Is Murder Bad for Business and Real Income? The Effects of Violent Crime on Economic Activity

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Abstract

High levels of violence are associated with lower income and higher inequality. This paper studies the channels through which violence (measured by the homicide rate) impacts economic outcomes, and thus whether investments in violence reduction have significant economic returns. I estimate the effects of violent crime on local wages, prices, and production using unique firm-level panel data and rich information on consumer prices in Colombia. To estimate causal effects, I exploit exogenous reductions in violent crime driven by U.S. international anti-drug expenditures; these resulted in greater violence reductions in municipalities with higher political competition (namely closely contested elections) in the past. I find that higher homicide rates lower housing rents and increase prices. Wages also increase, but only for white-collar workers. Putting all these forces together, real wages fall for both types of worker, but more so for blue-collar workers. These estimates, in combination with a theoretical model, allow me to compute that when homicide rates increase 10%, white- and blue-collar workers' welfare (measured as utility of consumption) is reduced 2.8% and 6.3%, respectively. Consequently, violent crime increases inequality as measured by real incomes or by welfare. Aggregate production also falls 2.1%, mostly because firms reduce production, although there is also a small decrease in the number of firms.

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1 Introduction

Violence remains a development challenge today. Every year, approximately 11% of global GDP is spent to address and contain violence (IEP, 2013).[1] Despite the fact that more than 65% of these resources are spend in developing countries, the most violent countries and regions, based on the homicide rate,[2] are also the poorest and most unequal, as shown in Figure 1. Violent crime not only imposes direct costs on society through mortality,[3] but also induces indirect economic costs by distorting workers' and firms' decisions. These distortions are reflected in market prices and market size, and ultimately affect consumer welfare. However, with the exception of housing prices and GDP,[4] there is limited evidence on the effects of violent crime on local markets, and no work that investigates its effects on inequality.

This paper estimates the effects of violent crime on market prices (non-housing prices, wages, and housing rents) and market size (average production and firm exit) by examining unique firm-level and rich consumer pricing data matched to homicide rates in Colombia. With the exception of the elasticities of housing rents to violent crime,[5] these elasticities have not been identified before.[6] It also investigates the extent to which homicide rates have heterogeneous effects, specifically whether it affects high- and low-skilled workers equally (blue- and white-collar). This facilitates the characterization of the types of agents who are

[1]Of these amount 51% are accounted for by military expenditures.

[2]Violent deaths per 100,000 inhabitants are the most consistent measure of violent crime available over time and space. In 2012, Southern Africa and Central America were the sub-regions with the highest homicide rates on record with averages over 25 victims per 100,000 inhabitants, followed by South America, Middle Africa, and the Caribbean with average rates between 16 and 23 homicides per 100,000 inhabitants.

[3]See Soares (2006) for a review of the mortality costs of violence.

[4]A large group of studies uses hedonic pricing models to identify the effects of urban crime on property prices–e.g., Thaler (1978), Hellman and Naroff (1979), Lynch and Rasmussen (2001), Bowes and Ihlanfeldt (2001), Gibbons (2004), and Linden and Rockoff (2008). They find a negative elasticity of housing prices with respect to urban crime. See Appendix B for a detailed list of the point estimates of these studies. Another group of literature investigates the effects of violence on aggregate economic activity. Cross country studies find negative effects of violence on economic activity (e.g., Organski and Kugler, 1977, Alesina and Perotti, 1996, Collier, 1999, Imai and Weinstein, 2000, Murdoch and Sandler, 2004, Hoeffler and Reynal-Querol, 2003, Blomberg and Mody, 2005, Busse and Hefeker, 2007, Abadie and Gardeazabal, 2008, Justino and Verwimp, 2008, and Cerra and Saxena, 2008). Within-country studies find mixed results depending on the type of violence analyzed. Evidence on the effects of terrorism and internal conflict points to negative effects on economic growth (e.g., D'Addario, 2006, Arunatilake et al., 2001, Abadie and Gardeazabal, 2003, Deininger et al., 2003, and Pshiva and Suarez, 2006). Evidence on the effects of international wars points to insignificant long term effects on economic activity (e.g., Davis and Weinsten, 2002 and Miguel and Roland, 2011).

[5]See Appendix B for a detailed list of the 16 papers that identify this elasticity.

[6]It most be mentioned however that using similar data Camacho and Rodriguez (2013) study the effects of conflict on the probability of firm exit. The authors find a positive relation between conflict and the probability of firm exit.

more vulnerable to violent crime and the analysis of the effects of violent crime in inequality.

To estimate causal effects of violent crime, I make use of the large reductions in violence caused by large U.S. transfers (measured through the intensity of the U.S. international anti-drug expenditures) sent in the late 1990s to improve security conditions in Colombia. These expenditures were disbursed across areas based on population alone, but they affected municipalities differently depending on the original location of illegally armed groups. According to most historical accounts the illegal armed groups were originally located in areas that had high political competition through an episode known as *La Violencia* (1948-1958).[7] As a consequence of this episode, illegal armed groups were created and first located in areas with higher political competition, proliferating all forms of violence, and dis-empowering the local governments. I use the interaction of local political competition in 1946 with the level of U.S. transfers as my instrument for violence. Consequently, my variation comes from the fact that when security conditions improve across the country, areas with higher political competition in 1946 (namely areas with more contested elections), reduced violence more proportionally when security transfers from the U.S. were higher.

I find large effects of violent crime on a series of market prices, including wages, rents, and non-housing living costs. In particular, I find evidence of a small wage compensation for violent crime; however, it is only statistically significant for white-collar workers. My estimates suggest that when homicide rates increase in 10%, white-collar workers nominal wages increase by about 1%. Data on internal migration from the 2005 Colombian population census suggests that one of the reasons only white-collar workers see compensating wage rises is that they have lower geographic mobility costs (as found by Cullen and Levitt, 1999, and Malamud and Wozniak, 2010). Additionally, I find that higher violent crime induces firms to increase output prices, and that in turn, non-housing living costs are drastically increased in more violent areas. This result is confirmed by the behavior of local food prices: when homicide rates increase 10%, retail food prices increase 6%. The increase in food prices, coupled with firms' pricing behavior, strongly suggests an increase in non-housing living costs in more violent areas. I also find that housing rents decrease in response to higher levels of homicide rates. Specifically, when homicide rates increase 10%, housing rents decrease 4%. However, the effects are too small to compensate for the increase in non-housing living costs. Overall, a 10% increase in homicide rates causes real income for blue- and white-collar workers to decrease 1.3% and 0.6%, respectively. Consequently, violent crime increases income inequality.

[7] There is strong historical evidence supporting this argument (see Guzmán et al., 2006, Sarmiento, 1985, Henderson, 1984, Pécaut, 2001, and Roldán, 2002). The political competition index was created with information from the previous presidential elections to the period of *La Violencia* (1948-1958).

With regard to the effects on market size, I find that higher input costs, higher wages, and workers' migration (which reduces output demand) drive firms to reduce production, and ultimately, causes some firms to exit the market. Specifically, when homicide rates increase 10%, firms' production declines 1.7%, and the number of firms in the market is reduced 0.4%.[8]

I then propose a theoretical framework that allows me to compute welfare effects using the estimated elasticities.[9] The model presents an economy divided into municipalities that face different levels of violence. In the model, violence reduces workers utility by acting as a local disamenity–e.g, by increasing the probability of being harmed and the stress of living in more dangerous environments. Additionally, violence increases firms' marginal cost through additional expenditures on security. The model predicts that when violence increases, workers move to areas with lower violence, thereby pushing up wages. Higher wages and higher security-costs induce firms to increase output prices in a setting with monopolistic competition. In turn, higher prices coupled with workers' migration reduce local demand. Hence, aggregate production falls generating negative profits until some firms exit the market. The overall effects of violence on workers' welfare and firms' aggregate production can be expressed as a function of the elasticities of market prices and size with respect to violence. The model can also be used to compute willingness to pay for a violence reduction.

I find negative effects of violent crime on workers' welfare and firms' production, but with some degree of heterogeneity on their magnitude. The overall elasticity of workers' welfare with respect to violent crime is -0.46, about -0.28 for white-collar workers, and -0.63 for blue-collar workers.[10] Consequently, blue-collar workers are twice as affected to changes in homicide rates and are willing to pay a higher percentage of their income to reduce violent crime (relative to white-collar workers). The elasticity of aggregate production with respect to violent crime is estimated to be -0.21; only half as large as the elasticity of welfare with respect to violent crime (-0.47). Hence, by only considering the effects of violent crime on aggregate production, the negative effects of homicide rates are underestimated.

I address concerns related to the validity of my identification strategy. Specifically, my estimates are only valid if there are no time-varying covariates correlated with U.S. international anti-drug expenditures that also have heterogeneous effects across areas with different

[8]These results are in-line with Camacho and Rodriguez (2013) who identify a negative effect of violence on the probability of firm exit using the same data.

[9]The model combines recent frameworks of multiple regions proposed by Redding (2012) and traditional local labor models formulated by Roback (1982) and Rosen (1979), and extends them to include violence.

[10]These elasticities are statistically significant.

levels of political competition in 1946. For example, this occurs if an increase in U.S. international anti-drug expenditures induces the local governments or central governments to change their behavior in different ways within areas with different degrees of political competition. For instance, they could reduce expenditures in areas that received relatively large transfers, or instead choose to complement external funds with more internal funds. I address these concerns by showing that there is no correlation between public expenditures from local governments (as a total and by type) and my instrument, and no correlation between the central government's transfers to municipalities (as a total and by type) and my instrument. I also show my results are robust to controlling for the variation in 45 observable covariates. These observables comprise all the information available at the municipality level in Colombia.[11]

This paper is structured as follows. Section 2 presents the theoretical model, section 3 describes the data, section 4 presents the empirical strategy, sections 5 and 6 present the results, section 7 presents some robustness checks, and finally, the last section offers some concluding remarks.

2 Model Setup

This section presents the theoretical framework for understanding the effects of violence on local markets, which I use to derive the welfare and aggregate production consequences of violence. The purpose of the model is to provide a link between the estimated (observable) effects of violence and its welfare effects. The model combines simple ingredients previously presented in models of multiple regions by Redding (2012) with labor supply models formulated by Roback (1982) and Rosen (1979), and extends them to include violence.[12] It describes an economy divided into municipalities, indexed by m, that face different levels of violence.[13] Each municipality is composed of workers and firms and is endowed with a fixed stock of quality-adjusted housing.[14]

[11] A municipality is a small political subdivision akin to a county in the U.S. There are 1,119 municipalities in Colombia, about 300 are included in this study since 87% of the sample is located in these areas.

[12] For a more recent application see Serrato and Zidar (2014).

[13] Violence is assumed to be exogenous for modeling purposes, but the empirical section will account for this issue.

[14] Housing is included in the model because extensive previous work has shown that violent crime negatively impacts housing prices, which in turn will affect workers' welfare. See appendix B for a review of the point estimates of the 16 studies that identify the effects of violent crime on housing rents.

2.1 Workers' Problem

Each worker has one unit of labor that is supplied inelastically with zero disutility.[15] Workers face different levels of violence according to their location. For workers, violence acts as a municipality disamenity and reduces utility. There is ample empirical evidence on the negative effects of violence on workers' utility. For example, Youngstrom et al. (2003), ODonnell et al. (2011), Ramirez (2012), and Leavitt et al. (2014) show that all forms of exposure to violence, including witnessing, being a victim, and knowing victims are correlated with several types of behavioral disorders.[16]

Additionally, workers are imperfectly mobile across locations. Following Redding (2012) restrictions to mobility are introduced assuming that workers have idiosyncratic preferences for each location (x_{im}) drawn from a known distribution. Idiosyncratic preferences can also be understood as idiosyncratic mobility costs for each location, which are independently drawn across workers and locations.[17]

In sum, each worker i, located in municipality m, maximizes utility over housing (h_{im}) and a composite good of tradable varieties (C_{im}) facing wages (w_m), rents (r_m), a non-housing good price index (P_m), violence (v_{mt}), and an idiosyncratic mobility cost (x_{im}). Specifically, workers solve the following problem:

$$\max_{C_{im}>0, h_{im}>0} \left[\left(\frac{C_{im}}{\alpha} \right)^{\alpha} \left(\frac{h_{im}}{1-\alpha} \right)^{1-\alpha} \right]^{\beta} \left[\frac{1}{v_m} \right]^{1-\beta} x_{im}$$

$$s.t \qquad P_m C_{im} + r_m h_{im} = w_m + T \tag{1}$$

with:

$$C_{im} = \sum_{k \epsilon M} \left[\int_0^{N_k} c_{jmk}^{\rho} dj \right]^{1/\rho}$$

where N_k denotes the number of firms and T represents non-labor income, which comes via lump-sum transfers of the total revenue collected through housing rents.[18] Given this setup each worker chooses the region that offers him the highest utility. Moreover, wages

[15] Inelastically supplied labor is a common assumption in local labor markets such as Rosen (1979) and Roback (1982). More recent examples can be found in Moretti (2011).

[16] Similar results are presented by Ghobarah et al. (2003), Camacho (2008), Bundervoet et al. (2009), and Akresh et al. (2011), who find negative impacts of civil war exposure on height-for-age-z-scores for children, prenatal stress, and future health risks (even several years after the end of the conflict).

[17] This assumption is necessary to guarantee different levels of welfare across locations. Otherwise, in the case of perfect mobility workers will move between locations until the welfare is equalized across locations.

[18] Ownership is symmetrical across individuals as in Helpman (1998).

and utility differ across locations. The corresponding indirect utility function that describes workers' maximum welfare given market prices and violence is then given by:

$$V_{im}(P_m, w_m, r_m, v_m) = [(w_m + T)P_m^{-\alpha} r_m^{\alpha-1}]^{\beta}[1/v_m]^{1-\beta} x_{im} \tag{2}$$

Hence, higher violence reduces workers indirect utility in each location inducing some workers to migrate to other areas. In turn, migration flows are reflected in changes in wages, non-housing prices, and housing rents. Thus, by affecting workers' migration decision, violence indirectly affects market prices.

2.2 Firms' Problem

Each firm j acts as a monopolistic competitor producing a unique and differentiated product.[19] Firms are immobile across locations and face different violence intensity (v_m) depending on the municipality in which they are located.[20] Violence increases firms' marginal costs as found by Goldberg et al. (2014), who compiles strong evidence on the higher security costs that firms face when violence is higher for multiple cities and countries in the world.[21] In addition, firms produce their outputs using only labor.[22]

Following Redding (2012), to produce a variety, a firm must incur a fixed cost of F units of labor and a variable costs that is increasing in violence.[23] Hence, the amount of labor ($l_m(j)$) required to produce $y_m(j)$ units of variety j in municipality m is given by:

$$l_m(j) = F + MC(v_m)y_m(j) \tag{3}$$

where $MC(v_m)$ represents the marginal costs incurred by the firm which are an increasing

[19] This assumption allows to test whether violence has an effect on the extensive (average production) and intensive margin (firm exit) of production. If firms are assumed to act as price takers, then violence will only affect the extensive margin of production (firm exit).

[20] This assumption follows the behavior observed in Colombian data where firms' mobility between municipalities occurs for only 2% of the sample. However, the results of the model hold as long as there are some restrictions to firms' mobility, which in practice is always the case, given that firms have invested on infrastructure in each location.

