Immigrant Networks in the Labor Market

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Abstract

Using unique survey data linked to social security records and the large influx of Venezuelan immigrants to Colombia in recent years, this paper reexamines the role played by referral networks in the labor market. By explicitly accounting for both the urban and the social space, this paper provides new insights into the mismatch between the residential location and labor outcomes of immigrants. Referrals are a critical source of information about available jobs for immigrants, particularly for recent arrivals, but struggle to improve the quality of the match between firms and workers. The misalignment between where immigrants live and where they can find suitable employment opportunities reinforces occupational downgrading and increases the persistence of informal employment.

Keywords: immigration; social interactions; referrals; labor outcomes; informality.

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1. Introduction

Three common characteristics describe immigrants in developing countries: *(i)* they are highly unevenly distributed throughout space, both across and within cities; *(ii)* they report extensive use of personal contacts in the job search, with substantial variation across geographical units; and *(iii)* informal employment is more prevalent among immigrants. Despite differences between countries, these features have shown to be persistent over time, suggesting an interdependency between the urban and social space, and immigrants' labor market outcomes. Considering that the intensity with which immigrants use personal contacts to find jobs has substantial spatial variation, as illustrated in Figure 1, immigrants' residential location likely affects the flow of information about job opportunities. For instance, while personal contacts can help workers find jobs, particularly for newly arrived immigrants, the absence of alternative sources of job information at the local level might constraint workers to less suitable employment opportunities. This can in turn induce new immigrants to wage or occupational downgrading.

I present new evidence on the empirical relationships between referral networks and labor market outcomes of immigrants and how they interact with the urban structure. I take advantage of the large influx of Venezuelan immigrants to Colombia in recent years and use information from a unique household survey data linked to social security records covering all workers and firms in the formal sector in the largest Colombian metropolitan area. I observe both the use of referrals and detailed geographic location of immigrants and firms.

Some of the evidence presented in the paper may be insufficient to establish a causal relationship between a worker's referral network and his or her labor market outcomes. As immigrants are not randomly allocated to neighborhoods or the use of referrals, differences in outcomes may simply reflect preferences for certain locations or the use of a particular job search channel based on observable or unobservable features or individual characteristics, creating a correlation between individual and group outcomes. I provide evidence of the extent of sorting across locations, firms, and the use of referrals.

I find that immigrants display widespread use of social contacts to find jobs, but that the frequency by which workers rely on their personal contacts to search for jobs varies with the business cycle. In addition, although referral networks are generally productive to find jobs, they don't seem to improve the quality of the match between firms and workers. This is associated with the high use of referrals in industries with large number of informal jobs and in occupations with low 'skill' content. Thus, the higher use of referrals by immigrants does not necessarily signal high-quality networks. In the absence of information about available jobs using other search methods, mainly due to weak assimilation, informal job referrals may be the only way for immigrants of finding jobs.

Further, since many individual outcomes vary much more *between* groups of workers rather than *within* them and the location and density of agents defines the degree of information sharing, I then turn my focus to the geographical or spatial dimension of networks. I provide strong evidence indicating that referral networks are highly residence-based. On the one hand, living in the same block increases the probability of working together, defined either as working at the same block or establishment. These effects are stronger among pairs where both individuals are low-educated and among immigrants, particularly for workers that arrived recently to the country. On the other hand, recently arrived immigrants tend to be employed in the same occupations as their co-nationals who immigrated earlier and live in the same neighborhood. In addition, results suggest that the rate at which immigrants find jobs is increasing and concave with network size but can decrease for very large networks. Now, although residence-based networks play an important role in job acquisition for immigrants, they are characterized by spatial and social mismatch. Workers with lower accessibility to employment opportunities and more isolated networks are likely to experience worse labor market outcomes.

Taking into account the strong spatial structure of referrals, I then study the effects of referral networks on immigrants' location choices and show how these choices affect job transitions. I leverage the introduction of a large-scale regularization policy to understand immigrants transition from informal (low-wage) to formal (high-wage) jobs. Using employer-employee data, where I observe employment spells in the formal sector and changes in residential locations, I provide a new explanation for the persistence of informal employment among immigrants in developing countries. The evidence presented here suggest that residence-based networks constrain immigrants' access to formal jobs through at least two channels: occupational downgrading upon arrival and spatial mismatch. Both reinforcing each other. The misalignment between where workers live and where they can find suitable employment opportunities lowers the quality of their referral networks, making it harder for immigrants to receive or find job offers in the formal sector. In addition, the early occupational downgrading of immigrants and their clustering in space affects their future employment prospects, increasing the persistence of informal employment.

This evidence is consistent with predictions from a model of spatial job referral networks. Network externalities and commuting costs determine suitable employment opportunities for immigrants. Immigrants with low number of interactions with workers employed in the formal sector will optimally search for informal jobs and work closer to their place of residence. A derivation of the aggregate informal-to-formal job transition rate shows that it is independent of the job-finding rate in the informal sector and is increasing and concave in the job-finding rate in the formal sector. Thus, workers with fewer contacts employed in the formal sector have a lower probability of being referred, reducing their probability of moving to formal jobs.

Related literature. This paper contributes to different strands of literature. First and most closely related is the large literature studying referrals and job search. A first subset of papers have found extensive evidence of the use of referrals in the labor market and a relationship with workers' outcomes.[1] For instance, the evidence suggest that referral networks are highly ethnically stratified and residence based (Bayer et al., 2008; Giuliano et al., 2009; Hellerstein et al., 2011), and are usually productive in matching workers with potential employers by increasing the arrival rate of job offers (Goel & Lang, 2019), particularly for new labor market entrants (Kramarz & Nordström Skans, 2014), or by providing a higher starting salary (Dustmann *et al.*, 2016), inducing lower turnover (Brown et al., 2016), or increasing performance (Beaman & Magruder, 2012; Pallais & Sands, 2016; Heath, 2018).[2]

A second set of papers has focused on the spatial dimension of networks, estimating neighborhood effects (Damm, 2014; Hellerstein *et al.*, 2014). An early example of the geographic extent of information transmission for job search is Topa (2001), finding geographic correlations in patterns of unemployment across neighborhoods. His results suggest significant social interactions across neighboring tracts that explain the patterns of employment and wages of geographically closed individuals. While there is large evidence indicating an active role of residential-based networks in the labor market, evidence of the *magnitude* of these effects is less robust. Except from studies that use random (or quasi-random) assignment of workers to neighborhoods (e.g., Damm, 2014), the identification of neighborhood effects has been challenging, as confounding factors arise from sorting, common shocks, or measurement error. In addition, appropriate data sets are difficult to find.

These challenges are also present when trying to tease out the mechanisms in place and how they work. Usually, the empirical evidence on the role of referrals has been interpreted as a reduction of search frictions by allowing workers to exchange information about job openings. However, there are contrasting views on the type of network structure that matters in the job search process. For instance, Granovetter (1973) shows that acquaintances (i.e. those with whom individuals have less frequent interactions) may be more useful to gain information about job opportunities rather than close friends. In this sense, having a larger and diverse information set is more significant. However, some empirical evidence suggests that while strong and weak ties work as complements, strong ties provide more relevant information about jobs, particularly when this information is related to an individual's decision to migrate (Giulietti et al., 2018). Other views suggest that individuals who share common characteristics provide more relevant information about jobs (Currarini et al., 2009) or that the 'quality' of the network is more relevant in explaining labor market outcomes for workers (Calvó-Armengol, 2004; Calvó-Armengol & Jackson, 2004).[3]

This paper complements this strand of the literature in four important ways. The first stems from a combination of unique survey and administrative data with a

[1] The empirical evidence, going back to the sociology literature (Rees, 1966; Granovetter, 1973), suggest that about one in two jobs is acquire using social contacts. For a comprehensive review of the theoretical and empirical literature see Ioannides & Loury (2004), Beaman (2016), and Topa (2019).

[2] Direct evidence of the strength of residential networks at the very granular level is presented by Heath (2018). In her sample of garment workers in Bangladesh, 45 percent of referrals occur between workers living in the same extended family compound.

[3] The tendency of individuals to form close relationships with others who are similar to themselves—in some characteristic—is known as homophily.

large immigrant shock, which contains detailed information about the use of referrals, geographical information for each worker-employment pair, immigrants' work authorization status, and employment spells. Using this information, I am able to document a new set of stylized facts that highlight the interdependency between the urban and the social space, as well as provide a novel explanation for the persistence of informal employment among immigrants.

Second, I provide evidence on the extent that immigrant's sorting across locations and firms drives different estimates of the social interaction effects. Commonly, the literature has focus on very local interactions (e.g., at the block-level) by assuming that while people may choose their neighborhood, it is less likely that they choose their immediate neighbors. I show the conditions under which this assumption is likely to hold when studying ethnic networks. Since the focus is only on labor market effects, I argue that it is reasonable to take the network as exogenous, especially because new immigrants follow previous immigrants to where they live, for example, through family reunification.

