

# Is Informality Good for Business? The Impacts of IDP Inflows on Formal Firms

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## Abstract

This article examines the effects of large inflows of internally displaced persons (IDPs), who are primarily absorbed by the informal sector, on the behavior of formal manufacturing firms in Colombia. To identify causal effects, we employ annual firm-level panel data between 1995 and 2010 and exploit the fact that, when conflict intensifies, forcefully displaced individuals tend to migrate to municipalities where people from their origin locations settled earlier. We find that large inflows of IDPs induce sizable negative effects on the output of formal firms. We are not, however, able to distinguish significant effects of inflows of IDPs on firm entry, prices, or the input demands of formal manufacturing firms.

**JEL Classification:** D22, J61, O17.

**Keywords:** Forced Migration, Firms, Informality.

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# I Introduction

Forced displacement due to violence and conflict has hit an all-time high. By the end of 2017, the number of individuals forcibly displaced reached 68.5 million ([UNHCR, 2018](#)). Sudden and large inflows of forced migration may induce sizable effects on hosting economies, not only by increasing demand for public services, but also by modifying the decisions made by workers and firms. To adequately guide public policy to help forced migrants and their hosts cope with these shocks, it is crucial to properly understand these effects.

This article explores the effects of a sudden and large wave of internally displaced persons (IDPs), who are primarily absorbed by the informal sector, on the behavior of formal firms in Colombia. Previous literature has largely focused on examining the effects of voluntary migrants on firm behavior within countries with a low incidence of informality.<sup>1</sup> The effects of a large wave of low-skilled forced migrants, however, deserves a separate analysis, for several reasons. First, forced migrant inflows are disproportionately concentrated in developing countries with large informal sectors. In fact, according to a recent report of the United Nations Refugee Agency, 86 percent of the world's forcefully displaced individuals are in low and middle-income countries close to conflict situations ([UNCHR, 2015](#)) and the World Bank estimates that this figure is actually higher and closer to 99 percent ([World Bank, 2016](#)). If forced migrants join the informal sector upon arrival, formal firms may be negatively affected by the migration shock via the unfair competition of informal firms that do not pay taxes or comply with regulations. Second, forced migrants have characteristics that are drastically different from those of voluntary migrants. Forced migrants are less likely to be positively self-selected in terms of skills than are economic migrants, whose migration decisions are more tied to expected labor market success ([Chiswick, 1999](#)). They face great uncertainty about the duration of their stays in hosting economies and are more likely

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<sup>1</sup>[Lewis, 2011](#); [Kerr et al., 2015](#); [Dustmann and Glitz, 2015](#); [Ottaviano et al., 2018](#), for example, study the impact of voluntary migrants on firm outcomes. In these studies—as is to be expected when considering a standard labor demand and supply model—a increased number of immigrants pushes wages down, causing reductions in operation costs and changes in capital-labor ratios (see [Lewis, 2011](#) and [Dustmann and Glitz, 2015](#) for examples). Consequently, many of these studies find evidence of unskilled immigration having positive effects on total employment, firm output, and firm creation ([Kerr et al., 2015](#); [Dustmann and Glitz, 2015](#)).

to be affected by trauma and distress, since they tend to have recently fled from wars (Moya et al., 2012). These characteristics may complicate the efficient integration of displaced individuals into formal reception markets.

We focus on the case of Colombia because its unique characteristics make it an ideal case with which to pursue this study. The escalation of the Colombian armed conflict in the late 1990s and the 2000s induced large sudden flows of displaced individuals. According to data from the Human Rights Observatory, internal conflict in Colombia between 1995 and 2010 displaced approximately 5.8 million people, which is roughly 11 percent of the total population in 2010. Colombia also collects among the most complete and rich firm-level panel data available for the study of firm behavior in developing countries. The Annual Manufacturing Survey, a census of all manufacturing firms of more than 10 employees, includes plant-year level information on sales, wages, employment, and capital as well as product-plant-year information on output and input prices.

To identify causal effects, we use a panel-instrumental variable methodology. We construct the instrumental variable for inflows of IDPs following the standard approach in the literature, which combines early settlements of migrants with time trends on migration outflows.<sup>2</sup> Our geographic variation comes from the fact that IDPs move disproportionately to municipalities where there are early settlements of populations from their municipalities of origin. Our time variation comes from observed outflows of displaced populations by municipality and year due to conflict shocks. We construct the predicted inflow of immigrants by combining municipal cross-sectional information from the Colombian population census of 1993 (the last population census before the intensification of the conflict) with time-varying data on the total number of individuals expelled from each municipality. Our instrument is a strong predictor of the observed inflows of IDPs between 1995 and 2010.<sup>3</sup>

We find that large inflows of IDPs induce sizable negative effects on formal firms' production

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<sup>2</sup>See Card, 2001 and Altonji and Card, 1991 for the pioneer approaches and Lewis and Peri, 2015 for a review of the literature on applications.

<sup>3</sup>A new criticism of the validity of this type of shift-share instrument was recently proposed by Jaeger et al. (2018). The authors suggest that using pre-settlements of migrants in countries where migration flows are stable in time confounds short- and long-term causal effects. Our identification strategy is not sensitive to their critique because the inflows of forced migrants were sudden and large in scale as a consequence of the intensification of armed conflict.

but no significant changes in firm entry, prices, or input demands. Our estimates suggest that when inflows of IDPs increase by 1 percent, the production of formal firms drops by approximately 0.3 percent. These correspond to sizable effects, given that the average municipality registered an annual growth of 22 percent in the number of forcefully displaced individuals received between 1995 and 2010 in Colombia. Based on these numbers, a naïve, back-of-the-envelope calculation would suggest that formal firms located in the average municipality should have seen an approximately 6.6 percent annual decrease in their formal production between 1995 and 2010 as a result of the large number of IDPs.

Our main estimates include fixed effects by firm and year, and as such are not sensible to aggregate time trends or time-invariant firm characteristics. We also show that our estimates are robust to the inclusion of a battery of controls, including regional time trends, violence and conflict-related covariates, and differential pre-trends in economic conditions, government size, and violence levels.

When exploring the mechanisms driving our results, we document that larger inflows of displaced populations are positively associated with an increase in the size of the informal sector. This may be explained by the characteristics of the forcefully displaced populations. Forcefully displaced individuals commonly arrive in new locations without legal identification documents, tend to have low education levels, lack experience in jobs that have high local demand (as many IDPs move from rural to urban areas), and may be affected by traumatic events that complicate their integration into formal markets (see [Ibáñez and Moya, 2006](#)). IDPs thus tend to look for low-tier jobs, which are most likely available in the informal sector (as documented extensively by [Amaral and Quintin, 2006](#); [Perry, 2007](#); [Galiani and Weinschelbaum, 2012](#); [La Porta and Shleifer, 2014](#); [Meghir et al., 2015](#)), increasing its size.

An increase in the size of the informal sector may induce negative effects on the performance of formal firms, in several ways. Formal firms, for example, face higher costs relative to informal firms as they pay taxes, fees, and higher wages for their employees ([La Porta and Shleifer, 2014](#)). Informal firms can thus usually offer lower prices, thereby competing unfairly with formal

businesses. Unfair competition from informal firms can also slow down the process in which inefficient firms can be replaced by more efficient competitors and negatively affect the incentives of formal firms to innovate and adopt new technologies, as these innovations can be easily stolen (Perry, 2007). At the same time, since informal firms are able to use public goods, but do not pay for them, they lower their quality and crowd out their use by formal firms (Besley and Persson, 2013).

Our results are in line with anecdotal evidence from several media outlets, which consistently report the close connection between forced displacement and the size of the informal sector in Colombia. More particularly, journalists document that forcefully displaced individuals have a hard time integrating into formal markets given their previous experience in agriculture (which is not common in urban areas) and their low education levels, and that, consequently, often their only economic choice is to work as self-employed individuals and join the informal sector selling products on the streets (see IPS, 1999; El Espectador, 2009; El Tiempo, 2010; El Tiempo, 2014; for some examples). Reports also suggest that even if displaced populations manage to find a job in the formal or informal sectors, they have a high likelihood of receiving less favorable labor conditions than the rest of the population with comparable characteristics (see Huffington Post, 2010; La Silla Vacía, 2012).

This paper contributes to two strands of economic literature. One strand it contributes to is the research exploring the effects of unskilled migration on firm-level outcomes. Papers examining the effects of unskilled migration on firms have focused mainly on developed economies.<sup>4</sup> These studies examine firm-level outcomes such as productivity, imports, exports, investments, wages, entry, exit, and relative skill mix. Their findings suggest that immigrants have positive effects on firm-level outcomes.<sup>5</sup> This study contributes to this literature by documenting the effects of unskilled

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<sup>4</sup>These include the cases of Spain (Carrizosa and Blasco, 2009), the United States (Lewis, 2011), Italy (Accetturo et al., 2012), the United Kingdom (Ottaviano et al., 2018), and Germany (Dustmann and Glitz, 2015).

<sup>5</sup>For instance, these studies typically document greater firm productivity, driven mainly by lower production costs and skill complementarities in the workplace. They also examine the effects of immigration on capital investments, where the results are mixed. Lewis (2011), for example, finds that plants in areas that received more unskilled immigrants were less likely to adopt automation machinery, which served as a buffer for the effects of immigration on wages. Accetturo et al. (2012) and Ottaviano et al. (2018), in contrast, find that firms in Italy and the United Kingdom increase their capital investments in response to immigration from developing countries, arguably because firms tend

migration in an economy with a large informal sector and by examining the case of forcefully displaced migrants, whose characteristics differ drastically from those of voluntary migrants.

This paper also adds to the growing number of studies that examine the impact of forced migrants in hosting economies. Most of this literature has been focused on the United States and the Middle East and documents the impact of refugee inflows on employment and prices (see [Borjas and Monras, 2017](#); [Clemens and Hunt, 2017](#); [Del Carpio and Wagner, 2015](#); and [Ceritoglu et al., 2017](#) for examples). The paper that is most similar to this study is that of [Altindag et al. \(2018\)](#), who study the impact of Syrian refugee migration on firm behavior in Turkey. In contrast to our results, these authors document that refugee inflows had a positive impact on firm creation in the construction and restaurant sectors in Turkey and no impact in the other sectors of the economy. The difference between our findings and theirs may be explained by the fact that Colombian IDPs had previously worked primarily in agriculture, whereas the previous employment of Syrian refugees was more diverse. IDPs in Colombia, consequently, were completely absorbed by the informal sector, whereas there was some integration of refugees into formal firms in Turkey (although not necessarily into formal jobs within those firms). Our paper thus contributes to this literature by identifying the effects of a forced displacement shock from a low-skilled population that, before the onset of conflict, had been primarily concentrated in agriculture and that was thus mostly absorbed by the informal sector upon arrival in hosting locations in the short term.

## II Colombian Context

According to information from the Colombian Human Rights Observatory, between 1995 and 2010 approximately 5.8 million people were internally displaced by violence in Colombia, accounting

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to offset the skills-downgrading effect with more capital accumulation. The latter also finds that immigration acts as a substitute for offshoring by lowering the intermediate imports from the immigrants' countries of origin and tends to increase exports to the immigrants' countries of origin because it helps reduce information barriers and trade costs. Finally, [Dustmann and Glitz \(2015\)](#) find that the responses of firms to an influx of immigrants in Germany depends on their sector of economic activity. While firms in the non-tradable sector respond by lowering wages, their tradable sector counterparts primarily respond by scaling up their employment and changing their skill mix. In addition, they also find a positive net entry effect of firms in the tradable sector (i.e., firm creation minus exit).

for approximately 11 percent of the total Colombian population of 2010 (see Figure I). The number of displaced individuals, however, may be even higher, since these figures only include individuals who searched for governmental support when arriving at their new locations. The same data suggest that, between 1995 and 2010, 82 percent of municipalities received at least one of these migrants (see panel b of Figure I).