[21] Their city studies include Ciudad Juarez, Medellin, Mexico City, Rio de Janeiro, and Tijuana, while, their country-level studies include Jamaica, Nepal, and Rwanda.

[22] This assumptions was imposed for simplicity. However, a more complicated of the version in which firms produce using labor and other firms outputs as their inputs of production yields similar results.

[23] Firms can sell locally or to other municipalities. As long as there are some barriers to trade the results of the model hold. In practice, this is always the case since there are always transportation costs between regions.

function of violence. Profit maximization implies that equilibrium prices are a constant mark-up over marginal costs so that the prices offered by firm j at municipality m are given by:

$$P_m(j) = [\frac{\epsilon}{1+\epsilon}]MC(v_m) \tag{4}$$

where ϵ denotes the elasticity of demand. Replacing the constant mark-up condition into the free entry condition yields the equilibrium output. Thus in this context, by increasing firms' marginal costs, violence reduces the equilibrium intensive margin of production:

$$y_m^*(j) = \frac{F(\epsilon - 1)}{MC(v_m)}$$

Given $y_m^*(j)$, the labor market clearing condition implies that the total number of firms in each municipality (N_m), is proportional to the endogenous supply of workers. Thereby, violence also affects the extensive margin of production:

$$N_m^* = \frac{L_m(v_m)}{F\epsilon} \tag{5}$$

Consequently, the number of firms in each municipality is a decreasing function of violence because higher violence induces workers migration. In brief, violence reduces the aggregate production within each municipality by reducing the production of the firms that stay in the market (intensive margin) and by driving firms to exit (extensive margin).

2.3 Violence Incidence on Welfare and Aggregate Production

The effects of violence on workers' welfare can be approximated by the effects on their indirectly in their indirect utility of consumption, which captures the direct effects of violence on utility as well as the indirect effects through changes in prices. Additionally, the effects on firms' aggregate production in each municipality can be estimated as the sum of the effects of violence on firms' intensive and extensive margin of production. Specifically:

Proposition 1. *Given the indirect utility function presented in equation (2). The effects of violence on the utility of consumption of worker i at municipality m can be expressed as:*

$$\frac{dV_{im}}{dv_m} = \underbrace{\frac{\partial V_{im}}{\partial P_m}\frac{\partial P_m}{\partial v_m} + \frac{\partial V_{im}}{\partial w_m}\frac{\partial w_m}{\partial v_m} + \frac{\partial V_{im}}{\partial r_m}\frac{\partial r_m}{\partial v_m}}_{\textit{Market/Indirect effects}} + \underbrace{\frac{\partial V_{im}}{\partial v_m}}_{\textit{Direct disutility effects}} \tag{6}$$

Moreover, the elasticity of firms' aggregate production with respect to violence within each municipality m is given by:

$$\epsilon_{Yv} = \frac{dlog(Y_m)}{dlog(v_m)} = \underbrace{\frac{\partial log(\bar{y_m})}{\partial log(v_m)}}_{\text{intensive margin effects}} + \underbrace{\frac{\partial log(N_m)}{\partial log(v_m)}}_{\text{extensive margin effects}} = \epsilon_{yv} + \epsilon_{Nv} \tag{7}$$

where $Y_m = N_m \bar{y_m}$ denotes the aggregate production in municipality m at period t given the total number of firms (N_m) and the average production per firm ($\bar{y_m}$).

Equations (6) and (7) are at the center of my empirical analysis. In the next sections I identify empirically the effects of violence on market prices (i.e., non-housing prices, rents, and wages) and market size (i.e. firm exit and production) to then quantify equations (6) and (7).

The model predicts the direction in which violence should affect market prices and size. When violence is higher firms are expected to increase output prices to offset the higher costs they face. Additionally, workers' migration will induce wages to increase and housing prices to fall given the fixed housing supply within each municipality. Higher costs and lower sales due to workers' migration reduce firms' profits, so that ultimately, the number of firms in the market is reduced.

3 Data

I use Colombian annual data between 1995 and 2010 to carry out my empirical analysis. Colombia offers an ideal setting to identify the effects of homicide rates for at least three reasons. First, there was drastic municipal and annual variation in homicide rates during the period of analysis. Second, in the early 90s there was intense violent crime, making Colombia the second most violent country in the world after El Salvador. However, this violent episode was followed by a remarkable recovery in security conditions. In particular, homicide rates dropped in 48% during the period of analysis. Third, it is a developing country with excellent micro data on firms' behavior and consumer retail food prices.

3.1 Data on Violent Crime

Data on violent crime by municipality is available from the Observatory of Human Rights of the Colombian Vice Presidency. I use intentional homicide rates per 100,000 inhabitants as a measure of violence because they are available for the whole period of study and for all of the municipalities in the country. This is not the case for any other available indicators. Moreover, this is the only available measure of violent crime consistently measured across countries and regions of the world, which facilitates the interpretations and comparison on the results of this study.

Figure 2 (right panel) presents the time evolution of intentional homicide rates for the period of interest. It shows that violent crime was drastically reduced after 2002 with the election of Álvaro Uribe as president. Uribe's primary policy objective was to improve security conditions across the country. Consequently, homicide rates declined by 48% between 1995 and 2010, from 65.8 to 33.97 homicides per 100,000 inhabitants, respectively.

Figure 3 presents the geographic distribution of intentional homicide rates for 2002 and 2011, the years before and after the sharp decline in violent crime. The figure suggests that the violent crime reduction was focused on the center of the country (around the capital city). Additionally, the figure shows the strong geographic variation on homicide rates during the period of analysis. I exploit the annual and municipal variation in homicide rates to identify the effects of violent crime.

When considering the correlation between homicide rates and other measures of violence more representative of the Colombian armed conflict (such as armed actions, attacks, clashes between groups, and deaths in battle),[24] I find that both types of violence are correlated; however, this correlation is low. The highest correlation occurs between homicide rates and armed actions, with a value of 0.2. This suggests that, although the intensity of the armed conflict influences homicide rates, the main variation in homicide rates is driven by other variables. Moreover, because more than 87% of the firm-level data is located in urban areas and the Colombian armed conflict mainly takes place in the rural areas, this study identifies the effects of more general forms of violent crime, rather than violence induced by conflict.

3.2 Data on Market Prices and Size

I use three main sources of information. The first source of information is the *Encuesta Anual Manufacturera* [Annual Manufacturing Survey], collected by the *Departamento Nacional de Estadística, DANE*, the Colombian statistical agency. The data set is a census of all the manufacturing plants with ten or more workers or value of total output larger than 65 million of 1992 Colombian pesos (approximately USD$95,000). Once a plant is included in the survey, it is followed over time until it goes out of business. Moreover, all multi-plant

[24] Available through the Conflict Analysis Resource Center (CERAC).

firms are included even if only one of them satisfies the selection criteria. The data set is an unbalanced panel data of approximately 16,016 firms (16,776 plants) for the period between 1995 and 2010, which amounts to a total of 124,247 observations.

In conjunction with the standard plant information, the census contains information on all physical quantities and prices (valued at factory-gate prices) of each output and input used or produced by each plant. In this paper, firms' prices are defined as the plant-product-year observation estimated by dividing the value of revenues or expenditures by physical quantities. Appendix A presents the descriptive statistics of the survey for 1995 and 2010.[25] I use this data to estimate the effects of homicide rates on firms' output prices, wages, production, and exit decision.[26]

A secondary source of information are local retail food prices collected by the Colombian Ministry of Agriculture. The data covers average annual retail prices of the 500 most consumed food products (according to sales) within 53 municipalities located in 20 departments from 1996 to 2010. I use this data to study the effects of homicide rates on retail food prices.

The third source of information are the Colombian National Household Surveys between 1995 and 2010. These surveys are representative at the national level and correspond to cross sections collected annually. They are also collected by the Colombian statistical agency and contain information on workers' and households' socioeconomic characteristics. I use this data to estimate the effects of homicide rates on housing rents and recover key parameters of the indirect utility function.

4 Identification Strategy

My empirical analysis proceeds in two steps. First, I estimate the effects of homicide rates on market prices (non-housing prices, housing rents, and wages) and market size (firm production and exit). Then I combine the estimated elasticities with equations (6) and (7) to quantify the effects of violent crime on workers' welfare (measured as utility of consumption) and firms' aggregate production.

To identify the effects of violent crime I exploit the municipal and annual variation in

[25] The tables report a drop in average production and wages between 1995 and 2010. This is only observed when the variables are expressed in dollars given the drastic depreciation of the Colombian peso between those years. Yet, the values increased in Colombian pesos during this period.

[26] All variables expressed in monetary terms (except wages) were transformed into real values using a producer price index generated for each firm using 1995 as a base year. The index was constructed using a Laspeyres methodology.

homicide rates between 1995 and 2010.[27] The municipal standard deviation of homicide rates across years is presented in Figure 2 (left panel). It confirms that there is a large geographic variation in violent crime during the period of interest. Firms' exposure to violence corresponds to the homicide rates observed in the municipality where they are located. The specification of interest is given by:

$$log(y_{jmt}) = \gamma_0 + \gamma_1 log(v_{mt}) + k_j + g_t + \epsilon_{jmt} \tag{8}$$

where y_{jtm} represents market prices or size observed for firm j, at year t, and located at municipality m, v_{mt} are homicide rates, ϵ_{jmt} is the error term, and k_j and g_t are fixed effects by firm (or municipality) and year.[28]

The identification of γ_1 is challenging given the endogeneity concerns between homicide rates and market outcomes, even after controlling for firm or municipality fixed effects. Specifically, firm or municipality fixed effects only solve issues of cross section endogeneity that correspond to static differences between areas with high and low levels of violent crime. However, time-feedback effects may be still taking place. For example, in the case of firms' production, time-feedback effects may take place in two different directions. First, when production is high, economic conditions may improve, inducing less poverty, less violent crime, and better economic conditions as documented by Miguel et al. (2004) and Miguel and Satyanath (2011). This is the so-called *grievance* channel, as defined by Collier and Hoeffler (2004). It implies that high-production areas tend to be less violent, whereas low-production areas tend to be more violent. Hence, the gap in production increases with time across areas with different levels of violent crime. In this setting, γ_1 will be upward biased. In contrast, as suggested by Dube and Vargas (2013), a rise in contestable income via an increase in production, may also increase violent crime by raising gains from income appropriation. This is the so-called *greed or rapacity* channel, which suggests that violent crime may be equally significant in areas with high and low production. In this situation, γ_1 will be biased towards zero.[29]

[27] Colombia is divided into 1,119 municipalities, they are approximately equivalent to a U.S. county.

[28] Specifically, for the estimates of the effects of homicide rates on firm exit decision and rents the model only includes fixed effects at the municipal level.

[29] Time-feedback effects also increase prices in areas with low and high violent crime, which complicates the identification of its effects. For example, in areas with high levels of violent crime firms' costs are higher given the additional security expenditures. In turn, higher prices and reduce purchasing power, which further fuels violent crime. However, areas with low violent crime also face higher prices given they likely also have high agglomeration. Higher prices induce selection so that only the wealthiest individuals tend to stay. Because the wealthiest individuals are also likely to be the most educated, violent crime is further reduced. Hence, the estimates of γ_1 will be biased towards zero.

To address for endogeneity concerns, I use a panel-instrumental variable methodology. Firm or municipality fixed effects solve the cross section endogeneity problems, whereas the instrument for homicide rates addresses the time-feedback effects between homicide rates and market outcomes. In sum, I estimate the effects of homicide rates through the following specification:

$$log(y_{jmt}) = \gamma_0 + \gamma_1 log(v_{mt}) + k_j + g_t + \epsilon_{jmt} \tag{9}$$

$$log(v_{mt}) = \theta_0 + \theta_1 PC_{mt} + k_j + g_t + u_{jmt} \tag{10}$$

where y_{jmt} represents the outcomes of firm j, located in municipality m, at year t, v_{mt} represents homicide rates, PC_{mt} is the instrument for violent crime (explained in detail in the next section), and k_j and g_t represent firm (or municipality) and year fixed effects. In this specification, γ_1 will identify the elasticity of the firms' outcomes with respect to violent crime. The identification strategy is valid so long as the exclusion restriction (i.e., $corr(PC_{mt}, \epsilon_{jmt}|k_j, g_t) = 0$) and relevance assumption are satisfied.[30]

4.1 Instrumenting for Homicide Rate

The time variation of the instrument is driven by changes in U.S. international anti-drug expenditures. Around the mid 1990s Colombia became the top producer of cocaine, which was mainly exported to the U.S.[31] Consequently, beginning in 1995 the U.S. began sending approximately 30% of its international anti-drug expenditures each year to improve security conditions in Colombia.[32] Conditional on local population, these resources were to be spent evenly across municipalities.[33] According to the annual budget of the Office of National Drug Control Policy of the White House (ONDCP), between 1995 and 2010 the U.S. disbursed 18.27 billion dollars to reduce the international supply of illegal drugs.[34] The time evolution of these expenditures is presented in Panel (B) of Figure 4.[35] Panel (A) of the same figure

[30] The relevance assumption, as defined by Imbens and Angrist (1994), Abadie (2003) and Angrist et al. (1996) requires a strong correlation between violent crime and the instrument.

[31] See the annual World Drug Reports by the United Nations Office of Drugs and Crime.

[32] According to official documents this condition was imposed to guarantee that the resources reached the poorest and most politically unrepresented regions of Colombia.

[33] Yet, within each municipality these resources could be spent in different ways.

[34] There is no record of U.S. international anti-drug expenditures to Colombia before 1995 in the official documents of ONDCP or Colombian data. For this reason, I assume they are very small or nearly zero.

[35] To whether the variation on my instrument is driven by a time trend I run all my estimates also restricted my sample for the period between 1998 and 2002 when there was a sharp increase and decline in

shows the changes in homicide rates per 100,000 inhabitants compared to the changes in U.S. international anti-drug expenditures. It suggests that there is a negative contemporaneous correlation between the changes in both variables.

The resources disbursed by the U.S. had different levels of effectiveness within different municipalities: they reduced violent crime more proportionally in areas where violent groups were more clearly established by targeting those groups and recovering the monopoly of authority. To identify these areas, I use a political competition index for 1946, which corresponds to the presidential elections previous to the episode of *La Violencia*, which historians point as the origin of the current illegally armed groups–e.g., Guzmán et al. (2006), Sarmiento (1985), Henderson (1984), Pécaut (2001), and Roldán (2002). *La Violencia* was a historical episode that took place between 1948 and 1958. It was period of strong violence between the two traditional political parties. In April of 1948, political competition between the *Liberales* [liberals] and *Conservadores* [conservatives] escalated dramatically to armed actions as the liberals' leader, Jorge Eliecer Gaitán, was assassinated. Although an amnesty was declared between parties in 1953, after which most of the armed groups were disarmed, poor economic conditions for former combatants coupled with low support for reintegration, facilitated the creation of new illegally armed groups.[36] Hence, the illegally armed groups were created and originally located in areas with higher political competition around *La Violencia*.

Once created, illegally armed groups spread all forms of violence where they were initially located. Consequently, governments with higher political competition in 1946 became less empowered and violent groups were also more clearly established in these areas. Hence, areas with a higher political competition during *La Violencia* have higher violent crime today. Moreover, when these areas received higher security expenditures, driven by higher U.S. international anti-drug expenditures, they were able to reduce violent crime more effectively by recovering the monopoly of authority and targeting these violent groups more precisely.

