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The Impacts of Internal Displacement Inflows on Host Communities in Colombia*

Emilio Depetris-Chauvin, Rafael J. Santos†

Abstract

Using Colombia as a case study, this report provides new empirical evidence on the impact of inflows of internally displaced persons (IDPs) on host communities. The focus is on three outcomes from several databases: relative rental and food prices, poverty, and public investment in education and health. A distance-weighted measure of outflows in the rest of the country is used as an instrument for inflows. To study the impact of IDP inflows on relative rental and food prices, this report exploits quarterly data over the period 1999–2014 for the 13 largest Colombian cities. On average, higher IDP inflows decrease rental prices, but the impact varies with income levels: rental prices increase (decrease) for low (high) income units. Surprisingly, higher IDP inflows are associated with lower food prices regardless of income level. The analysis for poverty is based on two strategies. The first exploits two census cross-sections to document a positive relationship between IDP inflows and unfulfilled basic needs at the municipality level, a measure of poverty widely used in Latin America. The second uses rich panel data to show that host community residents' household consumption decreases as new inflows arrive in their municipality. Albeit statistically significant, the economic magnitudes of the documented effects on rental and food prices, as well as on poverty, are rather small. Finally, this report uses annual municipality-level data on public investment in health and education, and finds no statistical relationship between these investments and IDP inflows. Concerns about data quality and the complexity of the connections between different levels of government hinder the interpretation of the results from this last exercise.

Key words: Internal displacement, host communities, rental prices, food prices, poverty, public finances

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1. Introduction

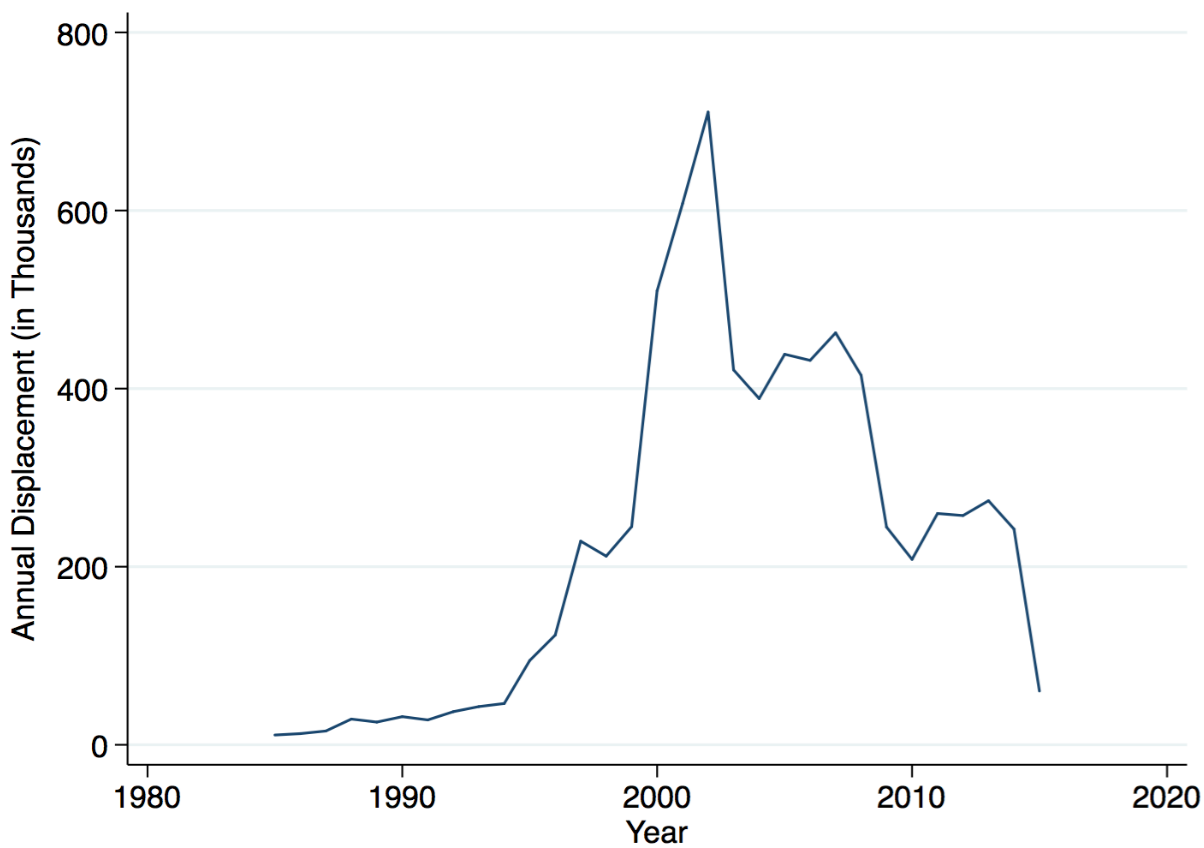
Millions of people are forcibly displaced from their homes by violent conflict each year. Research has focused on the effects of displacement on the migrants themselves. However, forced migration usually entails large population inflows to host communities that may be unprepared to receive them. Sudan, Rwanda, Tanzania, Turkey, and Uganda have become common case studies for new research that explores the impacts of forced migration on recipient countries. Yet the effects of forced displacement on host communities within migrants' countries of origin have somehow been neglected. Not only are internally displaced persons (IDPs) quantitatively important, but their effects on host communities might be larger.[1] IDPs integrate with the recipient population. While they might bring in new resources (such as cheap labor), they might also compete for existing resources. More generally, understanding the effects of IDPs on host communities is a first step toward creating rational political responses from local and central governments.

Using Colombia as a case study, this report provides new empirical evidence on the impact of IDP inflows on host communities. Colombia provides fertile research ground given that it has fairly accurate data on IDP inflows and outflows at a quarterly frequency. These data correspond to 6 million IDPs, representing 16 percent of the world's IDP total. The dynamics of the Colombian conflict also provide researchers with time windows of extremely high displacement. As figure 1 shows, the period 2000–05 is a time frame of extremely high inflows, explained by various nonstate armed groups capturing and then protecting territories.

The report presents results for the effects of IDP inflows on three outcomes: First, it uses a balanced panel of cities and quarterly data (1999–2014) to estimate the causal effect of IDP inflows on relative housing rental prices and relative food prices. This is one of the preferred exercises given the quarterly frequency of the data and the fact that the analysis can exploit the massive displacement movement that occurred in 2000–05. As will be clear in the literature review, this also represents a considerable improvement with respect to previous work on prices and constitutes the first draft of a future research paper.

1. According to the United Nations High Commissioner for Refugees, as of 2014 there were 2.3 IDPs per international refugee (UNHCR).

Figure 1. Internal Displacement in Colombia



Second, the analysis explores the impact of IDP inflows on poverty using two strategies. It first exploits the 1993 and 2005 census cross-sections to measure Unfulfilled Basic Needs (UBN) at the municipality level—a common poverty measure in Latin America—and examines how UBN respond to past IDP inflows. The second strategy uses rich panel data to explore how the household consumption of host communities' residents varies as new inflows arrive in their municipality.

Third, the analysis uses yearly municipality-level data on public investment in health and education to analyze how these investments react to recent IDP inflows. Concerns about data quality and the complexity of the links between different levels of government require the results of this exercise to be interpreted with caution.

All of the empirical models take into account that the decision of where to migrate is not random. For example, IDPs might move to cities where they have more optimistic expectations for the future. As a result, using municipality-level inflows as an explanatory variable for any of the analysis's outcomes is plagued with endogeneity. In other words, variables that cannot be accounted for may confound any observed empirical relationships between IDP inflows and the outcome variables under study. To correct for such endogeneity, an instrumental variables (IV) strategy is used with a straightforward intuition: cities closer to municipalities with higher IDP outflows are more likely to receive higher inflows.[2] In technical terms, the instrument for inflows is a weighted sum of outflows in all municipalities except the host, where the weights are the inverse of the distance between the host and each municipality. That is, in years in which outflows are higher, municipalities that are closer to the sources of the outflows will receive more displaced people. To provide a robustness check against the possibility that the results are driven by local-level shocks correlated with both displacement in nearby municipalities and the outcomes of interest, the IV regressions are also run with an alternative instrument, removing IDPs from municipalities within 50 kilometers of the host city from the weighted sum. Results for these regressions are presented in the appendix.

To summarize the results, the inquiry finds that higher IDP inflows increase rental prices for low-income housing (price elasticity of 0.008 percent) but decrease rental prices for high-income residences (price elasticity of −0.011 percent). Unexpectedly, however, the results suggest that IDP arrival results in lower food prices. Aggregate poverty measures (UBN) worsen as past inflows increase (standardized coefficient of 0.61). More revealing, per capita household consumption for the nondisplaced residents of host municipalities also drops as IDP inflows increase. However, the impact (0.09 standard deviations) seems much less dramatic in comparison with the impact found using UBN as the dependent variable, which takes into account both the displaced and the nondisplaced. This analysis is unable to provide evidence of any significant relationship between investment in education (per pupil) or investment in health (per capita) and IDP inflows.

This report is organized as follows: Section 2 provides a literature review about the effects of IDP inflows on host communities. Section 3 discusses the potential impacts of IDP inflows on rental prices, and presents the corresponding data, the empirical strategy, and the results. Section 4 has a similar structure for poverty and section 5 for public finance. Section 6 concludes with policy implications.

2. Literature Review

Although closely related to the larger literature on the effect of immigration on local markets, the literature on the effect of forced displacement on receiving host communities is comparatively small. Research on the effect of forced displacement on the victims themselves has generated considerable interest. Yet studies on how displacement might create market shocks in host communities are equally important as policy makers seek to mitigate the market disruption caused by large, sudden migrations of individuals, as well as the unintended secondary effects of assistance to victims of conflict.

Particularly relevant for studying the effects of migration on housing markets, Saiz (2003) uses a standard difference-in-differences approach to examine the response of rental prices in Miami to the Mariel Boatlift immigration shock from Cuba, finding that prices rose between 8 and 11 percent more in Miami than in comparison cities, with low-income properties disproportionately affected. Saiz's comparison group is a set of American cities with similar preshock trends, and the study relies on the assumption that the boatlift constituted a natural experiment, using the strategy found in Card (1990) for estimating the effects of the

[2] In Colombia cities are equivalent to municipalities except that cities have different administrative functions, differences that are however not relevant for this research.

Mariel Boatlift on the Miami labor market. However, Angrist and Krueger (1999) demonstrate the pitfalls of this strategy, finding significant labor market effects in Miami for a placebo immigration shock that never actually occurred.

The Miami case is an example of the primary difficulties facing studies that aim to identify the effect of immigration or displacement shocks on markets. If migrants choose their new homes, the choice may be systematically related to perceptions about market conditions, making treatment and control groups incomparable. Although arguably exogenous shocks may exist that create natural experiments, limited data and the lack of appropriate control groups make it difficult to establish a counterfactual.

Saiz (2007) attempts to address these issues using immigration data from a much larger set of U.S. cities and using an IV strategy. With annual data on legal immigration inflows for 306 metropolitan areas between 1983 and 1998, Saiz (2007) instruments the annual immigration to these cities by multiplying the portion of 1983 immigrants settling in each metropolitan area by total annual U.S. immigration inflows. The results suggest that immigration inflows equal to 1 percent of a city's population are associated with a 1 percent increase in rent prices for housing, robust to different instruments and data sources.

Although empirically rigorous, the applicability of the conclusions from Saiz (2007) is less clear for situations of forced displacement in developing countries, where there is a larger presence of informal or poorly functioning markets, significant humanitarian assistance, and the perception that new arrivals might significantly harm local security.

