indicators of socioeconomic status based on these variables are much less sensitive to temporary disturbance on household welfare that similar indicator based consumption data.

3. Empirical methodology

Most economic models of crime focus on the incentives faced by prospective criminals. The main conclusions of these models are well known: the higher the return of criminal activities and the lower the probabilities of arrest and incarceration, the higher the individual propensity to commit crimes (see Becker, 1968; Ehrilch, 1973). These models, however, offer few clues as to which individuals are most likely to be the victims of crime. Most crime models, for example, do not offer any prediction as to whether crime affects mainly individuals from disadvantaged social groups—an important question, not only from a fairness viewpoint but also because it may yield some insights about the root causes of crime.

In this paper, we use the following specification to study the patterns of crime victimization in Latin America

$$Y_{ijct} = c + \mathbf{X}_{ijct}\beta + \mathbf{Z}_{jc}\theta + \lambda_c + \zeta_t + \varepsilon_{ijct}, \qquad (1)$$

where Y_{ijct} is a dummy variable showing whether a member of family i who lives in city j of country c was a victim of crime in year t, $\boldsymbol{X}_{ijct}$ is a vector of household characteristics (including education of the household head, relative socioeconomic status, and house ownership), $\boldsymbol{Z}_{jc}$ is a vector of city characteristics (including population size and population growth), λ_c is a country effect, ζ_t is a year effect, and ε_{ijct} is an individual error term.

Country effects are included to control for unobserved country attributes that do not change drastically over time (e.g., social capita and other cultural aspects).[7] Year effects are included to control for unobserved factors that vary uniformly over time (e.g., common macroeconomic shocks and changes in the questionnaire). Unless otherwise mentioned, the analysis below is robust to the exclusion of both country and year effects.

We use a Probit model to estimate Eq. (1). Linear probability models yield almost identical results, suggesting that our findings are robust to the choice of estimation method. In the second to last section of the paper, where we need to deal with some problems of simultaneous causation, we use a Maximum Likelihood Method to estimate a two-step Probit model with endogenous variables (see Newey and Whitney, 1987 for a theoretical discussion and Evans et al., 1992 for an application of this model).

Descriptive statistics of the most important covariates are shown in Table 1. The mean victimization rate of the sample is 38.6%, 72.7% of the households own a house, 30% own a car, and 6.8% live in “marginal” dwellings (i.e., those without access to water or sewage connections). More than 20% of the households

[7] One may argue that individuals living in safe countries may have a different perception of what it means to be victimized vis-a-vis individuals living in crime-ridden countries. Country-fixed effects control for these differences.

Table 1
Summary statistics

Variable	Observations	Mean	Std. dev.
Crime	27,134	0.386	–
Household size	27,474	4.871	2.13
Education of head	27,474	9.042	4.45
Head of house employed	27,474	0.821	–
Own a house	27,474	0.727	–
Own a car	27,474	0.299	–
Marginal household	27,474	0.068	–
< 20,000	27,474	0.088	–
20,001–50,000	27,474	0.090	–
50,001–100,000	27,474	0.085	–
100,001–300,000	27,474	0.154	–
300,001–700,000	27,474	0.134	–
700,001–1,000,000	27,474	0.075	–
1,000,001–2,000,000	27,474	0.151	–
> 2,000,000	27,474	0.223	–
Trust in police	26,783	0.342	–
Population growth	13,281	2.382	1.69

This table summarizes the data set that we actually used in our estimates. Although the original pooled Latinobarometro contains data for about 50,000 households, missing data for some variables reduces the subset that we can actually use to around 27,500 observations.

in the sample live in cities of more than 2 million inhabitants and only 8.8% live in cities of less than 20,000 inhabitants.

In the next sections, we focus on the effects of socioeconomic status, city size and city growth on the probability of being a victim of crime. We examine not only the independent contribution of these factors, but also how they interact with each other and with some country-level indicators. We show below that something can be learned about the root causes of crime by studying the patterns of crime victimization along these three variables.

4. Victimization and socioeconomic status

In this section, we study the effect of socioeconomic status on the probability of being a victim of crime. Our main results are summarized in Table 2. Column (1) shows that the probability of being victimized is substantially higher for the fifth and fourth quintiles and noticeable higher for the third quintile (the baseline group is the first quintile).[8] On average, an individual from the top quintile is 8

[8] Table 4 shows victimization rates by socioeconomic status for all the countries in the sample. With exception of Bolivia, Ecuador and Panama, crime rates at the fourth of fifth quintile.