U.S. international anti-drug expenditures. My results are robust to this test, they are not reported to save space, but the estimates are available upon request.

[36]Consequently, in 1964 adherents of the Cuban-style revolution founded the National Liberation Army (ELN, for its initials in Spanish). Later, in 1966, a second left-wing group called the Revolutionary Armed Forces of Colombia (FARC, for its Spanish name) was founded as the union of all the remaining communist guerillas. Initially, both groups claimed to defend the interests of the rural poor, aiming to overthrow the government and install a Marxist regime. However, with time, both groups became primarily economically motivated (Dube and Vargas, 2013). Paramilitarism began in the late 1980s as an anti-insurgent response by land-owners and drug traffickers to the left-wing guerillas' actions in areas where the state was unable to provide security. In 1997, the paramilitary forces coalesced into the United Self-Defense Organization of Colombia (AUC, for its Spanish name). By 2003, the AUC declared a partial ceasefire, and some paramilitary blocks agreed to participate in a 'disarming program' that concluded in 2005. However, many of the combatants that were part of the AUC fused later into new criminal groups that are known today as *Bandas Criminales* (BACRIM, for its name in Spanish).

Exploiting this idea, I construct the instrument for homicide rates as the interaction of the U.S. international anti-drug expenditures and a political competition index for 1946–which corresponds to the presidential elections prior to the crisis of *La Violencia*.[37] The political competition index that I use was constructed by Chacón et al. (2011) with information from the results of the 1946 presidential elections by municipality as:

$$PC_m = 1 - \frac{|\%\text{Liberal votes}_m - \%\text{Conservative Votes}_m|}{100} \tag{11}$$

thus, PC_{mt} takes values between zero and one. Low values of the index corresponds to the case where one of the political parties had the absolute majority within a municipality. On contrast, high values correspond to cases of extreme political competition (equal vote share in each party). The index is available for 755 of the 1,119 Colombian municipalities and has a mean of 0.5. Specifically, the instrument for homicide rates is constructed as:

$$PC_{mt} = PC_m * \text{US-IAE}_t \tag{12}$$

where US-IAE_t represents the U.S. international anti-drug expenditures in millions of dollars of 1995. In sum, my identification comes from the fact that areas with higher political competition in 1946 had violent groups more clearly established and less empowered local governments. Hence, they were also more responsive to higher expenditures in security. The higher responsiveness of areas with higher past political competition to transfers in security is explained because these funds were used to recover the monopoly of authority. Suggestive evidence on this idea is presented in Panel (B) of Figure 4.[38] The figure shows the time evolution of homicide rate in areas with high and low political competition for 1946. It suggests that U.S. international anti-drug expenditures induce a reversal of fortune between the areas that had different levels of political competition. In other words, the gap in violence between these areas shrinks as U.S. international anti-drug expenditures are higher.

[37] The theoretical relation between political competition and violence has been studied recently by Chacón et al. (2011) and Dunning (2011). The authors show that when institutions are weak and several groups fight for power, democracy in peace is easier to achieve when one group is dominant. Otherwise, although both groups have a higher chance of winning elections, there is also a higher likelihood of success in challenging election results through armed action.

[38] A similar graph which divides municipalities in two groups according to the median level of violence only shows that both areas reduce violence in the same proportion and the gap between regions is the same across time.

4.2 Correlation between Homicide Rates and the Instrument

Evidence on the correlation between homicide rates and PC_{mt} is presented in Figures 5, 6, and 7. Figure 5 presents a fitted linear regression of the mean value of homicide rates against deciles of political competition for 1946. The sample used to construct this figure includes the homicide rates across the whole period of study (the same behavior can be replicated for each year between 1995 and 2010). The figure suggests that municipalities with higher political competition in 1946 have higher homicide rates today.

Figure 6 presents the same exercise for years with different levels of U.S. international anti-drug expenditures. The level of U.S. anti-drug expenditures is reported in the label in parentheses. The figure suggests that the positive correlation between homicide rates and past political competition is positive for every year. Moreover, it suggests that areas with higher political competition in 1946 reduce violent crime for proportionally when U.S. transfers were higher.

In addition, Figure 7 presents the absolute change in homicide rates from 1995 (the year with the lowest U.S. anti-drug expenditures) and 2010 (the year with the highest U.S. anti-drug expenditures). It confirms that the areas with the highest political competition index in 1946 reduced homicide rates more proportionally relative to the other areas in response to higher U.S. transfers.

A formal test for the correlation between the instrument and homicide rates is presented in Table 2. The table presents the results of the first stage regression of the logarithm of homicide rates on PC_{mt} including fixed effects by firm and year as described in equation (10). Column (1) presents the first stage regression using PC_{mt} as an instrument, and columns (2) and (3) present the results of the regression using each PC_m and US-IAE$_t$ as instruments. The last two columns are presented as evidence of the individual contribution of each variable towards the instrument.

The results for column (1) confirm that there is a strong correlation between the instrument and homicide rates. The coefficient on the instrument has a negative sign and is statistically significant. Thus, as predicted, municipalities with a higher political competition index for 1946 reduce violent crime more proportionally when there are higher U.S. security transfers. The partial R^2 is 8% and the F-test for excluded instruments takes a value of 86.07,[39] alleviating concerns of finite sample bias due to weak instruments (as defined by Bound et al., 1995). Moreover, the estimates in columns (2) and (3) confirm that each of

[39]For the case of a single endogenous regressor, Staiger and Stock (1997) suggest rejecting the hypothesis of weak instrument if this F-statistic is higher than 10.

the variables has a strong correlation with violence and affect it in the expected direction. In particular, homicide rates are higher today in municipalities that had a higher political competition index in 1946, whereas higher U.S. anti-drug expenditures have a negative correlation with homicide rates.

The last section of the paper presents several robustness checks that support the validity of the exclusion restriction.

5 Incidence of Violent Crime in Local Markets

This section presents the estimates of the elasticities of homicide rates on market size (average production and exit) and prices (non-housing prices, housing rents, and nominal wages). The estimates correspond to the results of equations (9) and (10), where (v_{mt}) is homicide rates per 100,000 inhabitants.

5.1 Effects on the Intensive and Extensive Margin of Production

Table 3 presents the estimates of equations (9) and (10) using the logarithm of real production as dependent variable (otherwise referred to as the intensive margin of production). The results presented in column (1) suggest that the OLS estimates of the effects of homicide rates on real production are biased towards zero, in-line with the *rapacity* channel discussed in section 4. The results on columns (2) and (3) suggest negative effects of violence on firms' production, which is consistent with the previous results by Alesina and Perotti (1996), Abadie and Gardeazabal (2003), Fielding (2003), Singh (2013), Collier and Duponchel (2010), and Klapper et al. (2013).[40] When endogeneity is addressed the coefficients increase in absolute value. My preferred estimates, presented in column (3), suggest that when homicide rates increase 10%, firms' production declines 1.7%.[41]

To estimate the effects of homicide rates on the total number of firms (the extensive

[40]These papers find negative effects of violence on firms' stock market returns and productivity. However, there is evidence of heterogeneous effects. For example, Guidolin and La Ferrara (2010) study the effects of the end of the Angolan civil war on stock market returns of firms operating in the diamond sector. The authors find that the sudden death of the rebels' leaders, which marked the end of the civil war, was detrimental for incumbent firms because violence acted as a barrier to international competition.

[41]I also check for the effects of violence across the distribution of production in Appendix C using quantile regressions. For this purpose, I combine the methodology proposed by Buchinsky (1998) to control for selection and Lee (2007) to control for endogeneity. A detailed description of the methodology is presented in Appendix C with the results. I find that the effects of violence are similar across the distribution of real production, so small and big firms are equally affected by violence.

margin of production), I aggregate the firm data by municipality. The results are presented in Table 4 and suggest that when homicide rates increase 10%, the total number of firms in a given municipality declines 0.4%.[42] This result is in-line with Camacho and Rodriguez (2013), who use the same data to study the effects of guerrilla and paramilitary attacks on the probability of firm exit.[43]

Following equation (7), the aggregate production-violence elasticity corresponds to the sum of the elasticities of the number of firms and firms' production with respect to homicide rates. The values for these elasticities were identified in Tables 3 and 4. They suggest that when violence increases 10%, aggregate production falls 2.1%;[44] this implies that the 48% decline in Colombia's homicide rates from 1995 to 2010, increased aggregate production 9.96%.

5.2 Effects of Violent Crime on Housing and Non-housing Prices

Table 5 presents the estimates of equations (9) and (10), taking the logarithm of firms' real output prices as the dependent variable. In these estimates, I test for the sensitivity of results to the inclusion of firm fixed effects, year fixed effects, product classification fixed effects,[45] product-time fixed effects, and controls for other municipality covariates listed in Appendix D.[46]

The estimates are presented in Table 5 and suggest a positive and sizable effect of homicide rates on firms' real output prices. As expected, the effects of violence on firms' prices grow when correcting for endogeneity. My preferred estimates are presented in column (4), which account for endogeneity for the sample of firms that stays in the market. They suggest

[42] I find similar results using the same specification and information on the total number of firms registered at the Chambers of Commerce and collected by *Confecamaras*, the association of Chamber of Commerce in Colombia. The institution collected data on the total number of firms registered across the country from 2000 to 2005 for 996 municipalities in Colombia.

[43] They find that a one standard deviation increase in the number of guerrilla or paramilitary attacks increases the probability of plant exit 5.5 percentage points.

[44] My estimates are a lower bound of the effects of violent crime on aggregate production because $E(log(y_{jm})) \leq log(E(y_{jm}))$. To test whether this problem was important, I estimate equations (9) and (10) using aggregate production by municipality as the dependent variable. Aggregate production is constructed as the sum of the production of all firms within each location and time period. The results are similar and suggest that when homicide rates increase 10%, aggregate production within each municipality falls 2.31%. I report the elasticity using firm-level data because it allows to control for time varying industry fixed effects as well as for firm time invariant characteristics.

[45] I use the four first digits of the International Standard Industry Classification codes to create the fixed effects; they include around 115 products.

[46] According to Kugler and Verhoogen (2012) the inclusion of controls by product classification and time-product trends is crucial to exclude the variation in prices explained by the dynamics of each product's industry.

that when homicide rates increase 10%, real output prices increase 5.3%.

Since in practice there are input-output linkages, firms may possibly face higher input prices when violence is higher. To check if this is true, I estimate the same specification using the logarithm of real input prices as the dependent variable. The results are presented in Table 6 and show a similar behavior. Column (4) suggest that when homicide rates increase 10%, the input prices faced by firms increase 2.0%. Thereby, firms increase output prices disproportionately more than the increase in input prices that they face.

These changes in prices represent a sizable effect of homicide rates. For example, Kugler and Verhoogen (2012) use the same data between 1982 and 2005 to estimate the elasticity of real output and input prices to firms' size. They find that a 10% increase in employment results in 0.26% and 0.12% higher real output and input prices, respectively.

The behavior of local retail food prices shows a similar behavior. In Table 7 I estimate equations (9) and (10) using data on retail food prices. The results in column (4) suggest that when homicide rates increase 10%, real food prices increase 5.9%. This represents further evidence that non-housing living costs are higher in areas with higher violent crime given food prices have the largest weight in the Colombian CPI. [47]

To estimate the effects of homicide rates on nominal housing prices I use data from the National Household Surveys.[48] Specifically, I estimate equations (9) and (10) for the cities available on the National Household Survey including fixed effects by year and municipality and controlling for individuals age, education, gender, number of children, and marital status. As shown in Table 8, I identify an elasticity of housing prices with respect to violence of -0.38 (s.e. 0.15), in line with the 15 studies that have identified this parameter (their point estimates are reported in Appendix B).[49]

[47]Particularly, according to the *Departamento Administrativo Nacional de Estadística*, the Colombian statistical agency, food consumption represents approximately 42% of the consumer price index and is the most relevant item for living costs, excluding housing prices. I exclude housing prices in these calculations because they have a separate term in the welfare estimates in equation 6. The second biggest item in terms of weight is transportation with 25%, followed by education with 5%, clothing with 2%, and other categories with smaller shares.

[48]During the period of analysis these surveys had several methodological changes. From 1995 to 2005 the surveys are available for the 13 cities and from 2006 and 2010 they are available for the main 24 cities of the country.

[49]Specifically, all the studies identify a negative effect of violent crime on housing prices with an elasticity range between -0.1 and -3, and an average of -1.16.

5.3 Effects of Violent Crime on Wages

The theoretical model predicts that higher levels of violence increase wages because workers leave more violent areas. This section estimates the wage-violence elasticity, which corresponds to running a hedonic wage equation in the spirit of Rosen (1986).

As mentioned by Kniesner et al. (2010) and Lavetti (2012), the estimation of a hedonic equation on wages should ideally include information by individual and by firm.[50] However, despite the richness of the data used in this paper, information on both firms' and workers' characteristics is unavailable. Hence, I only include fixed effects by firm. Although most estimates in the literature use workers' heterogenity, recent studies have called attention to the relevance of firms' heterogeneity in explaining wage variation (e.g., Card et al. (2013)).[51]

Table 9 reports the estimates of equations (9) and (10) using the logarithm of nominal average wages as the dependent variable. I find evidence of a small but positive wage compensation to violence. As for the previous cases, the elasticity of violence on wages grows in absolute value when corrections for endogeneity. The estimates in column (2) suggest that when homicide rates increase 10%, nominal wages increase 0.7%.

To test for heterogeneous effects of violence by type of worker, I use the logarithm of nominal average wages for white- and blue-collar workers. Table 10 present the results, which suggest that only white-collar workers are compensated for higher violence.[52] In particular, when violence increases 10%, white-collar workers' wages increase 0.9%.

I use IPUMS census data to test whether heterogeneous effects of violence on wages may be partially driven by differential mobility costs for individuals with higher skill levels. I use the Colombian population census for 2005, the only census available during the period of analysis. In the census, households are asked for their location five years ago. Despite the fact that there is no information on the type of work each individual performs, I use years of schooling and complete secondary as measures of types of skill.

[50] Some studies also include fixed effects for matching effects between firms and workers which solves the endogeneity caused by endogenous switching. This is only relevant when there is an idiosyncratic productivity component associated with potential job match in the theoretical model, which is not the case in this paper.

[51] For instance, Frías et al. (2012) suggest that two thirds of wage variation can be explained by firm heterogeneity, and Abowd et al. (2002) show that workers' and firms' heterogeneity have equal importance in explaining wage variation. Estimates by Lavetti (2012) show that a wage's hedonic equation that only includes firms' heterogeneity can explain as much as 66% of the wage variation in a linear or a non-linear model. See Table 6, 7, and 10 of Lavetti (2012).

[52] My estimates mainly correspond to the urban areas of Colombia where 87% of my sample is located. To check whether migration from the rural to urban areas was accounting for the results observed for blue-collar workers I run the estimates excluding the 13 main cities of the country where 92.3% of the registered migration from rural to urban places takes place. The results are robust to this exercise, they are not reported to save space, but the estimates are available upon request.