The escalation of the Colombian conflict -fought between the country's guerrilla groups, paramilitary vigilantes, and armed forces- was the main reason for forced displacement in the late 1990s and the early 2000s (Engel and Ibáñez, 2007).<sup>6</sup> Forced displacement, more specifically, was not a causal by-product of the Colombian conflict, but an extremely common strategy of war used by illegal armed groups to weaken the enemy's popular support, clear regions for illegal crop growing and drug trafficking, and expropriate lands and natural resources (Ibáñez and Vélez, 2008). According to Ibáñez, Moya, and Velásquez (2006), for instance, between 1993 and 2002 displaced individuals lost 1.2 million hectares of land.

## II.1 Characterizing Internally Displaced Migrants

The annual cumulative displaced population from 1995 to 2010, according to the *Registro Único de Víctimas* (RUV) from the Colombian Human Rights Observatory is presented in Figure I.<sup>7</sup> The figure shows that the number of displaced individuals began to increase dramatically between 1996 and 2002 in Colombia, when the internal conflict was most intense, as shown by the evolution of

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<sup>6</sup>As documented in Rozo (2018), the Colombian internal armed conflict intensified in the middle of the twentieth century with the formal creation and growth of illegal armed groups. In 1964, adherents of a Cuban-style revolution founded the National Liberation Army (known by its Spanish acronym, ELN). Later, in 1966, a second left-wing group, the Revolutionary Armed Forces of Colombia (FARC in Spanish), was founded as the union of all the remaining communist guerrillas. Initially, both groups claimed to defend the interests of the rural poor, aiming to overthrow the government and to install a Marxist regime. In time, however, the motivations of both groups became primarily economic. Paramilitarism began in the late 1980s as an anti-insurgent response by landowners and drug traffickers to left-wing guerrillas' 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 in Spanish). By 2003, the AUC had declared a partial ceasefire, and some paramilitary blocs agreed to participate in a "disarming program" that concluded in 2005. Many of the combatants that had been part of the AUC, however, later fused into new criminal groups that are known today as *Bandas Criminales* (BACRIM), illegal armed groups that obtained financial resources, mainly through extortion and drug trafficking, to carry on their activities.

<sup>7</sup>The data is publicly available at: <http://rni.unidadvictimas.gov.co/RUV>

conflict-related variables such as armed actions and clashes between armed groups (see panel b of Figure II). Since then, forced displacement has been decreasing slowly in conjunction with a softening of conflict intensity and violence.<sup>8</sup>

Data from RUV also suggests that the cumulative population of forced migrants is balanced in terms of gender (51 percent women) and that most are of working age. Most head of households, however, are women; men tend to stay in their municipalities of origin in order to care for assets and land or to actively participate in the armed conflict. Colombia's forced migrants are also young. In particular, 39 percent of forcefully displaced individuals were 15 years old or younger at the time of displacement, this percentage is disproportionately larger than this age group within the population of Colombia as a whole (28 percent). Indeed, 15.5 percent of forced migrants were younger than 5 years of age at the time of migration. Households also tend to be bigger as several members of the extended family tend to live together to save on housing costs ([Unidad para la Atención y Reparación de Víctimas, 2013](#)). Previous studies, using surveys given to migrants who were forcefully displaced, also report that this population has low education levels (around 5 years of education) ([Ibáñez and Moya, 2006](#); [Garay, 2008](#); [Carrillo, 2009](#)).

Several studies have attempted to characterize the migration decision of forced migrants using surveys. Their findings suggest that forced displacement in Colombia mostly originates from rural areas, where the internal armed conflict has taken place. In that sense, the migration decision of forced migrants is mainly driven by safety concerns related to the presence and activities of illegal armed groups. In particular, data from RUV suggests that for the 59 percent of individuals for whom information is available on the cause of displacement, 54 percent of migration cases were attributed to the activities of illegal armed groups and 84 percent were attributed to a death threat ([Unidad para la Atención y Reparación de Víctimas, 2013](#)). Most displaced individuals, consequently, had previously worked primarily in agriculture ([Ibáñez and Moya, 2006](#); [Carrillo, 2009](#)). Households that had access to basic public services, had better economic opportunities, or had private property showed a lower probability of migrating ([Engel and Ibáñez, 2007](#); [Ibáñez](#)

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<sup>8</sup>The problem is still ongoing, however. At the time of writing, in mid-2017, the years forceful displacement rate has already surpassed 800.



and Moya, 2010). In areas with extreme levels of violence, however, owning land increased the probability of displacement because these household were targeted for extortion by illegal armed groups (Engel and Ibáñez, 2007).

Forced migrants in Colombia have moved to areas where they had friends or relatives and that were closer in distance to their municipalities of origin (Ibáñez and Moya, 2006; Carrillo, 2009; Lozano-Gracia et al., 2010). Yet, in regions with extreme violence, individuals preferred to relocate to more distant locations and to cities that were more populated; they were attracted to the sense of anonymity both provide (Carrillo, 2009; Lozano-Gracia et al., 2010). Other criteria migrants take into account when choosing their destinations includes the provision of public goods and the population density of the destination municipality (Carrillo, 2009; Lozano-Gracia et al., 2010).

Households who migrate have incurred substantial losses in physical assets left behind in their municipalities of origin and have suffered human capital depreciation due to household disintegration or post-traumatic stress disorders (see Ibáñez and Moya, 2010 for a quantification of these welfare losses). Most households, in addition, move to urban areas, where there is little demand for their agricultural experience. Many of them, consequently, face extreme hardship upon arrival in their new locations, facing living conditions less favorable than those of the urban poor (Vélez, 2002; Ibáñez and Moya, 2006). Ibáñez and Moya (2006), more particularly, estimate that the consumption of displaced households falls by 35.7 percentage points upon migration and drops even further during the year following displacement.

## **III Data**

### **III.1 Firm data**

Our main source of information is the *Encuesta Anual Manufacturera* (Annual Manufacturing Survey), collected by the *Departamento Nacional de Estadística* (DANE), the Colombian statistics agency. These data set is a census of all manufacturing plants with ten or more workers or with a

total output value larger than 65 million in 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. The survey includes information on all production-related variables, including employment and wages. 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 article, firms' prices are defined as the plant-product-year observation estimated by dividing the value of revenues or expenditures by physical quantities. This data set is regarded as one of the best and most complete sources of information for studying firm behavior in developing countries (Kugler and Verhoogen, 2011). The data set covers the years 1995 to 2010, though its data distinguishing employment and wages by white- and blue-collar workers is only available after the year 1999.<sup>9</sup>

Our sample consists of all municipalities where more than two formal firms with ten or more workers are observed.<sup>10</sup> These municipalities are typically more populated, have higher economic activity (see Appendix I for a comparison of the municipalities in the manufacturing sample and those not included). They also were strong recipients of IDP during the period of study (see Figure I), had lower levels of conflict-related violence, although higher levels of urban crime (measured through homicide rates) relative to the rest of the country (see panel a of Figure II).

Figure V shows the annual evolution of the mean of all the firm outcomes employed in this study.

## III.2 Internal Forced Displacement

Municipal data on forced displacement caused by violent conflict was obtained from the *Registro Único de Víctimas* (RUV, Registration of Victims) from the *Unidad para la Atención y Reparación Integral de las Víctimas* of the Colombian government. This is the best source of information on in-

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<sup>9</sup>The data also contains information on firms' average output and input prices. We do not use this data, however, as it highly concentrated in the biggest cities for which geographic variation is considerably lost.

<sup>10</sup>Municipalities where only one firm was observed were dropped from the sample by DANE due to confidentiality concerns.

individuals who were displaced by violence because it combines all official sources available where individuals registered upon arrival in the new locations (even if they registered with authorities a long time after their arrival, in which case they are included in the year in which they arrived in the data). Although not all individuals register, these data are an excellent approximation of the total number of individuals received in each municipality because being registered is a condition for accessing any type of governmental support from local authorities. To be registered, individuals have to declare their displacement under oath, attest to the exact dates of the event, their municipality of origin, and some of their socioeconomic conditions, as well as to describe the facts leading to their displacement.

The RUV data, consequently, offers information on the municipalities from which migrants were expelled and into which they were received. It is available annually by municipality between 1984 and 2016. In this paper, however, we focus on the period between 1995 and 2010 because it is the period for which firm data is also available. The time evolution of total displacement is presented in Figure I and shows strong variation between 1995 and 2010. The total number of receiving municipalities is presented in panel b of the same figure (Colombia has 1,122 municipalities).

Figure III presents the geographic distribution of the intensity of migration outflows and inflows of individuals as a share of the mean population between 1995 and 2010. The upper panel of the figure presents the intensity index, which reveals that the municipalities that lost a significant portion of their population to forced displacement were mainly located on the west and between the middle and the south of Colombia. The mean intensity index for all the municipalities is 0.17, suggesting that, on average, all Colombian municipalities lost approximately 20% of their population to forced migration between 1995 and 2010. The variance, however, is high (s.e. 0.25). There are also approximately 45 municipalities that saw an intensity index of 100 percent, suggesting that their population was depleted by forced migration. The figure also shows that the forced migration that originated in the center of the country was of relatively low intensity.

The lower panel of the figure shows the pressure index, defined as the total number of forcefully

displaced individuals who arrived in a municipality as a share of the municipal mean population between 1995 and 2010. The pressure index is a good proxy for the congestion of public goods and services as a consequence of forced displacement in the municipalities where these populations arrive. The pressure index has a mean value of 10 percent (s.e. 0.19). Although forced migration was substantial during the period of analysis, the figure reveals that most of the receiving municipalities did not face pressure indexes that are extremely large. In fact, only 38 municipalities have pressure indexes of more than 50 percent, suggesting that forcefully displaced migrants tend to move to urban areas with large populations. Similar results were documented by Carrillo (2009) and Lozano-Gracia et al. (2010). For instance, according to the data from RUV, Bogotá, the Colombian capital city, received almost 10 percent of the total number of migrants. Migrants may decide to move to urban areas in search of better economic opportunities (i.e., a larger labor market), a sense of safety due to anonymity, and to move away from conflict areas, which were predominantly rural during the period of analysis.

## IV Empirical Strategy

Identifying the effects of IDP inflows on firms' behavior is challenging, since migrants do not move to random locations. The displaced populations, for instance, may have chosen to move to more populated, less violent areas where local authorities have better control of the territory, where there are better economic opportunities, and where illegal armed groups are not active. To correct for these biases, we use a panel-instrumental variable approach. Our main specification is given by the following equations:

$$\text{Log}(Y_{jmt}) = \gamma_1 \text{IDP}_{mt} + X_{mt} \Gamma' + \gamma_t + \gamma_j + \epsilon_{jmt} \quad (1)$$

$$\text{IDP}_{mt} = \theta_1 \text{Predicted Inflows}_{mt} + X_{mt} \Theta' + \theta_t + \theta_j + \mu_{jmt} \quad (2)$$

where  $j$  stands for firm,  $m$  stands for municipality, and  $t$  stands for year;  $Y$  represents the firm decisions (including production, prices, and input demands);  $IDP_{mt}$  represents the ratio of IDP inflows to population of working age (multiplied by 100 to ease interpretation);<sup>11</sup>  $X_{mt}$  is a vector of municipal controls;  $\gamma_t$ ,  $\gamma_j$ ,  $\theta_t$ , and  $\theta_j$  represent year and firm fixed effects; and  $Predicted\ Inflows_{mt}$  is the instrumental variable, defined as

$$Predicted\ Inflows_{mt} = \sum_{j=1 \in J} \left[ Forced\ Migration\ Outflows_{jt} \times \frac{Migrants_{mj}^{1993}}{Total\ Migrants_m^{1993}} \right] \times 100 \quad (3)$$

where *Forced Migration Outflows<sub>jt</sub>* measures the number of individuals who were displaced by violence in municipality  $j$  and year  $t$ ;  $J$  represents the total group of municipalities; *Total Migrants<sub>m</sub>* is the total number of individuals who live in municipality  $m$ , but who were not born there in 1993; and *Migrants<sub>mj</sub>* are the total number of individuals born in municipality  $j$  who are living in municipality  $m$  in 1993. We use the year 1993 to construct the instrument because in that year the Colombian statistics agency collected the last population census before the large wave of forced displacement took place in Colombia (see Figure I). *Predicted Inflows<sub>mt</sub>*, therefore, is constructed following the original idea by Card (2001) and Altonji and Card (1991) (see Lewis and Peri, 2015 for a literature review), which exploits the fact that individuals tend to migrate disproportionately into regions in which they have relatives, friends, or family (commonly known in the migration literature as early settlements of migrants) because these people provide the migrants with support networks.