Alix-Garcia and Saah (2010), Baez (2011), and Maystadt and Verwimp (2014) estimate the effects of the arrival of Burundian and Rwandan refugees in Tanzania on labor and food markets and children's health outcomes in host communities, all using the distance between host communities and refugee camps or country borders to create an artificial (proxy) measure of refugee inflow intensity. Using monthly food price data from 38 Tanzanian markets between 1992 and 1998, Alix-Garcia and Saah (2010) exploit the variation in distance between refugee camps and markets, and the size of the refugee population over time, finding that refugee inflows increased prices, while in-kind food aid to refugees partially offset the increase. The authors suggest that the increase in food prices had a small redistributive effect on the wealth of urban and rural households using radio, bicycle, and cement floor ownership as proxies for household wealth. They find that refugee presence negatively affected wealth in urban households, but increased ownership in rural households.

Cortes (2008) exploits variation across U.S. cities and over time in the relative size of the low-skilled immigrant population to estimate the causal effect of immigration on prices of nontraded goods and services, finding a sizable negative impact of the price of immigrant-intensive services, such as housekeeping and gardening. Again, while IDP are indeed low-skilled immigrants, the Colombian institutional context under analysis is arguably very different from the one in the United States.

Lacking data on refugee numbers, Baez (2011) uses communities' distance to the border and community leaders' answers to a survey on the refugee problem in their areas as proxies for the intensity of exposure to refugee inflows. Using period, community, and cohort fixed effects, the results show that children in communities with greater refugee inflows saw poorer outcomes on a variety of health indicators.

Maystadt and Verwimp (2014) use household-level panel data from 1991–94 and a difference-in-differences methodology, finding that refugee inflows increased hosts' aggregate consumption, although agricultural workers and self-employed nonagricultural workers may have been harmed by labor market competition with the influx of low-wage workers and small entrepreneurs. Notably, the finding for agricultural workers conflicts somewhat with the results obtained by Alix-Garcia and Saah (2010).

For Darfur, Alix-Garcia, Bartlett, and Saah (2012) use an ordinary least squares (OLS) model to test the sensitivity of weekly food prices in the city of Nyala to weekly humanitarian assistance and estimated monthly refugee inflows between 2005 and 2007, including fixed effects for month and season, and a time trend. They find no evidence that international food aid affected local food markets, although the increased presence of refugees was associated with an increase in food prices. Similarly, the presence of international aid workers was associated with higher rent and housing prices, although this evidence is purely qualitative. No group of comparison cities is available for either food or housing prices, making it difficult to establish causality.

The identification strategies in the refugee literature mentioned above are highly dependent upon assumptions about the random placement of refugee camps and the appropriateness of communities farther from international borders as a valid counterfactual for border communities with higher refugee exposure. As might be expected for refugee situations in a developing-country context, their data tend to be limited and to cover relatively short periods.

Kreibaum (2016) also relies on the exogeneity of migration shocks to estimate the effect of Congolese refugees on Uganda in another example of a difference-in-differences model. However, as a robustness check the author takes a different identification approach by using a two-stage least squares strategy, instrumenting district-level refugee presence with the total annual refugee inflows to Uganda divided by a district's distance to the border. The results suggest the Ugandan population benefited from increased consumption and access to public services, although the consumption of households depending on transfers may have been harmed.

The existing literature on the effect of the arrival of forcibly displaced persons on housing prices, food prices, holistic poverty indicators, and private and public consumption is limited. Alix-Garcia, Bartlett, and Saah (2012) are the only authors to examine the effect on housing prices, although their evidence is qualitative and unable to determine causality. Kreibaum (2016) and Maystadt and Verwimp (2014) are the only two studies that use household consumption as the outcome of interest, and Alix-Garcia and Saah (2010) provide the only study that comes close to examining how labor market and consumer price effects might jointly influence poverty in host communities, though their indicator is household wealth and it is only roughly proxied by ownership of a few basic items.[3] Importantly, while Baez (2011) suggests

[3]. In two unpublished working papers, Maystadt and Duranton (2014) and Maystadt (2011) present additional evidence on the effect of refugee arrival on poverty in host communities in Tanzania, using similar data and identification strategies as Maystadt and Verwimp (2014). Using household consumption divided by average village price levels (Maystadt and Duranton 2014) and an indicator for household income below the local poverty line (Maystadt 2011), both find that refugee arrival improved the situation of the host population, and helped poor households in particular. Reduced transportation costs, higher agricultural productivity, and income diversification are pointed to as possible channels.

the effect of refugees on education and health outcomes of children in host communities may result from the diversion of public resources to aid refugees, the study does not empirically confirm this channel. In fact, no existing literature was found for the effect on public spending.

This work provides the first empirical evidence on how internal displacement might affect housing prices in a developing-country setting, an important literature gap identified by Ruiz and Vargas-Silva (2013) in their excellent review of the forced migration literature. In addition, rich panel data are used to estimate how consumption of the host population reacts to changes in internal displacement inflows. Finally, available data allow this investigation to take a first look at how public investment responds to the arrival of IDPs.

This work differs from the above studies in three important ways: context, data, and identification strategy. In this sense, it is perhaps most similar to the work of Calderón-Mejía and Ibáñez (2015), who study the impact of internal forced displacement on urban labor markets in Colombia. Particularly, Calderón-Mejía and Ibáñez (2015) focus exclusively on the impact of IDPs on wages. With detailed data on massacres and forced displacement in the country, these authors instrument the arrival of forcibly displaced populations to the main cities in Colombia with a distance-weighted measure of massacres in other Colombian municipalities, finding that workers who compete with displaced victims for jobs are negatively affected by the arrival of IDPs. That is, wages of low-skilled workers decrease with the arrival of IDPs.

The Colombian case provides a new perspective within this literature because its context differs significantly from the African cases. Although a small number of studies examine the impact of refugees on host communities, most do so in an international refugee setting, and all of these contexts assume that victims are housed in refugee camps, while in-kind food aid is provided and international humanitarian aid workers have a large presence. The conclusions for the impact on local markets cannot necessarily be extended to the Colombian context of IDPs settling directly in host communities without camps and without the presence of international relief workers. Some displaced individuals in Colombia whose cases have been determined to meet certain urgency requirements do receive some short- or medium-term emergency aid provided by the Registro Único de Víctimas (RUV) that allows monthly payments of up to 1.5 times the Colombian minimum monthly wage. Additionally, transition assistance in the form of employment programs or access to food or housing is provided on a case-by-case basis to displaced individuals whose situations have not been determined to meet the emergency assistance requirements (Law 1448 of 2011; Prada and Poveda 2012). However, the reality of how this assistance is implemented is far from ideal. Only 50 percent of displaced individuals who registered between 2002 and 2004 received any assistance at all, and for much of the period in this study, most qualifying individuals received an assistance package for only three months (Human Rights Watch 2005). Therefore, unlike in the refugee literature, isolating the impact of an inflow of IDPs on host communities (particularly on prices and poverty) from the potential direct effect of aid and governance assistance is less difficult.

Second, this analysis uses high-quality data. For example, in the price estimations, quarterly data (including directly measured quarterly inflows) over a 17-year period are used, allowing variation over low- and high-intensity displacement periods to be observed. This period includes a 2001–05 shock with particularly high-intensity displacement; in addition, several pre- and postshock years can be observed.

Ruiz and Vargas-Silva (2013) also suggest that the lack of data availability from all three periods (pre-, during, and postshock) is one of the biggest challenges for studies on the impact of refugee presence. In contrast to previous studies using refugee inflow estimates or rough proxies, the data on IDP movements used in this analysis are derived from administrative records, allowing for a more exact measure of migration intensity. Similarly, the poverty indicator comes from the Unfulfilled Basic Needs (UBN) index found in Colombia's 1993 and 2005 censuses, providing a more holistic indicator of poverty than is found in other studies.

Finally, the literature on the effect of the arrival of forced migrants on markets in host communities has only recently begun using instruments to address the endogeneity issues common to the literature. Outside of Colombia, Kreibaum (2016) is the only author who employs instrumental variables. Still, this strategy relies on strict assumptions about the exogeneity of the distance of communities to an international border. By contrast, the strategy in this analysis is more similar to that of Calderón-Mejía and Ibáñez (2015), and provides an additional source of arguably exogenous variation across cities: displacement outflows. The inflow of IDPs into Colombia's 13 largest metropolitan areas is instrumented using a distance-weighted matrix relating these cities to all other Colombian municipalities, multiplied by the displacement outflows in each municipality at each time point. This strategy is common in the labor and housing market literature and is a variation on the Bartik shock (Bartik 1991). However, its use is relatively new to the forced migration literature.

3. Rental and Food Prices

A. Potential Impact of IDP Inflows on Rental Prices

This section presents a simple theoretical framework for analyzing the potential effect of IDP inflows on rental prices in host communities. To the extent that such inflows represent an increase in the total population of a given location, this analysis hypothesizes that increasing IDP inflows will generate a demand-side shock in the rental housing market that will eventually push average rental prices up.[4] Moreover, the poverty conditions of IDPs are such that they will presumably compete for rental units in the low-income segment. Therefore, it is postulated that the impact of IDP inflows on rental prices should be larger for low-income tenants and less pronounced for middle-income tenants.

Additionally, no effect, or even a negative effect, should be expected on prices for high-quality rentals (that is, the high-income rental market). The potential negative impact of IDP inflows on the high-income rental market could operate through two distinct channels, one on the demand side and the other on the supply side. On the demand side, large inflows of poor immigrants could be perceived as a negative amenity by wealthy residents (Saiz 2003), thus pushing high-income rental prices down. Large population inflows might also generate congestion externalities that drive down housing prices. Anecdotal evidence suggests that large inflows of IDPs are associated with perceptions among the native population of increased crime and other social problems. On the supply side, large IDP inflows may affect the high-income housing production process by providing a cheaper labor force, pushing the supply curve of rental

[4]. Most IDPs will live in rental units, thus the rental housing market would experience substantial pressure from the increasing IDP-induced demand. According to Alcaldía Mayor de Bogotá (2004), more than 70 percent of IDPs in Bogotá pay rent, whereas fewer than 5 percent are homeowners.

units outward, and thereby lowering prices. In this sense, there is evidence for Colombia suggesting that IDP inflows indeed reduce the wages of unskilled urban workers (Calderón-Mejía and Ibáñez 2015). However, this supply-side effect should be expected to operate with some lags.

B. Data

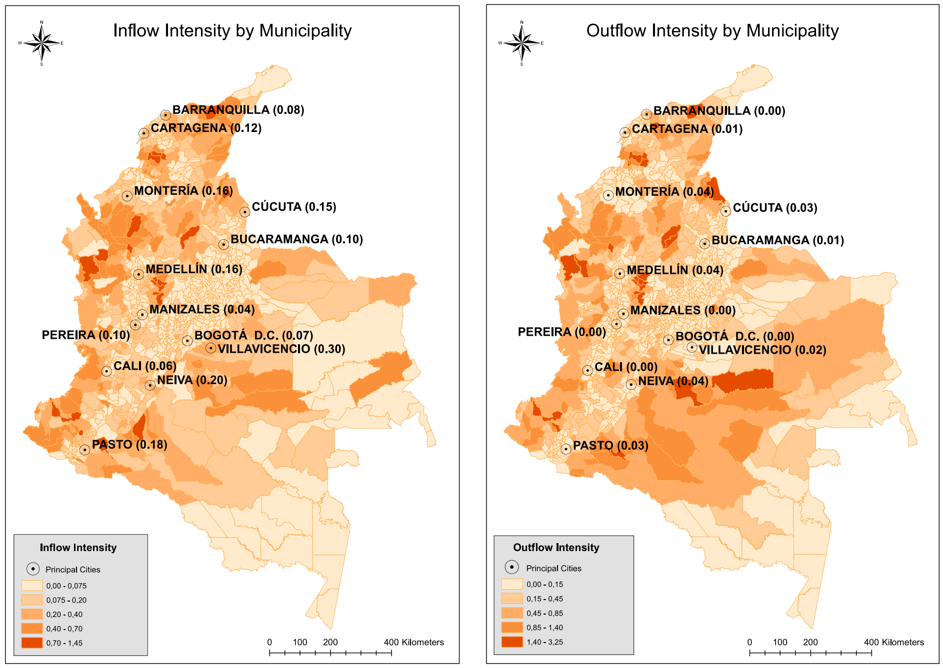
This investigation focuses on the 13 largest Colombian cities for which data on both IDP inflows and rental prices are available at quarterly frequency for the period 1999–2014.[5] The data used come from two main sources. First, a detailed data set on IDP flows from the Registro Único de Víctimas (RUV), collected by the Colombian government registry for IDPs (the Registro Nacional de Información), is exploited. The RUV includes information on IDPs' current residence, date of forced migration, and origin. This information allows quarterly data on IDP inflows and outflows at the municipality level to be constructed. The two panels in figure 2 provide information on the intensity of inflows (left panel) and outflows (right panel) of IDPs by municipality. In these maps, the two intensity measures are calculated as the ratio of accumulated migrants (either inflows or outflows) over the period 1999–2014 to municipality total population in 1999.