Table 2
Relative socioeconomic status and probability of victimization, Probit estimation: marginal effects

	(1)	(2)	(3)
Second quintile	0.0006 (0.009)	0.002 (0.01)	−0.003 (0.01)
Third quintile	0.034 (0.009)	0.035 (0.010)	0.020 (0.01)
Fourth quintile	0.066 (0.009)	0.065 (0.011)	0.044 (0.01)
Fifth quintile	0.081 (0.01)	0.075 (0.012)	0.054 (0.012)
Household size		0.006 (0.001)	0.006 (0.001)
Education of head		0.003 (0.0007)	0.003 (0.0007)
Employment of head		0.005 (0.008)	0.009 (0.008)
Own a house		−0.038 (0.006)	−0.035 (0.006)
Own a car		0.004 (0.008)	0.006 (0.008)
Marginal household		0.022 (0.013)	0.016 (0.013)
City size dummies	No	No	Yes
Number of observations	27,127	27,127	27,127
Obs. P	0.386	0.386	0.386
Pseudo R^2	0.016	0.018	0.035

All regressions include year and country dummies. Standard errors are reported in parenthesis. Baseline probability refers to the Normal Cumulative Distribution evaluated at the constant of the Probit estimation.

percentage points more likely to be a victim of crime than an individual from the bottom quintile.[9]

In column (2), we control for some key household attributes (education and employment of the head of the household, home and car ownership, and a few others) in order to investigate some obvious channels through which relative socioeconomic status could affect the probability of victimization. The effects of the different attributes are, for the most part, relevant, but cannot completely explain away the effect of socioeconomic status on the probability of victimization. Owning a house reduces the probability of victimization by 3.8 percentage points. Living in "marginal" households increases the probability of victimization by more than 2.0 percentage points, though this effect is not statistically significant at conventional levels. Finally, both employment of the household head and car ownership do not have an independents effect on the probability of victimization.

Column (3) shows the effects of socioeconomic status after controlling for the size of the city of residence. Wealth effects are smaller in this specification, suggesting that city size is an important channel through which socioeconomic status raises the probability of victimization. That is, richer people tend to live in

[9] In a recent study, Cruz (1999) finds that victimization rates (weighted by the inverse of the frequency) increase with socioeconomic status in Cali, Rio de Janeiro and José.

larger cities and larger cities tend in turn to have higher victimization rates (the latter effect is thoroughly examined in the next section).[10]

To investigate whether the relationship between socioeconomic status and the probability of victimization is affected by country-wide inequality, we add the urban Gini coefficient and its interactions with the quintile dummies to the previous specification (country fixed-effects are excluded in this case for obvious reasons). The results, not shown here, indicate that income inequality has a small effect on the distribution of crime across rich and poor households. As inequality increases, the rich bear a smaller share of all incidents of victimization. This may be due to several factors. First, more unequal societies often devote more public resources to protect the rich (Bourguignon, 1999). Second, more unequal societies often pursue with greater vehemence crimes against rich and middle income families.[11] And last, rich and middle-income families may find it easier to insulate themselves from crime in more unequal societies (spatial segregation, for example, tends to be higher in more unequal societies).

The relationship between relative socioeconomic status and crime is robust to changes in the sample of countries considered. In particular, we examine whether the reported coefficients change when we progressively exclude countries from our sample (according to the alphabetic order of their names).[12] We find that neither the size nor significance of the coefficients change substantially from one sample to the next.

Why do the wealthy bear a disproportionate share of all property crimes? This result is consistent with two general models. In the first model, criminals and victims are matched randomly and investments in private protection exhibit sharp diminishing returns, whereas in the second model criminals are matched disproportionately to wealthy victims and private investments in protection exhibit constant returns. In the first model, wealthy households invest very little in private protection, as they decide to bear some victimization risk instead of paying the high price of completely insulating themselves against crime (see Appendix A for a formal treatment of this idea). In the second model, wealthy households invest more in private protection but their investments are not enough to offset the

[10] The effect of socioeconomic status on criminal victimization appears to be large in Latin America than in the United States. The raw data for the United States shows that there is a small positive correlation between properly crime and household income (Bureau of Justicce Statistics, 1998). This correlation is negative, however, after controlling for demographic characteristics and city size. There is, in particular, a clear negative association between household income and the incidence of burglaries, assaults and common thefts (Glaeser and Sacerdote, 1999).

[11] The Latinobarometer offers indirect support to this idea. The correlation between the proportion of respondents in a country who state that all citizens in their country of residence are equal before law and the Gini coefficient is −0.45, indicating that more unequal societies tend to be more suspicious about the fairness of the justice system.

[12] The results are available from the authors upon request. We are grateful to an anonymous referee for suggesting this robustness check.

greater victimization risk associated with the tendency of criminals to go after them.