In this specification,  $\gamma_1$  will identify the percentage change in firm outcomes when the inflows of displaced individuals increases by 1 percentage point.

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<sup>11</sup>Working age population includes individuals 12 years and older as defined by the Colombian statistics agency.

## IV.1 Validity of the Identification Strategy

The first condition that must be met to guarantee the validity of our estimates is the relevance assumption. It requires that our instrument ( $Predicted\ Inflow_{mt}$ ) should be strongly correlated with the inflows of internally displaced populations ( $IDP_{mt}$ ). Figure IV shows the geographic distribution of inflows of forcefully displaced individuals and the predicted inflows constructed using equation (3) for the years 1995, 2000, 2005, and 2010. The figure suggests that there is a positive and strong correlation between both variables. A formal test is presented in Tables I, II, III, IV, and V which show the estimates of the first stage equation confirming a positive and significant correlation between  $Predicted\ Inflows_{mt}$  and  $IDP_{mt}$ . The tables also show that the F-statistic for excluded instruments is always higher than 10, alleviating concerns of biases induced by a weak instrument.

The second condition that must be met to guarantee that our estimates are valid is the exclusion restriction. It implies that the interaction of the aggregate time component of our instrument (forced migration outflows) and the geographic municipal component (earlier settlements of migrants), should only be correlated with firm outcomes through IDP inflows. Given that our estimates include fixed effects by year and firm (or municipality) aggregate time components or time-invariant firm characteristics are not a threat for our identification strategy. Our estimates will only be threatened by time-variable covariates (not controlled for in  $X_{mt}$ ) that may be correlated with the instrument and directly affect firm outcomes.

One relevant threat to our identification strategy is that since forced migrants are fleeing violence and conflict, they may be moving to areas with presumably lower levels of conflict. It is also possible that, upon arrival in their new locations, displaced individuals may be increasing local violence levels or eroding the rule of law either by becoming perpetrators or victims of violence. To account for these possibility we control in all our estimates by homicide rates (as a proxy for violent crime) and conflict variables (including clashes between armed groups and armed actions). Our results are robust to these exercises.

Another possible threat to our identification is that municipalities that had larger earlier settle-

ments of migrants also had different prevalent characteristics relative to the other municipalities before the conflict intensified, and these differences may be inducing divergent time patterns which are not explained by IDP inflows. It is possible, for instance, that municipalities with larger pre-settlements of migrants were more prosperous, less violent, had a different sector composition, or had larger government presence before the conflict induced the large forced migration wave. We account for all of these possibilities by including controls for interactions of year dummy fixed effects and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. We also include controls for department and year fixed effects to account for any regional time trends affecting firm behavior. All our estimates are robust to the inclusion of these controls.

Finally, we re-estimate all of our specifications scaling IDP inflows and our measure of Predicted Inflows by total population instead of working age population. The results of these exercises are presented in Appendix II and are very similar to our main estimates.

## **V Effects of IDP on Formal Firm's Decisions**

We estimate equations (1) and (2) for firm production, prices, and input demands using the Annual Manufacturing Survey. The survey only includes information on formal firms that comply with government regulations. The results presented in this section, consequently, describe the effects of IDP inflows only on the Colombian formal sector. We expand our analysis to the effects of IDP in the informal sector in the next section.

## V.1 Effects on production

First, we explore the impacts of IDP inflows on the intensive and extensive margin of production. The estimates of equations (1) and (2) using several proxies for the intensive margin of firm production are presented in Table I. We find negative effects of IDP inflows on all proxies of firm production. Our most preferred estimates are presented in panel C column (3) and include fixed effects by firm, year, and controls for differential time pre-trends. They suggest that when IDP inflows in a municipality increase by 1 percent, gross production of the firms located in that municipality decreases by approximately 0.3 percent. Table I also presents estimates of the effects of IDP inflows on intermediate and energy consumption pointing to similar results although slightly larger in size. These estimates correspond to sizable effects, considering that the average Colombian municipality registered an annual growth of 22 percent in the number of forcefully displaced individuals received between 1995 and 2010.

Table II presents the estimates of the effects of IDP inflows on the extensive margin of production measured as the total number of firms. The estimates for the number of firms were obtained by merging the manufacturing sample into municipality-year cells and adding the number of firms. We are not able to identify a significant impact of IDP inflows on the firm creation.

IDP inflows may affect firm production via several channels. First, large IDP inflows can prompt a positive supply shock, which could reduce wages (as documented by Card, 2001 and Borjas, 2003 for economically-driven migration in developed countries) or cause input substitution (as Lewis, 2011 has found for the United States), and through these mechanisms, lower the costs of production or increase productivity which could rise levels of production and firm entry. We test this mechanism by analyzing the impacts of IDP inflows on labor demand and nominal wages in the next sections.

Second, large IDP inflows can also increase local demand for products as a result of the larger local population. This channel, however, is unlikely as our results point to the opposite direction and because IDP may be consuming proportionally more goods and services from the informal sector where prices are typically lower.



Third, forcefully displaced individuals themselves may come up with new ideas or create new businesses or even increase the productivity of firms that employ them with their know-how. We argue that the size of this last channel, however, is small, since most forcefully displaced individuals only had labor experience in agriculture, had lower levels of education relative to local populations, and had few to no assets (see Vélez, 2002; Ibáñez and Moya, 2006; Ibáñez and Moya, 2006; Garay, 2008; Carrillo, 2009 for details).

Fourth, IDP inflows may be fully absorbed by the informal sector increasing the informality market share, as informal businesses are able to offer lower prices than the formal sector due to lower regulations, taxes, or quality.

Our results are in line with the last channel and are also consistent with the characteristics of the IDP in Colombia. IDP come from rural areas, have low education levels, are specialized in the agricultural sector, and move to urban areas. As such it is unlikely that they will join the formal sector upon their arrival at urban centers; specially considering we are only analyzing their effects in the short-term. What seems more plausible is that these populations are being absorbed completely by the informal sector and that the negative effects that we observe in formal firms may be driven by the higher competition coming from informal businesses. We explore this hypothesis in detail in the next section.

## **V.2 Effects on prices**

We next explore the effects of IDP inflows on firm prices. Considering that IDP are a population shock, it is plausible as was pointed earlier that they may be impacting output or input prices directly through an increase in consumption; that is, through an aggregate demand shock in output and input markets. We consider this possibility by estimating equations (1) and (2) using the average sale or purchase value of all outputs and inputs used or produced by all formal firms in the manufacturing census between 1995 and 2010. All estimates include firm and year fixed effects as well as product fixed effects, which correspond to the four-digit classification of the International Standard Industry Classification (113 four-digit codes). The results of this exercise are presented

in Table III and suggests that IDP inflows have not had a significant impact on input or output prices.

### V.3 Effects on input demands

Next, we explore whether IDP inflows had any impact on the firm's demand for inputs including labor and capital. The results of these exercise are useful to study the possibility that IDP may be increasing labor supply and as such may be modifying firms' optimal combination between labor and capital.

Our estimates of the impacts of IDP in total employment are presented in Table V. Additionally, we also estimate the effects of IDP inflows on employment and wages by type (blue- and white-collar) in Tables VII and VI, albeit only between 2000 and 2010 due to data availability.

We find no consistent evidence of a significant effect of higher IDP inflows on formal employment or wages of any kind. Although some of the results are statistically significant for employment effects, these effects are not consistent and disappear once a different set of controls are included in the estimates. Our results are in line with the argument suggesting that IDPs in Colombia have low levels of education and little experience on manufacturing jobs (see Ibáñez and Moya, 2006). In fact, as forced migrants in Colombia mostly moved from rural to urban areas, they previously worked on agricultural activities which have low demand on urban regions. Displaced individuals, hence, may be searching for low quality jobs as they lack experience, which ultimately may suggest that they will end up joining the informal sector.

We also explore the effects of IDP inflows on firms' capital demand measured as the logarithm of gross and net investment in Table IV. Similar to the estimates for employment, we are not able to distinguish a consistent statistically significant effect of IDP inflows in capital demand.

In sum, our results so far suggest that the effects of IDP on manufacturing formal firms are limited to their negative effects on the intensive margin of production with no other observed effects on prices or input demands. These results are consistent with the argument suggesting that

IDP inflows are completely absorbed by the informal economy in the short term. As such the negative effects of IDPs on formal firms may be explained by the negative impacts of an enlarged informal sector. We explore the validity of this hypothesis next.

## VI IDP Impacts on the Informal Economy

The informal sector accounts for a sizable share of total economic activity in developing countries and is mostly comprised of small firms with low productivity levels that can operate without being detected and that employ low-skilled workers (Amaral and Quintin, 2006; Perry, 2007; Galiani and Weinschelbaum, 2012; La Porta and Shleifer, 2014; Meghir et al., 2015). In Colombia, between 1995 and 2010, approximately 60 percent of the total workforce was informal (Mondragón-Vélez et al., 2010), a normal-sized informal sector relative to other developing countries in the region (Perry, 2007).<sup>12</sup>

Considering that displaced individuals arrive in new locations without legal identification documents, have low experience in urban jobs that have high local demand, and tend to have lower education relative to the rest of the Colombian population (Ibáñez and Moya, 2006), it is plausible that upon arrival at urban centers, IDPs take lower tier jobs, which are most likely to be available in the informal sector (Amaral and Quintin, 2006; Perry, 2007; Galiani and Weinschelbaum, 2012; La Porta and Shleifer, 2014; Meghir et al., 2015), increasing its size.

A larger informal sector may end up hurting formal firms' performance in several ways. Formal firms, for example, face higher costs relative to informal firms as they pay taxes, fees, and higher wages for their employees (La Porta and Shleifer, 2014). Informal firms, thus, can usually carry lower prices and costs competing in an unfair way with formal businesses. Beyond reducing the demand for formal firms' products via lower prices, unfair competition from informal firms could slow down the process in which inefficient firms can be replaced by more efficient competitors and negatively affect the incentives of formal firms to innovate and adopt new technologies (Perry,

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<sup>12</sup>Perry, 2007 find that 55 percent of workers in Latin America and the Caribbean will not have a pension when they retire.

2007). Competition with informal firms, consequently, may lead to productivity losses for the formal firms. In addition, since informal firms are able to use public goods but do not pay for them, this may lower the quality public goods and services and crowd out their use by formal firms (Besley and Persson, 2013). At the same time, higher informal competition may force formal sector firms to lower the quality of their products (as proposed by Banerji and Jain, 2007).