Third, the findings have strong external validity as there are no language barriers between immigrants and the general population in the country, reducing the usual two-dimensional analysis to a one-dimension study. Finally, the migration episode analyzed is of great interest. Only the wave of Syrian refugees to Turkey matches the relevance of the Venezuelan migration episode in recent years. Venezuelans are a relatively highly educated migration flow (compared to natives), share the language with the main host countries, and have benefited from favorable immigration policies, which makes this episode a best-case scenario for studying the economic integration of migrants.

The paper also adds to the broader literature on the role played by social networks in supporting migrants in their new locations, as reviewed by Munshi (2014, 2020). Extensive evidence supports the idea that social networks contribute to the employability and spatial mobility of their members (Borjas, 1995; Munshi, 2003, 2011; Edin et al., 2003; Beaman, 2012; Battisti et al., 2021).[4] However, little is known about their contribution to the observed mismatch between workers residential location and labor outcomes. My contribution is to show that immigrants choosing to locate in places with lower accessibility to employment opportunities and more isolated networks are likely to experience worse labor market outcomes.

A related strand of the literature has looked at the effect of living in large immigrant enclaves—and leaving these enclaves—in facilitating immigrant assimilation (Zhou, 1992; Portes & Rumbaut, 2014; Eriksson, 2020; Abramitzky et al., 2020). Whether immigrant networks and the enclaves where they are embedded are good or bad for recent migrants, particularly if they lack legal status, is an open question in economics and sociology. For instance, Abramitzky et al. (2020) document that Jewish immigrants who left a New York City enclave in the early 1900s

[4] One drawback from most of the literature is that it has implicitly assume that all members within the network are equally effective in providing referrals to new arrivals. However, more established immigrants may be a better source of job-related information for recent arrivals. One exception is Beaman (2012), who considers a differential effect of labor market networks by cohort.

experienced faster earnings growth than their neighbors who had the same occupation and decided to stay. Most of these studies, however, look at historical migration episodes, such as the Age of Mass Migration. By studying a recent and large migration episode and examining the effect of residential and ethnic networks in allowing immigrants to transition from informal to formal jobs, this paper contributes to this literature.

This paper also contributes to the literature studying the effects of amnesty programs on undocumented migrants. For example, Kossoudji & Cobb-Clark (2002) show that the regularization of 1.7 million undocumented workers in the United States through the 1986 Immigration Reform and Control Act (IRCA) increased wages for these migrants. In Europe, Monras et al. (2018) document better labor market outcomes for migrants after Spain regularized roughly 600,000 non-EU immigrants. They show that the effect on labor outcomes is driven by an increase in job opportunities in industries with fewer informal employment. More recently, using the Venezuelan migration episode to Colombia, Ibáñez et al. (2021) show that undocumented immigrants that were granted work permits faced better labor conditions, such as being able to increase their bargaining position and job satisfaction, or reporting lower self-employment rates.

The migration episode and data used in this paper provides a rare window into the understudied question of the effects of regularization on the labor market careers of migrants. The model and empirical results presented emphasize that policies that grant work permits to immigrants and referral networks are intertwined. This paper benefits by being able to measure legal status directly, which typically needs to be imputed. One specific connection between the literature and this paper is the relationship between legalization and worker productivity. Limited job opportunities for undocumented workers induces labor to be misallocated, reducing workers' productivity. This paper provides new facts on the extent of talent misallocation and shows that regularization policies can indeed allow workers to move to better jobs, but the effect is limited by the quality of the contacts that provide information to workers about job opportunities. Empirical evidence on this is still very limited (see for example Ortega and Hsin, 2022).

The remainder of the paper is structured as follows. Section 2 presents the data and discusses the institutional context. Sections 3 and 4 present empirical evidence on the role of immigrant networks in the labor market and the spatial extent of these networks. Section 5 examines how location choices determine job opportunities in the formal sector. Section 6 concludes.

2. Data and Institutional Context

2.1. Data

The analysis will focus on Venezuelan-born workers aged 15 to 64 years. Throughout the paper, I will often refer to this group just as immigrants. An immigrant is classified based on place of birth, as there is no consistent information on citizenship across data sets. I will draw from two distinct data sources through the different empirical exercises presented in the paper.

National Labor Force Survey. I begin by using the Colombian labor force survey (*Gran Encuesta Integrada de Hogares*, GEIH) to provide a general description of the extent of referral-use among the population. The GEIH is a monthly survey of about 20,500 household, representative at the national level. I use data covering the eight-year span from 2014 through 2021. Individuals are surveyed regardless of immigrants' migratory status. Immigrants' cohort of arrival can be identified based on information on where a person was living 1 and 5 years before being surveyed, and his or her place of birth. It also provides direct evidence of the use of referrals in the job search and provide sufficient information on labor market outcomes. A drawback of the GEIH, common to most labor force surveys, is that it oversamples workers with low attachment to the labor market.

Linked survey-social security data. The second and main data source links the latest household survey for Bogotá (EMB), collected between May and September of 2021, with social security record from the Statistical Register of Labor Relations (RELAB), covering the years 2018 to 2021. The first portion of the linked data, the EMB (*Encuesta Multipropósito de Bogotá*), provides information about the social and economic conditions of more than 100 thousand households.[5] The survey includes detailed demographic and employment information for all working age individuals, similar to the GEIH—including direct information on referrals and job search methods.

This data source has three key advantages compared to the GEIH. First, employed workers were asked to report the location (census block) where they work. The geographical information for each worker-employment pair provides the backbone of the analysis of residential-based networks. Second, individuals were asked if they were living in the same neighborhood 1 and 5 years before being surveyed. Third, based on multiple questions in the data one can infer immigrants' work authorization status.

The second portion of the link data, the RELAB, is based on all administrative record of payments to the social security system by both firms and workers. The key aspect of the data is that I can follow workers and firms between 2018 and 2021, identifying informal-to-formal employment transitions. This data source, however, has some shortcomings. First, the information covers essentially the universe of workers within firms in the formal sector. In other words, the data excludes half of all employees, as they do not report contributions to the social security system. Second, the data is recorded at the level of the employer, not at the establishment. Therefore, workers employed by firms with more than one establishment are pooled together in the data. Third, as information on wages is recovered from social security contribution, the distribution is both left and right censored at the minimum and maximum social security contribution and arranged into brackets. Right-truncation

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[5] Of the total households included in the survey more than 80% live in Bogotá. The rest of the sample includes households that live in one of the 21 municipalities that are part of the metropolitan area.

is not so much of an issue as the upper bound is 25 times the lower bound (i.e., the minimum wage), only affecting about 0.2% of the linked sample.

I keep all observations from the EMB even if an individual observation did not match to the RELAB data. Foreign-born workers aged 15 to 64 years represent 5.1 percent of workers in the EMB sample and 1.2 percent in the matched sample. They predominantly originate from Venezuela, the United States, and Ecuador. Of all foreign-born, Venezuelan immigrants account for 91 percent of workers in the EMB sample and 73 percent in the matched sample.

Table 1 shows descriptive statistics for natives and Venezuelan immigrants in both samples. Immigrants are mostly young and participate actively in the labor market. Now, there is a higher concentration of more qualified workers (as measured by educational attainment) in Bogotá—12 percentage points higher than the national share of workers with college or vocational training. While the use of referrals is lower in the EMB sample, it is still the main method to find jobs with most of the jobs being informal jobs (based on contributions to the social security system). Finally, most immigrants have been in the country for more than year and roughly half of those in the EMB sample report having a work permit.

2.2. Institutional context

As of August 2021, Colombia had received over 1.8 million Venezuelans, representing about 4 percent of the Colombian population.[6] The exponential increase in inflows from Venezuela since 2015 has been remarkable (see Figure A1 in the Online Appendix).[7] Between 2015 and 2018, the total stock of Venezuelan immigrants multiplied by nine and since then has doubled. However, as shown in Figure A2 in the Online Appendix, more than half of all Venezuelan immigrants were under an irregular (or undocumented) migratory status at the beginning of 2021.

To facilitate the insertion of this large population in the labor market, the Colombian government created different legal mechanisms. At the beginning of 2017, the government created a two-year special permit (*Permiso Especial de Permanencia,* PEP) that allowed Venezuelan-born immigrants with regular status (i.e., entered through authorized border controls and have not overstayed in the country) to stay and work in the country. However, because of the large number of irregular immigrants in the country, in 2018 this was expanded to cover around 440.000 undocumented immigrants that had voluntarily registered at the time using the Administrative Register of Migrants from Venezuela (RAMV). This not only allowed immigrants to work, but also gave them access to health and education services.

At the start of 2020 the government issued another type of PEP to promote formal employment (known as *Permiso Especial de Permanencia para el Fomento de la Formalización* – PEPFF). Under this mechanism, which had to be requested by the

[6] Roughly 21% of all Venezuelan immigrants were living in Bogotá.