Presumably, the first model applies to those crimes where the matching between criminals and citizens is mainly a matter of chance. Examples may include street crimes (including muggings and armed robberies) and common thefts. The second model applies to those crimes in which criminals carefully select their victims so as to maximize expected gains. Examples may include burglaries and kidnappings. The empirical results presented above are likely to be driven by a combination of these two forces. Although we lack the information to discriminate between these two alternative models, the evidence does not support the common view that the rich are usually more sought out by criminals in more unequal societies.

5. Victimization and city size

Crime has become a preeminently urban problem in developed and developing countries alike. In the United States, for example, there is a well-documented connection between city size and criminal rates. Anecdotal evidence suggests that such connection also holds in Latin America, which is particularly worrisome given this region's high levels of urbanization and urban concentration.[13]

Table 3 shows that, in Latin America, the probability of being a victim of crime is substantially higher in larger cities. A household living in a city of more than one million inhabitants is 20 percentage points more likely to be victimized than a household living in a city of less than 20,000 inhabitants (the baseline group in the regression). Surprisingly, the probability of victimization does not change much when the one-million-inhabitants threshold is surpassed. The evidence suggests, indeed, a natural division of cities in three groups: a first group composed of cities of less than 100,000 inhabitants that exhibit relatively low crime rates, an intermediate group composed of cities between 100,000 and one million inhabitants, and a high-crime group composed of cities of more than one million inhabitants. Interestingly, our results indicate that the city size effect is much larger in Latin America than in the United States. Thus, while in the United States, a household living in a city of one million inhabitants or more is 28% more likely to be victimized than a household living in a city between 50,000 and 100,000 inhabitants, the corresponding figure for Latin America is 71%.[14]

Table 4 shows that the positive connection between city size and crime holds not only for the region as a whole, but also for most of the countries taken

[13] "Megacities" are much more common and are growing faster in Latin America that anywhere else in the world (Gaviria and Stein, 2000).

[14] See Glaeser and Sacerdote (1996) for the US figure.

Table 3
City size and probability of victimization, Probit estimation: marginal effects

	(1)	(2)	(3)
20,001–50,000	0.036 (0.015)	0.030 (0.015)	
50,001–100,000	0.023 (0.016)	0.014 (0.016)	
100,001–300,000	0.116 (0.015)	0.103 (0.015)	
300,001–700,000	0.134 (0.015)	0.118 (0.015)	
700,001–1,000,000	0.136 (0.017)	0.114 (0.017)	
1,000,001–2,000,000	0.199 (0.016)	0.182 (0.016)	
> 2,000,000	0.216 (0.015)	0.194 (0.016)	
Second quintile		−0.003 (0.010)	0.001 (0.017)
Third quintile		0.021 (0.010)	0.053 (0.018)
Fourth quintile		0.045 (0.011)	0.067 (0.019)
Fifth quintile		0.054 (0.013)	0.092 (0.022)
Size2			0.136 (0.019)
Size3			0.178 (0.019)
Second quintile * Size2			−0.019 (0.027)
Third quintile * Size2			−0.063 (0.024)
Fourth quintile * Size2			−0.058 (0.024)
Fifth quintile * Size2			−0.072 (0.027)
Second quintile * Size3			0.009 (0.024)
Third quintile * Size3			−0.019 (0.024)
Fourth quintile * Size3			−0.001 (0.027)
Fifth Quintile * Size3			−0.021 (0.026)
Number of observations	27,127	27,127	27,127
Obs. P	0.386	0.386	0.386
Pseudo R^2	0.023	0.027	0.027

Standard errors are reported in parenthesis. All regressions include country and year fixed effects. In columns (2) and (3), we also control for household characteristics. Baseline probability refers to the Normal Cumulative Distribution evaluated at the constant of the Probit estimation.

separately. As shown, for 14 of the 17 countries under analysis, victimization rates are the highest in the largest city.[15] Table 4 also shows that while most South American countries are represented in all city-size groups, only few of the Central American countries are represented in the larger city-size groups. Given this, it is fair to say that all results pertaining to cities with populations over one million apply exclusively to South American countries.

To explore the channels through which city size affects crime rates, we add household and city characteristics to the specification shown in column (1) of Table 3. The results of column (2) indicate that the implied elasticity between city size and crime drops by about 8% in this case, suggesting that in Latin America only a small fraction of the effect of city size on crime can be accounted for by

[15] The results are also very robust to the progressive exclusion of countries (according to their names' alphabetic order) from the sample.