To test how higher IDP inflows affect the size informal sector we employ information from the Colombian household surveys. We test whether larger IDP inflows are indeed affecting the size of the informal sector by classifying all workers age 15 and 62 into two groups according to whether their primary job is part of a sectors that tends to have high levels of informality (such as retail sales and construction) or low levels of informality (such as financial services, machinery production, production of chemical or pharmaceutical products, and highly technical jobs). Sector classification codes are only available in the labor force surveys beginning in 2002. Our sample, consequently, spans between 2002 and 2010. Data from 2002 to 2005 comes from the *Encuesta Continua de Hogares* and the *Gran Encuesta Integrada de Hogares* from 2006 to 2010. Both surveys are comparable across time, but the later introduced improvements such as new questions and a sharp increase in the number of municipalities surveyed. From 2002 to 2005 we can only identify the exact location of workers located in the 13 main cities of Colombia (i.e., 13 municipalities), but beginning in 2006 we observe their locations in 609 municipalities.

We estimate a linear probability model for the probability of being employed in these sectors on IDP inflows including fixed effects by year, municipality, month (when the survey was collected), individuals covariates (such as gender, marital status, education level, and household size), and municipal controls (including all the controls included in our previous estimates). The results are presented in Table VIII and largely suggest that the probability of begin employed in a highly informal sector increases with higher IDP inflows. Additionally, the effects of IDP inflows on the employment probability within highly formal sectors are not significant and even has a negative sign. Particularly, our estimates in Panel C and column 2 suggest that when the share of IDP increases in 1 percent, the probability of being employed in a highly informal sector increases by

0.2%.

Our estimates suggest that higher IDP inflows are positively associated with a larger informal sector. An enlarged informal sector may arise since IDPs may be primarily working inside this sector and through a demand shock for the goods and services produced within this sector which are presumably cheaper, and hence, may be more appealing to economically challenged IDPs.

## **VII Discussion**

This paper investigates the effects of inflows of IDPs on the behavior of firms in an economy segmented into a normal-sized formal sector and a large informal sector as is commonly observed in most developing countries. Our findings strongly suggest that larger inflows of displaced individuals who are fully absorbed by the informal sector have sizable negative effects on the performance of formal firms.

Our estimates suggest, more particularly, that when inflows of IDPs increase by 1 percent, the production of formal firms drops approximately by 0.3 percent. We argue that the effects of inflows of IDPs on formal firms seem to be mainly driven by the positive association of larger inflows of displaced individuals and the size of the informal sector. As forcefully displaced individuals tend to have low education levels and a lack of experience in occupations that have high local demand (because many IDPs move from rural to urban areas), they may be taking low-tier jobs that are most likely offered in the informal sector, thus increasing its size.

Our results highlight the importance of national policies and international cooperation efforts in facilitating the integration of IDPs—and also international refugees—into formal labor markets. They suggest that in contexts where IDPs or refugees are not allowed to work formally, their participation in the informal economy could negatively affect firms operating in the formal sector. In addition, our results highlight the importance of the initial conditions in shaping the effects of IDPs and refugees, as they could exacerbate the negative effects of informality on the host economy.

Finally, despite the unique data employed for this study, our analysis is limited to the effects of IDPs on the formal sector because there is no similar data available for firms operating in the informal sector. Empirically exploring the effects of IDPs on informal firms remains an important area for future research.

## References

- Accetturo, A., M. Bugamelli, and A. R. Lamorgese (2012). Welcome to the machine: firms' reaction to low-skilled immigration. *Bank of Italy Temi di Discussione (Working Paper) No 846*.
- Altindag, O., O. Bakis, and S. Rozo (2018). Blessing or burden? The impact of refugees on businesses and the informal economy. *SSRN. Working Paper N. 3188406*.
- Altonji, J. G. and D. Card (1991). The effects of immigration on the labor market outcomes of less-skilled natives. In *Immigration, Trade, and the Labor Market*, pp. 201–234. University of Chicago Press.
- Amaral, P. S. and E. Quintin (2006). A competitive model of the informal sector. *Journal of Monetary Economics* 53(7), 1541–1553.
- Banerji, A. and S. Jain (2007). Quality dualism. *Journal of Development Economics* 84(1), 234–250.
- Besley, T. and T. Persson (2013). Taxation and development. In *Handbook of Public Economics*, Volume 5, pp. 51–110.
- Borjas, G. J. (2003). The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market. *The Quarterly Journal of Economics* 118(4), 1335–1374.
- Borjas, G. J. and J. Monras (2017). The labour market consequences of refugee supply shocks. *Economic Policy* 32(91), 361–413.

- Card, D. (2001). Immigrant inows, native outows, and the local labor market impacts of higher immigration. *Journal of Labor Economics* 19(1), 22–64.
- Carrillo, A. C. (2009). Internal displacement in Colombia: humanitarian, economic and social consequences in urban settings and current challenges. *International Review of the Red Cross* 91(875), 527–546.
- Carrizosa, M. T. and A. S. Blasco (2009). Immigration and firm performance: a city-level approach/inmigración y comportamiento empresarial: una aproximación a escala de ciudad. *Investigaciones Regionales* (15), 111.
- Ceritoglu, E., H. B. G. Yunculer, H. Torun, and S. Tumen (2017). The impact of Syrian refugees on natives' labor market outcomes in Turkey: evidence from a quasi-experimental design. *IZA Journal of Labor Policy* 6(1), 5.
- Chiswick, B. R. (1999). Are immigrants favorably self-selected? *American Economic Review* 89(2), 181–185.
- Clemens, M. A. and J. Hunt (2017). The labor market effects of refugee waves: Reconciling conflicting results. *NBER Working Paper N. 23433*.
- Del Carpio, X. V. and M. C. Wagner (2015). The impact of Syrians refugees on the Turkish labor market. *World Bank Policy Research Working Paper* (7402).
- Dustmann, C. and A. Glitz (2015). How do industries and firms respond to changes in local labor supply? *Journal of Labor Economics* 33(3 Part 1), 711–750.
- El Espectador (2009, April). La situación de los desplazados. <http://www.elespectador.com/articulo137806-situacion-de-los-desplazados>.
- El Tiempo (2010, August). Fuerza laboral de desplazados impacta salarios informales. <http://www.eltiempo.com/archivo/documento/MAM-4088271>.

- El Tiempo (2014, February). Desempleo entre los desplazados es del 35,5%. <http://www.eltiempo.com/archivo/documento/CMS-13528618>.
- Engel, S. and A. M. Ibáñez (2007). Displacement Due to Violence in Colombia: A Household-Level Analysis. *Economic Development and Cultural Change* 55(2), 335–365.
- Galiani, S. and F. Weinschelbaum (2012). Modeling informality formally: households and firms. *Economic Inquiry* 50(3), 821–838.
- Garay, L. J. (2008). Proceso nacional de verificación de los derechos de la población desplazada. *First Report to the Colombian Constitutional Court*.
- Huffington Post (2010). Colombia's Internally Displaced People.
- Ibáñez, A. M. and A. Moya (2006). *Cómo el desplazamiento forzado deteriora el bienestar de los hogares desplazados? análisis y determinantes del bienestar en los municipios de recepción*.
- Ibáñez, A. M. and A. Moya (2010). Vulnerability of victims of civil conflicts: empirical evidence for the displaced population in Colombia. *World Development* 38(4), 647–663.
- Ibáñez, A. M. and C. E. Vélez (2008). Civil conflict and forced migration: The micro determinants and welfare losses of displacement in Colombia. *World Development* 36(4), 659–676.
- Ibáñez, A. M., A. Moya, and A. Velásquez (2006). Hacia una política proactiva para la población desplazada. *Bogotá: Universidad de los Andes, Secretariado Nacional de Pastoral Social Caritas Colombia*.
- IPS (1999, September). Colombia: Desplazados engrosan economía informal de Bogotá. <http://www.ipsnoticias.net/1999/09/repeticion-ciudades-de-america-latina-colombia-desplazados-engrosan-economia-informal-de-bogota/>.
- Jaeger, D. A., J. Ruist, and J. Stuhler (2018). Shift-share instruments and the impact of immigration. *NBER Working Paper N. 24285*.



- Kerr, S. P., W. R. Kerr, and W. F. Lincoln (2015). Skilled immigration and the employment structures of US firms. *Journal of Labor Economics* 33, S147–S186.
- Kugler, M. and E. Verhoogen (2011). Prices, plant size, and product quality. *The Review of Economic Studies* 79(1), 307–339.
- La Porta, R. and A. Shleifer (2014). Informality and development. *The Journal of Economic Perspectives* 28(3), 109–126.
- La Silla Vacía (2012, December). Desplazados dentro de su misma ciudad: las víctimas más invisibles en Colombia. <http://lasillavacia.com/historia/desplazados-dentro-de-su-misma-ciudad-las-victimas-mas-invisibles-en-colombia-40579>.
- Lewis, E. (2011). Immigration, skill mix, and capital skill complementarity. *The Quarterly Journal of Economics* 126(2), 1029–1069.
- Lewis, E. and G. Peri (2015). Immigration and the economy of cities and regions. In *Handbook of Regional and Urban Economics*, Volume 5, pp. 625–685.
- Lozano-Gracia, N., G. Piras, A. M. Ibáñez, and G. J. Hewings (2010). The journey to safety: conflict-driven migration flows in Colombia. *International Regional Science Review* 33(2), 157–180.
- Meghir, C., R. Narita, and J.-M. Robin (2015). Wages and informality in developing countries. *American Economic Review* 105(4), 1509–1546.
- Mondragón-Vélez, C., X. Peña, and D. Wills (2010). Labor market rigidities and informality in Colombia. *Economía* 11(1), 65–95.
- Moya, A. et al. (2012). Violence, emotional distress and induced changes in risk aversion among the displaced population in Colombia. In *Pacific Development Economics Conference, University of California, Davis*.

- Ottaviano, G. I., G. Peri, and G. C. Wright (2018). Immigration, trade and productivity in services: Evidence from UK firms. *Journal of International Economics* 112, 88–108.
- Perry, G. (2007). *Informality: Exit and exclusion*. World Bank Publications.
- Rozo, S. V. (2018). Is murder bad for business? Evidence from Colombia. *Review of Economics and Statistics*. *Forthcoming*.
- UNCHR (2015). Global trends: Forced displacement in 2015. Technical report.
- UNHCR (2018). Global Trends. Forced Displacement in 2017. Technical report.
- Unidad para la Atención y Reparación de Víctimas (2013). Informe nacional de desplazamiento forzado en Colombia 1985 a 2012. Technical report.
- Vélez, C. E. (2002). *Colombia poverty report*. World Bank.
- World Bank (2016). Forcibly displaced: Toward a development approach supporting refugees, the internally displaced and their hosts. Technical report, World Bank Report.