[7] Note that the fraction of all other foreign-born immigrants in the total population has remained stable over this period.

employer, undocumented immigrants were allowed to work in the country. More recently, in February 2021, the Colombian Government announced a ten-year Temporary Protection Status (TPS). This new status grants more than 1.74 million Venezuelans residing in the country by January 2021, and those entering via official checkpoints over the next two years, work authorization and access to healthcare and other essential services. The first TPS was issued on October 13, 2021.

3. How do immigrant referral networks work in the labor market?

In this section, I describe the general workings of informal job information networks. Using direct evidence on the use of relatives, friends, or acquaintances by immigrants when searching for jobs, I corroborate some of the main findings in the literature. I start by looking at the extent that immigrants use personal contacts to search for jobs, and how this varies by demographic characteristics, industries and occupations. Because immigrants do not randomly get a referral, I discuss whether it is reasonable to assume that immigrants' decision to use referrals is close to randomly assigned after controlling for basic demographics, and what would be the direction of the bias if selection is present. Then, I explore whether the use of referrals improves the quality of the match between firms and workers. Referral-use is measure as the share of wage and salary workers who report having used relatives, friends, or acquaintances to find their current job.

3.1. Selection into informal job information networks

Consistent with the empirical literature, immigrants report extensive use of relatives, friends, or acquaintances when searching for jobs. Table 2 shows that over half of all employed foreign-born workers in the country obtained their current job by using their personal networks. Now, among all foreign-born in the country, Venezuelan immigrants report the highest use of referrals with four out of five workers having found their jobs through social contacts. This finding would represent an upper bound in the empirical literature.[8] Use of personal contacts by job seekers is also high among Venezuelan immigrants, with half of them using friends and relatives as their main method to search for jobs.

A deeper look into the intensity with which Venezuelan-born immigrants use social contacts to search for jobs shows clear differences by cohort of arrival, age, education, and sector of employment. The use of referrals decreases with the time an immigrant has spent in the country, but overall remains high. The data shows that

[8] The literature finds that between 20% and 40% of job matches for ethnic workers in developed countries were made through their personal networks, with some minority groups going up to about 50% (Ioannides & Loury, 2004; Battu et al., 2011; Dustmann et al., 2016).

younger immigrants (aged 15 to 24 years) and those with at most a high school degree are more likely to have found their job through the use of personal contacts.[9]

Looking across types of employment it is clear that immigrants who are employed in the informal sector, i.e., with no social security coverage and no written contract, are more likely to have used referrals. Given that opportunities in the formal sector were limited only to immigrants with work authorization (visa or PEP), most Venezuelan-born immigrants often end up working informally. This reduces the scope for referrals in the formal sector. In addition, there are large differences in the use of referrals across industries and occupations. Figure 2 shows a positive relationship between the use of referrals and the incidence of informal employment in each industry, and a negative relationship with the 'skill' content of occupations.[10]

The use of referrals also varies with the business cycle. The data for Colombia suggest some evidence of an inverted U-shape relationship between the rate at which workers find jobs or at which worker-firm matches are split and the proportion of immigrants using personal networks to look for jobs (see the Online Appendix). A worker invests more time looking for a job through his personal network when more of his contacts are employed or finding a job is harder.

The main concern in the literature is that both workers and firms who rely more on the use of referrals in the job search are often inherently different from those who rely less on it, creating selection bias. By using the matched employer-employee data, I can remove any potential bias coming from differences in the use of referrals by low and high productivity firms. However, as the data does not follow workers over time, I cannot fully account for the non-random use of personal contacts by workers.

If immigrant workers with poor job prospects are disproportionately using referrals to find jobs, then it would be misguided to assign network effects, particularly negative outcomes, to the use of referrals because these workers already face weaker prospects. For instance, Table 3 shows that workers using referrals differ on certain observable characteristics to those using other search methods. The use of referrals is particularly prominent among younger, less experienced and lower educated workers. The use of referrals is also pronounced among immigrants arriving more recently and without a working permit and tends to match workers disproportionately with informal jobs. To reduce the extent of (negative) selection bias, I include a full set of individual controls. Results, however, should not necessarily be interpreted as being causal.

3.2. Referral-use and employment outcomes

[9] Some evidence at the national level shows that the use of job-related information coming from natives is significant for highly educated immigrant workers and increases with immigrants' age.

[10] I follow Lester et al. (2021) and classify occupations by the 'skill' content of each (employed) worker's reported occupation. I first calculate the median education level and median labor income of individuals for each four-digit occupation. Using the total number of workers in each occupation, I estimate the cumulative percent distribution for the education and income rankings, respectively. The NPB occupational index is the average of the two cumulative percentage distributions. Results are reported at the two-digit occupation level.

Informal networks are useful in finding a job. These allow immigrants to learn about job opportunities that may not be publicly advertised, thus increasing the information on the number of jobs available.[11] But can referrals increase the quality of the match between an employer and employee? I explore how job referrals affect immigrants' wages, job tenure, and downgrading decisions. Ideally one would measure downgrading based on a workers' previous job in their country of origin. Since there is no information in the data used on workers previous occupation before migrating, occupational downgrading is defined as being 'over-educated' in their current occupation relative to natives' median education level (Friedberg, 2000; Lebow, 2022).[12]

To provide a general description of the extent of downgrading at the national level, I present in Table A1 in the Online Appendix the job transition matrices of immigrants. The matrices use information from the second round of the Migration Pulse Survey on the last job held by immigrants in Venezuela and the current employment condition, for both occupations and industries. The data indicates that downgrading among immigrants in Colombia is prevalent. For instance, among those that held a managerial, professional, or technical job, roughly half are now working in lower skill-content occupations, such as sales and other elementary occupations. The data also shows large shifts in industries where immigrants work, with lower transitions for agricultural and construction workers.

Table 4, Panel A presents the results of regressing each of the six labor market outcomes considered on a dummy indicating whether the immigrant worker obtained his current job through a referral and a full set of individual controls.[13] The estimates suggest a strong negative relationship between being referred and a worker's starting wage, future wage growth, and occupational downgrading. Taken as such, the estimates imply that workers that find their job through social contacts earn a starting wage that is 9 percent lower than the one perceived by workers using other job search methods, are 15 percentage points less likely to see future wage growth, 5 percentage points more likely to be over-educated in their current occupation, and the distance between their level of education and the median for natives in their own occupation is higher, conditional on downgrading. When we look at workers employed only in formal jobs, we see a positive coefficient for the starting wage by not distinguishable from a null effect. Similarly, the estimate on job tenure is positive but not significant.

Although results in Panel A control for the sector of employment (formal vs. informal) to account for the possibility that results are a product alone of working in the informal sector and not the use of referrals, it does not account for workers'

[11] Goel & Lang (2019) show that social contacts are effective in increase the number of job offers rather than the type of offers.

[12] In the case of Colombia, Lebow (2022) finds that Venezuelan-immigrants are disproportionately employed in occupations in which natives are less educated.

[13] Results that include a municipality fixed effect are very similar but are not presented to maintain consistency with the estimates that include firm fixed effects. The inclusion of both municipality and firm fixed effects creates collinearity, so the former is excluded from regressions.

sorting into firms that make use of referrals at different levels.[14] For example, lower starting wages may just be indicative that referrals are used more by low-educated workers in low-wage (informal) firms. The empirical evidence shows that larger and more productive firms hire less through referrals relative to smaller and less productive firms (Holzer, 1987; Pellizzari, 2010). Dustmann et al. (2016) show that once we account for sorting into firms, workers hired through referrals earn higher wages, but experience slower wage growth. In Panel B, I address the possibility of workers' sorting into firms by including firm fixed effects. Since only workers that were matched to the social security data have information on the firm ID, the sample is reduced to those working in formal jobs. Therefore, these results might not speak to workers in informal jobs.

Once firm fixed effects are included, the effect on nominal starting wages cannot be confidently estimated as the sample results in an increasing number of singletons. It would also exclude important information about the starting wage of workers with longer tenure. However, using the starting wage bracket for all workers employed in the formal sector suggest no differential effect for referrals, with no effect on future wage growth. In addition, while workers hired through referrals seem to experience some occupational downgrading, they are more closely match to occupations with fairly similar skill requirements. The significant change in some of the estimates suggests that the sorting of workers into firms is not negligible. It also shows that referrals tend to lead workers disproportionately towards informal (low paying) jobs, increasing the extent of labor misallocation.

One downside from the data used here is that referrals from family and friends and those from professional networks are taken as one. Lester et al. (2021) shows that referrals from family and friends tend to be used more frequently to match workers with low-skill (low-paid) jobs while those from professional networks have the opposing relationship, matching workers with high-skill (high-paid) jobs. Therefore, the higher use of referrals by immigrants does not necessarily signal high-quality networks. In the absence of direct access to information about available jobs, mainly because of weak assimilation, informal job referrals may be the only way of finding a job for immigrants.

Finally, in Figure A3 in the Online Appendix, I examine whether better connected individuals tend to work closer to their place of residence as they may not need to search for jobs around the city. The estimates show that while immigrant workers and those working in informal jobs are more likely to work closer to their residential location, referrals are not significantly more—or less—likely to commute to work within some window of time.[15]

4. What is the spatial extent of immigrant referral networks?

[14] Estimates including firm size and sector (informal) dummies produce very similar results.