Table 4
Percent of crime victimization across city size[a]

	< 20	20–50	50–100	100–300	300–700	700–1000	1000–2000	2000 >
Argentina	* * *	11.06	31.5	17.99	39.62	28.54	38.02	**41.01**
	(0)	(91)	(65)	(82)	(137)	(374)	(671)	(1882)
Bolivia	* * *	* * *	* * *	37.94	**38.04**	31.46	36.78	* * *
	(0)	(0)	(0)	(46)	(561)	(486)	(673)	(0)
Brazil	* * *	* * *	* * *	* * *	* * *	**46.01**	43.28	36.35
	(0)	(6)	(16)	(16)	(27)	(118)	(161)	(428)
Colombia	* * *	* * *	* * *	31.61	33.54	30.37	* * *	**44.62**
	(0)	(0)	(0)	(589)	(64)	(107)	(0)	(447)
Costa Rica	30.15	38.14	46.91	43.01	**54.54**	* * *	* * *	* * *
	(593)	(311)	(180)	(195)	(104)	(0)	(0)	(0)
Chile	* * *	* * *	11.98	29.02	25.02	* * *	* * *	**33.73**
	(0)	(0)	(148)	(46)	(173)	(0)	(0)	(1066)
Ecuador	50.34	38.27	38.06	42.66	* * *	47.25	**62.41**	* * *
	(140)	(424)	(334)	(301)	(0)	(283)	(496)	(0)
El Salvador	47.46	44.11	34.19	47.14	**53.82**	* * *	* * *	* * *
	(267)	(176)	(136)	(114)	(47)	(0)	(0)	(0)
Guatemala	46.23	60.54	* * *	60.19	* * *	* * *	* * *	* * *
	(206)	(187)	(0)	(206)	(0)	(0)	(0)	(0)
Honduras	36.32	39.02	44.11	40.60	46.72	**66.60**	* * *	* * *
	(284)	(209)	(127)	(105)	(61.2)	(130)	(0)	(0)
Mexico	32.69	29.55	27.54	33.80	43.52	50.90	39.49	**58.22**
	(107)	(176)	(342)	(193)	(528)	(191)	(118)	(466)
Nicaragua	33.35	38.36	34.87	37.97	* * *	**48.01**	* * *	* * *
	(213)	(204)	(172)	(92)	(0)	(210)	(0)	(0)
Panama	22.45	28.35	31.36	**56.90**	38.34	* * *	* * *	* * *
	(484)	(500)	(224)	(43)	(469)	(0)	(0)	(0)
Paraguay	* * *	* * *	31.57	29.78	* * *	* * *	* * *	**38.16**
	(0)	(0)	(195)	(166)	(0)	(0)	(0)	(215)
Peru	* * *	26.73	25.64	43.99	34.34	35.52	* * *	**42.01**
	(0)	(30)	(44)	(412)	(672)	(122)	(0)	(1366)
Uruguay	* * *	* * *	20.19	29.97	* * *	* * *	**36.68**	* * *
	(0)	(0)	(237)	(370)	(0)	(0)	(1506)	(0)
Venezuela	30.00	42.64	45.82	48.44	47.93	35.96	**54.99**	* * *
	(110)	(134)	(69)	(152)	(252)	(57)	(528)	(0)

Source: Latinobarometer (1996–1998). Weighted data. Number of observations per country and city size is in parentheses.

[a]City size in thousands of inhabitants

differences among cities in household characteristics.[16] By contrast, Glaeser and Sacerdote (1999) find that in the United States a much larger fraction of the effect of city size on crime (33%) can be accounted for by household characteristics. This comparison suggests that the driving forces underlying this effect may be quite different in both places.

Column (3) explores the interaction between socioeconomic status and city size. We reduce the number of city-size brackets to the three groups mentioned above in order to facilitate the interpretation of the results. The interactions are negative for the most part, and statistically significant only for intermediate cities. All in all, the patterns of victimization do not vary consistently with city size—that is, neither rich nor poor households fare comparatively worse in large cities vis-a-vis small ones.

Fig. 3 shows the effects of city size on various types of victimization for the case of Colombia. Robberies grow monotonically with city size, as does the fraction of households reporting that crime is their main problem in their communities (perceived criminality). In contrast, homicides and assaults are much more common in medium-size cities (especially Cali and Medellín, two well-known drug-trafficking strongholds) than in Bogotá, which has a population of well over 4,000,000 inhabitants. These results hold up after controlling for household and city characteristics (e.g., the percentage of families in the city with unsatisfied basic needs, the percentage of individuals in the city with primary and secondary education, and so on).

What explains the connection between city size and crime? Three factors can be mentioned.[17] First, the returns to crime can be higher in larger cities, perhaps because larger cities usually present wealthier victims and more developed markets for second-hand goods. Second, the probability of arresting a criminal may be lower in larger cities, because either larger cities spend less in law enforcement or have lower levels of community cooperation with the police or require more officers per inhabitant to produce an arrest. And third, larger cities may have a disproportionate share of crime-prone individuals (e.g., idled males, distressed migrants, street children or drug abusers).