Several facts are worth mentioning: (1) the 13 largest cities are net receivers of IDPs; (2) the magnitude of the IDP influx shock in those cities could be substantially large, as in Villavicencio where the accumulated stock of IDPs received over 1999–2014 represents 30 percent of 1999 population; (3) IDPs are mainly expelled from rural areas and low population density municipalities; and (4) as is known, there is a high intensity of IDP outflows in areas of Colombia where armed conflict has been more intense, such as Antioquia, Cauca, Caquetá, Nariño, Valle del Cauca, Norte de Santander, Arauca, Putumayo, and Meta.

[5]. These 13 municipalities harbor almost 40 percent of the Colombian population, and hosted 28 percent of the displaced population as of December 2015.

Figure 2. Inflow and Outflow Intensity

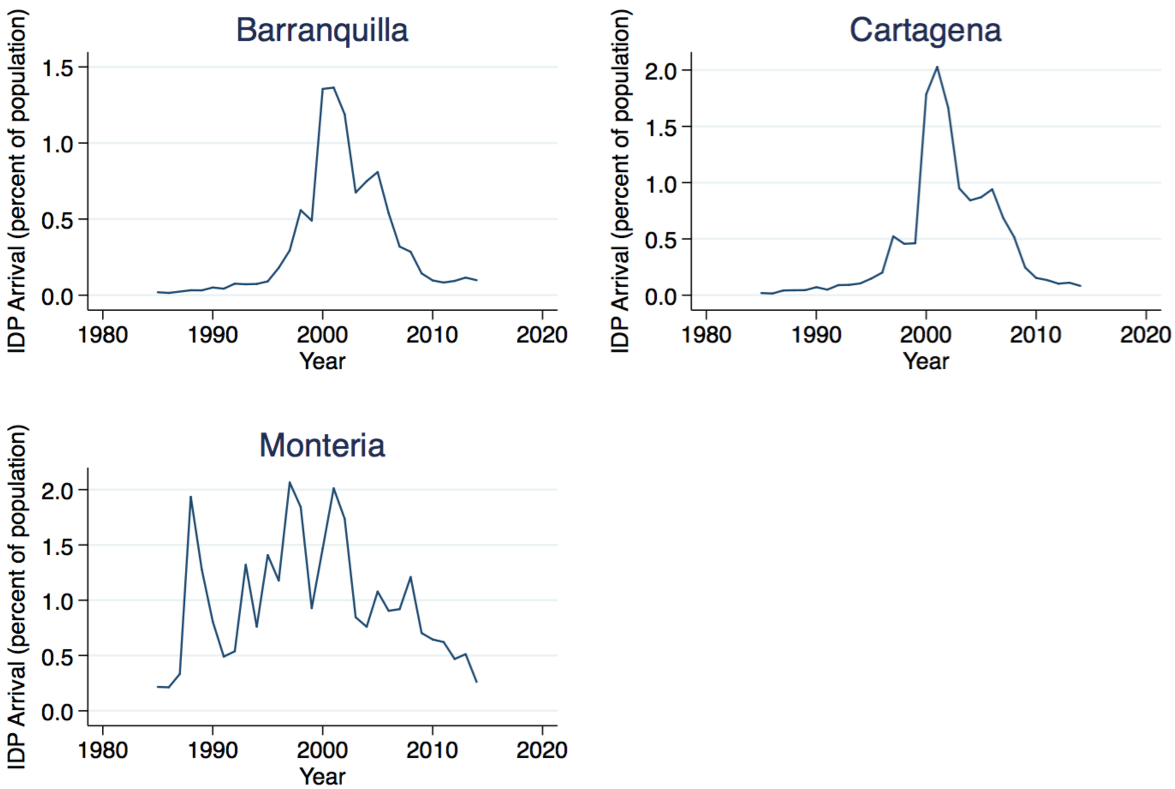
a. Inflows b. Outflows



(Source: authors' calculations)

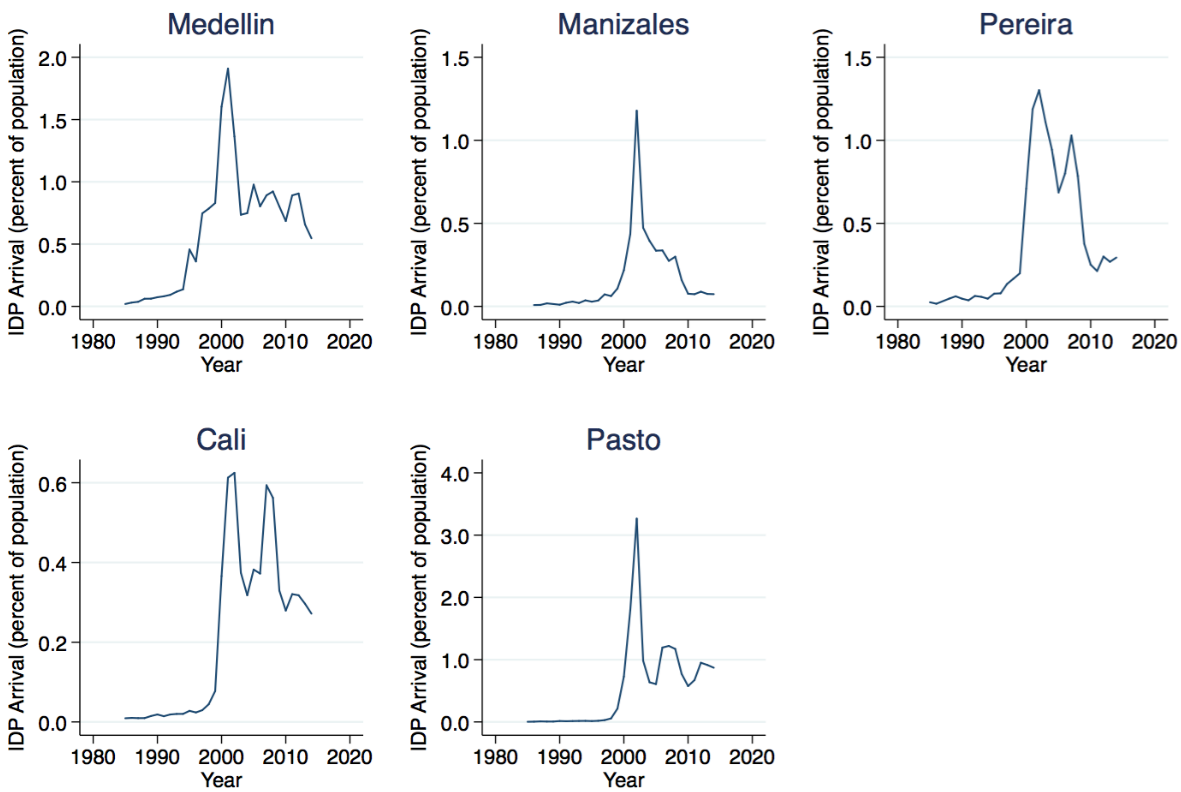
Figures 3, 4, and 5 depict the evolution of IDP inflow intensity (measured as the ratio of annual IDP inflow to municipality population) over the period 1985–2014 for the 13 Colombian cities in the analysis, divided into three regions (Northern, Eastern, and Central Colombia. These three figures provide information on the main source of variation in this analysis. Coinciding with the intensification of the armed conflict in the early 2000s, the 13 cities experienced a spike in IDP inflows during the period 2000–01. A group of cities, including Bogotá, Cali, and Neiva, faced a second peak at the end of the decade. Some cities, like Montería, followed a different path, with continual spikes and drops in IDP inflows over the period. As already stated, there is also substantial variation across cities in the intensity of IDP inflows. Here, Villavicencio again stands out, which in peak years received an inflow of IDPs equivalent to 3 percent of its original population.

Figure 3. IDP Inflows to Northern Colombia, 1985–2015



IDP = internally displaced persons.

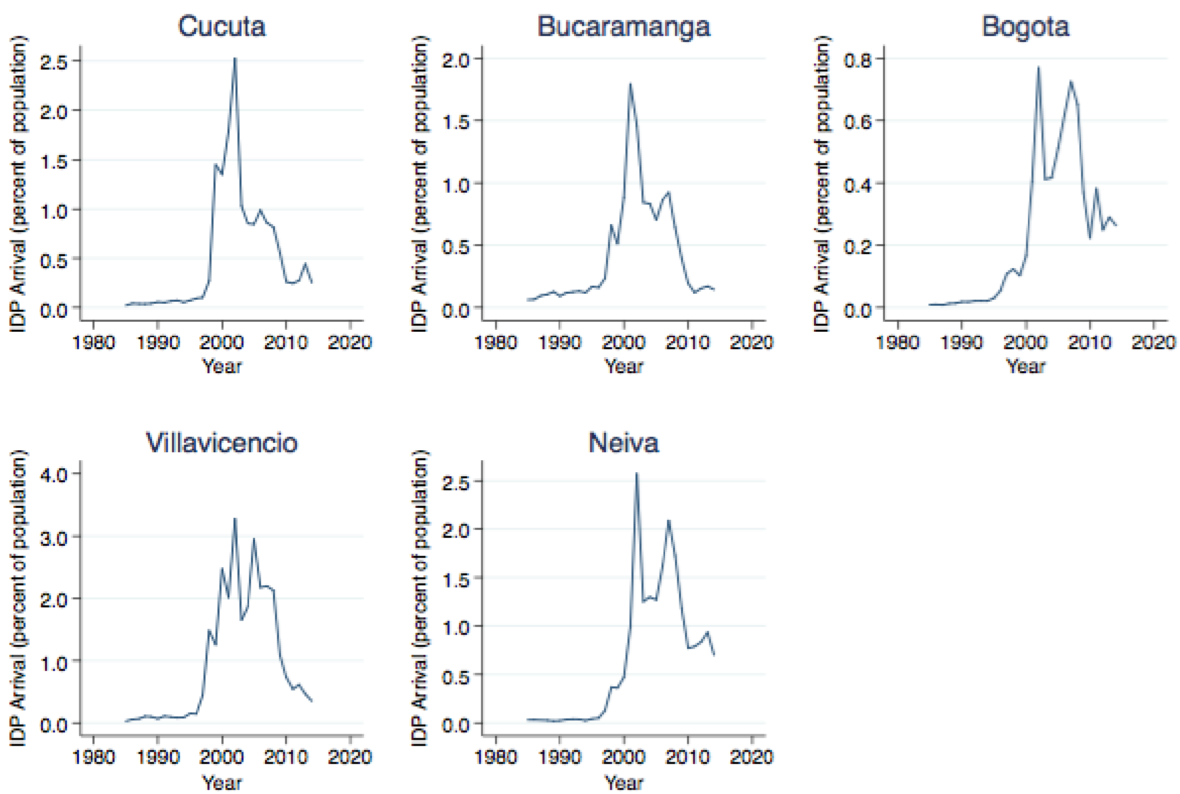
Figure 4. IDP Inflows to Eastern Colombia, 1985–2015



IDP = internally displaced persons.