**Table (I)** Impacts of IDP Inflows in the Formal Intensive Margin of Production

Dependent Variables (in logs)	Production			Intermediate Consumption			Energy Consumption		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<b>Panel A. Reduced Form</b>									
Predicted Inflows	-0.010** (0.0042)	-0.021*** (0.006)	-0.0111** (0.00476)	-0.013*** (0.005)	-0.020*** (0.007)	-0.0151*** (0.00495)	-0.019*** (0.005)	-0.021** (0.008)	-0.0194*** (0.00575)
R-squared	0.934	0.935	0.951	0.924	0.924	0.942	0.919	0.920	0.939
Observations	122,261	122,231	82,715	122,222	122,192	82,704	122,104	122,074	82,572
<b>Panel B. OLS</b>									
Share of IDPs (% Working Age Pop)	-0.011** (0.004)	-0.010 (0.006)	-0.003 (0.005)	-0.014*** (0.005)	-0.007 (0.007)	-0.004 (0.006)	0.004 (0.007)	-0.001 (0.012)	-0.002 (0.006)
R-squared	0.934	0.935	0.951	0.924	0.924	0.942	0.919	0.919	0.939
Observations	122,267	122,237	82,719	122,228	122,198	82,708	122,110	122,080	82,576
<b>Panel C. 2SLS</b>									
Share of IDPs (% Working Age Pop)	-0.027** (0.011)	-0.068*** (0.020)	-0.029** (0.012)	-0.034*** (0.012)	-0.067*** (0.024)	-0.040*** (0.013)	-0.050*** (0.013)	-0.069** (0.028)	-0.051*** (0.015)
Observations	122,261	122,231	82,715	122,222	122,192	82,704	122,104	122,074	82,572
<b>Panel D. First Stage</b>									
Predicted Inflows	0.374*** (0.015)	0.306*** (0.019)	0.328*** (0.025)	0.374*** (0.015)	0.306*** (0.019)	0.328*** (0.025)	0.374*** (0.015)	0.306*** (0.019)	0.328*** (0.025)
First Stage F-statistic	627.24	257.18	446.21	627.24	257.18	446.21	627.24	257.18	446.21
Observations	122,269	122,239	82,719	122,269	122,239	82,719	122,269	122,239	82,719
<b>Controls (for all panels)</b>									
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Department FE	No	Yes	No	No	Yes	No	No	Yes	No
Homicides Rates	No	Yes	No	No	Yes	No	No	Yes	No
Conflict Controls	No	Yes	No	No	Yes	No	No	Yes	No
Additional Controls	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Each coefficient corresponds to a separate regression. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors by firm are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.

**Table (II)** Impacts of IDP Inflows in the Formal Extensive Margin of Production

Dependent Variable (in logs)	Number of Firms		
	(1)	(2)	(3)
<b>Panel A. Reduced Form</b>			
Predicted Inflows	-0.021** (0.008)	-0.018* (0.010)	-0.0117 (0.00893)
R-squared	0.970	0.975	0.974
Observations	3,718	3,602	3,702
<b>Panel B. OLS</b>			
Share of IDP (% Working Age Pop.)	-0.004 (0.006)	-0.004 (0.007)	-0.004 (0.006)
R-squared	0.970	0.975	0.974
Observations	3,724	3,608	3,708
<b>Panel C. 2SLS</b>			
Share of IDP (% Working Age Pop.)	-0.021** (0.009)	-0.022 (0.014)	-0.012 (0.009)
Observations	3,718	3,602	3,702
<b>Panel D. First Stage</b>			
Predicted Inflows	1.002*** (0.207)	0.826*** (0.161)	1.004*** (0.025)
First Stage F-statistic	23.71	29.15	25.37
Observations	3,718	3,602	3,702
<b>Controls (for all panels)</b>			
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Year × Department FE	No	Yes	No
Homicides Rates	No	Yes	No
Conflict Controls	No	Yes	No
Additional Controls	No	No	Yes

*Notes:* Each coefficient corresponds to a separate regression. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors by municipality are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.

**Table (III)** Impacts of IDP Inflows in Input and Output Nominal Prices

Dependent Variables (in logs)	Nominal Output Price			Nominal Input Price		
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A. Reduced Form</b>						
Predicted Inflows	-0.006* (0.004)	-0.012** (0.006)	-0.002 (0.004)	0.005 (0.005)	0.004 (0.009)	0.008 (0.006)
R-squared	0.395	0.406	0.445	0.944	0.944	0.943
Observations	799,738	799,737	391,289	731,502	731,503	731,255
<b>Panel B. OLS</b>						
Share of IDP (% Working Age Pop.)	-0.002 (0.003)	-0.002 (0.005)	0.003 (0.005)	0.009 (0.006)	0.011 (0.007)	0.008 (0.006)
R-squared	0.395	0.406	0.445	0.944	0.944	0.945
Observations	799,738	799,737	391,289	731,502	731,503	731,255
<b>Panel C. 2SLS</b>						
Share of IDP (% Working Age Pop.)	-0.020* (0.011)	-0.047** (0.023)	-0.008 (0.013)	0.014 (0.016)	0.013 (0.036)	0.020 (0.016)
Observations	799,741	799,737	391,289	731,509	731,513	731,255
<b>Panel D. First Stage</b>						
Predicted Inflows	0.314*** (0.017)	0.247*** (0.018)	0.293*** (0.016)	0.315*** (0.017)	0.252*** (0.019)	0.392*** (0.019)
First Stage F-statistic	335.28	178.56	371.78	330.51	187.35	458.81
Observations	799,741	799,737	391,289	731,509	731,513	731,255
<b>Controls (for all panels)</b>						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Department FE	No	Yes	No	No	Yes	No
Conflict Controls	No	Yes	No	No	Yes	No
Homicides Rates	No	Yes	No	No	Yes	No
Additional Controls	No	No	Yes	No	No	Yes

Notes: Each coefficient corresponds to a separate regression. Product fixed effects correspond to the four-digit classification of the International Standard Industry Classification, which account for 113 four-digit codes. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors at the firm level are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.

**Table (IV)** Impacts of IDP Inflows in Capital Demand

Dependent Variables (in logs)	Net Investment			Gross Investment		
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A. Reduced Form</b>						
Predicted Inflows	-0.053*** (0.019)	-0.070** (0.027)	-0.040 (0.025)	-0.027** (0.013)	-0.030* (0.018)	-0.008 (0.017)
Observations	23,680	23,655	0.710	48,725	48,687	0.692
R-squared	0.707	0.711	23,669	0.691	0.694	48,709
<b>Panel B. OLS</b>						
Share of IDP (% Working Age Pop.)	0.001 (0.0229)	0.013 (0.0296)	-0.004 (0.026)	-0.012 (0.0143)	-0.014 (0.0191)	-0.010 (0.016)
Observations	0.707	0.711	0.710	0.691	0.693	0.692
R-squared	23,680	23,655	23,669	48,725	48,687	48,709
<b>Panel C. 2SLS</b>						
Share of IDP (% Working Age Pop.)	-0.146*** (0.055)	-0.240** (0.104)	-0.0942 (0.062)	-0.075** (0.036)	-0.107 (0.065)	-0.0197 (0.044)
Observations	23,680	23,655	23,669	48,725	48,687	48,709
<b>Panel D. First Stage</b>						
Predicted Inflows	0.353*** (0.013)	0.288*** (0.023)	0.328*** (0.025)	0.353*** (0.013)	0.288*** (0.023)	0.328*** (0.025)
First Stage F-statistic	711.12	151.57	446.21	711.12	151.57	446.21
Observations	82,758	82,738	82,719	82,758	82,738	82,719
<b>Controls (for all panels)</b>						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Department FE	No	Yes	No	No	Yes	No
Homicides Rates	No	Yes	No	No	Yes	No
Conflict Controls	No	Yes	No	No	Yes	No
Additional Controls	No	No	Yes	No	No	Yes

*Notes:* Each coefficient corresponds to a separate regression. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors at the firm level are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.

**Table (V)** Impacts of IDP Inflows in Labor Demand

Dependent Variables (in logs)	Total Employment			Nominal Wages		
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A. Reduced Form</b>						
Predicted Inflows	-0.010*** (0.0027)	-0.016*** (0.004)	-0.001 (0.004)	0.001 (0.0016)	0.001 (0.002)	-0.002 (0.002)
Observations	82,696	82,676	0.932	82,267	82,247	0.862
R-squared	0.931	0.932	82,657	0.861	0.862	82,228
<b>Panel B. OLS</b>						
Share of IDP (% Working Age Pop.)	-0.001 (0.00344)	-0.008* (0.00492)	0.0003 (0.004)	0.003 (0.00190)	0.0003 (0.00246)	0.002 (0.002)
Observations	0.931	0.932	0.932	0.861	0.862	0.862
R-squared	82,700	82,680	82,661	82,271	82,251	82,232
<b>Panel C. 2SLS</b>						
Share of IDP (% Working Age Pop.)	-0.028*** (0.007)	-0.055*** (0.016)	-0.00394 (0.010)	0.002 (0.005)	0.003 (0.008)	-0.00637 (0.006)
Observations	82,696	82,676	82,657	82,267	82,247	82,228
<b>Panel D. First Stage</b>						
Predicted Inflows	0.353*** (0.013)	0.288*** (0.023)	0.328*** (0.025)	0.353*** (0.013)	0.288*** (0.023)	0.328*** (0.025)
First Stage F-statistic	711.12	151.57	446.21	711.12	151.57	446.21
Observations	82,758	82,738	82,719	82,758	82,738	82,719
<b>Controls (for all panels)</b>						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Department FE	No	Yes	No	No	Yes	No
Homicides Rates	No	Yes	No	No	Yes	No
Conflict Controls	No	Yes	No	No	Yes	No
Additional Controls	No	No	Yes	No	No	Yes

*Notes:* Each coefficient corresponds to a separate regression. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors at the firm level are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.

**Table (VI)** Impacts of IDP Inflows in Nominal Wages by Type (2000-2010)

Dependent Variables (in logs)	Nominal Wages		Blue-collar Nominal Wages		White-collar Nominal Wages	
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A. Reduced Form</b>						
Predicted Inflows	0.001 (0.002)	-0.002 (0.002)	0.003 (0.002)	-0.002 (0.002)	0.001 (0.004)	-0.0002 (0.003)
R-squared	0.862	0.862	0.765	0.764	0.825	0.825
Observations	82,247	82,228	79,652	79,633	78,619	78,628
<b>Panel B. OLS</b>						
Share of IDP (% Working Age Pop.)	0.0003 (0.002)	0.002 (0.002)	0.001 (0.002)	0.002 (0.002)	0.002 (0.004)	0.006 (0.004)
R-squared	0.862	0.862	0.765	0.765	0.825	0.825
Observations	82,251	82,232	79,656	79,637	78,623	78,632
<b>Panel C. 2SLS</b>						
Share of IDP (% Working Age Pop.)	0.003 (0.008)	-0.006 (0.006)	0.009 (0.008)	-0.006 (0.006)	0.003 (0.013)	-0.0005 (0.009)
Observations	82,247	82,228	79,652	79,633	78,619	78,628
<b>Panel D. First Stage</b>						
Predicted Inflows	0.288*** (0.023)	0.328*** (0.025)	0.288*** (0.023)	0.328*** (0.025)	0.288*** (0.023)	0.328*** (0.025)
First Stage F-statistic	151.57	446.21	151.57	446.21	151.57	446.21
Observations	82,738	82,719	82,738	82,719	82,738	82,719
<b>Controls (for all Panels)</b>						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Department FE	Yes	No	Yes	No	Yes	No
Homicides Rates	Yes	No	Yes	No	Yes	No
Conflict Controls	Yes	No	Yes	No	Yes	No
Additional Controls	No	Yes	No	Yes	No	Yes

*Notes:* Each coefficient corresponds to a separate regression. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors at the firm level are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.