Can we discriminate among the different causes mentioned above? Although not completely, some clues emerge from the previous analysis. First, the effect of city size on crime cannot be explained by the presence of wealthier victims in larger cities. If that were the case, one would expect that, contrary to the evidence, this effect would decline substantially once we control for socioeconomic status and other household attributes. Second, the city-size effect cannot be explained by the fact that the rich (arguably the best victims) are easier targets in larger cities. If that was the case, one would expect that, again contrary to the evidence, the rich

[16] See Glaeser and Sacerdote (1996) for a detailed explanation of how to compute these elasticities.
[17] See Glaeser and Sacerdote (1996) for a formal treatment of this topic.

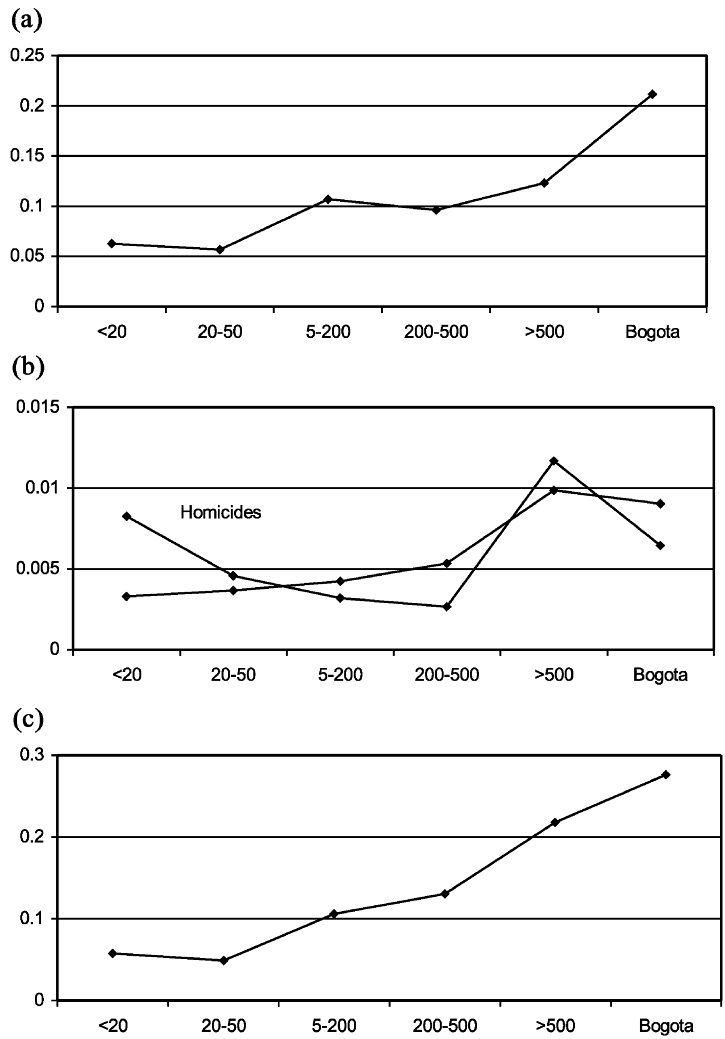

Fig. 3. (a) Robberies and city size in Colombia. (b) Homicides and assults and city size in Colombia. (c) Perceived criminality and city size in Colombia.

would be relatively more victimized as city size grows. So we are left, by elimination, with two possible explanations: larger cities have either lower probabilities of arrest or a higher proportion of individuals with a greater inclination toward criminal activities (or both).

Table 5 casts some doubts on the latter hypothesis. This table shows, for the case of Colombia, the relationship between city size and a few variables often deemed as strong predictors of high criminal incidence. These variables are the

Table 5
Crime risk factors and city-size in Colombia (percentage of households per city-size category)

City size	Broken families (%)	Idleness rates (%)	Percent of migrants (%)	Communities with drug problems (%)
< 20	21.3	30.1	14.2	14.9
20–50	22.0	33.6	8.5	8.1
5–200	25.3	30.3	11.3	14.2
200–500	25.1	33.7	10.6	22.8
> 500	25.4	33.6	6.3	21.1
Bogota	20.1	26.8	5.2	18.5

Bogota is the largest city in the country with a population of (1994 est.) 5,131,582 inhabitants. Source of data presented in table: Encuesta Nacional de Calidad de Vida (Colombia, 1997).

fraction of households in which at least one parent is absent, the fraction of idled men, the fraction of households that migrated to the city in question during the previous five years, and the fraction of community leaders reporting that drug consumption is a serious problem in their communities. With perhaps the exception of the latter variable, nothing in this table appears to suggest that larger cities in Colombia contain disproportionate fractions of crime-prone individuals. If anything, the opposite is true.