The second main source of data is the Colombian National Statistics Department (DANE). In particular, rental price data by income level for the 13 largest cities are used, as well as their respective overall consumer price indices (CPI). Considerable effort was spent trying to expand the set of cities, but complete data on other geographic areas is nonexistent. This analysis is thus restricted to working with a small number of observations; however, these are the cities where most displaced people settle.

Figure 5. IDP Inflows to Central Colombia, 1985–2015



IDP = internally displaced persons.

For the purposes of subsidizing public utilities, the Colombian government classifies urban housing units into different strata with similar economic characteristics. This system classifies areas on a scale from 1 to 6, with 1 being the lowest income area and 6 the highest. When computing rental price indices, the DANE classifies as low income, middle income, and high income the rental units in strata 1–2, 3–4, and 5–6, respectively. This study also uses an average rental price index from the DANE. When examining the impact of IDP inflows on rental prices, the focus is on relative prices. Therefore, rental prices in each municipality are deflated by the municipality's corresponding CPI. Finally, data on population estimates by municipality, also from the DANE, are used.

Table 1 reports summary statistics for the main variables used in this paper. The "within" and "between" standard deviations allow the variance of the main variables of interest to be decomposed. For instance, variation in rental prices within cities over time tends to be approximately seven times larger than variation across cities. Meanwhile, the between-city variation explains nearly two-thirds of the total variation in IDP inflows.

Table 1. Summary of Results

Variable		Mean	Standard deviation	Minimum	Maximum	Observations
Relative rental price	overall	0.0693063	0.0850329	−0.0541114	0.4019355	N = 832
(average)	between		0.0288337	0.0250033	0.1256754	n = 13
	within		0.0803881	−0.0672064	0.3455664	T = 64
Relative rental price	overall	0.0677475	0.0802482	−0.0579942	0.3452668	N = 832
(low income)	between		0.0294144	0.0290394	0.1122463	n = 13
	within		0.075101	−0.0580327	0.302504	T = 64
Relative rental price	overall	0.0687933	0.0890192	−0.0710145	0.4628994	N = 832
(middle income)	between		0.0314382	0.0185939	0.1375028	n = 13
	within		0.0837316	−0.0799142	0.3941899	T = 64
Relative rental price	overall	0.0710975	0.1088807	−0.0665324	0.4898574	N = 832
(high income)	between		0.0351275	0.0151789	0.1252758	n = 13
	within		0.1035114	−0.0704847	0.4449756	T = 64
IDP inflows	overall	7,065.203	1,085.538	3,871.201	9,934.114	N = 832
	between		0.9011544	5,310.768	8,806.747	n = 13
	within		0.6541245	4,883.385	9,067.655	T = 64
IDP outflows	overall	4,960.599	1,114.599	.6931472	8,516.994	N = 832
	between		0.911378	3,575.436	7,161.429	n = 13
	within		0.688978	1,648.368	8,263.348	T = 64
Population	overall	1,355.869	0.8980446	1,260.006	1,586.666	N = 832
	between		0.9321775	1,267.433	1,575.801	n = 13
	within		0.0583679	1,335.516	1,374.446	T = 64
Receptivity	overall	5,683.635	0.4822232	4,268.167	6,949.685	N = 832
	between		0.1676221	5,.483.036	5,945.931	n = 13
	within		0.4545021	4.406.499	697.187	T = 64
Remoteness	overall	427,450.3	108,870	313,331.4	628,247.2	N = 832
	between		113,247.4	313,331.4	628,247.2	n = 13
	within		0	427,450.3	427,450.3	T = 64

Note: N is the total number of observations, n the number of cities and T is the number of times we observe a city over time.

C. Empirical Strategy

To estimate the impact of IDPs on rental prices, both time and cross-sectional variation in the intensity of displacement inflows at the city level for the period 1999–2015 are exploited. In particular, this time frame allows the potential impact of the unusually large movements of IDP taking place in the early 2000s caused by the intensification of the Colombian conflict to be examined. The following equation is estimated:

$$\ln\left(P_{c,t}\right) = \alpha + \beta \ln\left(Inflows_{c,t-1}\right) + \eta' X_{c,t} + d_c + d_t + u_{c,t} \ , \qquad (1)$$

where the subscripts *c* and *t* denote city and quarter, respectively. The variable P is the relative price of rentals. Again, this analysis uses average rental price, as well as rental prices by income level (low, middle, high income). *Inflows* is the main treatment variable and represents the total number of displaced people arriving in the host city *c* during the time period (quarter) $t - 1$. The log-log specification presented in equation (1) facilitates the interpretation of the point estimate for β as a standard elasticity. The term $X_{m,t}$ [[AQ: Should this be $X_{c,t}$ as in the equation?]]is a vector of controls including the total population (in logs) and city-level linear trends, which control for city-specific trends that might be anticipated by IDPs. The terms d_c and d_t denote city and quarter fixed effects, respectively. This collection of fixed effects captures time-invariant city characteristics (the d_c) and quarter-specific conditions (the d_t) that may be related to the evolution of rental prices. Finally, u is a heteroscedasticity-corrected error term.

The study focuses on IDP inflows lagged one period for two main reasons. First, the potential demand shock from a varying number of people arriving in a given location may arguably take some time to translate into price fluctuations. Second, using a lagged independent variable may reduce concerns of reverse causality between IDP inflows and prices—prices obviously provide valuable information about the cost of living in a given city and thus may affect migration decisions. Of course, this approach of lagging the IDP inflow variable does not convincingly solve endogeneity problems since economic agents may anticipate the impact of future migration inflows and adjust prices or quantities demanded accordingly. Additionally, IDP inflows in $t - 1$ may also be capturing the effect of expectations about future economic growth of the city. We acknowledge that other channels of endogeneity may still persist, and it is precisely for that reason that an IV approach is followed.

As suggested above, estimating equation (1) by OLS may still lead to biased estimates of the impact of IDP inflows on rental prices, in part because IDPs do not choose their destinations randomly. Indeed, location decisions might be explained by other, unobserved determinants of rental prices in destination cities. For instance, migration decisions may depend on other prices (such as wages), cost of living, amenities, quality of public goods provision, and the perceived levels of violence and security of a given city. To address this potential concern, an IV approach is followed. The instrument, referred to as $receptivity_{c,t}$, is constructed based on data from the RUV and accounts for the intensity of IDP outflows generated in each Colombian municipality every quarter during the period 1985–2015. The $receptivity_{c,t}$ measure is a distance-weighted average of the outflows in all municipalities except city *c* during the quarter *t*. Formally, the equation is

$$receptivity_{c,t} = \sum_{m \in M \setminus \{c\}} outflows_{m,t} \times D_{m,c}^{-1} \quad , \qquad (2)$$

where $c \in C \subseteq M$ is a city in the sample of 13 large cities (which are also municipalities), which is a subset of the 1,100 Colombian municipalities. The term $D_{m,c}^{-1}$ is the geodesic distance between municipality m (origin of IDPs) and city c (destination of IDPs). The instrument thus suggests that the number of IDPs arriving in city c in time t increases in the number of outflows in other localities, but decreases in the distance from any locality to the city. This instrument is based on three ideas: First, large migration outflows of IDPs are mainly determined by violent events toward civilians in rural areas. Second, the timing and intensity of those violent events are arguably orthogonal to relevant characteristics of the host cities. Third, the closer the proximity of a host city to a municipality experiencing IDP outflows at a given time, the higher that host city's probability of receiving a large IDP inflow.[6] As mentioned earlier, a robustness check on the IV results is undertaken by rebuilding the instrument, but excluding IDP outflows from municipalities within 50 kilometers of the host city. These results are presented in appendix A.

D. Results

OLS RESULTS

IMPACT ON AVERAGE RELATIVE RENTAL PRICE

Table 2 provides the first statistical test for the potential impact of IDPs on rental prices. The table presents OLS estimates of different specifications of equation (1), for which the dependent variable is the log of the average relative rental price (that is, relative to the CPI of the city). The specification in column (1) only includes d_c and d_t as controls. The former captures time-invariant characteristics of the city, such as geographic conditions, and the latter captures city-invariant conditions specific to the quarter, such as international commodity prices or the nationwide effect of macroeconomic policies. In particular, it has been shown that international commodity price shocks affect conflict intensity in Colombia (Dube and Vargas 2013); thus, such shocks may also directly affect relative rental prices and IDP inflows.[7] Consistent with a demand-side shock story, results in column (1) suggest that relative rental prices are significantly and positively correlated with IDP inflows lagged one period. The point estimate from the log-log specification indicates that a 1 percent increase in IDP inflows is related to an approximately 0.013 percent increase in relative rental prices in a given quarter.

Nonetheless, the confounding effects of factors influencing both relative rental prices and IDP inflows within a city over time make these estimates unreliable. Indeed, when city-specific linear trends are included in column (2) of table 2, the point estimate of interest is halved, although it remains positive and strongly statistically significant. Adding total population (in logs) of the city as a control in column (3) does not alter previous results. The point estimate indicates that a 1 percent increase in IDP inflows is related to approximately a 0.006 percent increase in relative rental prices in a given quarter.

6. According to Ibáñez (2008), more than 50 percent of internally displaced households migrate within the same state, and almost 20 percent do so within the same municipality.
7. Note that adjusted R^2, which are mechanically large because of the battery of fixed effects, are reported. This is done for consistency across tables.

IMPACT ON RENTAL PRICES BY INCOME LEVEL

The discussion now turns to whether the impact of IDP inflows on rental prices varies with income levels, focusing on relative rental prices for low-, middle-, and high-income rentals. Unless stated otherwise, all specifications that follow include the full set of controls in equation (1) (that is, the controls included in column (3) of table 2). For comparison, column (1) of table 3 replicates the last specification of table 2. Results in column (2) of table 3 show that relative rental prices for low-income consumers is significantly and positively correlated with IDP inflows. The magnitude is very similar to that found in table 2. Column (3) of table 3 also shows that higher IDP inflow intensity is statistically associated with higher relative rental prices for middle-income consumers. The investigation does not find, however, any statistically significant association between IDP inflows and relative rental prices for high-income consumers (column (4) of table 3).

Table 2. IDP and Rental Prices, OLS

	(1)	(2)	(3)
ln (IDP inflows)$_{t-1}$	0.0129***	0.00544***	0.00549***
	(0.00367)	(0.00149)	(0.00150)
ln (population)$_t$			−0.306
			(0.198)
Observations	832	832	832
Adjusted R^2	0.810	0.977	0.977
City fixed effects	Y	Y	Y
Time fixed effects	Y	Y	Y
City-specific linear trend	N	Y	Y

Note: IDP = internally displaced persons; OLS = ordinary least squares. Robust standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Weighting the previous OLS regressions by city population in table 4 improves the precision of the estimates remarkably, particularly for relative rental prices for low-income consumers. To put it in context, Villavicencio received almost 12,000 IDPs in 2002, which represented a 70 percent increase from 2001.[8] Taking the point estimate from column (2) of table 4 at face value would suggest that rental prices for low-income consumers went up 0.7 percent above the overall CPI in Villavicencio during 2002 (CPI inflation in Villavicencio was 6.6 percent in 2002) because of that particular IDP inflow shock.

8. As of 2014 more than 10 percent of Villavicencio’s population are IDPs.

Table 3. IDP and Rental Prices by Income Level, OLS

	(1) Average	(2) Low income	(3) Middle income	(4) High income
ln (IDP inflows)$_{t-1}$	0.00549***	0.00474**	0.00649***	0.00300
	(0.00150)	(0.00219)	(0.00192)	(0.00237)
ln (population)$_t$	−0.306	−0.701***	−0.172	0.478
	(0.198)	(0.240)	(0.253)	(0.344)
Observations	832	832	832	832
Adjusted R^2	0.977	0.955	0.969	0.954

Note: IDP = internally displaced persons; OLS = ordinary least squares. Robust standard errors in parentheses. All regressions include time and city fixed effects, as well as a city-specific linear trend.