In brief, I run a probit model for the probability of migrating in 2005 on mean homicide rates from 2000 to 2005 in the municipality where the individual was located in 2000, a measure of the education observed in 2005, the interaction of the former two variables, gender, age, and regional controls (i.e., department controls). Table 11 reports the results of this exercise, suggesting that workers with higher education have a higher probability of migrating. Additionally, workers that lived at municipalities with higher homicide rates between 2000 and 2005 also have a higher probability of migrating. Moreover, all the interactions for violence and education are significant and have a positive sign, which present strong evidence of higher mobility restrictions for lower skilled workers when facing a violence shock.

Since I am using the level of education observed in 2005 (after migrating), it may be argued that workers may have increased their education after migrating. To address this threat, I re-estimate the probit model only for workers that had more than 25 and 30 years in 2000 (before migrating). This group of individuals has lower chances of increasing their education in their new location. The results are reported in columns (3) and (4) and show a very similar behavior.[53] These results are in-line with empirical evidence found by Cullen and Levitt (1999) and Malamud and Wozniak (2010) for the U.S.[54]

When considering the size of the effects of violence on wages, they seem small relative to the effects of other wage shocks.[55]

[53]Data on international out-migration from Colombia supports this claim. According to the International Organization for Migration, in 2005 there were around 3.3 million Colombians living abroad (Ramírez et al., 2010). This estimate was obtained by using the population Census of 2005, which recorded whether a member of a household was living abroad permanently and in which country. The 2005 U.S. Census suggests that, around 1 million of these Colombians were living on the U.S. and 37% of these immigrants have graduated from college (before migrating). In contrast, that same year only 14% of Colombian residents graduated from college (Medina and Posso, 2009).

[54]Cullen and Levitt (1999) examine the relationship between crime and urban flight in the main cities of the U.S. by type of worker. The authors use city-level data covering the last three decennial census years for 127 U.S. cities with populations greater than 100,000 in 1970. They find that migration decisions of highly educated households are particularly responsive to changes in crime. Similar evidence has been presented by Malamud and Wozniak (2010). They examine whether or not higher education is a causal determinant of geographic mobility using the 1980 U.S. Census. The authors use state-cohort level variation in college completion arising from draft avoidance behavior among men at risk for conscription into the Armed Forces during the Vietnam conflict as a source of exogenous variation in the probability that a man completed college. They show that this variation increased migration rates substantially among affected cohorts. They find that college education increases the probability of a long-distance move for the marginal college graduate significantly. One of the mechanisms at hand is that college education increases the set of possible occupations available for recent graduates. This result is in line with a large empirical literature that has documented that the local labor supply elasticity is larger for high-skill workers than for low-skill workers. For example, Bound and Holzer (2000) find that in response to demand shifts less educated workers drop substantially.

[55]For example, Cortes (2008) uses U.S. data to study the effects of low-skilled immigration on wages. Her results suggest that when there is a 10% increase in the share of low skilled immigrants in the labor force, blue-collar wages decrease 2%. Moreover, Dustmann et al. (2013) uses U.K. data to study the effects of

6 Measuring the Welfare Consequences of Violent Crime

6.1 Effects of Violent Crime on Workers' Real Income

Before making any parametric assumptions, it is worth considering what could be the effects of violence on real income based on the elasticities identified in the last section. Let PI represent an aggregate price index of housing and non-housing goods. Then, a simple accounting exercise of the effects of violence on real income is given by:

$$\frac{\partial ln(w/PI)}{\partial ln(v)} = \frac{\partial ln(w)}{\partial ln(v)} - \frac{\partial ln(PI)}{\partial ln(v)} \quad (13)$$

an approximation of the effects of violent crime on the price index (PI) can be obtained using the estimated elasticities of the effects of homicide rates on retail food prices (0.59) and housing rents (-0.38) and the weights of non-housing and housing expenditures in the Colombian CPI. The weights of non-housing and housing goods on the Colombian CPI take values of 42% and 30.1%, respectively.[56] Replacing these values into equation (13) I find that when homicide rates increase 10%, the real income of white- and blue-collar workers is reduced 0.6% and 1.3%, respectively. Consequently, higher homicide rates increase income inequality. Moreover, blue-collar workers are two times as sensitive to the effects of homicide rates relative to white-collar workers.

6.2 Effects on Workers' Welfare

The effects of homicide rates on real income ignores that violence not only affects workers indirectly through changes in market prices, but also by inducing direct effects on utility. For example, workers may be losing utility when they are exposed to more dangerous environments. I use equation (6) to estimate the elasticity of workers' welfare with respect to homicide rates. This elasticity accounts for the direct and indirect effects of homicide rates. In this context, the welfare effects of violent crime are approximated through its effects on workers' utility of consumption.

I use the estimates identified in the last section to recover the partial derivatives on the

immigration on the wage distribution. They find that an additional inflow of immigrants of 1% of the native population reduces wages in the low percentiles (i.e., 5th percentile) 0.6%, but increases the median wage 0.6%.

[56] The other categories included in the CPI correspond to health, education, transportation, communications, and entertainment. Together they account for 28% of the CPI.

effects of homicide rates on market prices.[57] The other terms of equation (6) are derived using the average indirect utility function that solves the workers' problem as stated in equation (2) across all individuals in each municipality.[58] The values for α and β are set to 0.82 (s.e. 0.021) and 0.98 (s.e. 0.15) based on the identification strategy described on Appendix F.[59]

Table 12 presents the results of this exercise.[60] They suggest that when homicide rates increase 10%, welfare declines for all workers 4.6%. However, there are heterogeneous effects of violence by type of worker. Specifically, the welfare-violence elasticity for white-collar workers is 0.28 and for blue-collar workers is 0.63. Consequently, blue-collar workers are two times more responsive to violence than white-collar workers. Thus, higher violence increases welfare inequality.[61] The heterogeneous effects of violence on welfare are mainly induced by the differential effects that violence has on workers' wages by type of skill given all workers face similar living costs. Thus, by increasing the wag gap, violence increases welfare inequality.

When decomposing of the effects of violence into the direct disutility created by violence and the welfare losses due the indirect effects caused by changes in market prices according to equation (6), I find that the indirect effect of homicide rates account for the majority of the total welfare losses induced by violence.[62]

Additionally, my results suggest that the elasticity of welfare with respect to violence (i.e, -0.46) is at least twice as big as the elasticity of aggregate production on violence (i.e.,

[57] By combining the estimated elasticities with the observed mean values of P_m, w_m, and r_m.

[58] Which will be given by:

$$V_m(P_m, w_m, r_m, v_m) = [(w_m + F)P_m^{-\alpha} r_m^{\alpha-1}]^{\beta}[1/v_m]^{1-\beta}\bar{x_m}$$

The value for the average locality shock by municipality was set to 1. From this expression, I derive the four missing partial derivatives and use observed mean values of P_m, w_m, r_m, and v_m to estimate their magnitudes. The specific values I use are presented in Appendix E.

[59] Similar values were obtained by Davis and Ortalo-Magné (2011) for the share of housing consumption expenditures using U.S. data. Standard errors were computed using the delta method.

[60] I also computed the welfare effects of violent crime by assuming a CES utility function. Although there are some changes in the order of magnitudes the ordering of the effects is the same. In particular, the effects of violent crime on welfare are always larger than the effects of violent crime on aggregate production. In addition, blue-collar workers are always more affected by violent crime. This result remains of changed for any utility function in which violence affects the marginal utility of housing and non-housing consumption, that is where violence is a multiplicative term to consumption or housing and acts as a local disamenity for workers. The results are available upon request, yet they are not reported to save space.

[61] Tests on the sensitivity of the results to changes on the parameter values suggest that the magnitude of the effects changes with different values of β. Nevertheless, the order of the effects is always the same as long as violence reduced the marginal utility of consumption. Specifically, the welfare effects of homicide rates are always bigger than the effects identified for real income, and blue-collar workers are two times more responsive to violence than their white-collar counterparts.

[62] However, the estimates are not including the costs of human lives lost.

0.22). Thus, by only considering the effects of violence on GDP, the incidence of violence is underestimated. Hence, welfare effects are more informative because they incorporate the indirect costs of violence, caused by changes in market prices.

6.3 Willingness to Pay for a Reduction in Violent Crime

Following Just et al. (2005), Fleurbaey (2009), and Fleurbaey and Blanchet (2013), workers' willingness to pay for a reduction in violence could be approximated by solving:

$$V(P_0, (w_0 + T), r_0, v_0) = V(P_1, [(w_1 + T) - A], r_1, v_1) \tag{14}$$

where 0 and 1 represent two municipalities such that $v_0 > v_1$ and A represents the amount of income taken away from a worker to restore his original welfare level. It is a measurement of the willingness to pay to reduce violence from v_0 to v_1. Given the indirect utility function described in equation (2), A can be estimated as:

$$A = (w_1 + T) - (w_0 + T)[\frac{P_1}{P_0}]^{\alpha}[\frac{r_1}{r_0}]^{1-\alpha}[\frac{v_1}{v_0}]^{1-\beta} \tag{15}$$

The results of this exercise are presented in Figure 8.[63] The graph presents the percentage of income that a worker is willing to give up to reduce homicide rates to 1 per 100,000 inhabitants.[64] For example, the figure shows that at a value of 20 homicides per 100,000 people, workers' are willing to pay 27% of their income to reduce violence to 1 homicide per 100,000 inhabitants.

The figure shows that both white- and blue-collar workers have similar willingness to pay to reduce violent crime when violence is low. However, as violent crime increases, blue-collar workers have a higher willingness to pay, relative to white-collar workers. This gap eventually converges to a difference of around 20% of income. The figure shows that when violent crime is higher than 60 homicides per 100,000 people, blue- and white-collar workers are willing to pay 50% and 30% of their income to reduce violent crime, respectively. For the Colombian

[63] I use the mean values of the observed variables described in Appendix E and the elasticities estimated in previous sections to recover the implied wages, prices, and rents for each value of homicide rates. Thus, I observe a different value of wages, rents and local prices for each level of violence. I combine these values with the estimates for α and β obtained following the methodology presented in Appendix F. I calculate A fixing homicide rates in municipality 1 at 1 homicides per 100,000 inhabitants (i.e., $v_1 = 1$) and allowing the value of v_2 to vary between 2 and 70 homicides per 100,000 inhabitants.

[64] The willingness to pay to reduce homicide rates to zero, is not presented because in that case the second term of equation (15) is zero, which implies that workers are willing to give their whole income to be in that situation, which in itself is not a very useful result.

case, where homicide rates were 32.2 per 100,000 people in 2012, the estimates suggest that workers will be willing to pay on average 33.5% of their income to have homicide rates drop to 1 per 100,000 people.

In sum, blue-collar workers are willing to pay a higher percentage of their income to reduce violence relative to white-collar workers. This occurs because blue-collar workers do not receive a wage compensation when violence is high, but still they face higher living costs. Moreover, higher mobility costs for blue-collar workers and worst outside options for this population may be a relevant driving factor of this result. This suggest that collection of resources to reduce violence may be more problematic in areas with more violence given blue-collar workers have lower resources. This points to the importance of international aid to support countries that face very high levels of violence and also may partly explains the persistence of violence in poor countries.

7 Robustness Checks

My estimates are valid as long as the exclusion restriction is satisfied. In the context of equations 9 and 2 this occurs if $E[\epsilon_{jmt} PC_{mt} | k_j, g_t] = 0$. Because the estimates include fixed effects by firm (or municipality) and year, the identification is not threatened by static differences between areas with different political competition or by aggregate time trends. A violation of the exclusion restriction will only occur if there are time-varying covariates correlated with the U.S. international anti-drug expenditures, that have differential effects within areas with different political competition. For example, the exclusion restriction would be violated if when U.S. international anti-drug expenditures are high, the local or central governments change their behavior, crowding-out other expenditures in different proportions in areas with different political competition.

I address these concerns by showing no correlation between the instrument and the behavior of local and central governments. Table 13 presents the results of a regression of the municipal income or expenditures (as a total and by type) in the instrument, which suggests no correlation of the instrument with behavior of the municipal government. Additionally, I repeat the same exercise on the transfers send by the central government to each municipality (as a total and by type) in Table 14. The results also suggest no correlation of the behavior of the central government with the instrument.

To present further evidence on the validity of the exclusion restriction, I control for 45 covariates available by municipality in the final estimates and find no sensitivity of the results. The covariates can be grouped into: i) demographics (e.g., population by sex and age and interactions between these variables), ii) public income (e.g., tax and non-tax income collected by municipalities and by type), iii) public expenditures, and iv) other variables (e.g., school enrollment and rain). A detailed list of the 45 covariates used as controls is presented in Appendix D. They comprise all the information available at the municipality level. The estimates including the controls are presented in Tables 3, 4, 5, and 9.

7.1 Ruling Out Differential Time Pre-trends

Another threat to the identification strategy is the existence of time pre-trends between areas with different political competition that may explain the effects observed today. I address this concern in Figure 9 by showing there are no systematic differences in population growth between areas with different political competition in 1946. For this purpose, I use information from the population censuses of 1912, 1918, 1928, and 1938.[65] This is a strong test, since no differences in population growth will indicate no comparative advantages of living in one of these areas, assuming small mobility restrictions.

I also check for differences in time pre-trends on ten other covariates available between 1940 and 1945 by municipality.[66] For this purpose, I run a regression of each of these covariates onto the political competition index and year interactions. In the absence of pre-time trends, these interactions should not be significant. Table 15 presents the results, which confirm the expected behavior. These findings are not surprising. Specifically, historians have pointed out that political violence around 1946 was not correlated to socio-economic or geographic characteristics. For instance, after compiling evidence on the causes of *La Violencia*, Guzmán et al. (2006) mention that:"...the violence during those years did not respect race or economic status, it took place in regions of minifundia or latifundia, among the prosperous and the miserable, in deserts and plains, and in the valleys and mountains."

8 Conclusions

This paper studies the effects of violent crime on local markets. For this purpose, I exploit the annual and municipal variation of homicide rates in Colombia between 1995 and 2010, and employ rich and unique firm-level and consumer food prices panel data. I instrument for

[65]The data was digitized from the *Anuarios de Estadística General* collected by the *Contraloría General de La República* and published in 1932 and 1946 (see DCG (1932) and DCG (1946)).

[66]They were also digitized from *Anuarios de Estadística General* collected by the *Contraloría General de La República*.

homicide rates using the interaction between a political competition index for 1946 and U.S. international anti-drug expenditures. The utilization of the index is motivated by ample historical evidence suggesting that the current violence spell originated in a previous violent episode that took place between 1948 and 1958–i.e., *La Violencia.* As a consequence of this episode, illegal armed groups were created and first located in areas with higher political competition, proliferating all forms of violence, and dis-empowering the local governments. Consequently, my variation comes from the fact that when security conditions improve across the country, areas with higher political competition in 1946 (namely areas with more contested elections), reduced violence more proportionally when security transfers from the U.S. were higher.

I find that firms respond to violent crime by increasing their output prices. Hence, areas with higher violent crime also have higher non-housing living costs. Additionally, I find that when homicide rates increase workers leave, which results in lower housing rents and a small wage increase; however the wage increase is statistically significant only for white-collar workers. Empirical evidence suggests that higher mobility restrictions for workers of lower skill prevent their wages from rising. Altogether, when violence increases 10%, real income for blue- and white-collar workers decreases 1.3% and 0.6%, respectively. Additionally, higher input costs, higher wages, and lower local demand (through an increase in workers migration) lead firms to reduce their average production, and ultimately a few firms exit the market.