Table (VII) Impacts of IDP Inflows in Labor Demand by Type (2000–2010)

Dependent Variables (in logs)	Employment (1)	(2)	Blue-collar Employment (3)	(4)	White-collar Employment (5)	(6)
<b>Panel A. Reduced Form</b>						
Predicted Inflows	-0.016*** (0.004)	-0.001 (0.004)	-0.020*** (0.005)	-0.003 (0.004)	-0.018*** (0.005)	-0.004 (0.005)
R-squared	0.932	0.932	0.919	0.919	0.911	0.910
Observations	82,676	82,657	79,823	79,804	81,250	81,229
<b>Panel B. OLS</b>						
Share of IDP (% Working Age Pop.)	-0.008* (0.005)	0.0003 (0.004)	-0.006 (0.005)	0.001 (0.004)	-0.010* (0.006)	0.0002 (0.005)
R-squared	0.932	0.932	0.919	0.919	0.911	0.910
Observations	82,680	82,661	79,827	79,808	81,254	81,233
<b>Panel C. 2SLS</b>						
Share of IDP (% Working Age Pop.)	-0.055*** (0.016)	-0.004 (0.010)	-0.068*** (0.017)	-0.007 (0.011)	-0.063*** (0.019)	-0.010 (0.013)
Observations	82,676	82,657	79,823	79,804	81,250	81,229
<b>Panel D. First Stage</b>						
Predicted Inflows	0.288*** (0.023)	0.328*** (0.025)	0.288*** (0.023)	0.328*** (0.025)	0.288*** (0.023)	0.328*** (0.025)
First Stage F-statistic	151.57	446.21	151.57	446.21	151.57	446.21
Observations	82,738	82,719	82,738	82,719	82,738	82,719
<b>Controls (for all panels)</b>						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year × Department FE	Yes	No	Yes	No	Yes	No
Homicides Rates	Yes	No	Yes	No	Yes	No
Conflict Controls	Yes	No	Yes	No	Yes	No
Additional Controls	No	Yes	No	Yes	No	Yes

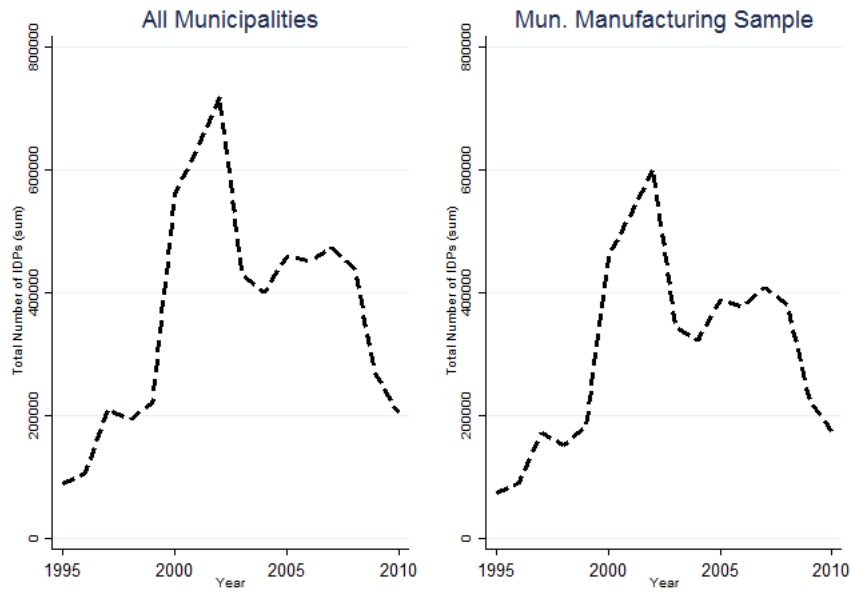
Notes: Each coefficient corresponds to a separate regression. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors at the firm level are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.

**Table (VIII)** Impacts of IDP inflows in Employment in Informal and Formal Sectors

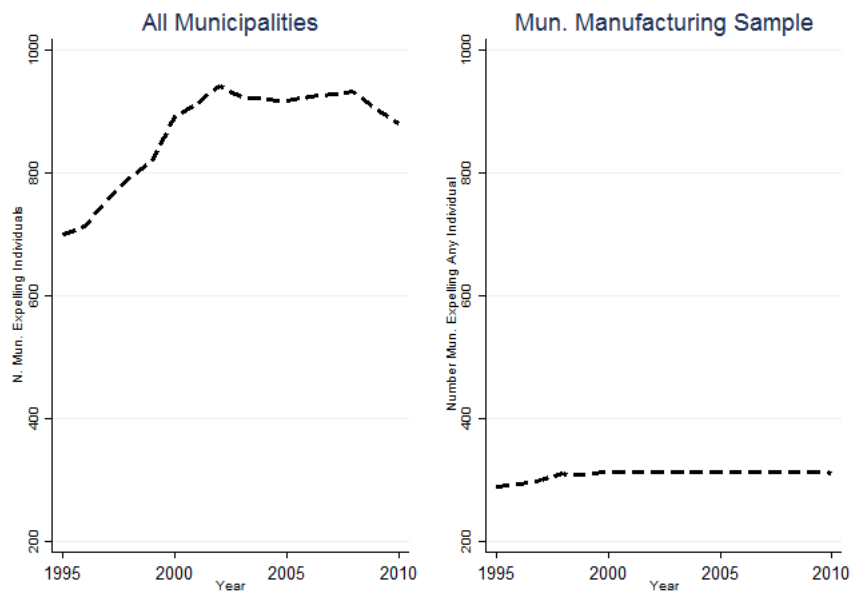
Dependent Variable	All Sectors	Highly Informal Sectors	Highly Formal Sectors
	(1)	(2)	(3)
<b>Panel A. Reduced Form</b>			
Predicted Inflows	0.001*** (0.0004)	0.002*** (0.0004)	-0.00002 (0.00005)
R-squared	0.328	0.398	0.017
Observations	2,797,614	2,323,262	474,347
<b>Panel B. OLS</b>			
Share of IDPs (% Working Age Pop.)	0.0003 (0.0002)	0.0003 (0.0002)	-0.00001 (0.00002)
R-squared	0.328	0.398	0.017
Observations	2,797,614	2,323,262	474,347
<b>Panel C. 2SLS</b>			
Share of IDPs (% Working Age Pop.)	0.001** (0.0006)	0.002** (0.0007)	-0.00003 (0.00008)
Observations	2,797,614	2,323,262	474,347
<b>Panel C. First Stage</b>			
Predicted Inflows	0.774*** (0.177)	0.794*** (0.179)	0.656*** (0.166)
First Stage F-statistic	16.12	16.69	13.68
Observations	2,797,614	2,323,262	474,347
<b>Controls for all Panels</b>			
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Individuals Covariates	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes

Notes: Each coefficient corresponds to a separate regression. Individuals covariates include gender, marital status, education level and household size, and additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors at the municipality level are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.