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

Table 4. IDP and Rental Prices by Income Level, OLS, Weighted by Population

	(1) Average	(2) Low income	(3) Middle income	(4) High income
ln (IDP inflows)$_{t-1}$	0.00864***	0.00931***	0.00879***	0.00434
	(0.00135)	(0.00195)	(0.00177)	(0.00288)
ln (population)$_t$	0.163	0.316	−0.0250	−0.314
	(0.216)	(0.305)	(0.261)	(0.416)
Observations	832	832	832	832
Adjusted R^2	0.983	0.961	0.976	0.965

Note: IDP = internally displaced persons; OLS = ordinary least squares. Robust standard errors in parentheses. All regressions include time and city fixed effects, as well as a city-specific linear trend.

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

Table 5 provides a simple falsification test. Specifications are estimated in which future levels of IDP inflows (one year forward or in $t + 3$) replace the main explanatory variable (that is, IDP inflows in $t - 1$). The exercise finds that future levels of IDP inflows are not statistically related to any of the four relative rental prices. Reassuringly, the coefficient estimates are indeed near zero.

Table 5. Falsification Test: Future IDP and Rental Prices by Income Level, OLS

	(1)	(2)	(3)	(4)
	Average	Low income	Middle income	High income
ln (IDP inflows)$_{t+3}$	0.0000352	-0.00225	0.000984	0.000609
	(0.00154)	(0.00190)	(0.00200)	(0.00214)
ln (population)$_t$	−0.294	−0.696***	−0.157	0.486
	(0.201)	(0.240)	(0.257)	(0.345)
Observations	831	831	831	831
Adjusted R^2	0.977	0.955	0.969	0.954

Note: IDP = internally displaced persons; OLS = ordinary least squares. Robust standard errors in parentheses. All regressions include time and city fixed effects, as well as a city-specific linear trend.

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

INSTRUMENTAL VARIABLES RESULTS

Although the previous OLS results are consistent with a demand-side-shock impact of IDP inflows on relative rental prices, the estimated coefficients might still be biased, mainly because IDPs do not choose their destinations randomly. This section presents IV estimates of the reduced form relationship presented in equation (1).

Table 6 explores the strength of the proposed instrument.[9] Column (1) shows a positive and statistically significant unconditional relationship between IDP inflows and receptivity (as defined in page 13). Since both variables are in logs, the point estimate can be interpreted as an elasticity that is very close to 1. The proposed instrument exhibits strong predictive power (the implied first-stage F-statistic is 306) and alone explains more than 20 percent of the overall variation of IDP inflows. Column (2) adds city and quarter fixed effects and finds qualitatively similar results with an even stronger first stage. The implied first-stage F-statistic when city-level linear trends are added in column (3) is 180.06, suggesting that, conditional on the previously mentioned trends and both city and quarter fixed effects, receptivity is indeed a strong instrument. Adding population in column (4) does not wash out the strong predictive power of the proposed instrument. Finally, the specification in column (5) serves as a validity check showing that receptivity measures in $t + 1$ and $t + 2$ are statistically insignificant explanatory variables for IDP inflows and do not alter the strength of the instrument. Figures 6a and 6b, respectively, depict the unconditional and conditional (including the full set of controls) strong positive relationship between IDP inflows and

9. Other specifications for the reduced form relationship of IDP inflows and receptivity were also experimented with and found that receptivity in $t - 1$ is also a statistically significant predictor of IDP inflows in t. The point estimate is, however, three times smaller than for the case of receptivity in t. Adding receptivity in $t - 1$ in the first stage does not quantitatively affect the IV results. No other lag of receptivity is statistically significant in the first stage.

the receptivity measure.

Figure 6. First-Stage Results

a. Unconditional b. Conditional on Full Set of Controls

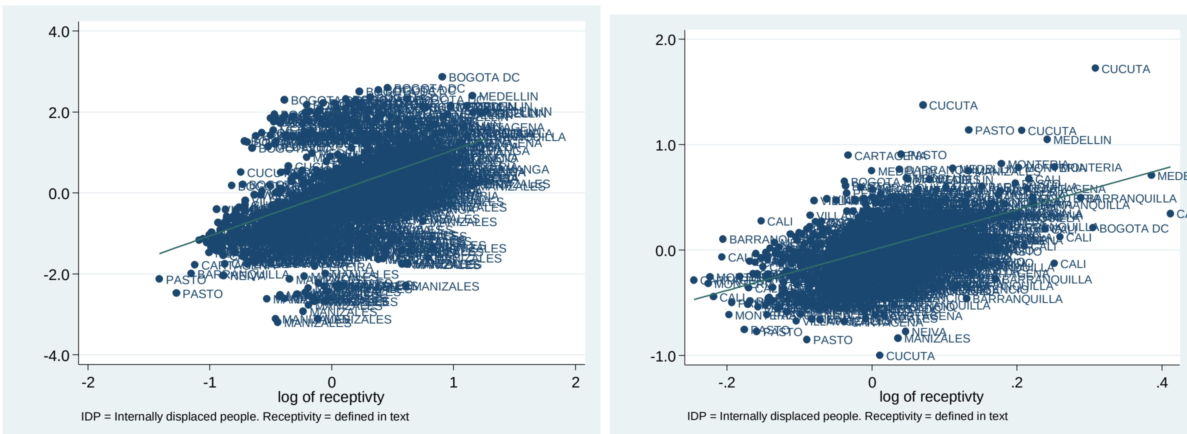


Table 7 presents IV estimations for the same specifications presented in table 4 to causally establish the impact of IDP inflows on rental prices in the host communities for varying levels of income. Column (1) of table 7 shows that the IDP inflows elasticity for the average relative rental price is statistically significant and 20 percent larger than in the OLS case. The elasticity is even larger for rental prices for low-income tenants, suggesting that a 1 percent increase in IDP inflows translates into a 0.008 percent increase in relative prices for the low-income segment of the rental market. Interestingly, the analysis does not find any effect for IDP inflows on relative rental prices for the middle-income segment (column (3)). It does show, however, that IDP inflows negatively affect relative rental prices for high- income tenants. One possible explanation for this result is that large IDP inflows could be perceived as a negative amenity by wealthy residents, thus pushing high-income rental prices down. Anecdotal evidence suggests that large inflows of IDPs have been associated with perceptions of crime and other social problems. Alternatively, the uncovered relationship might be explained by cheap labor provided by IDPs fueling expansions in the construction sector, such as the 2001–04 boom. Finally, when IDP inflows are as large as in Colombia’s principal cities, one cannot discard congestion externalities. For example, as transportation systems become congested and sidewalks become crowded with street vendors, higher strata residents suffer from these externalities without receiving the housing demand shock implied by the arrival of low-income forced migrants.

Table 6. First-Stage: IDP Inflows and Receptivity

	(1)	(2)	(3)	(4)	(5)
ln (receptivity)$_t$	1.061***	1.688***	1.910***	1.916***	1.811***
	(0.0607)	(0.0652)	(0.141)	(0.142)	(0.190)
ln (population)$_t$				−1.917	−2.120
				(3.978)	(3.971)
ln (receptivity)$_{t+2}$					0.172
					(0.179)
ln (receptivity)$_{t+1}$					0.0399
					(0.200)
Observations	832	832	832	832	832
Adjusted R^2	0.221	0.902	0.935	0.935	0.935
City fixed effects	N	Y	Y	Y	Y
Time fixed effects	N	Y	Y	Y	Y
City-specific linear trend	N	N	Y	Y	Y

Note: IDP = internally displaced persons. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

How large are the estimated impacts? The elasticity of the effect of IDP inflows on average relative rental prices is 0.0065. The sample average of log relative rental prices is 0.07 with a standard deviation of 0.08. The sample average of log IDP inflows is 7.06 with a standard deviation of 1.09. Thus, the standardized coefficient of $\widehat{\beta}$ is 0.09. That is, a 1 standard deviation increase in the independent variable translates into a 0.09 standard deviation increase in the dependent variable.

Displacement in 2002 was particularly harsh. During the first quarter the average across cities reached a high point of 2,951. Santa Martá, in the Colombian Caribbean, had the second- highest change in IDP flows between 2001:Q1 and 2002:Q1, behind Bogotá. In Santa Martá displacement increased by 12,178 persons between these two quarters. According to the estimates in this analysis, this increase in IDP inflows would translate into a 0.026 percent increase in average rental prices, a 0.034 percent increase in low-income rental prices, and a 0.047 percent decrease in high-income rental prices. To get a sense of these magnitudes, they can be compared with the unconditional average change in rental prices in the same quarter between two consecutive years. Those are −0.014 percent (average), −0.01 percent (low income), and −0.021 percent (high income). Thus, the estimates are large in the sense that large inflows can dominate the unconditional evolution of prices.

It is difficult to compare these estimates with those in other papers since, in the context of forced migration, few papers use actual inflows. Additionally, papers that use rental prices as the dependent variable are not in a forced-migration context. However, these results can be compared with the two papers most related to this report. Calderón-Mejía and Ibáñez (2015), in their work on the effect of IDP inflows on wages, find larger elasticities (−0.08). Turning to a paper that estimates the effects of population inflows on rental prices, Saiz (2007) finds that immigration inflows equal to 1 percent of a city's population are associated with a 1 percent increase in rent prices for housing. In our framework, an IDP inflow equivalent to 1 percent of the average city population would result in an increase of 0.025 percent in average relative rental prices. Thus, even if hard to compare rigorously, these estimates seem smaller than estimates of the effects of IDP inflows on prices from other studies. This is not surprising since (1) the push in labor supply might be much larger than the push in housing demand, and in the short term both labor demand and housing supply might be inelastic; (2) IDPs have less purchasing power than economic migrants; and (3) this analysis finds heterogeneous effects (the decrease in high-income rental prices) that pull the average effect downward. In sum, our educated guess (given that estimates are not directly comparable) is that the estimates in this study are lower than those found in other studies.

If the IV regressions are weighted by municipality population, as in table 8, the results are qualitatively similar to those in table 7, although the coefficients are much larger.

Table 7. IDP and Rental Prices by Income Level, IV

	(1) Average	(2) Low income	(3) Middle income	(4) High income
ln (IDP inflows)$_{t-1}$	0.00643**	0.00845**	0.00395	−0.0115**
	(0.00264)	(0.00381)	(0.00313)	(0.00553)
ln (population)$_t$	−0.308	−0.710***	−0.167	0.511
	(0.198)	(0.241)	(0.254)	(0.347)
Observations	832	832	832	832
Adjusted R^2	0.977	0.955	0.969	0.952

Note: IDP = internally displaced persons; IV = instrumental variables. Robust standard errors in parentheses. All regressions include time and city fixed effects, as well as a city-specific linear trend.

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

Now a robustness check is performed for the validity of the proposed instrument. Particularly, interaction terms between the quarter dummies are added to the main specification (that is, a time fixed effect), as is a measure of remoteness based on the average distance from the host city to all other Colombian municipalities. We believe this is a stringent test.

Nonetheless, the results presented in table 9 suggest that the proposed instrument was not picking up the potential effect of a time-varying nationwide shock amplified by the remoteness of the host city. For instance, this robustness check should mitigate concerns that the proposed instrument was confounding with varying transportation costs, which depend on gas prices (absorbed by the first term of the interaction, that is, quarter dummies) and average distance required to reach city *c* (partially accounted for by the remoteness measure, the second term in the interaction).

Table 8. IDP and Rental Prices by Income Level, IV, Weighted by Population

	(1)	(2)	(3)	(4)
	Average	Low income	Middle income	High income
ln (IDP inflows)$_{t-1}$	0.0118***	0.0230***	0.00477	−0.0184***
	(0.00247)	(0.00416)	(0.00309)	(0.00659)
ln (population)$_t$	0.199	0.474	-0.0714	−0.576
	(0.221)	(0.335)	(0.262)	(0.457)
Observations	832	832	832	832
Adjusted R^2	0.983	0.958	0.976	0.961

Note: IDP = internally displaced persons; IV = instrumental variables. Robust standard errors in parentheses. All regressions include time and city fixed effects, as well as a city-specific linear trend.