Thus, at least in the case of Colombia, the greater criminal prevalence in larger cities may have more to do with law enforcement and less to do with the presence of either individuals at risk or better victims. Of course, additional evidence is needed to generalize this conclusion.

6. Victimization and city growth

In this section, we study whether the probability of victimization is higher in more rapidly growing cities. In theory, rapid urban growth may raise crime for many reasons, including a higher concentration of richer individuals (attracted by rising opportunities in cities), congestion of law enforcement and social services, massive unemployment, and increasing poverty. In practice, however, few studies have explored the connection between these two variables.

We measure city growth as the annual rate of population growth from 1985 to 1995. Our main source of data is the United Nations data set on urban agglomerations. For cities that are not included in this data set, we use different sources, mainly country-specific statistical abstracts. For a few other cities, however, we could not get reliable estimates of population growth. As a result, adding population growth to our specification entails the loss of a few thousand observations, meaning that we cannot readily compare the results of this section to our earlier results.

Table 6
City growth and probability of victimization, Probit estimation: marginal effects

	(1)	(2)	(3)
Coefficient on city growth	0.0147	0.0196	0.020
(Standard error)	(0.0055)	(0.0062)	(0.0074)
Other variables	–	Wealth and household characteristics	Wealth, city size and household characteristics
Number of observations	17088	14961	12950
Number of cities	69	69	67
Pseudo R^2	0.016	0.022	0.023

All regressions include country and year fixed effects.

Table 6 presents the main results of this section. Column (1) reports the effects of population growth on victimization rates after controlling for country and year effects. As shown, city growth has a positive and statistically significant effect on crime rates. On average, an increase of one percentage point in the rate of population growth will increase the probability of victimization by almost 1.5 percentage points.

Column (2) reports the effects of city growth on the probability of victimization after we add the quintile dummies and other household characteristics. As shown, city-growth effects are even larger in this case. Similarly, city growth effects remain practically unchanged after controlling for the size of the city.

On the whole, the estimates presented above suggest that rapid urbanization is associated with a substantial increase in crime. Moreover, because higher criminal rates may actually reduce population growth (they often curtail migration rates by causing people to flee cities), these estimates are likely to underestimate the effect of city growth on crime.[18]

What explains the connection between city growth and crime? Our results indicate that the relationship between city growth and crime cannot be attributed to the characteristics of the victims. Thus, the higher levels of crime in faster growing cities are not driven by the concentration of high-income households in these cities. We are left with two possible explanations: rapid urban growth increases crime by attracting (or nurturing) a larger share of crime-prone individuals or urban growth diminishes the effectiveness—and hence the reputation—of law enforcement institutions.

Below, we offer some preliminary evidence consistent with the latter idea. We first show that confidence in the police is lower in rapidly growing cities, we then show that victimization rates are higher in cities with lower levels of confidence in

[18] Cullen and Levitt (1999) show that in the United States, each additional reported crimes leads, on average, to one fewer resident.

Table 7
Correlations between crime, population growth and confidence in institutions (correlations are at the city level)

	Crime	Population growth	Confidence in police	Confidence in judiciary	Confidence in president	Confidence in political parties
Crime	1.000	0.227	−0.467 *	−0.276 *	−0.192 *	−0.274 *
Population growth		1.000	−0.398 *	−0.347 *	−0.086	−0.307 *
Crime in police			1.000	0.589 *	0.517 *	0.535 *
Crime in judiciary				1.000	0.481 *	0.570 *
Crime in president					1.000	0.592 *
Crime in political parties						1.000

Correlations marked with (*) are significant at the 5% level.

Table 8
Crime victimization and confidence in the police and judiciary (dependent variable: probability of being victimized), marginal effects

	PROBIT	IV PROBIT (President)	IV PROBIT (Political Parties)	IV PROBIT (President, PP)
Confidence in police	−0.189	−0.1504	−0.270	−0.135
(Standard error)	(0.055)	(0.185)	(0.205)	(0.151)
Number of observations	17,097	12,737	16,870	12,737
Number of cities	151	149	151	149
Pseudo R^2	0.026	–	–	–

All regressions include country and year fixed effects as well as controls for household attributes and city size. Cities with fewer than 30 observations were excluded from the sample.

the police, and finally, we show that there appears to be a causal link going from low confidence in the police to higher victimization rates.