**Figure (I)** Inflows of IDPs in Colombia (1995-2010)

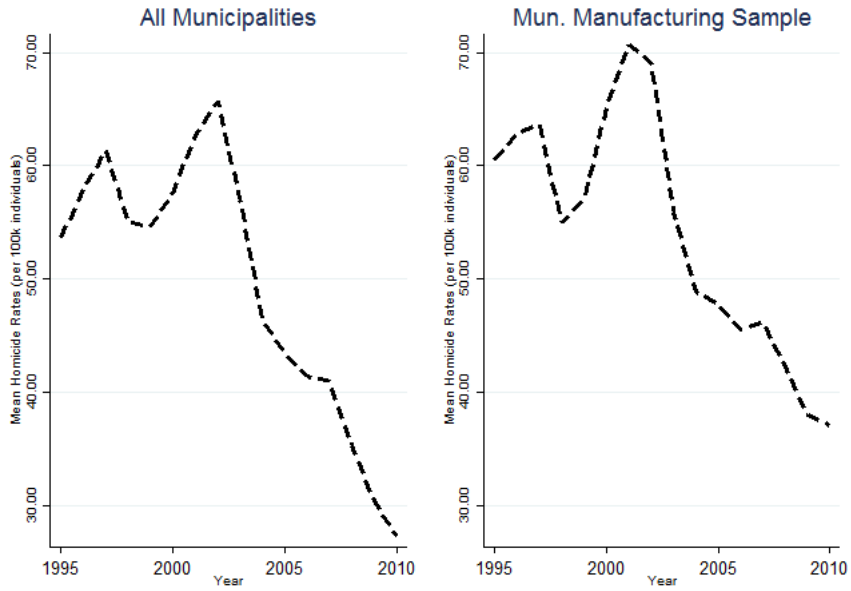


**(a)** Total Number of Individuals

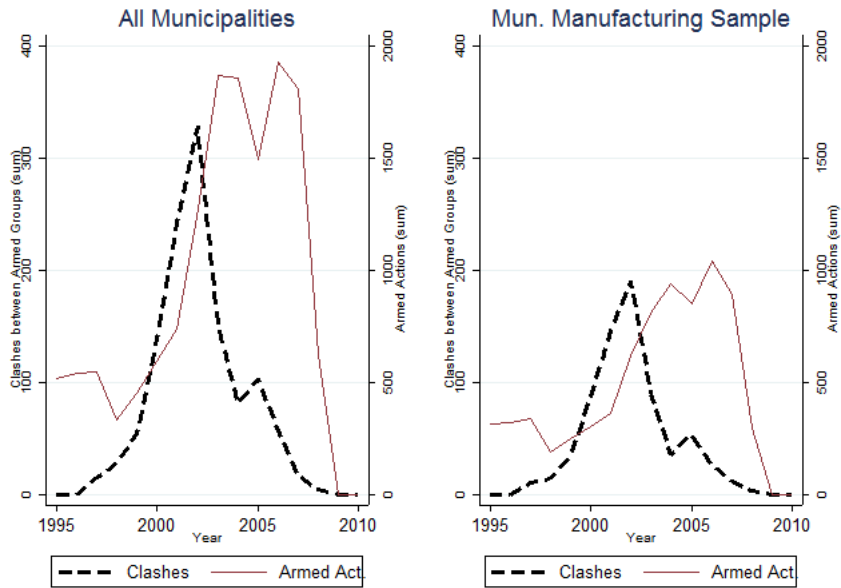


**(b)** Total Number of Hosting Municipalities

**Figure (II)** Violent Crime and Conflict in Colombia (1995-2010)

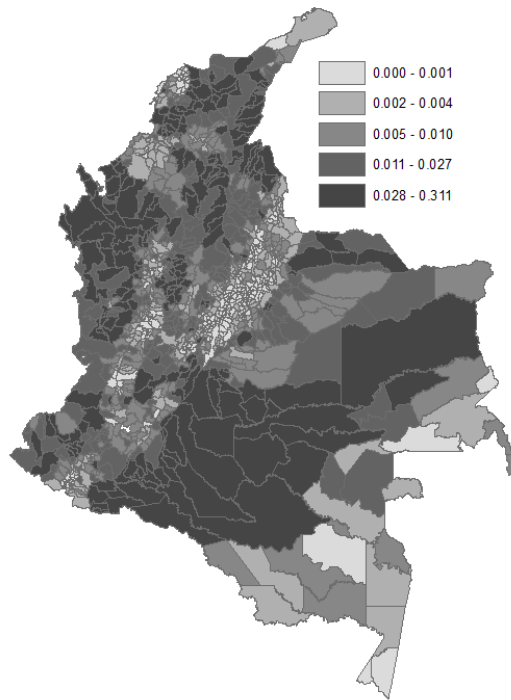


**(a)** Violent Crime: Homicide rates (per 100K individuals)

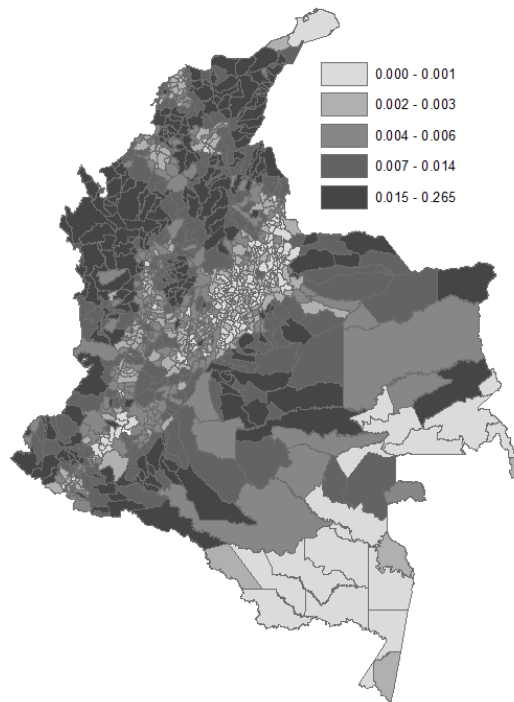


**(b)** Armed Internal Conflict

**Figure (III)** Intensity and Pressure Migration Indexes

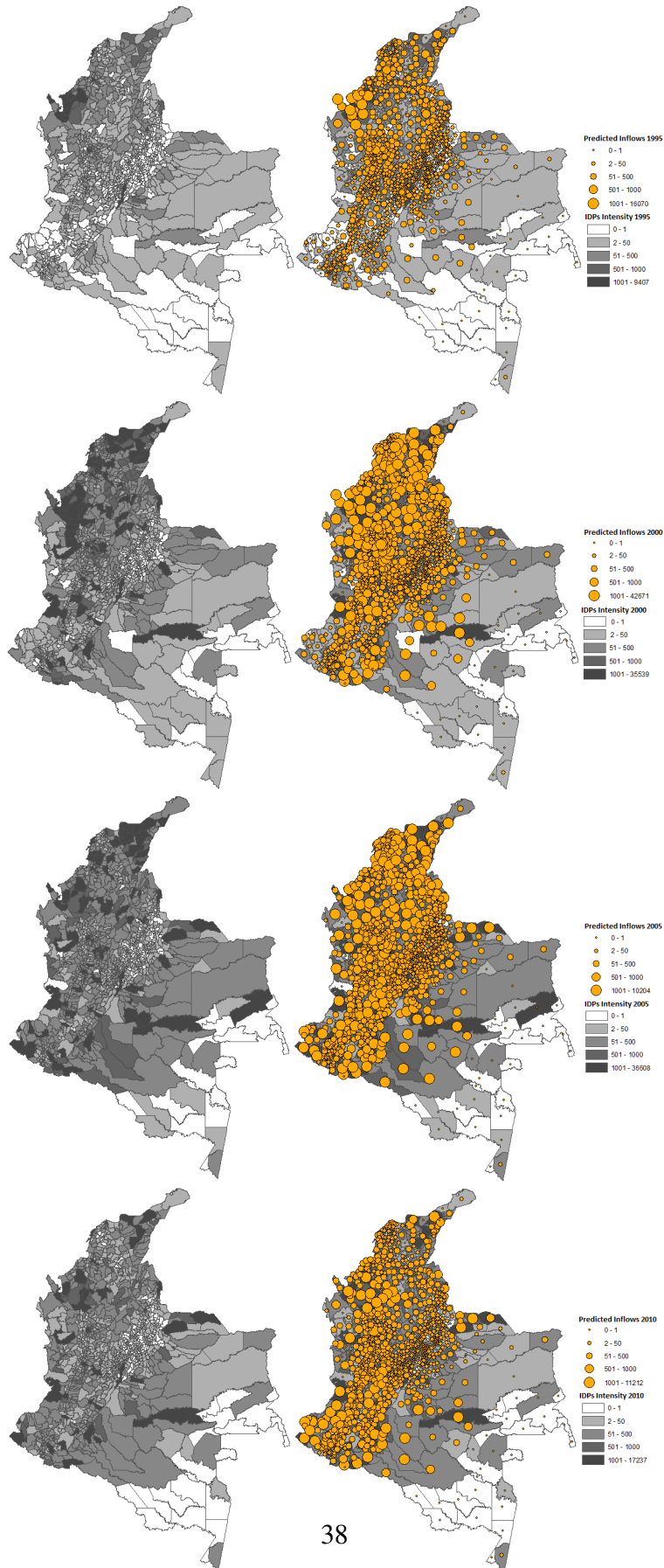


**(a)** Intensity Index: Total Outflows / Mean Population (1995-2010)

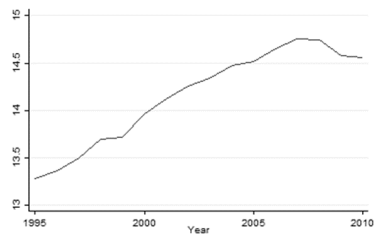


**(b)** Pressure Index: Total Inflows / Mean Population (1995-2010)

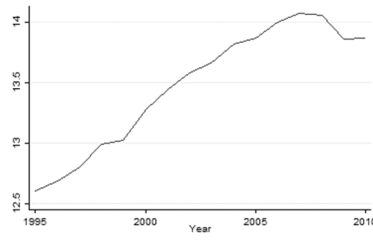
**Figure (IV)** Predicted and Observed IDP Inflows



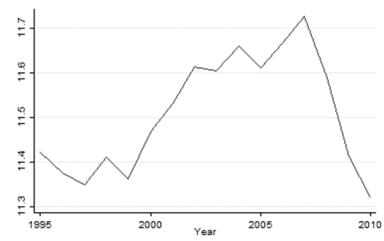
**Figure (V)** Mean Firm Outcomes (variables in logs)



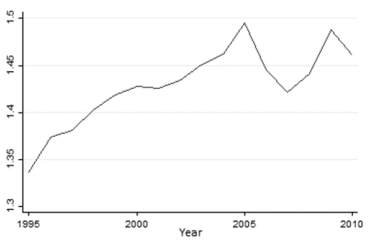
**(a)** Production (\$COL)



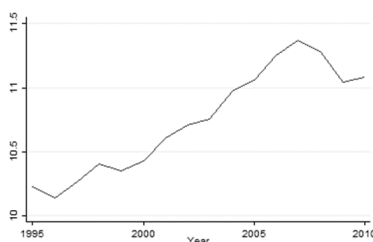
**(b)** Intermediate consumption (\$COL)



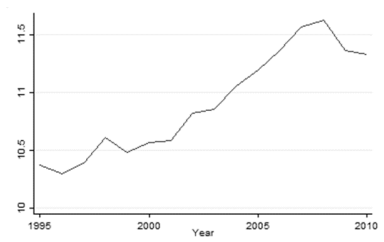
**(c)** Electric Energy (Htz)



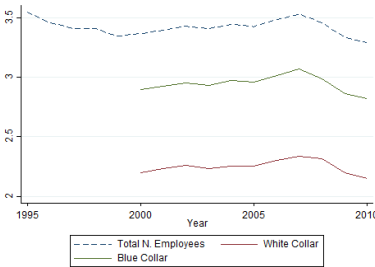
**(d)** Number of firms



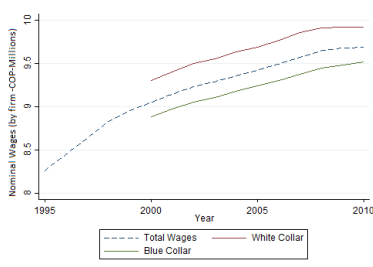
**(e)** Gross investment (\$COL)



**(f)** Net investment (\$COL)



**(g)** Employees



**(h)** Wages (\$COL)

**Appendix I: Characterizing the Municipalities in the Manufacturing Sample**

Mean Values of all Municipalities in Colombia vs. Municipalities in Manufacturing Sample				
Variable (mean values)	All sample	Excluded from Manufacturing Sample	Manufacturing Sample	Manufacturing Sample
Rural Population	9,862.67	6,232.21		19,045.86
Urban Population	27,313.09	3,457.95		87,574.27
Total Population	37,038.08	9,645.72		106,599.10
Working Age Population	31,144.88	7,585.76		85,112.57
Infant Mortality	23.29	24.10		21.23
Municipal GDP	359,164.90	65,235.67		1,058,189.00
Poverty Rates	0.51	0.51		0.52
Individuals Received (IDPs)	347.74	577.70		1,885.52
N of Municipalities	1123	806		317



**Appendix II: Re-scaling by Total Population**

**Table (II.1)** Effects of IDP Inflows on the Intensive Margin of Production

Dependent Variables (in logs)	Production		Intermediate Consumption		Energy Consumption				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<b>Panel A. Reduced Form</b>									
Predicted Inflows	-0.010** (0.004)	-0.021*** (0.006)	-0.011** (0.005)	-0.013*** (0.005)	-0.020*** (0.007)	-0.015*** (0.005)	-0.019*** (0.005)	-0.021** (0.008)	-0.019*** (0.006)
R-squared	0.934	0.935	0.951	0.924	0.924	0.942	0.919	0.920	0.939
Observations	122,261	122,231	82,715	122,222	122,192	82,704	122,104	122,074	82,572
<b>Panel B. OLS</b>									
Share of IDP (%Total Population)	-0.014** (0.006)	-0.014* (0.008)	-0.004 (0.007)	-0.018*** (0.006)	-0.009 (0.009)	-0.006 (0.007)	0.004 (0.009)	-0.005 (0.014)	-0.003 (0.008)
R-squared	0.934	0.935	0.951	0.924	0.924	0.942	0.919	0.919	0.939
Observations	122,267	122,237	82,719	122,228	122,198	82,708	122,110	122,080	82,576
<b>Panel C. 2SLS</b>									
Share of IDP (%Total Population)	-0.034** (0.014)	-0.086*** (0.026)	-0.038** (0.016)	-0.045*** (0.016)	-0.085*** (0.030)	-0.052*** (0.017)	-0.065*** (0.017)	-0.088** (0.035)	-0.067*** (0.019)
Observations	122,261	122,231	82,715	122,222	122,192	82,704	122,104	122,074	82,572
<b>Panel D. First Stage</b>									
Predicted Inflows	0.291*** (0.011)	0.240*** (0.014)	0.432*** (0.033)	0.291*** (0.011)	0.240*** (0.014)	0.432*** (0.033)	0.291*** (0.011)	0.240*** (0.014)	0.432*** (0.033)
First Stage F-statistic	723.55	312.68	494.61	723.55	312.68	494.61	723.55	312.68	494.61
Observations	122,269	122,231	82,719	122,269	122,231	82,719	122,269	122,231	82,719
<b>Controls (for all panels)</b>									
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Department FE	No	Yes	No	No	Yes	No	No	Yes	No
Homicides Rates	No	Yes	No	No	Yes	No	No	Yes	No
Conflict Controls	No	Yes	No	No	Yes	No	No	Yes	No
Additional Controls	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Each coefficient corresponds to a separate regression. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors at the firm level are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.

**Table (II.2) Effects of IDP Inflows on the Extensive Margin of Production**

Dependent Variable (in logs)	Number of Firms		
	(1)	(2)	(3)
<b>Panel A. Reduced Form</b>			
Predicted Inflows	-0.021** (0.008)	-0.018* (0.010)	-0.012 (0.009)
R-squared	0.970	0.975	0.974
Observations	3,718	3,602	3,702
<b>Panel B. OLS</b>			
Share of IDP (% Total Population)	-0.006 (0.008)	-0.006 (0.009)	-0.005 (0.009)
R-squared	0.970	0.975	0.974
Observations	3,724	3,608	3,708
<b>Panel C. 2SLS</b>			
Share of IDP (% Total Population)	-0.028** (0.013)	-0.029 (0.019)	-0.016 (0.013)
Observations	3,718	3,602	3,702
<b>Panel D. First Stage</b>			
Predicted Inflows	0.739*** (0.147)	0.614*** (0.116)	0.733*** (0.148)
First Stage F-statistic	25.35	30.85	26.33
Observations	3,718	3,602	3,702
<b>Controls (for all panels)</b>			
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year X Department FE	No	Yes	No
Homicides Rates	No	Yes	No
Conflict Controls	No	Yes	No
Additional Controls	No	No	Yes

*Notes:* Each coefficient corresponds to a separate regression. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors at the firm level are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.