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

E. Potential Impact of IDP Inflows on Food Prices

This analysis hypothesizes that the arrival of IDPs will result in an increase in food prices, particularly for the low-income segment. The resulting population increase creates a positive demand-side shock, putting upward pressure on prices. At the same time, the transfer of large numbers of workers from rural, agricultural regions to Colombia's cities is expected to reduce agricultural output, again putting upward pressure on prices. While this price increase may be partially offset if IDP arrival reduces wages in host communities, as suggested by Calderón-Mejía and Ibáñez (2015), the net effect is expected to be an increase in food prices. Another possibility working in the opposite direction from a demand shock is the existence of food aid programs that could depress food prices by introducing a positive supply shock. It has been shown for Tanzania that food aid may negatively affect some food prices (Alix-Garcia and Saah 2010). Although such programs do exist in Colombia, food security appears to be low among the internally displaced population (IDMC 2011).

Table 9. Robustness Check: IDPs and Rental Prices by Income Level, IV, Controlling for Trends by Remoteness

	(1)	(2)	(3)	(4)
	Average	Low income	Middle income	High income
ln (IDP inflows)$_{t-1}$	0.00793***	0.00902***	0.00633**	−0.00678
	(0.00239)	(0.00325)	(0.00296)	(0.00531)
ln (population)$_t$	−0.0108	0.239	−0.316	−0.350
	(0.203)	(0.245)	(0.262)	(0.356)
Observations	832	832	832	832
Adjusted R^2	0.980	0.962	0.971	0.956

Note: IDP = internally displaced persons; IV = instrumental variables. Robust standard errors in parentheses. All regressions include time and city fixed effects, as well as a city-specific linear trend. All specifications include as additional controls interactions between remoteness and quarter dummies.

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

To test this hypothesis, the same models run for rental prices are used, replacing relative rental housing prices with relative food prices. Results for the OLS regressions are presented in table 10. Unexpectedly, the estimates are negative for all regressions, and significant for all except the low-income segment.

Of course, migrants' preferences may be biasing these results. When victims of violence are displaced, they are more likely to prefer a city where the cost of living is low, all else equal. Using the receptivity instrument introduced in the rental housing prices section, the exercise follows an IV approach in an attempt to remove this endogeneity. Results for the second-stage regression are presented in table 11. Again, the results are unexpectedly negative and highly significant, here with a larger effect size than in the OLS estimates, and also significant for the low-income segment.

One explanation for these results could be that the negative effect on local wages found by Calderón-Mejía and Ibáñez (2015) works to reduce food prices and simply outweighs the expected positive impact on food prices resulting from the increased demand that would come with the arrival of a large number of new residents. The results from Calderón-Mejía and Ibáñez (2015) show that the negative effect on wages was particularly strong for self-employed workers, especially those with little education. Though purely speculative, it is possible that some of these self-employed workers opened small grocery stores or street vending stalls. Thus, in addition to the potential for reducing demand via lower wages, the influx of new labor into the urban host communities could also have reduced food prices by increasing competition among food vendors.

Table 10. OLS Estimates for IDP Arrival and Food Prices, by Income Level

	(1) Average	(2) Low income	(3) Middle income	(4) High income
ln (IDP inflows)$_{t-1}$	−0.00320**	−0.00235	−0.00306**	−0.00720***
	(0.00143)	(0.00169)	(0.00143)	(0.00133)
ln (population)$_t$	0.760***	1.337***	0.507***	0.219
	(0.143)	(0.170)	(0.142)	(0.144)
Observations	832	832	832	832
Adjusted R^2	0.956	0.942	0.957	0.965

Note: IDP = internally displaced persons; OLS = ordinary least squares. Robust standard errors in parentheses. All regressions include time and city fixed effects, as well as a city-specific linear trend.

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

Table 11. Second-Stage Estimates for IDP Arrival and Food Prices, by Income

	(1) Average	(2) Low income	(3) Middle income	(4) High income
ln (IDP inflows)$_{t-1}$	−0.0129***	−0.0127***	−0.0127***	−0.0149***
	(0.00282)	(0.00316)	(0.00282)	(0.00282)
ln (population)$_t$	0.782***	1.360***	0.529***	0.237
	(0.149)	(0.175)	(0.149)	(0.145)
Observations	832	832	832	832
Adjusted R^2	0.952	0.938	0.953	0.963

Note: IDP = internally displaced persons. Robust standard errors in parentheses. All regressions include time and city fixed effects, as well as a city-specific linear trend. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

An additional, more worrisome possibility is that additional sources of endogeneity are present in the food prices regressions, causing the instrument to fail. When the OLS falsification test presented in table 5 is run again, replacing rental prices with food prices, the results are negative and highly significant for all income segments. As table 12 shows, the two-stage least squares strategy does not correct this problem. In fact, the estimates shown in table 12 suggest that the impact of future displacement is even larger than the impact of lagged displacement presented in table 11.

One explanation for this finding is that lower food prices may actually work to increase violence, creating a reverse causality effect in the estimates that the instrument fails to remove. For example, to the extent that lower food prices may imply lower income in the agricultural sector, farmers may substitute cultivation of illicit crops, such as coca, for low-revenue-generating crops.

Table 12. Second-Stage Estimates for the Falsification Test with Food Prices, by Income Level

	(1)	(2)	(3)	(4)
	Average	Low income	Middle income	High income
ln (IDP inflows)$_{t+3}$	−0.0169***	−0.0135***	−0.0179***	−0.0217***
	(0.00285)	(0.00332)	(0.00288)	(0.00322)
ln (population)$_t$	0.754***	1.333***	0.501***	0.206
	(0.149)	(0.171)	(0.149)	(0.159)
Observations	831	831	831	831
Adjusted R^2	0.952	0.940	0.952	0.960

Note: IDP = internally displaced persons. Robust standard errors in parentheses. All regressions include time and city fixed effects, as well as a city-specific linear trend.

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

This could be especially true when prices are lower in the nearest market for farmers' goods, such as the nearest of Colombia's 13 main metropolitan areas. This increased cultivation of illicit crops should increase violence and forced displacement in these areas. The instrument would fail to remove the reverse causality in this case. This could also explain the larger effect magnitudes for future displacement because farmers would need time to react to new price information before making crop-substitution decisions. However, it is important to note that these reverse causality problems are specific to the food prices case, and should not be present in the other estimates, such as those for rental housing prices, where the instrument continues to meet the exclusion restrictions for a valid instrument.

4. Poverty

Empirical strategies similar to those for prices are used to evaluate the impact of IDP inflows on poverty measures. However, the structure of the data and the samples are different. First these data are presented, then adapted versions of the econometric models described above are examined, and finally the results are presented and discussed.

A. Data

The poverty outcomes used in this analysis come from two sources. One source corresponds to measures of UBN from the censuses of the National Department of Statistics (DANE). UBN is a measure of the percentage of poor households in the municipality, a measure of poverty that is commonly used in Latin America. A household unit is classified as poor if it lives in an inappropriate dwelling, if it lacks access to basic public services such as sewerage and running water, if its members live in overcrowded rooms, if any children between 7 and 11 years of age do not attend school, or if it presents a high dependency ratio. The censuses of 1993 and 2005 contain two cross-sections of UBN data for which the observation unit is the municipality ($N = 1{,}100$).

Table 13. Poverty: Descriptive Statistics of Main Variables

		Mean	Standard deviation	Observations
Panel A: Census cross-sections				
UBN 1993		53.03	19.20	1,033
UBN 2005		44.77	20.72	1,108
100 × Inflows/population	1993	0.30	0.78	1,033
100 × Inflows/population	2005	7.03	16.49	1,108
Panel B: ELCA panel				
Consumption (pesos)	270,069.94		242,816.77	18,925
100 × Inflows/population	0.876		1.05	18,925

Note: UBN = Unfulfilled Basic Needs. Robust standard errors in parentheses.

Both panels report summary statistics of our main variables. Panel A focuses on the censuses while panel B focuses on the household panel-data.

The second source of poverty outcomes is the Encuesta Longitudinal Colombiana de la Universidad de los Andes (ELCA). This is a longitudinal survey conducted by the Universidad de Los Andes that follows a random sample of households in urban and rural areas below the 67th percentile of wealth in 2010. Longitudinal data from the two existent waves, 2010 and 2013, are used. A measure of real per capita consumption expenditures at the household level is constructed, aggregating detailed household expenditures on consumption items. This measure (abbreviated as Consumption from now on) is a monthly average analogous to that used by the

Colombian Department of Statistics to determine whether a household falls below the poverty line. For instance, for 2010, a household falls below the poverty line if monthly Consumption is less than 207,005 pesos (US$82) in urban areas or less than 123,502 pesos (US$48.62) in rural areas (these definitions correspond to those of the National Department of Statistics). This research sticks to the variable in levels.

Measures of inflows and the corresponding receptivity instrument are computed at the municipality level. For the census cross-sections, total inflows during the previous five years are used: from 1988 to 1992 for the 1993 census and from 2000 to 2004 for the 2005 census. For the ELCA panel, which is distributed across 79 municipalities in 2010, the total inflows during the two years previous to each round are used.

The measures of inflows are either the natural logarithm of 1 plus total inflows or the percentage of inflows that the host municipality receives. The tables clearly indicate which measure is used in each specification.

Descriptive statistics for the main variables used in the poverty section are presented in table 13. These summary statistics are useful for interpreting the magnitudes of the estimates. The census data (panel A in table 13) again reflect the large increase in displacement during the period 2000–04. In this period, average inflows are more than two orders of magnitude larger than in the period 1989–92.

B. Empirical Models

With each of the cross-sections of the census the following regression is estimated,

$$UBN_m = \alpha + \beta IDPInflows_m + \eta' C_m + \epsilon_m \quad , \qquad (3)$$

where UBN_m represents unfulfilled basic needs for municipality m, α is a constant term, $IDPInflows_m$ is one of the two measures of past inflows, C_m is a vector of controls, and $\boldsymbol{\epsilon_m}$ is a heteroscedasticity corrected standard error. Equation (3) is estimated by OLS or by two-stage least squares using, as before, $Receptivity$ as an instrument. Because past inflows are measured for longer time spans (in contrast with the quarterly data), here receptivity is measured for the same period. The set of controls always includes the average distance to other municipalities to ensure that receptivity is not being confounded with remoteness. The log of the municipality's population is also controlled for.

The ELCA panel data allows a much more rigorous test of the effects of displacement inflows on poverty outcomes to be performed. The analysis takes full advantage of the panel structure of the ELCA to estimate equation (4),

$$Consumption_{hmt} = \delta IDPInflows_{mt} + \gamma' G_m + d_h + d_t + v_{hmt} \ , \quad (4)$$

where $Consumption_{hmt}$ is the monthly per capita consumption of household h living in municipality m at time t. $Inflows$ has the same meaning as above, G are controls that include average distance to other municipalities, d_h are household fixed effects, and d_t are time dummies. The term v_{htm} is the error term, which allows for intracluster correlation at the municipality level to correct for the fact that this is the level at which IDP inflows are observed.

C. Results

UNFULFILLED BASIC NEEDS

Table 14. Unfulfilled Basic Needs and IDP Inflows: Cross-Sections OLS

	(1) UBN1993	(2) UBN2005	(3) UBN1993	(4) UBN2005
ln (inflows + 1)	2.283***	1.533***		
	(0.273)	(0.304)		
100 × Inflows/population			3.774***	0.167***
			(0.558)	(0.0419)
ln (population)	−8.250***	−7.496***	−5.679***	−5.311***
	(0.565)	(0.626)	(0.451)	(0.394)
ln (distance)	44.79***	37.39***	44.10***	39.28***
	(1.983)	(2.160)	(2.022)	(2.091)
Observations	1,033	1,108	1,033	1,108
Adjusted R^2	0.394	0.343	0.378	0.344

Note: IDP = internally displaced persons; OLS = ordinary least squares. Robust standard errors in parentheses.