[15] In a similar exercise, Zárate (2021) shows that informal workers in Mexico City spend less time commuting and work closer to their home relative to formal workers.

As immigrants tend to be spatially concentrated, physical distance still plays an important role in social interactions. Not only are day-to-day activities (e.g., commuting or shopping) typically local, but the frequency of exchanges among individuals tend to decrease with geographical distance.[16] Thus, distance seem to play an important role in facilitating information flow at the very local level. In this section, I examine if job information networks have an important spatial dimension and then see how important is the neighborhood in determining immigrant's labor market outcomes.

Ideally, one would like to have data on the structure of interactions of individuals in the social space, with information on both the set of agents each individual worker is connected to and direct evidence of diffusion of job offers through the network. In the absence of such information, the literature has often relied on qualitative evidence or correlations in the behavior of individuals who are geographically close to one another and share demographic traits to make assumptions on the degree of information sharing.[17] In what follows, I define the network as belonging to a residential neighborhood. I attempt to isolate the effects of geographic proximity from information diffusion that is valuable for forming good matches in the labor market.

4.1. Location choices, endogeneity, and network effects

The evidence shows that immigrants choose to locate where they have networks (previous co-nationals). Since immigrants are not randomly allocated to neighborhoods, it is possible that differences in outcomes may simply reflect differences in unobserved location characteristics, which creates a correlation between individual and group outcomes. Immigrants are likely choosing the place that will confer the greatest benefits on their outcomes.

Under a more general setting, treating the population composition within neighborhoods as exogenous might be a strong assumption, especially when the residential location is a household decision that could be affected by search outcomes (Edin et al., 2003). However, because new immigrants follow previous immigrants to where they live, for example, through family reunification, I argue that it is reasonable to take the network as exogenous in the sense that it is very unlikely that we would see more dispersion if it became easier to find a job through other channels. As a reference, 90% of immigrant workers employed had no previous information on employment opportunities before moving to their current place of residence.[18]

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[16] There is strong evidence that geographical distance is inversely related to the intensity of social interactions (Marmaros & Sacerdote, 2006; Kim et al., 2017). In addition, the evidence suggests that the probability of a social link between two individuals follows a power law (Kleinberg, 2000; Liben-Nowell et al., 2005; Lambiotte et al. 2008; Levy & Goldberg, 2014). Put differently, the probability of a social link is proportional to the inverse of the square of the distance between the two individuals. This has become to be known as *"the gravitational law of social interaction"*.

[17] There is a well-established literature in sociology documenting the extent of social ties with immediate neighbors (Wellman & Wortley, 1990; Moore, 1990; McPherson et al., 2001).

[18] This information comes from the Migration Pulse Survey.

On the other hand, even when workers choose their residential neighborhood, often based on where previous migrants live, they are less likely to choose their direct neighbors. Constraints on the housing market (e.g. available units for rent) create spatial variation of immigrants between blocks within a neighborhood. Therefore, one can reduce the extent of bias from sorting into neighborhoods based on observable characteristics by looking at very local interactions (at the block-level).

In Table 5, I provide some intuition on the extent of sorting at the block-level. For each block in the sample, I randomly select a single worker and estimate the fraction of individuals in the block (not including the randomly selected worker or someone in the same household) who share the listed characteristic. If there is no block-level sorting, then one would expect that the distribution of individual characteristics resembles that of the neighborhood. In practice, after we include neighborhood fixed effects, the average characteristics of the block should not predict the characteristic of the randomly selected individual. The results in Table 5 provide some support to the idea that sorting is limited at the very local level. While the R^2 and pairwise correlations do not drop to zero in all cases, they fall considerably when only the within–block group variation is isolated. The remaining correlation for a workers' ethnicity is precisely showing that immigrants indeed tend to cluster in certain locations and so we should expect strong network effects. Because clustering is high, the remaining variation in educational attainment is not surprising. This could be simply capturing network homophily, which is likely determined at the home country.

4.2. Residence-based labor market networks

I now examine whether individuals interacting very locally, i.e., living in the same census block, exchange information about jobs. I start by documenting whether the main finding in Bayer et al. (2008), Hellerstein et al. (2011), and Schmutte (2015) holds up in the Colombian data and is particularly strong in the case of immigrants. These studies find that neighbors are more likely to be employed together, both when considering a block of employment or an establishment.

I estimate the propensity for a job switcher, first-time employee or transitioning out of unemployment, or recent arrival (less than a year) to work in the same census block or establishment as one of his neighbors. Social interaction effects are identified by comparing this propensity with the baseline probability of working in the same block or establishment for individuals residing in the same reference group (*sector*) but not on the same block. For this portion of the analysis, I use the EMB-RELAB dataset to construct a sample that contains individuals living in Bogotá, who are currently employed, who are between 15 and 64 years of age, who do not work at home, for whom we have complete data on place of work, and who did not move to another neighborhood in the last year or were living in another country one year before.

I construct a sample of pairs, matching job switchers to workers that did not change jobs in the last twelve months.[19] I keep all pairs that reside in the same reference group (*sector*) and do not belong to the same household. The baseline probability of working in the same block of employment for two workers that live in the same sector but not on the same block is 0.11 percent and raises to 1.35 percent for workers living in the same block. In the case of pairs matching two immigrant workers, the baseline probability of working together is 0.50 percent compared to 6.21 percent when living in the same block.

Let i (job switcher) and j (job stayer) be a pair of workers living in the same sector; W_{ij} is a dummy variable equal to one if i and j work in the same block (resp. establishment)[20]; R_{ij} is a dummy variable equal to one if both workers live in the same block; $\boldsymbol{X}_{ij}$ is a vector of characteristics that describe the pair of workers (as displayed in Table 6); and ρ_g denotes a residential sector fixed effect.[21] The notation intentionally follows Bayer et al. (2008) and Schmutte (2015). I estimate the following equation:

$$W_{ij} = \rho_g + \beta' \boldsymbol{X}_{ij} + \left(\alpha_0 + \alpha_1' \boldsymbol{X}_{ij}\right) R_{ij} + \varepsilon_{ij} \, . \tag{1}$$

The key assumption that allows the identification of the social interaction effect (α_0) is that workers are not sorted across blocks once we account for all the variation across sectors that influences search outcomes. In the previous section, the results in Table 5 provide some support for this identification strategy.

A way of addressing the possibility of sorting within neighborhoods based on unobserved individual characteristics, is to extend equation (1) by including individual fixed effects (λ_i and λ_j), as each worker appears multiple times in the sample of pairs:

$$W_{ij} = \lambda_i + \lambda_j + \beta' \boldsymbol{X}_{ij} + \left(\alpha_0 + \alpha_1' \boldsymbol{X}_{ij}\right) R_{ij} + \varepsilon_{ij} \, . \tag{2}$$

The empirical strategy also reduces the concern from reverse causality, i.e., the idea that a workers' decision about where to live is driven by information from coworkers or friends and acquaintances in the workplace. Since I match job switchers with workers that did not change their job, and both where living in the same neighborhood a year before, it is unlikely that referrals flow in the opposite direction.

[19] In the sample of establishments, a job switcher is any worker (employed or unemployed) who began working for a firm at any point in time going back one year before the date he/she was surveyed and meets the other criteria. For example, an unemployed worker at the time of the survey who within the previous year started working for a firm (as detailed in the RELAB) but lost his/her job before being surveyed is considered as a job switcher.

[20] An establishment is defined as a combination of block of employment and firm code. Workers with no information on block of employment and working in firms with less than ten workers are assumed to be working in the same establishment if they share the same firm.

[21] The inclusion of block-group fixed effects accounts for unobserved attributes that are common to individuals who live in the same neighborhood (*sector*), such as access to public transportation.

In addition, this reduces the concern that the effects are being driven by those who are likely to provide referrals rather than receive it, as was the case in Bayer et al. (2008) and Hellerstein et al. (2011). The estimates are likely measuring the referral effect for those who indeed need the referral and present low attachment to the labor market.

The results for the propensity of working in the same block (columns 1 and 2) and in the same establishment (columns 3 and 4) are presented in Table 6. I report estimates only for the average social interaction effects, α_0 and α_1. Panel A presents results for equation (1) while Panel B shows results for equation (2). The baseline estimates indicate that the probability that neighbors work in the same block is positive and statistically significant. Living in the same block increases the probability of working together by 1.28 percentage points, or a twelve-fold increase relative to the probability of working together but not living in the same block. Results that include individual fixed effects are slightly larger, suggesting a negative bias from unobserved block-level sorting. These results are far greater to those found in the literature.[22] The large effects found here reflect at least two things: the widespread use of referrals in the population and the size of the reference group. Pertaining to the latter, Bayer et al. (2008) noted that the social interaction effect is increasing in population density. The size of the reference group (sector) used here is considerable larger than the definition of a U.S. census block group.[23]

Allowing for heterogeneity in the social interaction effect (column 2) indicates that exchanges are stronger among pairs where both individuals are low-educated and among immigrants, particularly when the job switcher arrived recently to the country. The negative effect for highly educated workers suggests that their personal networks are more spatially disperse as they rely less on referrals, particularly from friends and relatives. These results are consistent with common empirical findings in the literature. Results also point to referrals being less pronounced when both immigrants are allowed to work or have assimilated, measured as being in the country for more than five years.