**Table (II.3)** Effects of IDP Inflows on Input and Output Prices

Dependent Variables (in logs)	Nominal Output Price		Nominal Input Price			
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A. Reduced Form</b>						
Predicted Inflows	-0.006*	-0.012**	-0.002	0.005	0.003	0.008
R-squared	(0.003)	(0.006)	(0.004)	(0.005)	(0.009)	(0.006)
Observations	0.395	0.406	0.445	0.944	0.944	0.943
	799,738	799,737	391,289	731,502	731,503	731,255
<b>Panel B. OLS</b>						
Share of IDP (% Total Population)	-0.003	-0.003	0.003	0.012*	0.015	0.011
	(0.004)	(0.006)	(0.006)	(0.007)	(0.009)	(0.008)
R-squared	0.395	0.406	0.445	0.944	0.944	0.945
Observations	799,738	799,737	391,289	731,504	731,508	731,255
<b>Panel C. 2SLS</b>						
Share of IDP (% Total Population)	-0.026*	-0.059**	-0.010	0.018	0.016	0.026
	(0.014)	(0.029)	(0.016)	(0.020)	(0.050)	(0.021)
Observations	799,741	799,737	391,289	731,514	731,518	731,255
<b>Panel D. First Stage</b>						
Predicted Inflows	0.245***	0.197***	0.227***	0.247***	0.200***	0.303***
	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)
First Stage F-statistic	391.76	220.87	350.94	383.42	227.53	523.15
Observations	799,741	799,737	391,289	731,514	731,518	731,255
<b>Controls (for all panels)</b>						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year Department FE	No	Yes	No	No	Yes	No
Homicides Rates	No	Yes	No	No	Yes	No
Conflict Controls	No	Yes	No	No	Yes	No
Additional Controls	No	No	Yes	No	No	Yes

Notes: Each coefficient corresponds to a separate regression. Product fixed effects correspond to the four-digit classification of the International Standard Industry Classification, which account for 113 four-digit codes. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors at the firm level are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.

**Table (II.4)** Impacts of IDP Inflows in Capital Demand

Dependent Variables (in logs)	Net Investment			Gross Investment		
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A. Reduced Form</b>						
Predicted Inflows	-0.053*** (0.019)	-0.070** (0.027)	-0.040 (0.026)	-0.027** (0.013)	-0.030* (0.018)	-0.008 (0.017)
R-squared	0.707	0.711	0.710	0.691	0.694	0.692
Observations	23,680	23,655	23,669	48,725	48,687	48,709
<b>Panel B. OLS</b>						
Share of IDP (%Total Population)	0.002 (0.030)	0.018 (0.040)	-0.004 (0.034)	-0.017 (0.018)	-0.018 (0.025)	-0.014 (0.021)
R-squared	23,680	23,655	0.710	48,725	48,687	0.692
Observations	0.707	0.711	23,669	0.691	0.693	48,709
<b>Panel C. 2SLS</b>						
Share of IDP (%Total Population)	-0.189*** (0.0711)	-0.313** (0.134)	-0.123 (0.082)	-0.097** (0.047)	-0.137 (0.084)	-0.026 (0.057)
Observations	23,680	23,655	23,669	48,725	48,687	48,709
<b>Panel D. First Stage</b>						
Predicted Inflows	0.273*** (0.009)	0.223*** (0.017)	0.432*** (0.033)	0.273*** (0.010)	0.223*** (0.017)	0.432*** (0.033)
Observations	794.17	170.89	494.61	794.17	170.89	494.61
First Stage F-statistic	82,763	82,738	82,719	82,764	82,738	82,719
<b>Controls (for all panels)</b>						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year X Department FE	No	Yes	No	No	Yes	No
Homicides Rates	No	Yes	No	No	Yes	No
Conflict Controls	No	Yes	No	No	Yes	No
Additional Controls	No	No	Yes	No	No	Yes

Notes: Each coefficient corresponds to a separate regression. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors at the firm level are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.

**Table (II.5)** Impacts of IDP Inflows in Labor Demand

Dependent Variables (in logs)	Total Employment			Nominal Wages		
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A. Reduced Form</b>						
Predicted Inflows	-0.009*** (0.003)	-0.016*** (0.004)	-0.001 (0.004)	0.001 (0.002)	0.001 (0.002)	-0.002 (0.002)
R-squared	0.931	0.932	0.932	0.861	0.862	0.862
Observations	82,696	82,676	82,657	82,267	82,247	82,228
<b>Panel B. OLS</b>						
Share of IDP (%Total Population)	-0.001 (0.005)	-0.0107* (0.006)	0.001 (0.005)	0.004 (0.002)	0.0001 (0.003)	0.003 (0.003)
R-squared	82,700	82,680	0.932	82,271	82,251	0.862
Observations	0.931	0.932	82,661	0.861	0.862	82,232
<b>Panel C. 2SLS</b>						
Share of IDP (%Total Population)	-0.036*** (0.010)	-0.071*** (0.021)	-0.005 (0.014)	0.003 (0.006)	0.003 (0.010)	-0.008 (0.007)
Observations	82,696	82,676	82,657	82,267	82,247	82,228
<b>Panel D. First Stage</b>						
Predicted Inflows	0.273*** (0.010)	0.223*** (0.017)	0.432*** (0.033)	0.273*** (0.010)	0.223*** (0.017)	0.432*** (0.033)
Observations	794.17	170.89	494.61	794.17	170.89	494.61
First Stage F-statistic	82,766	82,738	82,719	82,765	82,738	82,719
<b>Controls (for all panels)</b>						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year X Department FE	No	Yes	No	No	Yes	No
Homicides Rates	No	Yes	No	No	Yes	No
Conflict Controls	No	Yes	No	No	Yes	No
Additional Controls	No	No	Yes	No	No	Yes

Notes: Each coefficient corresponds to a separate regression. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors at the firm level are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.

**Table (II.6)** Impacts of IDP Inflows on Nominal Wages by Type (2000-2010)

<b>Dependent Variables (in logs)</b>	Nominal Wages		Blue-collar Nominal Wages		White-collar Nominal Wages	
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A. Reduced Form</b>						
Predicted Inflows	0.001 (0.002)	-0.002 (0.002)	0.003 (0.002)	-0.002 (0.003)	0.001 (0.004)	-0.0002 (0.003)
Observations	0.862	0.862	0.765	0.764	0.825	0.825
R-squared	82,247	82,228	79,652	79,633	78,619	78,628
<b>Panel B. OLS</b>						
Share of IDP (% Total Population)	0.0001 (0.003)	0.003 (0.003)	0.002 (0.003)	0.003 (0.003)	0.003 (0.006)	0.007 (0.005)
R-squared	0.862	0.862	0.765	0.765	0.825	0.825
Observations	82,251	82,232	79,656	79,637	78,623	78,632
<b>Panel C. 2SLS</b>						
Share of IDP (% Total Population)	0.003 (0.010)	-0.008 (0.007)	0.012 (0.010)	-0.008 (0.007)	0.003 (0.017)	-0.001 (0.012)
Observations	82,247	82,228	79,652	79,633	78,619	78,628
<b>Panel D. First Stage</b>						
Predicted Inflows	0.223*** (0.017)	0.432*** (0.033)	0.223*** (0.017)	0.432*** (0.033)	0.223*** (0.017)	0.432*** (0.033)
First Stage F-statistic	170.89	494.61	170.89	494.61	170.89	494.61
Observations	82,738	82,719	82,738	82,719	82,738	82,719
<b>Controls (for all panels)</b>						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year X Department FE	No	Yes	No	No	Yes	No
Homicides Rates	No	Yes	No	No	Yes	No
Conflict Controls	No	Yes	No	No	Yes	No
Additional Controls	No	No	Yes	No	No	Yes

*Notes:* Each coefficient corresponds to a separate regression. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central government transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors at the firm level are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.

**Table (II.7)** Impacts of IDP Inflows on Employment by Type (2000-2010)

<b>Dependent Variables (in logs)</b>	<b>Employment</b> (1)	<b>Blue-collar Employment</b> (2)	<b>White-collar Employment</b> (3)	<b>White-collar Employment</b> (4)	<b>White-collar Employment</b> (5)	<b>White-collar Employment</b> (6)
<b>Panel A. Reduced Form</b>						
Predicted Inflows	-0.016*** (0.004)	-0.001 (0.004)	-0.020*** (0.005)	-0.003 (0.004)	-0.018*** (0.005)	-0.004 (0.005)
Observations	0.932	0.932	0.919	0.919	0.911	0.910
R-squared	82,676	82,657	79,823	79,804	81,250	81,229
<b>Panel B. OLS</b>						
Share of IDP (% Total Population)	-0.011* (0.006)	0.001 (0.005)	-0.007 (0.007)	0.002 (0.005)	-0.013* (0.007)	0.0003 (0.006)
R-squared	0.932	0.932	0.919	0.919	0.911	0.910
Observations	82,680	82,661	79,827	79,808	81,254	81,233
<b>Panel C. 2SLS</b>						
Share of IDP (% Total Population)	-0.071*** (0.021)	-0.005 (0.014)	-0.088*** (0.022)	-0.010 (0.014)	-0.081*** (0.025)	-0.013 (0.017)
Observations	82,676	82,657	79,823	79,804	81,250	81,229
<b>Panel D. First Stage</b>						
Predicted Inflows	0.223*** (0.017)	0.432*** (0.033)	0.223*** (0.017)	0.432*** (0.033)	0.223*** (0.017)	0.432*** (0.033)
First Stage F-statistic	170.89	494.61	170.89	494.61	170.89	494.61
Observations	82,738	82,719	82,738	82,719	82,738	82,719
<b>Controls (for all panels)</b>						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year X Department FE	No	Yes	No	No	Yes	No
Homicides Rates	No	Yes	No	No	Yes	No
Conflict Controls	No	Yes	No	No	Yes	No
Additional Controls	No	No	Yes	No	No	Yes

*Notes:* Each coefficient corresponds to a separate regression. All regressions include firm and year fixed effects. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central governments transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Standard errors are clustered at the firm level. Clustered standard errors are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.



**Table (II.8)** Impacts of IDP inflows in Employment in Informal and Formal Sectors

Dependent Variable	All Sectors	Highly Informal Sectors	Highly Formal Sectors
	(1)	(2)	(3)
<b>Panel A. Reduced Form</b>			
Predicted Inflows	0.001*** (0.0004)	0.001*** (0.0004)	-0.00002 (0.00005)
Observations	2,797,614	2,323,262	474,347
R-squared	0.328	0.398	0.017
<b>Panel B. OLS</b>			
Share of IDP (% Total Population)	0.0004 (0.00003)	0.0004 (0.00003)	-0.00001 (0.000003)
R-squared	0.328	0.398	0.017
Observations	2,797,614	2,323,262	474,347
<b>Panel C. 2SLS</b>			
Share of IDP (% Total Population)	0.002** (0.00008)	0.002** (0.00009)	-0.00005 (0.00001)
Observations	2,797,614	2,323,262	474,347
<b>Panel D. First Stage</b>			
Predicted Inflows	0.583*** (0.134)	0.598*** (0.136)	0.497*** (0.127)
First Stage F-statistic	15.66	16.23	13.28
Observations	2,797,614	2,323,262	474,347
<b>Controls (for all panels)</b>			
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Individuals Covariates	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes

Notes: Each coefficient corresponds to a separate regression. Individuals covariates include controls for gender, marital status, education level, household size, homicide rate. Additional controls include interactions of year dummies and i) armed attacks by illegal armed groups in 1995, ii) fatal victims of attacks in 1995, iii) homicide rates 1995, iv) public expenditures in 1995, v) central governments transfers to health, education, and other expenditures in 1995, vi) number of financial institutions in 1995, vii) number of tax collection offices in 1995, viii) 2000 GDP share in agriculture, services, and industry, ix) municipal tax income in 1995, and x) night light density in 1995. Clustered standard errors are reported in parentheses. \*\*\* significant at the 1%, \*\* significant at the 5%, \* significant at the 10%.