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

Table 14 shows the parameter estimates derived from estimation of equation (3). All columns use UBN as the dependent variable and all columns control for population and average distance to other municipalities. Column (1) uses the cross-section of 1993, and the definition of IDP inflows is in logs. The parameter estimate of interest, $\widehat{\beta}$, is equal to 2.28 with a standard error of 0.27. The interpretation of this coefficient is that a 1 percent increase in (IDP inflows + 1) is associated with an increase of 0.023 in poverty as measured by UBN, or 0.04 percent with respect to the mean. Similarly, for 2005, an increase of 1 percent in (IDP inflows + 1) is significantly associated with an increase of 0.015 in UBN, or 0.03 percent with respect to the mean.

Columns (3) and (4) of table 14 use an alternative measure of inflows, the percentage of the host municipality population received as inflows in the previous five years. Results are qualitatively similar: more IDP inflows are correlated with more poverty. How large are these correlations? We can calculate standardized coefficients using the statistics in table 13. The corresponding standardized coefficients are 0.15 and 0.13, which are not quantitatively negligible.

The OLS results are informative, but too many omitted variables at the municipality level could be accounting for the documented association. Imagine, for example, that IDPs take into account the quality of public goods in their migration decisions. In this case, inflows would be positively correlated with, say, school quality, but school quality would in turn be negatively correlated with UBN. The consequence of this would be OLS estimates that are biased downward. Instead of trying to control for all of these omitted factors, the analysis relies on an IV strategy in which inflows are instrumented with a distance-weighted sum of IDP outflows in the rest of the country, the $Receptivity$ measure (in logs). Results of the IV estimates are presented in table 15.

Table 15. Unfulfilled Basic Needs and IDP Inflows: Cross-Sections IVs

	(1) UBN1993	(2) UBN2005	(3) UBN1993	(4) UBN2005
ln(Inflows + 1)	5.351***	4.225***		
	(0.555)	(0.771)		
100 × Inflows/population			11.27***	0.770***
			(2.061)	(0.175)
ln (population)	−12.11***	−11.31***	−.283***	−5.258***
	(0.845)	(1.156)	(0.477)	(0.594)
ln (distance)	44.53***	32.48***	42.33***	36.03***
	(2.105)	(2.715)	(2.062)	(2.812)
First-stage F-statistic	122.636	143.308	22.730	33.053
Observations	1,033	1,108	1,033	1,108
Adjusted R^2	0.323	0.292	0.286	0.115

Note: IDP = internally displaced persons; IV = instrumental variable; UBN = Unfulfilled Basic Needs. Robust standard errors in parentheses.

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

Table 15 has the same structure as table 14, except that it also now reports the first-stage F-statistic. As in the sample of prices, receptivity is a strong predictor of inflows, either in logs or normalized by population, although the F-statistic is much larger for the logged variable. The IV estimates confirm the sign of the OLS estimates, but they are generally three times larger. Standardized coefficients of the parameters in columns (3) and (4) are 0.45 and 0.61, respectively.

UBN are indeed increasing in IDP inflows. However, this is not really the effect of IDP inflows on host communities since a nontrivial share of displaced people are included in the calculation of UBN. Besides, the results so far might just reflect a reallocation of poor people (IDPs) across municipalities. To get closer to the true effect of IDP inflows on host communities, a distinction needs to be made between the established host population and the newly arriving displaced population. Data from the ELCA panel allows the exercise to accomplish this, using the method described in the following subsection.

ELCA PANEL

Equation (4) is now estimated, which allows us to assess how changes in IDP inflows at the municipality level translate into changes in household per capita consumption. These are the central results for poverty outcomes.

Table 16. Per capita Consumption Expenditures and IDP Inflows: ELCA panel

	(1)	(2)	(3)	(4)
	OLS	OLS	IV	IV
ln (Inflows + 1)	−10,936.2		−64,860.6***	
	(7,985.2)		(23,339.7)	
100 × Inflows/population		−10,370.1***		−44,494.7*
		(3,582.0)		(23,807.7)
ln (population)	25,038.1**	115,358.1	112,926.3	−80,416.2
	(11,363.1)	(116,416.1)	(208,156.3)	(167,365.7)
t2013(Dummy for second wave in the panel)	34,563.2***	3,3141.1***	12,373.2	25,278.5***
	(5,427.2)	(4,086.2)	(10,501.5)	(7,140.1)
First-stage F-statistic			6.487	2.650
Observations	16,514	15,626	15,626	15,626
Adjusted R^2	0.571	0.577	0.570	0.569

Note: IV = instrumental variable; OLS = ordinary least squares. Standard errors clustered at the municipality level in parentheses. Fixed effects at the household and time levels.

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

Table 16 presents results of estimating equation (4) by OLS and IV using the two measures of inflows. The sample is restricted to nonmigrant households (94.64 percent), and the way in which their welfare (Consumption) responds to the arrival of IDPs to their municipality is examined. Across specifications, the message is consistent:

higher IDP inflows translate into lower per capita consumption. The estimate in column (4), $\hat{\delta} = 44{,}4494.7$(standard error = 23,807.7) implies that a 1 standard deviation increase in inflows (1.03, see Table 13 where we present descriptive statistics of inflows) entails a decrease in Consumption of 0.09 standard deviations, a smaller effect compared with the effect on UBN, as expected since here the analysis is not taking into account those who are displaced by violence. A 1 standard deviation increase in IDP inflows would be more than enough to nullify average consumption growth in the period (t2013 = 25278.5). Again, the IV estimates are higher than the OLS estimates, a result that is consistent with relatively richer areas receiving more inflows.

5. IDP Inflows and Public Finances

This section examines the potential impact of IDP inflows on local public finances, specifically on public investment, at the municipality level. Colombia is an interesting case study given its high degree of municipality-level decentralization when compared with other Latin American countries. The funds available to local governments come either from the central government or from local taxes. The central government automatically transfers funds to municipalities using complex fiscal rules established in the SGP (Sistema General de Participaciones). Transfers from the central government also depend on the extraction of mining and oil resources in the municipality (royalties). Local taxes comprise property taxes, business taxes, and the oil surcharge. The extent of autonomy that municipalities have in investing transfers from the government varies from one municipality to another according to their size and to the achievement of some specific goals. Municipalities are autonomous in the investment of their own revenues. Here the analysis focuses on total investment in health and education (from all sources of funding), independent of the autonomy of the municipality. The empirical exercise is thus quite simple: it analyzes how expenditures in education and health change as inflows increase.

The empirical strategy is similar to the one used to evaluate the impact of IDP inflows on prices (see subsection 3C). However, the structure of the data and the samples are different. The analysis exploits a panel of Colombian municipalities for which a series of expenditure data in education and health, as well as the number of students covered, is available for the period 2000–06. This section starts by presenting these data, then presents adapted versions of the econometric models described above, and finally presents and discusses the results.

A. Data

Local public finance data at the municipality level come from Dirección Nacional de Planeación, the Colombian Department of National Planning. Two expenditure series are exploited: investment in education per enrolled student and investment in health per inhabitant. The regressions use the logarithm of these variables (plus 1) as dependent variables. The data on the total number of enrolled students come from Formulario C600 (DANE), a census of education institutions. Sample size varies depending on the availability of the expenditure data. Information from 903 municipalities is used in the analysis of investment in education and health. Instead of using the dependent variables in logs, simple rates could be used. However, to simplify interpretation of coefficients and to reduce dispersion in the data, the analysis continues to use logs. Nonetheless, the conclusions are unmodified if we simply use the rates.

B. Empirical Strategy

To estimate the impact of IDP on public expenditures the following equation is estimated:

$$\ln\left(1 + y_{m,t}\right) = \alpha + \beta \ln\left(1 + Inflows_{m,t-1}\right) + \eta' X_{m,t} + d_m + d_t + u_{m,t}\ , \quad (5)$$

where the subscripts m and t denote municipality and year, respectively. The variable y is one of the two expenditure outcomes under study: either investment in education per enrolled student or investment in health per inhabitant. The treatment variable is IDP inflows lagged one period and the control variables are the same as in the rental price analysis. Because the set of municipalities is larger than that used in the price regressions, a number of observations in this sample have zero IDP inflows. Therefore, 1 is added to the inflows when taking the logarithm, to prevent losing these observations. Again, estimating equation (5) by OLS may still lead to biased estimates of the impact of IDP inflows. Therefore, the IV approach is repeated using the receptivity measure at the municipality level.

C. Results

IMPACT ON INVESTMENT IN EDUCATION

An influx of IDPs may lead to an increase in school enrollment. As such, this exercise asks whether an increasing number of IDPs could translate into lower levels of investment in education per enrolled student in the municipality. Table 17 presents estimates from different OLS and IV specifications. Column (1) only includes d_m and d_t as controls, with results suggesting a statistically significant negative association between IDP inflows and investment in education per student. Adding municipality-specific linear trends (in column (2)) and controlling for total population of the municipality and the interaction of remoteness with time dummies (in column (3)) does not qualitatively alter the previous result. The implied elasticity suggests that a 1 percent increase in IDP inflows would entail a reduction in education investment of 0.021 percent. Column (4) estimates the last specification by IV using the receptivity instrument. Despite the fact that the first stage is quite strong (F-statistic = 275.7) and that the sign of point estimates remains negative, the analysis does not find, under the standard levels of confidence, any statistically significant relationship between IDP inflows and investment in education. When the regression is weighted by municipality population, a statistically insignificant relationship is again found.

IMPACT ON INVESTMENT IN HEALTH

Focusing on investment in health, in general, the OLS estimates in table 18 suggest that there is no statistical association between IDP inflows and investment in health per inhabitant at the municipality level. The exception is column (1), which indicates that an increment of 1 percent in IDP inflows is associated with a 0.018 percent increase in health investment in per capita terms. The result in column (1) is significant at the 5 percent level but it becomes insignificant when adding controls. Similarly, when using the IV specifications, no empirical evidence of an impact of IDP inflows on investment in health is found. Although the IV point estimates are indeed negative, the analysis fails to reject the null hypothesis of a zero effect at standard significance levels in both the unweighted (column (4)) and weighted (column (5)) cases.

Table 17. Investment in Education and IDP Inflows: City Panel

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	IV	IV-Weighted
ln (1+IDP inflows)$_{t-1}$	−0.0192*	−0.0212**	−0.0205*	−0.0854	−0.244
	(0.00989)	(0.0106)	(0.0104)	(0.0587)	(0.157)
ln (population)$_t$			0.346	0.339	-0.970
			(1.712)	(1.714)	(2.960)
Observations	6,311	6,311	6,311	6,311	6,311
Adjusted R^2	0.387	0.555	0.562	0.558	0.752
City-specific linear trend	N	Y	Y	Y	Y
Remoteness-year interaction fixed effects	N	N	Y	Y	Y
First-stage F-statistic	.	.	.	275.7	93.53

Note: IDP = internally displaced persons; IV = instrumental variables; OLS = ordinary least squares. Robust standard errors in parentheses. All regressions include time and city fixed effects.

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

The inquiry was unable to detect a causal relationship between investment in per capita terms and previous-period IDP inflows. For the education variable, some IDPs might enroll in school and appear in the denominator, but this is likely to be minimal since the investigation was focusing on IDP inflows in $t - 1$. For the health variable, the population measures are estimated by DANE and do not take into account IDP inflows. Thus, the education and health measures can be thought of as capturing investments relative to the host population. Surprisingly, the data do not allow us to conclude that the arrival of IDPs crowds out the investment that host students and inhabitants receive from the government.

However, these regressions must be interpreted carefully for two reasons: First, a better understanding is needed of how the arrival of IDPs unleashes expenditures from the different levels of government, and this requires a deep understanding of the political economy of decentralization, an important task that is beyond the scope of this report. Second, the preliminary analysis of the expenditure data suggests that these are noisy measures, which complicates the statistical analysis and might be reflected in the noisiness of the estimates.