Turning to the propensity of working in the same establishment, the baseline estimates still suggest a strong positive effect. Estimates including covariates suggest that while interactions when both individuals in the pair are immigrants are positive, they are not statistically significant. Note that the sample of establishments is constrained to formal firms. Therefore, immigrant referrals seem to be more prevalent to obtain jobs in informal firms. Likewise, since more than 95 percent of firms in Colombia are microenterprises, employing one or a few workers, interactions at the block of employment and not necessarily at the establishment level seem to play an important role for knowing about job opportunities. This is particularly true in developing countries.

[22] Bayer et al. (2008) find an increase over the baseline ranging from 33% to 88% depending on the definition of the reference group. Schmutte (2015) finds an increase of 18% using a sample of establishments.

[23] Since we have only a sample of blocks within sectors, reducing the size of the reference group significantly decreases the sample size.

Finally, in Section B.2 in the Online Appendix, I explore the effect of block-level network strength on labor market outcomes. I construct a measure of potential good matches based on the estimated parameters presented in column 2 in Table 6. This measure accounts for both the size and homophily of the network. Since this measure does a better job of capturing referral effects for workers who are less attached to the labor market, I focus on the sample of workers that lost their job due to the COVID-19 pandemic or that were living in another country 12 months before. Results for the complete sample (including natives) indicate that an increase in network strength is associated with a higher probability of finding an informal job, being self-employed, working closer to home, and working more hours; but it is associated with lower wages. Now, results are no longer statistically different from zero when we consider only the sample of Venezuelan-born immigrants. Nonetheless, results seem to be somewhat in line with the findings in Section 3, where direct referrals are more likely to help workers find informal (low-wage) jobs.

4.3. Clustering at industries and occupations

I now examine whether there is clustering at industries and occupations from immigrants living in the same neighborhood. The empirical evidence suggest that immigrants choose their occupation after choosing their location (Logan et al., 2002). The occupational choice of recently arrived immigrants has been found to be highly correlated with the occupations of previous immigrants (Lafortune & Tessada, 2012; Patel & Vella, 2013). This clustering has created immigrant niches where immigrants are overrepresented in certain occupations relative to the weight of immigrants in total employment in the country (Eckstein & Peri, 2018). These immigrant niches in specific occupations can be sustained over time as new immigrants arrive to a location and are referred to job opportunities through social networks.

I check whether immigrant workers employed in the same industry or occupation are likely to live in the same neighborhoods.[24] By matching recently arrived immigrants with more established immigrants, I estimate the share of 'coworkers' with whom each immigrant worker is a neighbor, defined as living in the same sector. I compare this ratio with a measure of the extent of clustering that would potentially occur if workers were assigned randomly to industries and occupations, holding constant the size distribution of workers across industries and occupations. All details of the computation are described in Section B.3 in the Online Appendix.

I find evidence of clustering in Table 7. To some extent, recently arrived immigrants are employed in the same occupations as their co-nationals who immigrated earlier. On average, 1 percent of all established immigrants working in a given industry lived in the same neighborhood of a newly arrived immigrant employed in the same industry. For an occupation the clustering observed is 0.8 percent. When workers are randomly allocated to industries or occupations, the

[24] This follows broadly the approach presented in Hellerstein et al. (2011) to study clustering of neighbors at establishments.

clustering is only 0.5 percent. The difference between both measures is statistically significant.

Panel B in Table 7 presents the top five industries and occupations by observed clustering. For instance, there is substantial clustering in the manufacturing of canvas and related products, where 60 percent of earlier immigrants employed in that industry live in the same neighborhood of a recently arrived immigrant employed in the same industry. In the case of occupations, shoe and leather workers display the highest observed clustering. On average, a recently arrived immigrant making or repairing shoes and leather products lived with 10 percent of all established immigrants working in that occupation.

4.4. Network structure and the job-finding rate

Does the network size and quality affect the rate at which workers find jobs? To examine this, I estimate the probability of finding a job for workers who lost their job after the Covid-19 shutdowns (an idiosyncratic shock to the employer) or are recent arrivals and see if it differs for workers who reside in neighborhoods with a larger network compared to otherwise similar workers with smaller networks. I measure network size as the immigrant density in the neighborhood to account for differences in the size of geographical units. I use two definitions of neighborhoods: UPZs and sectors.[25]

Figure 4(a) plots the predicted probability of finding a job for different network sizes. Results indicates that at the UPZ-level the relationship between immigrant's network structure (namely size) and the job-finding rate is non-monotonic. The probability of finding a job is increasing with the size of the network but can drop for very large networks.[26] In addition, the results of the underlying logistic regression (not shown) indicate that the quality of an immigrant's network, measured by the neighborhood unemployment rate, is associated with a higher job finding rate. In lower quality networks, immigrants have a lower probability of finding a job after being displaced.

These findings suggest the presence of congestion effects. On one hand, a larger network can provide more job-related information, increasing the chances of finding a job. On the other hand, a very large network creates competition for the same sources of information, limiting the efficiency of the network to match workers with job opportunities (Calvó-Armengol & Zenou, 2005; Beaman, 2012). However, this

[25] UPZs are large neighborhoods that share common socio-economic characteristics and are used to coordinate urban development policies within the city. A sector is similar to a U.S. census tract.

[26] At a larger geographic scale, Wahba and Zenou (2005) show using data on governorates in Egypt that the probability of finding a job through friends and relatives is increasing and concave with network size. They also find that for very large networks the probability decreases. A recent paper by Moretti and Yi (2023), using data for the U.S., studies the benefits of labor market size for job seekers. The authors find that displaced workers in large labor markets experience a significantly shorter unemployment spell and that the probability of finding a job is concave with city size—but no evidence of a critical point after which the probability decreases.

relationship is not robust to using a lower geographical definition of a neighborhood (Figure 4(b)), potentially driven by the smaller sample size.

4.5. Spatial and social mismatch

Spatial mismatch refers to the disconnect between where people live and where ('good') jobs are located, making it difficult for individuals to access job opportunities.[27] Thus, workers with poorer (physical) job access are likely to experience worse labor market outcomes. The social mismatch hypothesis, on the other hand, states that certain groups of workers (e.g., blacks and immigrants) mostly interact among themselves as a result of residential segregation, reducing the degree of information exchange about job opportunities.[28]

I now examine whether distance to jobs (spatial mismatch) and residential segregation (social mismatch) affect immigrants' labor outcomes. I use a gravity-based accessibility measure at the neighborhood-level as a proxy for spatial mismatch. This measure incorporates both the distance between residential and workplace locations and the 'potential' demand for jobs at a particular employment zone. It captures the share of jobs in the city that can be accessed by a worker living in a certain neighborhood. I use two measures of social mismatch: an isolation index, which captures extent to which immigrants are exposed only to one another, and the fraction of immigrants in the neighborhood participating in a social organization. Details on the construction of all measures are described in Section B.4 in the Online Appendix.

A two-way plot suggests that there is no evident relationship between the job accessibility measure and both measures of social mismatch (see Figure A4 in the Online Appendix). In other words, immigrants living in neighborhoods located farther from jobs do not seem be mostly interacting among themselves. However, neighborhoods with a higher concentration of immigrants seem to be less job accessible and have a lower job density of high-income jobs.

To establish the existence of spatial or social mismatch, I regress six labor market outcomes at the individual level on both the job accessibility and network isolation measures. Results reported in Table 8 using all working-age Venezuelan-born immigrant workers (Panel A), show a positive and significant correlation between the measure of job accessibility and immigrants' labor force participation, (log) wage, job tenure, and length of unemployment, and a negative correlation with unemployment and informality. Results also indicate that network isolation is associated with higher labor force participation and informality, and lower wages and employment tenure. To some extent this is indicative of both spatial and social

[27] There is plenty empirical evidence showing that distance to jobs negatively affects workers outcomes. Some examples include Ihlanfeldt & Sjoquist (1990), Holzer (1991), and Andersson et al. (2018). For a review of the literature refer to Kain (2004) or Gobillon et al. (2007). Theoretically, Zenou (2015) provides support for both the spatial and social mismatch hypothesis.

[28] This is based on Granovetter's (1973) idea that weak ties are superior to strong ties in the job search.

mismatch, as workers with lower accessibility to employment opportunities and more isolated networks are likely to experience worse labor market outcomes.

Now, because immigrants can change their residential location and move to a place where they face better prospects, job accessibility and isolation index are not necessarily exogenous. To address this issue, in Panel B, I restrict the sample to immigrants that lost their job due to the Covid-19 restrictions and were living in the same neighborhood the year before. Some results, however, loose their significance.