By combining the estimated elasticities with a theoretical model I find that when homicide rates increase, blue-collar workers' welfare losses are two times as high as the ones experienced by white-collar workers. This points to a relevant channel through which higher violence reinforces the inequality: if intense violence increases living costs, and wages are only partially compensated for white-collar workers, violence increases inequality, potentially fueling further social unrest and violence.

Moreover, I find that blue-collar workers are willing to pay a higher percentage of their income to reduce violence relative to white-collar workers; blue-collar workers' wage does not increase when violence is high, but still they face higher living costs. This suggest that collection of resources to reduce violence may be more difficult in areas with more violence, given the poorest workers are the ones willing to pay more. This points to the importance of international aid to support countries that face very high levels of violence.

In sum, I find that reductions in violent crime have large economic returns. A back-of-the-envelope calculation suggests that the 48% decline on homicide rates that took place between 1995 and 2010 in Colombia, increased aggregate production by 8.1% and worker's welfare 22.5%. However, my estimates are a lower bound of the total social costs of violent crime.

Specifically, my estimates do not measure the costs of violent crime on mortality. They only account for the effects of violent crime on the population that survives violent episodes. Other studies have dealt with the mortality costs associated with violence. For instance, by using cross country data for 73 countries Soares (2006) estimates that, on average, one year of life expectancy lost to violence is associated with a yearly social cost of 3.8% of GDP. The author estimates that the health dimension of the welfare costs of violence corresponds to a yearly value of 9.7% of the Colombian GDP.

Additionally, this paper can only identify the short term local effects of violence. It does not account for the long-term effects of violent crime on foreign direct investment as studied by Pshiva and Suarez (2006). This type of analysis is constrained by the unavailability of micro data on domestic or foreign direct investment. Yet, violence reduction are expected to have a positive impact on the country's risk perception, which in turn, should spike investment.

Despite the fact that this paper uses unique and rich data on firms' and consumer food prices, there are still some limitations to the data. My estimates mainly deal with the effects of violent crime on the most populated cities of the country where the majority of the economic activity is concentrated (317 municipalities in Colombia). Yet, there is no available data to asses the effects of violent crime on rural areas, which restricts the analysis of the general equilibrium effects of violent crime in Colombia. In addition, there is no data on the extent in which violence increases informality since there is no data for the size of this sector. This is a relevant constraint, specially for developing countries were the size of the informal sector is so significant. For instance, according to estimates of the Colombian statistical department in the last 10 years, approximately 50% of all the Colombian employed population was informal.

Next steps in these research agenda include identifying the main determinants on the global drop on violence, which corresponds to one of the most significant developments of humanity (Pinker, 2011; Goldstein, 2011; and HSR, 2011).[67] In addition, fruitful insights

[67] The number of people killed in battle has dropped by a thousandfold over the last centuries (Pinker, 2011). Similarly, homicide rates in Europe, the only continent with available data from the beginning of the millennium, declined from 100 to 0.8 per 100,000 people between the year 1200 and 2000 (Eisner, 2003). The violence reduction has been more pronounced in the second half of the 20th century, both in the number and intensity of international wars and internal conflicts (Pinker, 2011 and Goldstein, 2011). In the 1950s, there were around six international wars fought per year, with approximately 20,000 people killed on average per year. In contrast, since the beginning of the 21st century, there was only one war per year and the number of individuals killed fell to 3,000 people/year. Moreover, since the end of the Cold War, the number of civil conflicts has declined sharply, and between 1970 and 2008, the number of battle deaths of countries with civil wars fell 90% (HSR, 2011). Global homicide rates, which have only been consistently measured since 1995, have steadily decreased to 8.9 per 100,000 inhabitants for 2011.

may be gained by testing the results of this paper on a developed country.

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9 Tables and Figures

Table 1: Violent Crime in Colombia Relative to Other Regions of the World

Intentional Homicide rate per 100,000 people (average)			
Region	1995-2000	2001-2005	2006-2010
Latin America	20.39	22.97	19.26
North America	6.82	6.92	7.39
Eastern Africa	5.48	11.18	4.66
Northern Africa	1.75	5.35	1.20
Southern Africa	38.76	28.77	24.44
Asia	4.77	3.62	3.49
Europe	3.84	3.47	2.47
Oceania	1.43	2.96	3.56
Top 10% (Most Violent)	32.00	34.10	38.40
Lowest 10% (Least Violent)	0.70	0.70	0.70
Colombia	**66.29**	**57.04**	**35.98**
World Total	8.85	7.97	9.60

Note: Intentional homicide rates per 100,000 people is defined as all the unlawful deaths purposefully inflicted on a person by another person per 100,000 inhabitants. Source: Data from the Global Study on Homicides of the United Nations Office of Drugs and Crime.

Table 2: First Stage Regression of homicide rates on PC_{mt}

Dependent Variable: Log ($Hom\ Rate_{mt}$)			
	(1)	(2)	(3)
PC_{mt}	-0.05***		
	(0.00)		
PC_m		1.42***	
		(0.08)	
$U.S. - IAE_t$			-0.03***
			(0.00)
Firm FE	Y		Y
Year FE	Y	Y	
Clustered errors (mun)	Y	Y	Y
Partial R-squared	0.08	0.18	0.04
F-test excluded inst.	86.07	23.50	256.16
Obs.		124,247	
N. of Clusters		317	

Note: The table presents the results of the first stage regression for the specification presented in equations (9) and (10) and given by:

$$log(v_{mt}) = \theta_0 + \theta_1 PC_{mt} + k_j + g_t + u_{jmt}$$

where m represents municipality, t year, and j firm. Violent crime (v_{mt}) is measured through homicide rates per 100,000 people. PC_{mt} is defined as the interaction of the political competition index of 1946 and U.S. international anti-drug expenditures in millions of dollars of 1995 ($US - IAE_t$). Standard errors clustered at the municipality level are presented in parentheses. *** Significant at 1% level, ** Significant at 5% level, and * Significant at 10% level.

Table 3: Effects of Violent Crime on Firms' Real Production

Dependent Variable: Log ($Real\ Production_{jmt}$)			
	OLS	2SLS	2SLS
	(1)	(2)	(3)
Log ($Hom\ Rate_{mt}$)	-0.01***	-0.18***	-0.17***
	(0.00)	(0.03)	(0.04)
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
Municipality's characteristics			Y
R-squared	0.08	0.11	0.14
Obs.		124,247	
N. of Clusters		317	
First Stage. Dependent Variable: Log ($Hom\ Rate_{mt}$)			
PC_{mt}		-0.05**	-0.05**
		(0.00)	(0.00)
F-excluded instrument		86.07	96.14
Partial R-squared		0.08	0.11

Note: The table presents the results of the specification presented in equations (9) and (10) and given by:

$$log(y_{jmt}) = \gamma_0 + \gamma_1 log(v_{mt}) + k_j + g_t + \epsilon_{jmt}$$

$$log(v_{mt}) = \theta_0 + \theta_1 PC_{mt} + k_j + g_t + u_{jmt}$$

where y_{jmt} represents real production of firm j, located in municipality m, at year t, v_{mt} is measured as homicide rates per 100,000 people, and k_j and g_t represent firm and year fixed effects. PC_{mt} is defined according to equations (11) and (12). It corresponds to an interaction of the political competition index of 1946 and U.S. international anti-drug expenditures in millions of 1995. The other covariates included as municipality's characteristics are described in Appendix D. Real values were obtained using a municipality price index with base year 1995. Standard errors clustered at the municipality level are presented in parentheses. *** Significant at 1% level, ** Significant at 5% level, and * Significant at 10% level.

Table 4: Effects of Violent Crime on the Total Number of Firms by Municipality

Dependent Variable: Log (Number of firms)			
	OLS	2SLS	2SLS
	(1)	(2)	(3)
Log ($Hom\,Rate_{mt}$)	-0.02**	-0.04*	-0.04*
	(0.01)	(0.02)	(0.02)
Year FE	Y	Y	Y
Mun FE	Y	Y	Y
Municipality's characteristics			Y
R-squared	0.05	0.06	0.09
Observations		4,620	
Clusters (by muncod)		308	
First Stage. Dependent Variable: $Log(Homicide\,Rate_{mt})$			
PC_{mt}		-0.05***	-0.05***
		(0.01)	(0.01)
F-test excluded instrument		15.98	16.21
Partial R-squared		0.04	0.05

Note: The table presents the results of the following specification:

$$log(N_{mt}) = \gamma_0 + \gamma_1 log(v_{mt}) + k_m + g_t + \epsilon_{jmt}$$

$$log(v_{mt}) = \theta_0 + \theta_1 PC_{mt} + k_m + g_t + u_{jmt}$$

where N_{mt} represents aggregate number of firms at municipality m, at year t, v_{mt} is measured according to homicide rates per 100,000 people, and k_m and g_t represent municipality and year fixed effects. PC_{mt} is the instrument for homicide rates and is defined according to equations (11) and (12). It corresponds to an interaction of the political competition index of 1946 and U.S. anti-drug expenditures in millions of dollars of 1995. The other covariates included as municipality's characteristics are described in Appendix D. Standard errors clustered at the municipality level are presented in parentheses. *** Significant at 1% level, ** Significant at 5% level, and * Significant at 10% level.

Table 5: Effects of Violent Crime on Firms' Output Prices

Dependent Variable: Log ($Real\,Output\,Prices_{jmt}$)				
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Log ($Hom\,Rate_{mt}$)	0.07***	0.07***	0.51**	0.53**
	(0.02)	(0.02)	(0.22)	(0.26)
FE firm	Y	Y	Y	Y
FE year	Y	Y	Y	Y
Industry FE		Y	Y	Y
Industry-Year FE		Y		Y
Municipality's characteristics		Y		Y
R-squared	0.57	0.71	0.57	0.63
Obs.	116,468			
N. of Clusters	317			
First Stage. Dependent Variable: Log ($Hom\,Rate_{mt}$)				
PC_{mt}			-0.05***	-0.05***
			(0.01)	(0.01)
F-test excluded instrument			17.89	16.05
Partial R-squared			0.04	0.05

Note: The table presents the results of the specification presented in equations (9) and (10) and given by:

$$log(p_{jmt}) = \gamma_0 + \gamma_1 log(v_{mt}) + k_j + g_t + \epsilon_{jmt}$$

$$log(v_{mt}) = \theta_0 + \theta_1 PC_{mt} + k_j + g_t + u_{jmt}$$

where p_{jmt} represents real output prices of firm j, located in municipality m, at year t, v_{mt} is measured as homicide rates per 100,000 people, and k_j and g_t represent firm and year fixed effects. PC_{mt} is defined according to equations (11) and (12). It corresponds to an interaction of the political competition index of 1946 and U.S. international anti-drug expenditures in millions of 1995. Each observation corresponds to a plant-product-year unit. Industry fixed effects correspond to the four-digit classification of the International Standard Industry Classification (ISIC) for each product-plant-year observation. There are 115 four-digit codes and 29 departments in the sample. The other covariates included as municipality's characteristics are described in Appendix D. Real values were obtained using a municipality price index with base year 1995. Standard errors clustered at the municipality level are presented in parentheses. *** Significant at 1% level, ** Significant at 5% level, and * Significant at 10% level.

Table 6: Effects of Violent Crime on Firms' Input Prices

Dependent Variable: Log ($Real\, Input\, Prices_{jmt}$)				
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Log ($Hom\, Rate_{mt}$)	0.03***	0.09***	0.20**	0.20**
	(0.01)	(0.00)	(0.08)	(0.08)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE		Y		Y
Industry-Year FE		Y		Y
Other covariates		Y		Y
R-squared	0.28	0.56	0.3	0.51
Obs.		395,523		
N. of Clusters		317		
First Stage. Dependent Variable: Log ($Hom\, Rate_{mt}$)				
PC_{mt}			-0.06***	-0.06***
			(0.01)	(0.01)
F-test excluded instrument			18.28	18.72
Partial R-squared			0.05	0.05

Note: The table presents the results of the specification presented in equations (9) and (10) and given by:

$$log(p_{jmt}) = \gamma_0 + \gamma_1 log(v_{mt}) + k_j + g_t + \epsilon_{jmt}$$

$$log(v_{mt}) = \theta_0 + \theta_1 PC_{mt} + k_j + g_t + u_{jmt}$$

where p_{jmt} represents real input prices of firm j, located in municipality m, at year t, v_{mt} is measured as homicide rates per 100,000 people, and k_j and g_t represent firm and year fixed effects. PC_{mt} is defined according to equations (11) and (12). It corresponds to an interaction of the political competition index of 1946 and U.S. international anti-drug expenditures in millions of 1995. Each observation corresponds to a plant-product-year unit. Industry fixed effects correspond to the four-digit classification of the International Standard Industry Classification (ISIC) for each product-plant-year observation. There are 115 four-digit codes and 29 departments in the sample. The other covariates included as municipality's characteristics are described in Appendix D. Real values were obtained using a municipality price index with base year 1995. Standard errors clustered at the municipality level are presented in parentheses. *** Significant at 1% level, ** Significant at 5% level, and * Significant at 10% level.

Table 7: Effects of Violent Crime on Average Retail Food Prices

Dependent Variable: Log ($Real\,Food\,Price_{qmt}$)				
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Log ($Hom\,Rate_{mt}$)	0.09**	0.1***	0.56**	0.59**
	(0.04)	(0.02)	(0.31)	(0.35)
Municipality FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Product FE	Y	Y	Y	Y
Product-Year FE		Y		Y
Other Covariates				Y
R-squared	0.31	0.51	0.48	0.43
Obs.	44,724			
N. of Clusters	53			
First Stage. Dep Variable: Log ($Hom\,Rate_{mt}$)				
PC_{mt}			-0.01***	-0.01***
			(0.00)	(0.00)
F-test excluded instrument			11.89	14.08
Partial R-squared			0.06	0.06

Note: The table presents the results of the following specification:

$$log(f_{qmt}) = \gamma_0 + \gamma_1 log(v_{mt}) + \gamma_m + \gamma_t + \gamma_q + \gamma_{qt} + \epsilon_{jmt}$$

$$log(v_{mt}) = \theta_0 + \theta_1 PC_{mt} + \theta_m + \theta_t + \theta_q + \theta_{qt} + u_{jmt}$$

where f_{qmt} represents the average retail price of product q, at municipality m, at year t, and v_{mt} is measured according to homicide rates per 100,000 people. PC_{mt} is defined according to equations (11) and (12). It corresponds to an interaction of the political competition index of 1946 and U.S. international anti-drug expenditures in real values of 1995. Each observation on this sample corresponds to the real prices of the 500 most consumed products in the 53 municipalities, located in 20 different departments. The other covariates included as municipality's characteristics are described in Appendix D. Real values were obtained using a municipality price index with base year 1995. Standard errors clustered at the municipality level are presented in parentheses. *** Significant at 1% level, ** Significant at 5% level, and * Significant at 10% level.