Table 7 shows, among other things, that the levels of confidence in the police and the judiciary tend to be lower in faster growing cities. The correlation coefficient is in both cases close to 0.4 and statistically significant. Table 8 shows, for its part, that lower levels of confidence in the police are correlated with higher probabilities of victimization, even after controlling for household attributes and city size. On average, an increase of 20 percentage points in the level of confidence in the police will be associated with a decline in the probability of victimization of almost 4 percentage points.[19]

Needless to say, the confidence people bestow on the police is likely to be greatly affected by the incidence of crime, meaning that a causal connection between the incidence of crime and confidence in the police remains an issue. We attempt to solve this problem by instrumenting the level of confidence in the police using confidence in the president and political parties.

Our choice of instruments is based on two facts. First, the correlation between confidence in the police, on the one hand, and confidence in the president and political parties, on the other, is very high. As shown in the Table 7, the correlation coefficient is greater than 0.5 in both cases, meaning that both variables are good predictors of the level of confidence in the police in a city (perhaps because the confidence of all government institutions are determined by a common factor). And second, the instruments have little explanatory power when added directly to Eq. (1). The estimated coefficients are very small and always smaller than their estimated standard errors, and the variables did not add to the

[19] We assign to each person the average confidence on the police for his city of residence after excluding his own answer. We eliminated all households who live in cities that contain fewer than 30 observations in the sample.

explanatory power of the equation, meaning that confidence in the president and political parties are unlikely to have an independent effect on the probability of victimization.

In our estimation, we assume that the level of confidence in the police in a city can be written as the following linear model

$$c_{-ij} = \mathbf{x}_1\gamma_1 + \mathbf{x}_2\gamma_2 + \varepsilon_{-ij}, \qquad (2)$$

where c_{-ij} is the mean confidence in the police in city j after excluding individual i, $\mathbf{x}_1$ are the determinants of the probability of victimization and $\mathbf{x}_2$ are the exogenous variables, in this case, the levels of confidence in the president and political parties computed at the city level. We assume that the error terms of Eqs. (1) and (2) are distributed according to a bivariate normal distribution with correlation coefficient σ. We simultaneously estimate Eqs. (1) and (2) under the previous assumptions using a Maximum Likelihood procedure.[20]

Columns (2) to (4) of Table 8 present the Probit IV estimation results. As shown, the coefficient on confidence in the police remains negative and does not vary substantially, though is measured with smaller precision. Indeed, this coefficient is not significant in any of the IV estimations, reflecting, perhaps, a problem with our sample size (our confidence variables are measured at the city level). All in all, these results present suggestive (but no conclusive) evidence to the effect that there exists a causal link between lower levels of confidence in the police and higher probabilities of victimization.

In our view, the former results provide some support to our claim to the effect that the link between population growth and crime is partly driven by the overload of law enforcement institutions and the subsequent deterioration in their effectiveness and reputation.

7. Concluding remarks

In this paper, we draw a profile of the victims of crime in Latin America. We show that—at least in the case of property crime—the typical victims of crime in Latin America come from rich and middle class households and tend to live in larger cities. We also show that households living in cities experiencing high population growth are more likely to be victimized than household living in cities with more stable populations. We offer various explanations to these facts, and while we cannot yet provide definite answers to some of the questions raised by this paper, we are at least able to reject some plausible hypotheses.

[20] Specifically, we use a program written by Deon Filmer at the World Bank, available in the internet at http://glue.umd.edu/~gelbach/ado.

We have not attempted here to explain why crime rates are higher in Latin America than in other areas of world. However, our analysis suggests that the higher levels of urban concentration and the faster rates of population growth that are typical of many Latin American countries are partly to blame for the higher criminal rates. Of course, several other factors not mentioned in this paper are also very important. Drug trafficking, for example, is conspicuously absent throughout, as are social capital and other cultural elements.[21]

Acknowledgements

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Appendix A. A simple model of crime victimization

Are wealthy individuals more likely to be victims of property crime? The answer to this question depends on the relative strength of two opposing forces. On the one hand, the wealthy are more desirable targets for criminals and, on the other, they have more reasons to invest in private protection against crime. Here we investigate the circumstances under which the first force dominates the second, thus making wealthier individuals more likely to fall prey to criminals.

The structure of the model is simple. There are two actors (citizens and criminals) and two stages. In the first stage, citizens (who differ only in their wealth holdings) decide how much to spend in private protection. In the second stage, citizens are matched with criminals who in turn decide whether or not to commit a crime upon observing the wealth (w) of their prospective victims and their investments in private protection (e). Criminals make their decisions on the basis of mere pecuniary factors. They weigh in two factors: a successful criminal attempt will mean enjoying a bounty of α times w ($\alpha \leq 1$), and a failed criminal attempt—that occurs with probability p—will mean incurring a fine of F.