In addition, I examine the correlation between time commuting and the earnings of wage and salary workers and independent contractors. If those immigrants that report longer trips (in minutes) to their workplace location are also those with higher earnings, then this provides additional supports for the spatial mismatch hypothesis. Table A2 in the Online Appendix shows a positive and statistically significant correlation between commuting and (log) hourly wages.[29] Workers that commute an additional 10 minutes earn an extra 2 to 3 percent. Including a set of demographic characteristics and a dummy for work authorization slightly reduces the point estimates. This intends to account for the fact that skill workers are usually more mobile and that informal workers are more likely to commute shorter distances (Figure A3).

The evidence points to the spatial mechanisms: sorting into higher-wage (more productive) locations and commuting from more distant locations. For a sample including all working-age migrants, we see no relationship when we include workplace fixed effects, suggesting that workers are only willing to commute longer to locations with job offers that pay higher wages. For a more restrictive sample including only immigrants who suddenly lost their job due to Covid-19 restrictions and were living in the same neighborhood a year before, including residential fixed effects removes any correlation, indicating that immigrant workers who earn higher wages come from more distant locations.

5. Network quality and immigrants' informal to formal job transitions

Do immigrant networks hinder the move to better jobs? Do they increase the persistence of informal employment? While a large informal sector may allow irregular (or undocumented) immigrants to integrate more rapidly into the economy, this is a significant source of distortions in low- and middle-income countries with important implications for the long-run outcomes of immigrants. The distortions created by the mismatch between worker's skills and jobs, predominantly in the informal sector, suggest that any policy that lowers the barriers for immigrants to enter the formal sector may have first-order effects on immigrants' welfare. However, recent empirical evidence by Ibáñez et al. (2021), following the introduction of a large-

[29] Fournier (2021) finds strong evidence of a wage premium for commuting using French administrative data.

scale regularization program for undocumented immigrants in Colombia, suggests a very modest effect in the probability of working in the formal sector.

I will first present a theoretical framework that takes into account the strong spatial structure of referrals to understand the effects of referral networks on immigrants' location choices. I then show how these choices affect job transitions and use the introduction of a large-scale regularization policy in Colombia to estimate the role of networks.

5.1. Model: dual labor market with referrals

The starting point is the model of spatial job referral networks presented in an accompanying paper (Mesa-Guerra, 2023), which adopts a variant of the Rosen-Roback-type model by allowing workers to have preferences for locations and incorporating job search using both direct and indirect methods.

Consider a city comprised of two neighborhoods, 1 and 2. There is an initial allocation of immigrant workers in each neighborhood and firms entering freely in each neighborhood up to the point where the value of opening a job is zero.[30] Workers first choose where to live in and then where to search for work and face a commuting cost when working or searching outside their own neighborhood. Workers can find a job either by directly learning about a vacant job or by being referred to it by a social contact. However, search through the network is characterized by a non-monotonic relationship between the job matching rate and the network size. Larger networks increase the odds of finding a job through more information, but it also creates more competition for the same sources of information. Therefore, network externalities and commuting costs drive suitable employment opportunities for immigrants.

Consider two types of workers denoted by $m \in \{D, U\}$, documented and undocumented, and two sectors denoted by $a \in \{F, I\}$, formal and informal. Each worker-type represents an exogenous share of the total population. A worker's status conditions the jobs he can get; consistently, the type of job determines the type of worker than can fill a vacancy.

Documented workers can search for jobs in both sectors, while undocumented workers can only look for informal jobs. Since workers are embedded within a network of social relationships, the initial distribution of contacts will affect the probability that a worker finds a specific job. In particular, this will be driven by the local unemployment rate and the share of workers commuting between locations by worker- and sector-type.

For simplicity, assume that all formal jobs are located in neighborhood 1 while all informal jobs are located in neighborhood 2. This implicitly relates the choice of place of work with the type of job workers may acquire, meaning that choosing the place of work is the same as choosing the sector of employment. A direct implication of this is the segmentation of workers' residential location, such that a larger fraction of undocumented workers chooses to locate in neighborhood 2, where informal jobs are. If idiosyncratic preferences for neighborhoods are not very important, then

[30] This is a standard condition in search and matching models of the labor market.

undocumented workers are very sensitive to differences in expected payoffs between the two neighborhoods. In the limiting case, any difference in the probability of finding a job—net of rents and commuting costs—not offset by a corresponding difference in local amenities results in the entire population of undocumented workers choosing to locate in neighborhood 2.

In equilibrium, the expected value of type-m job seekers must be equalized across locations if both neighborhoods are populated by type-m workers. Because documented and undocumented workers face the same housing market within a neighborhood, demand for housing in a neighborhood is obtained by adding the type-specific demand curves.

To determine the optimal job search location of workers, note that firms affect the relative supply of worker-type labor by posting type-specific vacancies. Assume wages are determined by Nash bargaining and that there is a "wage penalty" for undocumented and informal workers such that $w_{Ijk}^{U} < w_{Ijk}^{D} < w_{Fjk}^{D}$.[31] Documented workers with low number of encounters with workers employed in the formal sector (i.e., small network size) will optimally search for informal jobs (i.e., search in neighborhood 2). Holding constant the neighborhood of residence, workers that initially hold an informal job and transition to a formal job face a cost which is equivalent to the commuting cost.

5.1.1. Transition rates

The theoretical framework can be used to assess the effect of immigration policies such as the regularization of undocumented workers. Since my focus is not on the effect of the policy per se but on how the policy affected informal-to-formal job transitions of previous undocumented immigrant workers, I now proceed to derive the aggregate transition rate for this group.

Assume all undocumented workers are regularized at time t. Regularization causes a change in the total labor supply of workers and a change in worker's productivity. Because of the relationship imposed on wages (more precisely on workers' productivity) for each sector, an unemployed worker accepts any job—assuming worker's value of the outside option is below the prevailing wage, and a worker employed in the informal sector will always accept a job offer in the formal sector. Modeling informal-to-formal job transitions is equivalent to modelling job-to-job transitions. I follow Shimer (2005b) but abstract from time aggregation bias.[32]

[31] Limited job opportunities for undocumented workers cause talent to be misallocated (e.g., occupational downgrading), reducing workers' productivity. This is consistent with empirical evidence. Undocumented immigrant workers earn 24% less per hour than documented immigrants in the informal sector, while documented immigrant workers in the formal sector earn 77% more per hour than those in the informal sector. This relationship holds after accounting for differences in observed individual characteristics, occupation, and industry, although the wage gap is smaller.

[32] Workers loose and find new jobs at very short intervals of time, but data is reported at larger intervals of time, for instance, on a monthly or quarterly basis. Thus, between the time new data is reported, some workers could have lost their jobs, and some unemployed workers might have found one.

Let $\tilde{\imath}_t$ denote the fraction of workers employed in the informal sector at time t. Then $\tilde{\imath}_t L_t$ is the total number of workers employed in the informal sector. For any t, this evolves according to:

$$\Delta(\tilde{\imath}_t L_t) = \lambda_{I,t} U_t - \tilde{\imath}_t L_t (\delta + \lambda_{F,t}), \tag{3}$$

where $\Delta X_t = X_{t+1} - X_t$. Total informal employment increases when unemployed workers find an informal job with (average) probability $\lambda_{I,t}$. But decreases when one of the $\tilde{\imath}_t L_t$ informal workers loses his job with probability δ or finds a job in the formal sector with (average) probability $\lambda_{F,t}$. Using the law of motion for total employment $\Delta L_t = \sum_a \lambda_{a,t} U_t - \delta L_t$ and the fact that $L_{t+1} = \Delta L_t + L_t$, we can rewrite equation (3) as:

$$\Delta\tilde{\imath}_t = \frac{(1-\tilde{\imath}_t)\lambda_{I,t} U_t - \tilde{\imath}_t \lambda_{F,t} N_t}{\lambda_{I,t} U_t + \lambda_{F,t} U_t + (1-\delta) L_t}. \tag{4}$$

In steady state, equation (4) can be written to solve for $\tilde{\imath}$:

$$\tilde{\imath} = \frac{\delta - \lambda_F \ell}{\delta + \lambda_F}, \tag{5}$$

where $\ell \equiv U/L$. For there to be a positive value of $\tilde{\imath}$ in steady state $\ell < \delta/\lambda_F < 1$ (empirically supported). The total number of job switchers during period t is:

$$\Delta_{I\to F,t} = \lambda_{F,t} \tilde{\imath}_t L_t\,. \tag{6}$$

Replacing equation (5) into (6) gives the informal-to-formal job transition rate:

$$\frac{\Delta_{I\to F}}{L} = \frac{\delta - \lambda_F \ell}{1 + \delta/\lambda_F}. \tag{7}$$

This rate is independent of the job-finding rate in the informal sector but is decreasing in the unemployment-to-employment ratio and is increasing in the separation rate. A higher number of unemployed workers relative to the total employed population indicates that the mass of potential workers transitioning from informal jobs to formal jobs is lower. A higher separation rate induces previously displaced workers to look for better jobs as noted by Shimer (2005b).