Table 8: Effects of Violent Crime on Housing Rents

Dependent Variable: Log ($Nominal\,Rents_{imt}$)				
	OLS		2SLS	
	(1)	(2)	(3)	(4)
Log (Hom R)	-0.04***	-0.05**	-0.31**	-0.38**
	(0.01)	(0.02)	(0.13)	(0.15)
Municipality Controls	Y	Y	Y	Y
Year Controls	Y	Y	Y	Y
Individual Controls: age, sex, education		Y		Y
R-squared	0.19	0.32	0.23	0.48
Obs.	22,913			

Note: The table presents the results of the following specification:

$$log(r_{imt}) = \gamma_0 + \gamma_1 log(v_{mt}) + \gamma_m + \gamma_t + \gamma_m + \Gamma' X_{imt} + \epsilon_{imt}$$

$$log(v_{mt}) = \theta_0 + \theta_1 PC_{mt} + \theta_m + \theta_t + \Theta' X_{imt} + u_{imt}$$

where r_{imt} represents the average nominal housing rents paid by individual i, at municipality m, at year t, and v_{mt} is measured according to homicide rates per 100,000 people. PC_{mt} is defined according to equations (11) and (12). It corresponds to an interaction of the political competition index of 1946 and U.S. international anti-drug expenditures in real values of 1995. The specification was estimated useing data from the National Household Surveys between 1885 and 2010. The other covariates included as municipality's characteristics are described in Appendix D. Robust standard errors are presented in parentheses. *** Significant at 1% level, ** Significant at 5% level, and * Significant at 10% level.

Table 9: Effects of Violent Crime on Nominal Wages

Dependent Variable: Log ($Average\,Nominal\,Wages_{jmt}$)		
	OLS	2SLS
	(1)	(2)
Log ($Hom\,Rate_{mt}$)	0.05***	0.07***
	(0.01)	(0.01)
Year FE	Y	Y
Firm FE	Y	Y
Municipality's characteristics	Y	Y
R-squared	0.41	0.42
Obs.	124,247	
N. of Clusters	317	

Note: The table presents the results of the specification presented in equations (9) and (10) and given by:

$$log(w_{jmt}) = \gamma_0 + \gamma_1 log(v_{mt}) + k_j + g_t + \epsilon_{jmt}$$

$$log(v_{mt}) = \theta_0 + \theta_1 PC_{mt} + k_j + g_t + u_{jmt}$$

where w_{jmt} represents nominal average wage of firm j, located in municipality m, at year t, v_{mt} is measured as homicide rates per 100,000 people, and k_j and g_t represent firm and year fixed effects. PC_{mt} is defined according to equations (11) and (12). It corresponds to an interaction of the political competition index of 1946 and U.S. international anti-drug expenditures in millions of dollars of 1995. The other covariates included as municipality's characteristics are described in Appendix D. Standard errors clustered at the municipality level are presented in parentheses. *** Significant at 1% level, ** Significant at 5% level, and * Significant at 10% level.

Table 10: Effects of Violent Crime on Nominal Wages by Type of Worker

Dep Variable: Log ($Average\,Nominal\,Wages_{jmt}$)		
	White-Collar	Blue-Collar
	2SLS	2SLS
	(1)	(2)
Log ($Hom\,Rates_{mt}$)	0.09***	0.03
	(0.01)	(0.02)
Year FE	Y	Y
Firm FE	Y	Y
Municipality's characteristics	Y	Y
R-squared	0.33	0.34
Obs.	40,048	
N. of Clusters	206	
First Stage. Dep Variable: Log ($Hom\,Rates_{mt}$)		
PC_{mt}	0.89***	0.86***
	(0.05)	(0.06)
F-excluded instrument	17.09	15.78
Partial R-squared	0.08	0.07

Note: The table presents the results of the specification presented in equations (9) and (10) and given by:

$$log(w_{jmt}) = \gamma_0 + \gamma_1 log(v_{mt}) + k_j + g_t + \epsilon_{jmt}$$

$$log(v_{mt}) = \theta_0 + \theta_1 PC_{mt} + k_j + g_t + u_{jmt}$$

where w_{jmt} represents nominal average wage of firm j, located in municipality m, at year t, v_{mt} is measured according to homicide rates per 100,000 people, and k_j and g_t represent firm and year fixed effects. The other covariates included as municipality's characteristics are described in Appendix D. Standard errors clustered at the municipality level are presented in parentheses. *** Significant at 1% level, ** Significant at 5% level, and * Significant at 10% level.

Table 11: Lower Mobility For Workers with Lower Levels of Skill

Dependent Variable = 1 if internal migration between 2000 and 2005

	Workers in Urban Areas			
	All workers		25> years	30> years
	(1)	(2)	(3)	(4)
Education (Years)	0.001***			
	(0.000)			
Secondary Education (complete)		0.008***	0.010***	0.004***
		(0.001)	(0.002)	(0.001)
Homicide Rate at municipality of origin	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Education* Homicide rate in mun of origin	0.0002***			
	(0.000)			
Secondary Education x Homicide rate in mun of origin		0.001***	0.001***	0.001***
		(0.000)	(0.000)	(0.000)
Controls: Gender, Age	Y	Y	Y	Y
Regional Controls (by department)	Y	Y	Y	Y
Pseudo R-squared	0.253	0.207	0.133	0.091
Obs.	692,700		572,957	475,549
Base Probability of Migration	0.099		0.092	

Note: The table reports the marginal effects of a probit model using a 10% extract from the Colombian population census of 2005. The municipality of origin corresponds to the location of the individual in the year 2000. The data was obtained from IPUMS. Robust standard errors are reported in parentheses. *** Significant at 1% level, ** Significant at 5% level, and * Significant at 10% level.

Table 12: Effects of Violent Crime on Workers' Welfare (Measured as utility of consumption)

Workers	Elasticity Welfare-Violence	Decomposition of Total Effects	
		Market Effects	Direct Disutility
All Workers	-0.46***	95.72%	4.28%
	(0.05)		
White-collar	-0.28*	94.65%	5.35%
	(0.05)		
Blue-collar	-0.63***	96.41%	3.59%
	(0.05)		

Note: the table presents the estimates of equation (6) where the partial derivatives on the effects violent crime to market prices were derived from the previous estimates and the mean values of each variable are reported in Appendix E. The values of α and β were set to 0.82 and 0.98 according to the identification strategy described in Appendix F. Standard errors were computed using the delta method. *** Significant at 1% level, ** Significant at 5% level, and * Significant at 10% level.

Table 13: Ruling out the Correlation between the Instrument and the Municipal Government Behavior

	Dependent Variables [expressed in real billions of pesos (1995=100)]							
	Income (Inc.)	Tax-Inc.	Non-tax Inc.	Expenditures (Exp.)	Admin. Exp.	Debt Exp.	*'Regalias'*	Fiscal Balance
PC_{mt}	0.005	-0.002	0.002	0.001	-0.001	0.002	-0.003	0.001
	(0.010)	(0.007)	(0.011)	(0.006)	(0.003)	(0.007)	(0.005)	(0.002)
Mun FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.944	0.942	0.943	0.944	0.944	0.944	0.942	0.941
Clusters				317				
Obs.				4,755				

Note: the table presents a regression of municipal public expenditures (as a total and by type) on the instrument (PC_{mt}). PC_{mt} is defined according to equations (11) and (12), and corresponds to the interaction of the political competition index of 1946 (PC_m) and U.S. international anti-drug expenditures in millions of dollars of 1995 ($US - IAE_t$). *'Regalias'* represent the income collected through taxes on mineral and oil exploitation. Standard errors clustered at the municipality level are presented in parentheses. *** Significant at 1% level, ** Significant at 5% level, and * Significant at 10% level.

Table 14: Ruling out the Correlation between the Instrument and the Central Government Behavior

Dep. Variable: Transfers from the Central Government to the Municipalities [Real billions of pesos (1995=100)]				
	Education Transfers	Health Transfers	Other Purposes	Total Transfers
PC_{mt}	0.000	-0.002	-0.013	0.000
	(0.002)	(0.005)	(0.047)	(0.001)
Mun FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
R-squared	0.960	0.960	0.960	0.960
N. of Clusters	317			
Obs.	4,755			

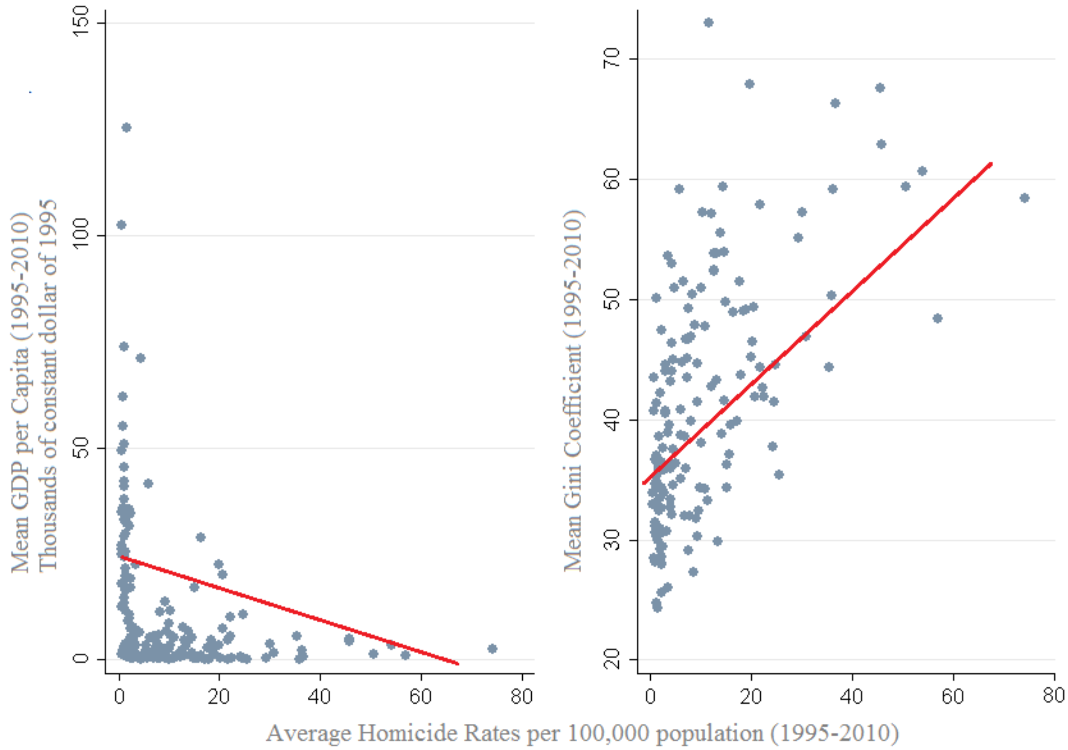
Note: the table presents a regression of the central government transfers to municipalities (as a total and by type) on the instrument (PC_{mt}). PC_{mt} is defined according to equations (11) and (12), and corresponds to the interaction of the political competition index of 1946 (PC_m) and U.S. international anti-drug expenditures in millions of dollars of 1995 ($US-IAE_t$). Standard errors clustered at the municipality level are presented in parentheses. *** Significant at 1% level, ** Significant at 5% level, and * Significant at 10% level.

Table 15: Excluding Differential Time Pre-trends between Areas with Different Political Competition Index Before 1946

	Dependent Variables									
	GPI	Rice Price	Meat Price	Egg Price	Milk Price	Potatoes Price	Coffee Price	Exports	Imports	Cattle Value
$PC_m * I(1941)_t$							0.04	-2.45	0.53	
							(0.23)	(3.70)	(3.90)	
$PC_m * I(1942)_t$	-0.26	0.05	-0.18	0.28	-0.15	-0.16	-0.15	3.84	4.3	
	(0.2)	(0.12)	(0.23)	(0.23)	(0.18)	(0.12)	(0.19)	(3.69)	(3.90)	
$PC_m * I(1943)_t$	0.12	0.02	-0.43	0.44	0.37	-0.23	0.08	-3.64	-1.09	
	(0.15)	(0.14)	(0.29)	(0.36)	(0.23)	(0.26)	(0.19)	(3.23)	(3.33)	
$PC_m * I(1944)_t$	-0.03	0.004	-0.52	0.88	-0.04	-0.09	-0.003	-3.12	-3.15	
	(0.13)	(0.18)	(0.43)	(0.33)	(0.29)	(0.14)	(0.18)	(3.16)	(3.33)	
$PC_m * I(1945)_t$	0.16	-0.05	0.11	0.41	0.02	0.05	-0.17	-3.67	-3.07	-2.18
	(0.22)	(0.22)	(0.65)	(0.39)	(0.28)	(0.24)	(0.18)	(3.15)	(3.33)	(3.10)
High FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.71	0.66	0.57	0.58	0.21	0.69	0.97	0.07	0.068	0.07
Years available	1941-1945	1941-1945	1941-1945	1941-1945	1941-1945	1941-1945	1940-1945	1940-1945	1940-1945	1944-1945
Obs.	420	420	420	420	420	420	114	63	64	1269

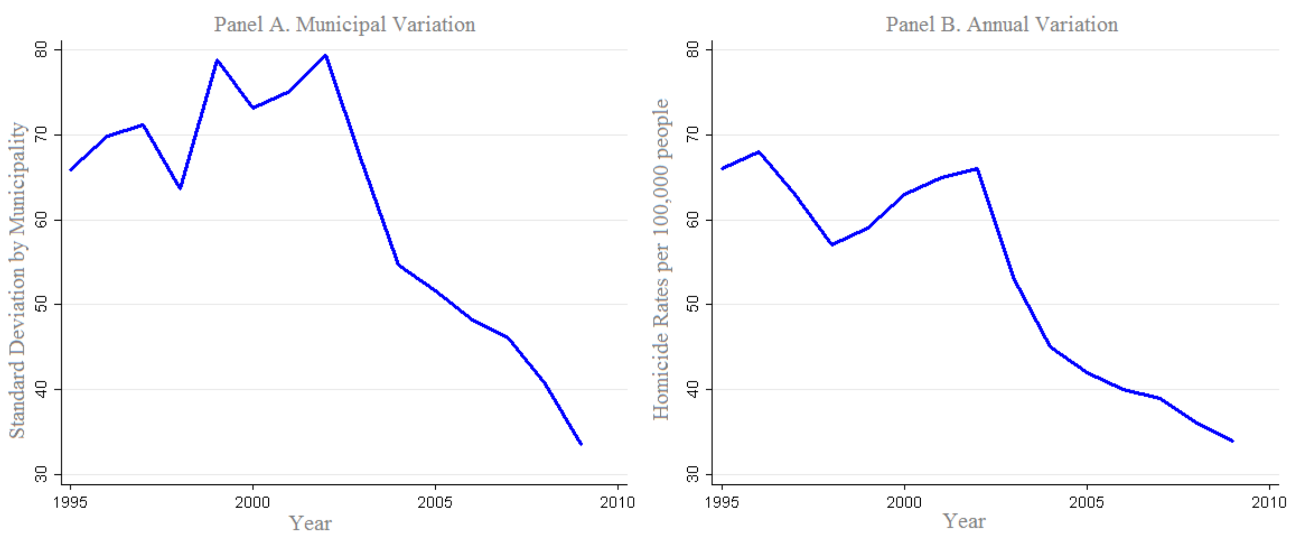
Note: the table presents a regression of the dependent variables observed before 1946 on the interaction of political competition in 1946 (PC_m) and dummy variables by years. GPI stands for General Price Index. Exports and Imports are expressed in millions and cattle value in hundreds of Colombian pesos. Standard errors clustered at the municipality level are presented in parentheses. *** Significant at 1% level, ** Significant at 5% level, and * Significant at 10% level.