Three additional assumptions are made. First, the probability of apprehension is assumed to increase monotonically with the expenses in private protection (i.e., $p = \mathbf{p}[e]$, where $\mathbf{p}' > 0$). Second, victims and criminals are assumed to be risk neutral. And last, criminals are assumed to have complete information in that they

[21] Lal (1998) argues, for example, that the reason why urbanization has not been so disruptive in Muslim countries is that in these countries people rely mainly on informal communities mechanism to control crime (e.g., Teheran, a city of 10 million inhabitants, has very low crime rates). This argument can explain, among other things, why congestion of law enforcement institutions has not had the same consequences in the Middle East as in Latin America.

observe their victim's wealth and are able to correctly infer their chances of being apprehended.

Thus, a criminal will attempt to victimize citizen i who possess a wealth of w_i and have invested e_i in private protection as long as the following inequality holds

$$(1-\mathbf{p}[e_i])\alpha w_i - \mathbf{p}[e_i]F > 0. \tag{A1}$$

Because all citizens are paired with criminals, citizen i can avoid being victimized only by investing at least h_i in private protection, where h_i corresponds to the expenses in private protection that would make a criminal indifferent between attempting to steal from i or not doing it because poses too high of a risk. In short,

$$h_i = \mathbf{p}^{(-1)}\left[\frac{\alpha w_i}{\alpha w_i + F}\right] \tag{A2}$$

where $\mathbf{p}^{(-1)}$ is the inverse of the function $\mathbf{p}$ that links private expenses in protection to the probabilities of punishing a criminal.

Eq. (A2) gives, for each level of wealth, the minimal expenses on private protection required to scare criminals away: any amount below h_i is insufficient and any amount above it is superfluous. Citizens face thus a binary decision; they either invest h_i in private protection or do not invest at all. Obviously, they will invest h_i only if it does not exceed the prospective losses of being victimized. That is, if

$$h_i \leq \alpha w_i. \tag{A3}$$

Wealthier individuals would need, all else being equal, greater investments in private protection to avoid victimization. This is immediately apparent from the first derivative of expression (A2) with respect to w,

$$\frac{\mathrm{d}h}{\mathrm{d}w} = \frac{\alpha F}{(F-\alpha w_i)^2\mathbf{p}'[h]} > 0. \tag{A4}$$

But are wealthier individuals willing to incur in the higher costs of private protection? Or will they instead prefer to bear some crime? As we shall see below, the answer to this question depends on the second derivative of h with respect to w.

Fig. 4 depicts the two types of relevant solutions of the model.[22] In the first case, Eq. (A2) is concave, h is below αw for higher values of w, the wealthy invest in private protection, and the poor are victimized. In the second case, Eq. (A2) is convex and the conclusion switches: the poor are the ones who invest in

[22] Fig. 4 summarizes all cases of economic interest. For same parameter values, the two curves in the graph will never intersect, meaning that all citizens are victims of crime or on citizens are victims of crime.

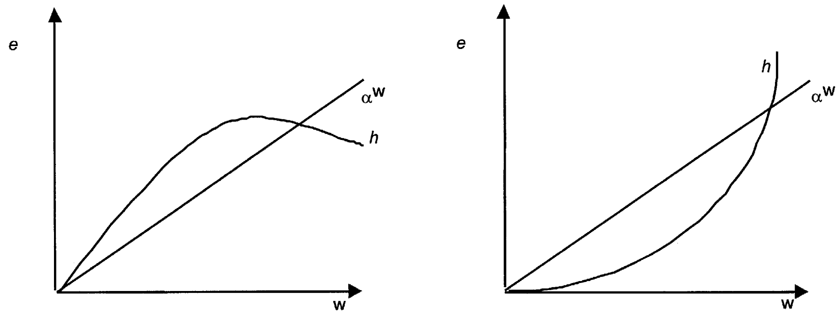

Fig. 4. Private investments in security versus criminal losses.

protection and the wealthy the ones who bear the brunt of crime. In short, all depends on the concavity of Eq. (A2).

What determines the concavity of Eq. (A2)? The answer is evident by looking at the second derivative of h with respect to w,

$$\frac{\mathrm{d}^2 h}{\mathrm{d}w^2} = -\frac{\alpha^2 F\left(2(F+\alpha w)\mathbf{p}'[h]^2 + F\mathbf{p}''[h]\right)}{(F+\alpha w)^4 \mathbf{p}'[h]^3}. \tag{A5}$$

Clearly, Eq. (A5) will be negative unless the second derivative of **p** is both negative and large in absolute value. So the wealthy will routinely invest in private protection in order to avoid victimization unless **p** exhibits sharp diminishing returns to scale. The intuition is straightforward; if the marginal returns of an extra peso spent in private protection against crime are *very* low, the wealthy will find it extremely expensive to reach the level of protection needed to avoid victimization and will rationally decide to bear some crime. Otherwise, they will invest the necessary amount to escape victimization.

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