For reasonable values of δ and ℓ,[33] the job transition rate is increasing in $(0, \lambda_F^{max}]$ and decreasing in $(\lambda_F^{max}, 1]$. This comes from the non-monotonic relationship between the job matching rate and the network size. In addition, workers with fewer

[33] Estimates using Colombian data suggest that the monthly average separation rate over the last two decades reaches 6.0% while the unemployed-to-employed ratio has oscillated between 0.1 and 0.2 for the most part.

contacts employed in the formal sector have a lower probability of being referred, reducing their probability of moving to formal jobs. Note that regularizing undocumented immigrants is both a positive shock to the labor supply of documented workers and a negative shock to the job-finding rate in the formal sector as the number of vacancies per worker decreases.

5.2. Empirical strategy

I leverage the introduction of a large-scale regularization policy in Colombia in 2018 to investigate whether referral networks affect the transition of immigrants from informal to formal jobs. I use the expansion of a two-year special permit (*Permiso Especial de Permanencia*, PEP) that allowed immigrants to stay and work in the country. The policy was set to cover about 440.000 undocumented immigrants that had voluntarily registered at the time using the Administrative Register of Migrants from Venezuela (RAMV).[34] While the RAMV was by no means implemented to grant work permits but for the sole purpose of identifying the number of undocumented Venezuelan-born immigrants living in Colombia, it was used as one of the requirements to apply for the PEP-RAMV.

By observing employment spells in the formal sector from 2018 to 2021 for immigrants who were eligible and obtained a PEP-RAMV, I can estimate the role of residence-based networks. I construct a network quality index for 2017, before the policy was announced. This measures the quality of social contacts in each neighborhood based on the extent to which information about formal (high-wage) jobs could potentially be diffused through the network, weighted by the size of the initial network. All details regarding the construction of the sample and the network index are presented in Section B.5 in the Online Appendix.

The goal is not to evaluate the effect of the PEP-RAMV, but to use the unexpected introduction of the policy to estimate network effects for those workers who faced a change of status. Therefore, I consider only PEP-RAMV holders who likely have not changed where they live.[35] The key assumption is that an individual's neighborhood of residence influences outcomes only through the composition of the neighborhood in 2017. I estimate the following linear regression model:

$$E[Y_i|PEP_i = 1] = \gamma_o + \gamma_1 Z_{k(i)} + \varphi' \mathbf{X}_i + \lambda' \mathbf{P}_{k(i)}\,, \tag{8}$$

[34] Registration in the RAMV was opened from April 6 to June 8 of 2018, while the expansion of the PEP was announced by the President on July 25 of 2018. Aside from being registered in the RAMV, a requirement was to have arrived to the country by August 2 of 2018. All permits were issued between August 2 and December 21 of 2018.

[35] Since I only observe movement of individuals from the year before to the survey (i.e., from 2020 to 2021), the main assumption, somewhat strong, is that the residential location of those workers who did not move in the past year has remained the same since 2017. Even if they moved at some point, by using a neighborhood score measured before the policy was implemented will reduce the bias from sorting into neighborhoods post-PEP-RAMV. In the data, 95% of immigrant workers did not change their residential neighborhood from the previous year.

where Y_i is one of three labor market outcomes for individual i: the probability of transitioning to a formal job within a year (end of 2019), the probability of transitioning to a formal job at any time between August 2018 and December 2021, and the probability of being employed formally at the end of 2021; Z_k is the network quality index for individual i, which is common across all workers living in neighborhood k; $\mathbf{X}_i$ is vector of individual demographic controls; and $\mathbf{P}_{k(i)}$ is a vector of observable neighborhood characteristics that influence search outcomes.

A concern commonly raised in the neighborhood effects literature is the bias resulting from individual sorting on unobservable attributes (to the econometrician), both at the individual and at the neighborhood level. Sorting captures the fact that different individuals live in different neighborhoods. Thus, differences in outcomes across neighborhoods may simply reflect sorting of workers across locations. Since sorting causes correlation between individual and neighborhood attributes, this is a potential source of bias. For instance, if high-ability workers sort into better neighborhoods based on unobserved preferences or better information on job opportunities, then one might expect the estimated effect of neighborhood quality on labor market outcomes to be overstated. The ideal identification strategy would make use of a random assignment of immigrants to neighborhoods. Unfortunately, our context does not provide such a clean identification.

Now, even if we take the network as exogenous, neighborhood characteristics are generally not randomly assigned. In other words, neighborhoods with high concentration of migrants are likely to have other characteristics that might determine labor outcomes of their residents. For instance, neighborhoods with a high concentration of immigrants fare worse in safety and environmental concerns (contamination, odors, noise, etc.), have on average lower socioeconomic conditions, and residents must commute longer distances as the density of jobs is lower in these neighborhoods (see Table A3 in the Online Appendix). However, measures of access to transportation, for instance the time it takes residents to get to the nearest station, are similar for both types of neighborhoods.[36]

In the context described here, the exogenous introduction of the policy mitigates to some extent the potential bias from sorting on unobservable attributes that predict program enrollment and formal employment. Immigrants' location decision before the policy was introduced could not have accounted for access to formal employment opportunities. Without the PEP, undocumented immigrants would have not been able to access formal jobs, only search for informal jobs. Identification then relies on sorting on observables. I condition on a set of observable individual attributes and amenities (e.g., distance to the main formal employment areas).

5.3. Results

[36] These facts also hold for the general population. Neighborhoods where most immigrants live tend to be also those with a larger local population (see Figure A5 in the Online Appendix).

Results in Table 9 suggest residence-based networks seem to constrain immigrants' transition from informal (low-wage) to formal (high-wage) jobs. Immigrants who settle in communities with a high concentration of unemployment, and workers in low-wage and informal jobs, are less likely to be employed formally one year after the policy was introduced (row *(a)*). For instance, an increase of 10 points in the neighborhood quality score (half a standard deviation) increases the probability of working in the formal sector somewhere between 0.7 and 1.0 percentage points, depending on the specification used. These effects are quite large once we consider that, on average, only 1.2 percent of immigrants in the sample were employed in the formal sector by the end of 2019.

A first (and naive) look of the results of rows *(b)* and *(d)* suggest that the strength of these effects diminishes as immigrants assimilate in the host community, which could be explained by expanding their social contacts or reallocating within the city. Both the network quality effect on the probability of being employed in the formal sector at any point in time between August 2018 and December 2021 and the probability that an immigrant is employed formally by the end of 2021 fall and are not distinct from zero. However, this is at odds with the observed drop in the average share of immigrants employed formally by 2021 to about 0.5 percent. A more compelling explanation is that the increase in the share of immigrants working in the formal sector, and hence the positive relationship with neighborhood quality, is seen in the first few years after the policy was put in place but was not sustained over time. In other words, while early on we see immigrants transitioning to formal employment, especially those with higher quality networks, over time some of those immigrants' move away from formal jobs, either to informal jobs or unemployment.

Although the evidence presented here suggest that low quality networks limit immigrants' access to formal jobs, other factors might potentially explain why we do not observe high rates of formal employment among immigrants. One potential explanation is that there were fewer formal sector jobs as a result of the pandemic recession. It has been documented in the literature that immigrants do relatively worse in recessions and better in expansions (Orrenius & Zavodny, 2010). Although essentially all formal employment lost during the first few months of the pandemic was regained by the end of 2020, it is still possible that the pandemic created a shift in the sectoral composition of the newly created employment that affects immigrants disproportionately by allowing fewer links that could provide a referral, as predicted by the model. However, if immigrants do better in expansions, then one would expect that during the economic rebound they would have at least regained the level of formal employment in 2019, which is not what we see in our results. It is also not driven by large inflows of immigrants, as the level remain fairly stable up until late 2021.

Another potential explanation presented in the literature is that immigrants may choose to remain in informal jobs despite having a PEP in order to be less visible to the tax authorities and continue their enrollment in subsidize healthcare. Now, this is unlikely to drive the results as the empirical evidence for Colombia suggest a large wage premium for immigrant working in the formal sector (Bahar et al., 2021).

Other potential explanations limiting the ability of immigrants to transition to formal jobs include discrimination by employers and lack of recognition or validation of academic or professional credentials for immigrants. This last explanation has some ground as among those who were working or looking for work and had a higher education degree, 90% had not had their diploma validated—similar numbers between men and women. Yet only a handful of professions are required to do this even to work in the private sector.

Based on the multiple evidence presented so far, at least two factors seem to form a direct path explaining how networks affect immigrants' access to formal jobs: occupational downgrading upon arrival and spatial mismatch. Both reinforcing each other. The misalignment between where workers live and where they can find suitable employment opportunities lowers the quality of their referral networks, making it harder for immigrants to receive or find job offers in the formal sector. In addition, the early occupational downgrading of immigrants and their clustering in space affects their future employment prospects, increasing the persistence of informal employment. This can result in a self-perpetuating cycle, where new immigrants enter the community and are referred to low-wage, informal jobs through social networks, making it more difficult for workers to transition to higher-wage, formal jobs.