Table 18. Investment in Health and IDP Inflows: City Panel

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV-Weighted
ln (1+IDP inflows)$_{t-1}$	0.0182**	0.00500	0.00718	−0.00451	−0.105
	(0.00864)	(0.00931)	(0.00910)	(0.0546)	(0.0935)
ln (population)$_t$			−2.488	−2.489	−7.807***
			(1.536)	(1.535)	(2.290)
Observations	6,321	6,321	6,321	6,321	6,321
Adjusted R^2	0.472	0.536	0.547	0.547	0.614
City-specific linear trend	N	Y	Y	Y	Y
Remoteness-Year interaction fixed effects	N	N	Y	Y	Y
First-stage F-statistic	.	.	.	278.2	93.95

Note: IDP = internally displaced persons; IV = instrumental variables; OLS = ordinary least squares. Robust standard errors in parentheses. All regressions include city and year fixed effects.

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

6. Public Policy Implications

Policy makers need to take into account a variety of considerations before implementing policies to address the unintended secondary effects of the arrival of large numbers of forced migrants. Are forced migrants integrating into the local housing market or are they put into designated housing, where they are not competing in the local market? Similar questions should be asked about the effects of their participation in other markets, such as those for food and labor. What is the current dynamic in urban-rural inequality, or in inequality between workers, small entrepreneurs, and owners of larger businesses? Given the specific context, how does a forced migration crisis affect these dynamics and to what extent are the redistributive effects undesirable and politically sustainable?

These questions should inform policy decisions, and are necessary and important given the great diversity in the circumstances of forced population movements across the world. Therefore, while the policy implications of this report's findings are practical and important, they should be interpreted with caution. Policy makers in any refugee or IDP setting will need to take into account important variables within the context in which they are operating. For this reason, this section takes a comparative approach to the discussion of policy implications.

HOUSING POLICY

The first and most obvious message from these results is that extreme violence resulting in mass displacement can have secondary effects beyond the direct victims of conflict.

Specifically, the arrival of large numbers of IDPs can increase housing rental prices for the existing residents of the communities that receive them. The results of this inquiry suggest this is especially true for the poorest segments of the population, while prices may actually fall in the high-income rental market, perhaps because proximity to large displaced populations reduces demand in high-income markets. This effect has largely been ignored by policy makers, but has important implications in Colombia, where displaced families generally receive housing subsidies from the government, working against segments of the nondisplaced population who receive no assistance. Indeed, housing programs should be aimed at assisting low-income groups regardless of their displacement status, not only to avoid envy and erosion in social cohesion, but also to facilitate the integration of the displaced people in host communities.

However, these effects will depend greatly on context, and policies addressing these effects should be adjusted accordingly. Evaluations from Miami, and the United States more widely, confirm this report's findings, and suggest that the arrival of large numbers of relatively low income migrants increases rental prices in the low-income housing segment. Yet, these results conflict with those of Alix-Garcia, Bartlett, and Saah (2012), who find that the arrival of displaced persons to Nyala from Darfur increased housing prices in high-income neighborhoods. Displaced persons in this context were placed in camps rather than integrating into the local housing market, while large numbers of high-income foreign aid workers settled in high-income neighborhoods. Policy makers may consider the lesson of the relative merits of providing housing subsidies versus constructing new housing. For both IDP and refugee settings, it is also important for policy makers to consider that the effect of these price increases may be redistributive rather than a deadweight loss. The wider implications of this wealth redistribution will also need to be considered.

POVERTY

Similarly, by using data from the ELCA panel and restricting observations to ensure the displaced population is excluded from the sample, this report's findings suggest that the arrival of IDPs in Colombia's largest cities has also reduced the consumption power of nondisplaced households in those cities. Part of this effect could be due to upward pressure on the demand side, and might be addressed through policies discussed in the previous subsection. On the supply side, the results from Calderón-Mejía and Ibáñez (2015) suggest that another aspect is downward pressure on native residents' employment prospects caused by competition with new arrivals. Thus, in the context of IDPs, policies need to take into account that the number of vulnerable people is increasing on two fronts: directly, from the arrival of IDPs, and indirectly, from the deteriorating standards of living of host community residents.

Here again the importance of context must be highlighted. The arrival of IDPs in Colombia's largest cities may lead to increased competition with local workers, suppression of wages, and increased difficulty in finding employment in those cities. In contexts in which displaced persons are concentrated in rural areas, they may compete more with agricultural workers, reducing food prices and raising the consumption power of urban workers. How aid is delivered is also important. If food assistance comes from local sources or displaced persons are given food subsidies, food prices may increase in the areas in which they are concentrated. If this assistance comes from foreign food supplies, pressure on food prices may be downward. Maystadt and Verwimp (2014) also underline the importance of considering the preferences of those forcibly displaced vis-à-vis native locals. One important message may be the need for more concerted resettlement efforts, taking into account local capacity to absorb displaced persons.

Of course, the effects of IDP shocks on host communities may dissipate in the long run as the economy returns to equilibrium, yet these long-run effects are not well studied (Ruiz and Vargas-Silva 2013). The duration of these effects would undoubtedly be of interest to policy makers because costly interventions may be less desirable if the effects generally only persist in some arbitrarily acceptable short term.

Finally, it is important to note that, albeit statistically significant, the economic magnitudes of the documented effects on rental and food prices, as well as on poverty, are rather small. Nonetheless, public perceptions might actually differ from the actual impact the forcibly displaced have on host communities. Therefore, in addition to the aforementioned policies aimed at tackling the potential distributional impact of the phenomenon under study, policies to inform the public and influence negative public perceptions that might not correspond to reality should also be considered by policy makers.

Appendix

Results for Inflows Instrument (Excluding IDP Outflows from Municipalities within 50 km)

Table A1. First-Stage for Price Regressions: 50+ km Instrument Robustness Check

	(1)	(2)	(3)	(4)	(5)
Inflow instrument 50+ km	1.012***	1.605***	1.481***	1.490***	1.472***
	(0.0638)	(0.0727)	(0.174)	(0.176)	(0.238)
ln (population)$_t$				−1.708	−1.905
				(4.427)	(4.457)
Inflow instrument 50+ km (t+2)					0.207
					(0.197)
Inflow instrument 50+ km (t+1)					−0.132
					(0.251)
Observations	832	832	832	832	832
Adjusted R^2	0.194	0.888	0.922	0.922	0.922
City fixed effects	N	Y	Y	Y	Y
Time fixed effects	N	Y	Y	Y	Y
City-specific linear trend	N	N	Y	Y	Y

Note: Robust standard errors in parentheses. Instrument is the sum of internally displaced persons (IDP) outflows from all other municipalities farther than 50 kilometers from the destination city, divided by the distance between the destination city and the muncipality of origin.

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

Table A2. Second Stage for Rental Prices: 50+ km Instrument Robustness

	(1)	(2)	(3)	(4)
	Average	Low income	Middle income	High income
ln (IDP inflows)$_{t-1}$	0.00454	0.00924	−0.00187	−0.0218**
	(0.00411)	(0.00611)	(0.00481)	(0.00872)
ln (population)$_t$	−0.303	−0.712***	−0.153	0.534
	(0.198)	(0.241)	(0.258)	(0.357)
Observations	832	832	832	832
Adjusted R^2	0.977	0.954	0.968	0.948

Note: Robust standard errors in parentheses. All regressions include time and city fixed effects, as well as a city-specific linear trend. Instrument is the sum of internally displaced persons (IDP) outflows from all other municipalities farther than 50 kilometers from the destination city, divided by the distance between the destination city and the muncipality of origin.

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

Table A3. Second Stage for Food Prices: 50+ km Instrument Robustness Check

	(1)	(2)	(3)	(4)
	Average	Low income	Middle income	High income
ln (IDP inflows)$_{t-1}$	−0.0177***	−0.0182***	−0.0173***	−0.0184***
	(0.00472)	(0.00530)	(0.00470)	(0.00444)
ln (population)$_t$	0.793***	1.373***	0.540***	0.245
	(0.157)	(0.183)	(0.157)	(0.149)
Observations	832	832	832	832
Adjusted R^2	0.947	0.932	0.948	0.961

Note: Robust standard errors in parentheses. All regressions include fixed effects for city and time, and a city-specific linear trend. Instrument is the sum of internally displaced persons (IDP) outflows from all other municipalities farther than 50 kilometers from the destination city, divided by the distance between the destination city and the municipality of origin.

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

Table A4. Second Stage for Household Consumption (ELCA Data): 50+ km Instrument Robustness Check

	(1)	(2)
	IV	IV
100 × Inflows/population	−44,160.1	
	(36,188.9)	
ln (inflows + 1)		−50,305.3
		(30,438.1)
ln (population)	−784,96.7	126,822.9
	(211,878.2)	(167,824.4)
t2013	25,355.6**	17,569.9
	(9,651.1)	(11,644.0)
First-stage F-statistic	1.387	3.596
Observations	15,626	15,626
Adjusted R^2	0.569	0.573

Note: IV = instrumental variables. Standard errors clustered at the municipality level in parentheses. All regressions include fixed effects for household and time.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0$.

Table A5. Second Stage for Investment in Education: 50+ km Instrument Robustness Check

	(1)	(2)
	IV	IV-Weighted
ln(1+IDP inflows)$_{t-1}$	−0.213*	−0.205
	(0.113)	(0.274)
ln(population)$_t$	0.325	−1.012
	(1.761)	(2.893)
Observations	6,311	6,311
Adjusted R^2	0.529	0.755
First-stage F-statistic	89.75	53.44

Note: Robust standard errors in parentheses. All regressions include fixed effects for city and time, a city-specific linear trend, and a remoteness-year interaction fixed effect.

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

Table A6. Second Stage for Investment in Health: 50+ km Instrument Robustness Check

	(1)	(2)
	IV	IV-Weighted
ln (1+IDP inflows)$_{t-1}$	−0.0441	−0.221
	(0.0967)	(0.162)
ln (population)$_t$	−2.493	−7.683***
	(1.534)	(2.274)
Observations	6,321	6,321
Adjusted R^2	0.544	0.594
First-stage F-statistic	91.00	53.69

Note: IDP = internally displaced persons. Robust standard errors in parentheses. All regressions include fixed effects for city and time, a city-specific linear trend, and a remoteness-year interaction fixed effect.

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

Table A7. IDP and Rental Prices by Income Level, IV

	(1) Average	(2) Low income	(3) Middle income	(4) High income
ln (IDP inflows)$_{t-1}$	0.00687**	0.0102**	0.00374	−0.0139**
	(0.00271)	(0.00402)	(0.00320)	(0.00555)
ln(CPI)$_t$	1.048***	1.186***	0.978***	0.740***
	(0.0655)	(0.0971)	(0.0721)	(0.108)
ln (population)$_t$	−0.279	−0.597**	−0.180	0.353
	(0.200)	(0.247)	(0.259)	(0.334)
Observations	832	832	832	832
Adjusted R^2	0.995	0.992	0.993	0.978

Note: CPI = consumer price index; IDP = internally displaced persons. Rental prices are in levels. Robust standard errors in parentheses. All regressions include fixed effects for city and time, a city-specific linear trend, and a remoteness-year interaction fixed effect.

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

Table A8. IDP and Food Prices by Income Level, IV

	(1) Average	(2) Low income	(3) Middle income	(4) High income
ln (IDP inflows)$_{t-1}$	−0.0103***	−0.00987***	−0.00993***	−0.0135***
	(0.00267)	(0.00306)	(0.00263)	(0.00270)
ln(CPI)$_t$	1.288***	1.303***	1.305***	1.154***
	(0.0514)	(0.0595)	(0.0518)	(0.0506)
ln (population)$_t$	0.956***	1.544***	0.714***	0.330**
	(0.148)	(0.172)	(0.149)	(0.146)
Observations	832	832	832	832
Adjusted R^2	0.999	0.998	0.999	0.999

Note: CPI = consumer price index; IDP = internally displaced persons; IV = instrumental variables. Food prices are in levels (not relative to CPI). Robust standard errors in parentheses. All regressions include fixed effects for city and time, a city-specific linear trend, and a remoteness-year interaction fixed effect.

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

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