Figure 1: The Poorest and Most Unequal Countries are also the Most Violent



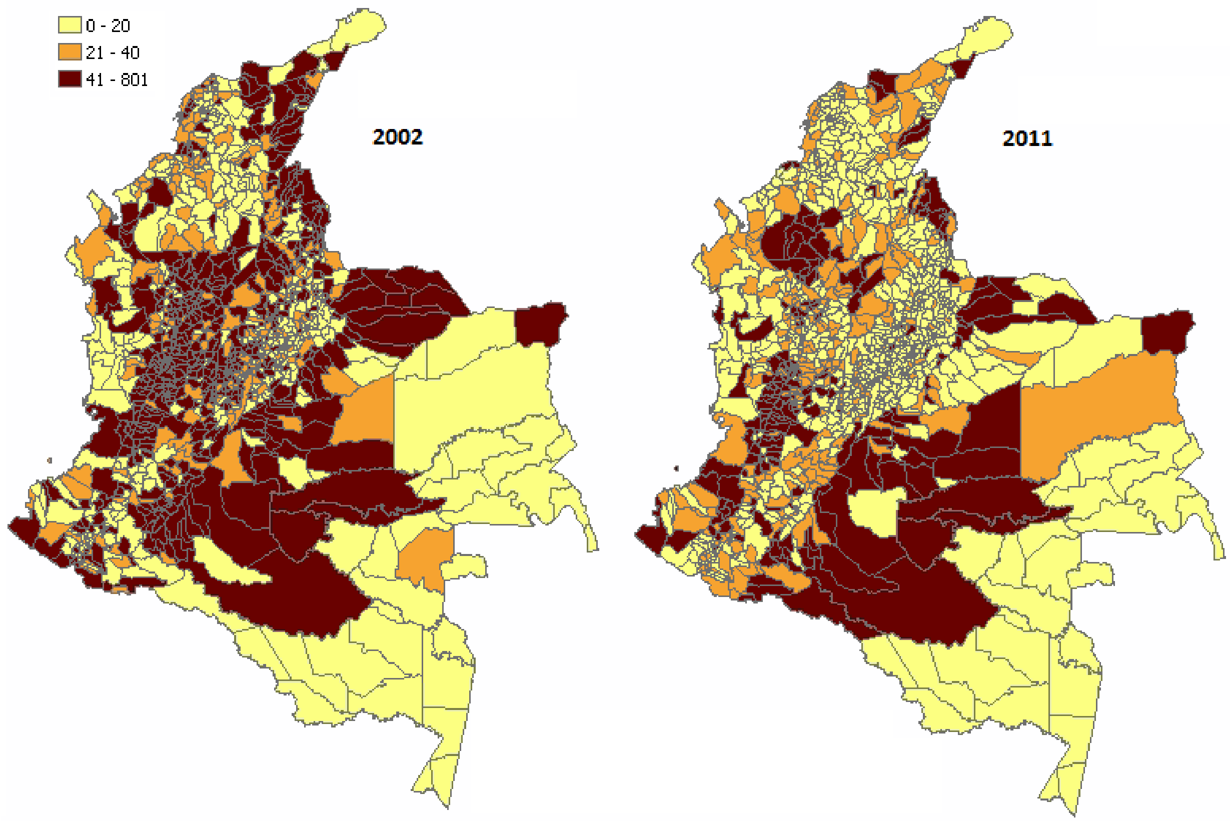
Note: The figure presents the correlation between: (i) the average GDP per capita and the average homicide rates (left panel), and (ii) the Gini coefficient and the average homicide rates (right panel). Averages were estimated between 1995 and 2010 for 194 countries of the world. Each dot in the figure represents a country and the line presents the fitted values of a regression of GDP per capita (left panel) and the Gini coefficient (right panel) on homicide rates. homicide rates come from the Global Homicide Study of the United Nations Office of Drugs and Crime. GDP per capita comes from the World Development Indicators of the World Bank. Finally, the Gini coefficient corresponds to a standardized index produced by the World Bank data from eight original sources: Luxembourg Income Study (LIS), Socio-Economic Database for Latin America (SEDLAC), Survey of Living Conditions (SILC) by Eurostat, World Income Distribution (WYD; the full data set is available here), World Bank Europe and Central Asia dataset, World Institute for Development Research (WIDER), World Bank Povcal, and Ginis from individual long-term inequality studies.

Figure 2: Municipal and Annual Variation of Homicide Rates in Colombia



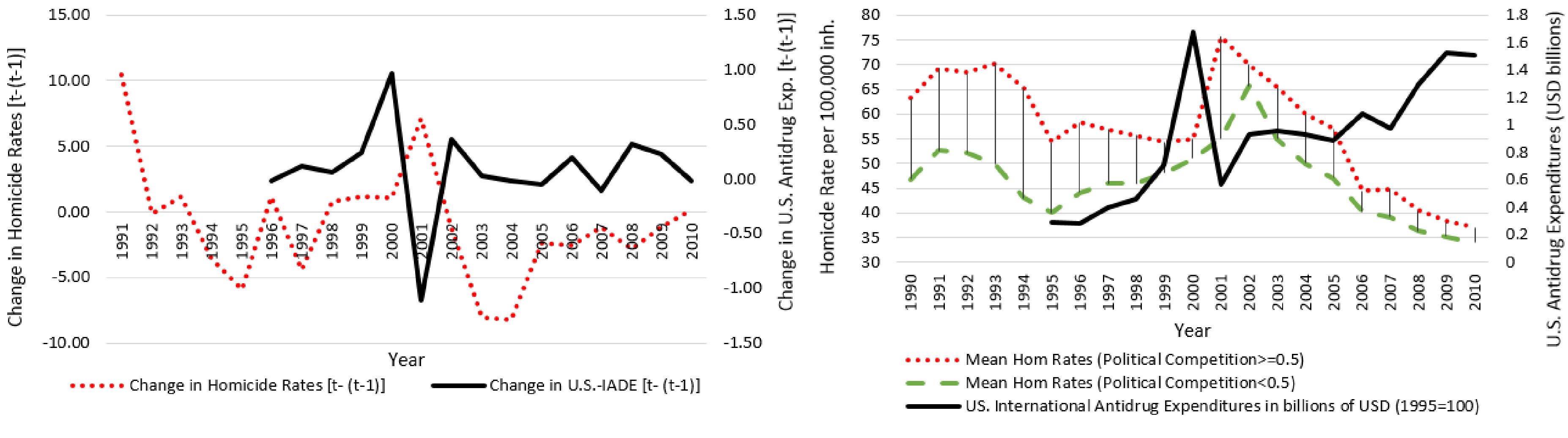
Note: The left panel presents the standard deviation of homicide rates per 100,000 people across municipalities and the right panel presents the time evolution of homicide rates per 100,000 people. Source: Observatory for Human Rights of the Colombian Vice Presidency.

Figure 3: Geographic Distribution of Homicide Rates by Municipality in 2002 and 2011



Note: The maps were elaborated with data from the *Instituto Colombiano Agustín Codazzi*, the Colombian geography agency. Data on homicide rates per 100,000 inhabitants comes from the Observatory for Human Rights of the Colombian Vice Presidency.

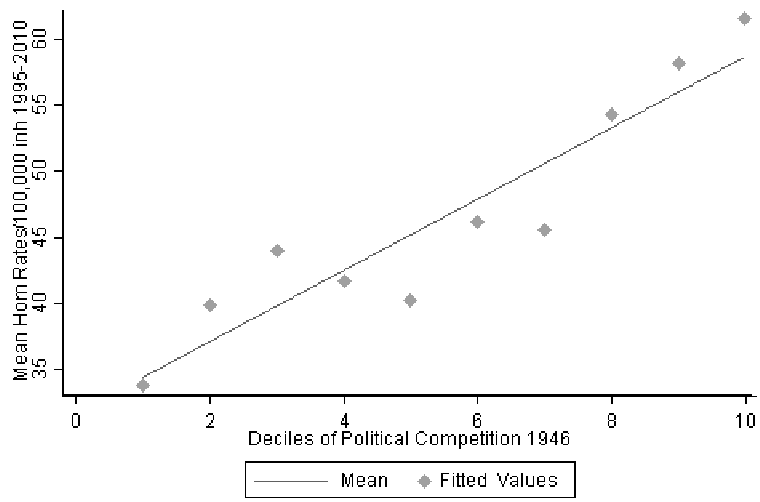
Figure 4: U.S. International anti-drug Expenditures and Homicide Rate in Areas with Different Political Competition in 1946



Panel (A) Panel (B)

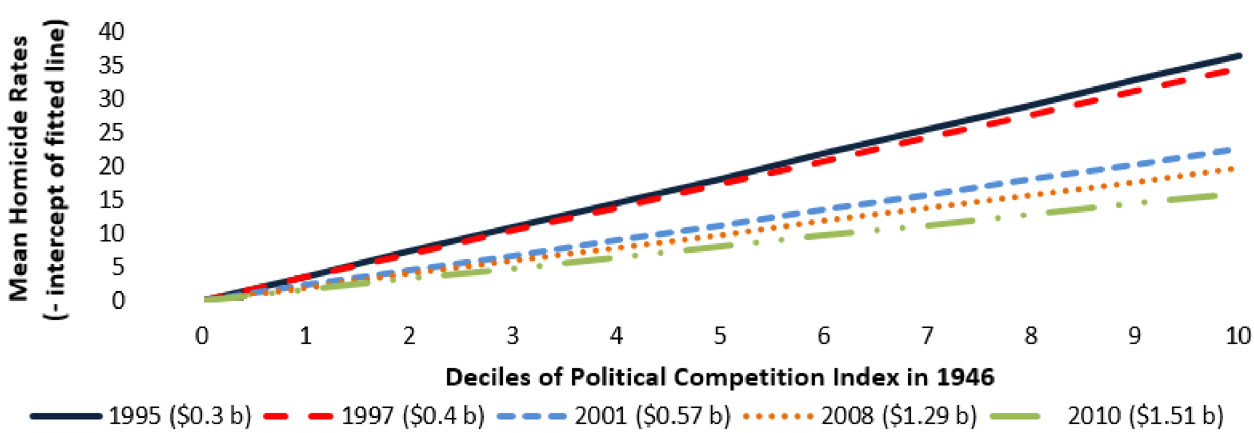
Note: Panel (A) compares the time evolution of changes in real U.S. international anti-drug expenditures and changes in homicide rates per 100,000 inhabitants. It suggests that both variables have a negative correlation. Panel (B) presents the time evolution of real U.S. international anti-drug expenditures and the average homicide rate per 100,000 inhabitants in areas with different levels of political competition in 1946. It suggests that U.S. transfers in security induced a reversal of fortune between areas with different levels of political competition in 1946. In particular, violent crime is reduced more quickly in areas with higher political competition for 1946 where illegally armed groups were originally located, and hence, where local governments were less empowered today.

Figure 5: Cross Section Correlation between Political Competition in 1946 and Homicide Rates Today



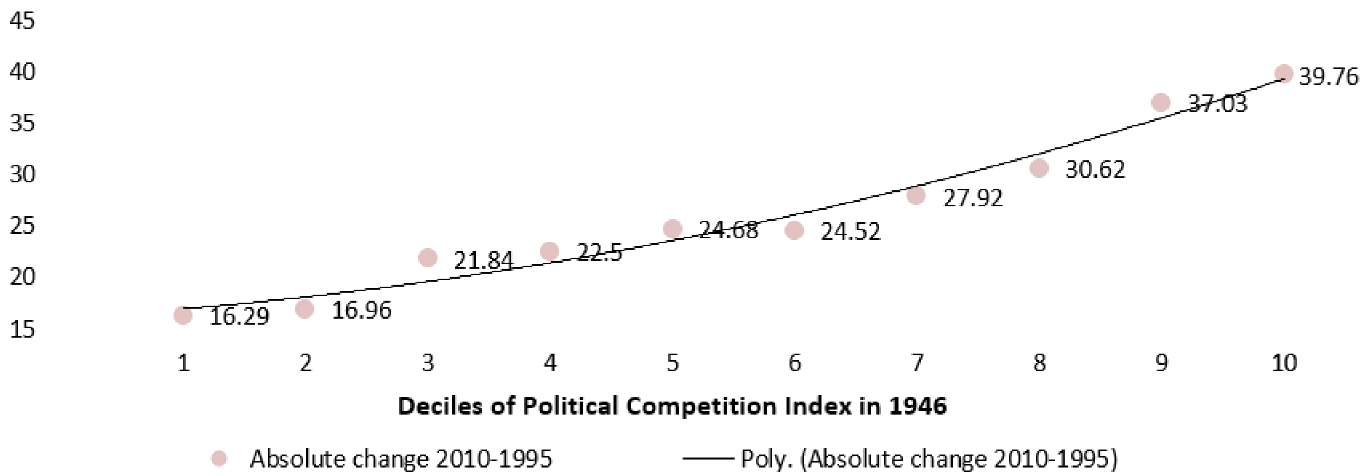
Note: The figure presents fitted values of a linear regression of mean homicide rates per 100,000 inhabitants for all municipalities between 1995 and 2010 on deciles of the political competition index in 1946.

Figure 6: Cross Section Correlation between Political Competition in 1946 and Homicide Rates Today for Years with Different U.S. anti-drug International Expenditures



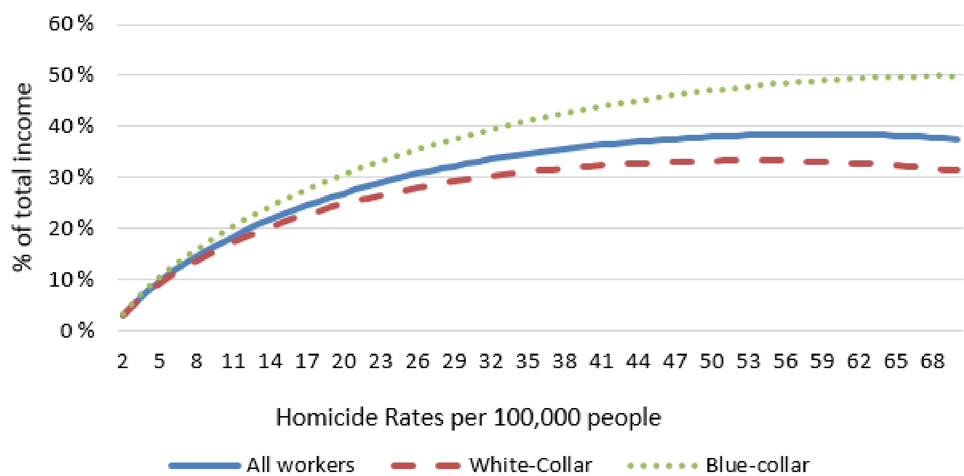
Note: The figure presents fitted values of a linear regression of homicide rates on deciles of the political competition index for years with different U.S. international anti-drug expenditures. The intercept was subtracted from each fitted line for comparison purposes. The level of U.S. international expenditures are reported in the label in parentheses. The figure suggests that: (i) there is a positive correlation between past political competition and homicide rates today for all years, and (ii) areas with higher political competition reduce violent crime more quickly when U.S. transfers are higher.

Figure 7: Areas with Higher Political Competition Reduced Violent Crime more Proportionally when U.S. anti-drug Expenditures are Higher



Note: The figure reports the absolute value of the change in homicide rates between 1995 (year with the lowest U.S. anti-drug International Expenditures) and 2010 (year with the highest U.S. anti-drug International Expenditures). They figure suggests that the areas with higher past political competition reduced violent crime more quickly when U.S. international anti-drug expenditures are higher.

Figure 8: Workers' Willingness to Pay for a Decline in Violence

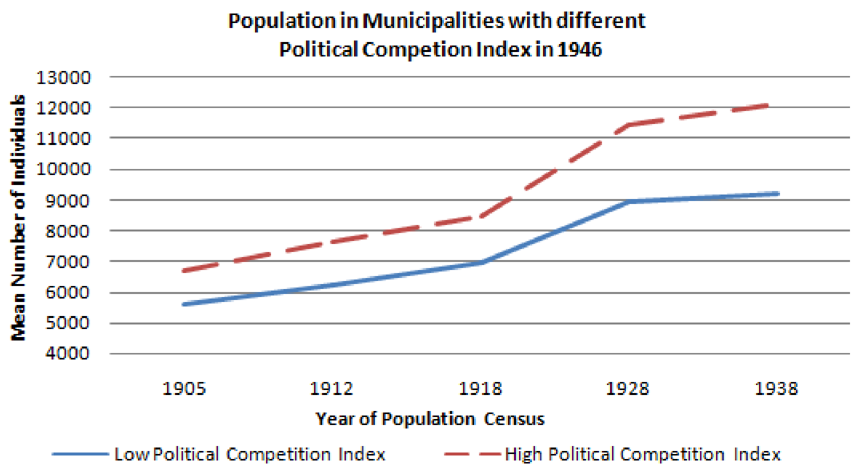


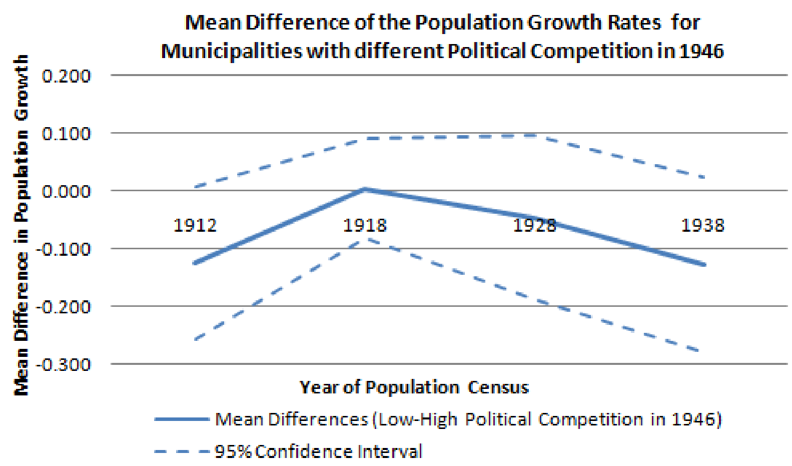
Note: The figure presents the estimates of the share of income that a worker with a level of violent crime reported in the horizontal axis will be willing to pay to have homicide rates equal to 1 per 100,000 people. The estimates are carried out using equation (15), which is derived by solving for T in the following expression:

$$V(P_0, (w_0 + T), r_0, v_0) = V(P_1, [(w_1 + T) - A], r_1, v_1)$$

where 0 and 1 represent two municipalities such that $v_0 > v_1$. In particular, for this case $v_1 = 1$. Moreover, $V(.)$ represents the indirect utility of the worker, P stands for the non-housing prices, $w + F$ represent labor and non-labor income, and r stands for housing rents.

Figure 9: Population Parallel Time Pre-trends Across Areas with Different Political Competition





Note: All municipalities with a political competition index higher than the median were classified as areas with high political competition index and vice versa. The information was digitized from the information on the population census available at the *Anuarios de Estadística General* collected by the *Contraloría General de La República* published between 1932 and 1946.

10 Appendices

A Descriptive Statistics

Table A.1: Descriptive Statistics for the Annual Manufacturing Survey

	1995		2010	
Variable	Mean	St. Deviation	Mean	St. Deviation
Age (years)	18.69	14.90	19.76	15.50
Multiplant	0.07	0.25	0.07	0.26
N of employees	82.08	180.51	66.79	155.82
Share male (% of total employees)	0.62	0.27	0.62	0.25
Real Average Monthly Wage (USD)	419.75	324.26	402.53	253.27
Number of inputs used	13.02	9.26	12.94	13.55
Number of final products	5.53	3.45	4.91	4.34
Real Annual sales (millions of USD)	8.20	4.40	7.90	8.05
Labor Share	0.34	0.19	0.32	0.19
Share blue (% total employees)	–	–	0.62	0.24
Exports (% of n. of plants)	–	–	0.21	0.41
Obs. (N. of Plants)	7,909		9,944	

Source: *Encuesta Anual Manufacturera* [Annual Manufacturing Survey] collected by the *Departamento Nacional de Estadística*–the Colombian statistical agency. The survey includes all manufacturing firms with more than 10 employees, with detailed information on all prices and physical quantities (valued at factory-gate prices) on inputs and outputs used/produced by each firm. The data is available for the period between 1995 and 2010. Note: * Exchange rates correspond to the average annual rates published by the Colombian central bank (it takes a value of $906 and $1912 Colombian pesos per U.S. dollar in 1995 and 2010, respectively).

B Literature on Rent-Violence Elasticity

An exhaustive review of the literature on the effects of crime on housing prices identifies 15 studies that present point estimates of the elasticity of rents with respect to crime. They are cited in the table below:

Authors	Year of publication	Location	Elasticity
Ihlanfeldt and Mayock	2010	Miami	-0.15
Naroff et al.	1980	Boston	-1.67
Burmel	1988	Chicago	-0.1
Gibbons	2004	London	-1
Pope	2008	Florida	-2.3
Linden and Rockoff	2008	North Carolina	-4
Buonnano et al.	2012	Spain	-1.27
Thaler	1978	Rochester	-3
Bowes and Ihlanfeldt	2001	Atlanta	-3
Hellman and Narrof	1979	Boston	-0.63
Clark and Cosgrove	1990	Mulitple locations	-0.125
Schwartz, Susin, and Voicu	2003	New York	-0.12
Ceccato and Wilhelmsson	2011	Sweeden	-0.04
Braakmann	2012	England and Wahles	-2%
Pope and Pope	2012	US, whole country	-0.35%

C Quantile Regression Estimates

To obtain the estimates of Panel B on Table 6 I combine the methodologies by Buchinsky (1996) to control for selection and by Lee (2007) to control for endogeneity. For all the steps where the inclusion of a power series of an inverse Mills ratio was necessary it was approximated through a second order polynomial following Staneva et al. (2010). Specifically, the following process was used:

1. Estimate the probability of exit and entry through a probit model. For the entry equation the independent variables include the three instruments (i.e., the dummy for CAEs, the interaction between the chambers of commerce location and the days needed to close a business, and the Bartik instrument for violence), lagged rural and urban population (by municipality), and lagged real per capita GDP (by department) obtained from DANE, the Colombian national statistical agency. The exit equation includes the same independent variables plus the lagged values of sales. Define the estimates of this step as $\hat{\beta}^o$.

2. Use the semiparametric least-square estimator used by Buchinsky (1998) and first formulated by Ichimura (1993) and given by:

$$\hat{\beta} = Arg\,Min_{\beta}\frac{1}{n}\sum_{i=1}^{n}(d_i - \hat{E}(d_i|X\beta)^2] \tag{16}$$

   to obtain the estimates for the coefficients in the selection equations, where $\hat{E}(d_i|X,\beta)$

$$\hat{E}(d_i|Z,\beta) = \frac{\sum_{j\neq i} y_j k((X_i'\beta - X_j'\beta)/h_n)}{\sum_{j\neq i} k((X_i'\beta - X_j'\beta)/h_h)} \tag{17}$$

   where $k(.)$ is the truncated normal kernel function. In the first round the truncation point is set at the standard errors of $X'\hat{\beta}^o$ (the estimates of step 1), and the kernel bandwidth is set to $n^{-1/5}$ to obtain $\hat{\beta}^1$.

3. Reset the symmetric truncation point to the standard errors of $X'\hat{\beta}^1 n^{-1/3}$ and h_n $X'\hat{\beta}^1 n^{-1/5}$ and solve again (16) to obtain the final $\hat{\beta}$.

4. Predict $X'\hat{\beta}$ and obtain the inverse Mills ratio of each equation.

5. Estimate the quantile regression of equation (12) including a second order polynomial of the inverse Mills ratio predicted for the entry and exit selection equations and predict the residuals.

6. Predict the inverse Mills ratio of the residuals of the previous step.

7. Estimate the quantile regression of equation (11) including the second order polynomials for the exit inverse Mills ratio, entry inverse Mills ratio, and residuals inverse Mills ratio from the last step.

Dep Variable: Log ($Real\ Production_{jmt}$)	0.1	0.25	0.5	0.75	0.9
Log ($Hom\ R_{mt}$)	-0.25***	-0.24***	-0.24***	-0.25***	-0.24***
[Boot-clust-er]	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Year dummies	Y	Y	Y	Y	Y
Selection Correction	Y	Y	Y	Y	Y
Pseudo R-squared	0.12	0.11	0.10	0.11	0.10
Obs.			124247		
N. of Clusters			317		

8. Estimate the standard errors by bootstrap clustering by municipality.

The estimates of this process are reported in the table. They suggest uniform negative effects of violence on firms across the distribution function of real production.

D List of Covariates

Number	Variables	Available	Source
1	Population 11 to 20 years	1995-2010	DANE
2	Population 21 to 30 years	1995-2010	DANE
3	Population 31 to 40 years	1995-2010	DANE
4	Population 41 to 50 years	1995-2010	DANE
5	Population 51 to 60 years	1995-2010	DANE
6	Population 61 to 70 years	1995-2010	DANE
7	Population 71 to +years	1995-2010	DANE
8	Male Population	1995-2010	DANE
9	Male-11 to 20 years Pop	1995-2010	DANE
10	Male-21 to 30 years Pop	1995-2010	DANE
11	Male-31 to 40 years Pop	1995-2010	DANE
12	Male-41 to 50 years Pop	1995-2010	DANE
13	Male-51 to 60 years Pop	1995-2010	DANE
14	Male-61 to 70 years Pop	1995-2010	DANE
15	Male-71+ years Pop	1995-2010	DANE
16	Tax Income	1995-2010	DNP
17	Non-Tax Income	1995-2010	DNP
18	Transfers Income	1995-2010	DNP
19	Capital Income	1995-2010	DNP
20	Income from 'Regalias'	1995-2010	DNP
21	Gov. Operational Expenditures	1995-2010	DNP
22	Debt Interest Expenditures	1995-2010	DNP
23	Other Expenditures	1995-2010	DNP
24	Capital Investment	1995-2010	DNP
26	Education Inv.	1995-2010	DNP
27	Health Inv.	1995-2010	DNP
28	Housing Inv.	1995-2010	DNP
29	Other Public Services Inv.	1995-2010	DNP
30	Transportation Inv.	1995-2010	DNP
31	Cultural Inv.	1995-2010	DNP
32	Agricultural Inv.	1995-2010	DNP
33	Environmental Inv.	1995-2010	DNP
34	Justice Inv.	1995-2010	DNP
35	Recreational Inv.	1995-2010	DNP
36	Vulnerable groups Inv.	1995-2010	DNP
37	Disaster prevention Inv.	1995-2010	DNP
38	Education Inv.*Public Services Inv	1995-2010	DNP
39	Education Inv*Justice Inv	1995-2010	DNP
40	Education Inv* Health Inv	1995-2010	DNP
41	Public Debt	1995-2010	DNP
42	Rain	1995-2010	CEDE
43	Primary Enrollment	1995-2010	Ministry of Educ
44	Secondary Enrollment	1995-2010	Ministry of Educ

E List of Parameter Values Used for Welfare Estimation

Variables	Values	Source	Period
% change in homicide rates 1995-2010	-0.48	Human Rights Observatory	1995-2010
Elasticity r and v	-1.16	Review of studies	–
α	0.80	National Household Survey	2000-2010
β	0.98	National Household Survey	2000-2010
v	51.86	Human Rights Observatory	1995-2010
r	5040.96	Colombian Statistical Department	1995-2010
P	238.87	Colombian Statistical Department	1995-2010
l	192.00	National Household Survey	2000-2010
w	6085.00	National Household Survey	2000-2010
F	91920.00	National Household Survey	2000-2010
w (white-collar)	8214.75	AMS and National Household Survey	1995-2010
w (blue-collar)	4868.00	AMS Household Survey	1995-2010

Note: AMS stands for Annual Manufacturing Survey.

F Estimates for α and β

The welfare estimates require the estimation of the parameters of the utility function. In order to do so I use the information available in the *Gran Encuesta Integrada de Hogares* [Colombian National Household Survey] between 2006 and 2010. These surveys are representative at the National level and correspond to cross sections collected annually and contain information on workers and households socioeconomic characteristics. They are collected and processed by the Colombian Statistical Department (DANE, for its initials in Spanish).

According to the theoretical model presented in section 2, the indirect utility of a worker i living at municipality m is given by:

$$V_{im}(P_m, w_m, r_m, v_m) = \Big[(w_m + F)P_m^{-\alpha} r_m^{\alpha-1}\Big]^{\beta}[1/v_m]^{1-\beta}x_{im} \tag{18}$$

which could also be expressed as:

$$V_{im} = V_m x_{im} \tag{19}$$

where:

$$V_m = \Big[\frac{w_m + F}{P_m^{\alpha} r_m^{1-\alpha}}\Big]^{\beta}[1/v_m]^{1-\beta} \tag{20}$$

Following, Redding (2012) I assume that the workers idiosyncratic shocks x_{im} are distributed frechet so that:

$$Pr(x_{im} < a) = e^{-a^{-\delta}} \tag{21}$$

From these assumptions, the amount of people living at m as a share of total population is given by:

$$s_m = \Big[\frac{V_m}{V}\Big]^{\delta} \tag{22}$$

where:

$$V = \Big[\sum V_m^{\delta}\Big]^{1/\delta} \tag{23}$$

Adding time subscripts and taking logs we can write:

$$ln(s_{mt}) = \underbrace{\delta\beta}_{a_1} ln(I_{mt}) - \underbrace{(\delta\alpha)}_{a_2} ln(P_{mt}) - \underbrace{\delta(1-\alpha)}_{a_3} ln(r_{mt}) - \underbrace{\delta(1-\beta)}_{a_3} log(v_{mt}) + \underbrace{\delta lnV}_{\gamma_t} + \epsilon_{mt} \tag{24}$$

In particular, the right hand side of the equation is lagged to reduce endogeneity problems. I estimate the previous specification for the 24 cities available on the National Household Survey from 2006 to 2010. The population shares s_{mt} come from the Colombian National Statistical Agency and are constructed with information from the population census of 2005 and the National Household Surveys. Based on this methodology I identify values of α=0.82

(s.e=0.021), β=0.98 (s.e.=0.15)