6. Concluding Remarks

Using a novel data set and the large influx of Venezuelan immigrants to Colombia in recent years, this paper provides evidence on the role of referrals in immigrants' labor market outcomes by focusing on the spatial dimension of social interactions. By explicitly accounting for both the urban and the social space, this research provides new insights for the mismatch between the residential location and labor outcomes of immigrants.

I find that referrals are a critical source for information about available jobs for immigrants, particularly for recent arrivals, but struggle to produce high quality matches. The misalignment between where immigrants live and where they can find suitable employment opportunities, reflecting the quality of referral networks, makes it harder for immigrants to receive good job offers, especially in the formal sector. In addition, the early occupational downgrading of immigrants and their spatial clustering increases the persistence of informal employment. These findings are essential in assessing the welfare effects of job information networks and understanding the economic integration of immigrants.

Finally, the evidence presented in this paper points to the need to account for referral networks in the design of immigration policies or labor market interventions, not exclusively for immigrants, particularly those interventions targeting the barriers that affect the access to formal employment. As some studies have shown, living in large immigrant enclaves may be detrimental to long-term economic assimilation.

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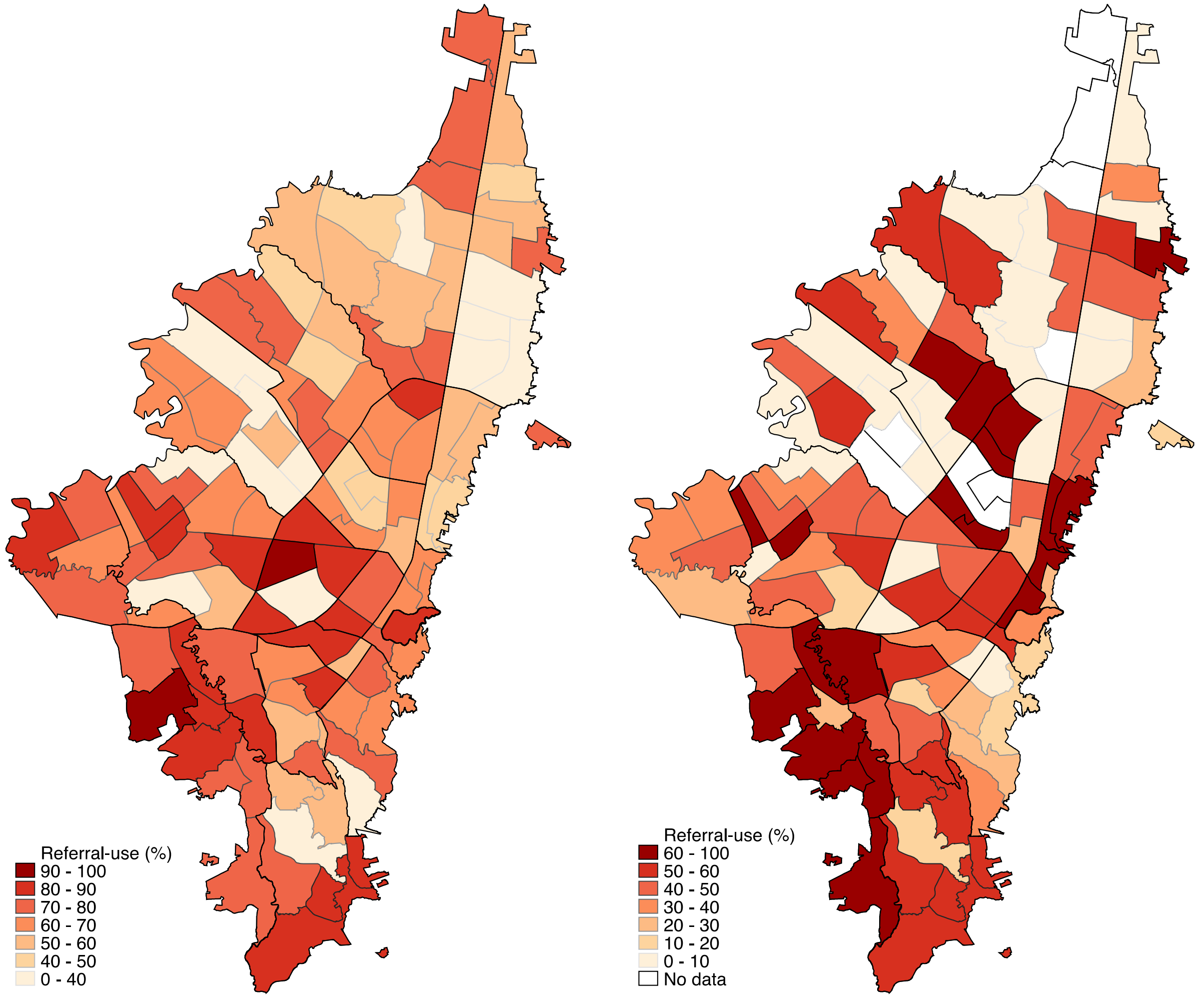
Figure 1: The spatial distribution of referral-use among immigrants

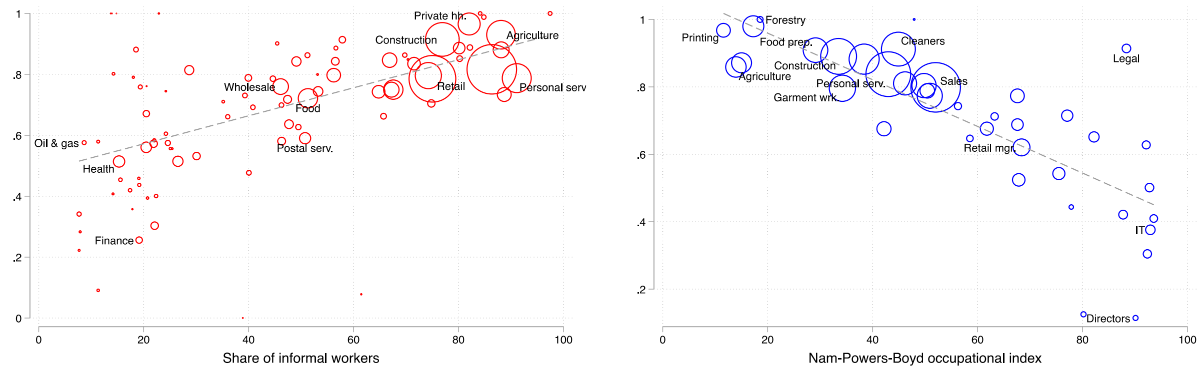


(a) Employed

(b) Job Seekers

Notes: The Figure shows the spatial distribution of the use of referrals across large neighborhoods (Zonal Planning Units–UPZ) in Bogotá. Panel (a) presents the share of employed immigrants (wage and salary workers) who report using relatives, friends, or acquaintances to find a job. Panel (b) presents the share of unemployed immigrants who report using referrals in their job search. Sample is restricted to Venezuelan-born immigrants aged 15 to 64 years. Localities boundaries are displayed in black. *Source:* 2021 EMB.

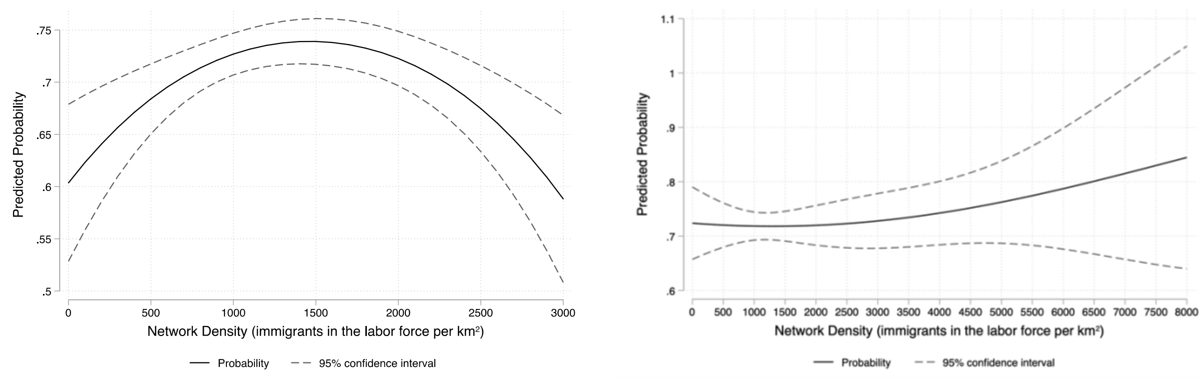
Figure 2: The use of referrals across industries and occupations



(a) Referral-use across Industries (b) Referral-use across Occupations

Notes: Panel (a) plots, for each two-digit industry code, the fraction of employed immigrant workers who report having obtained their current job through social contacts against the percentage of all workers in each industry without social security coverage. The share of informal workers is a weighted average of the index at the four-digit industry level. Panel (b) plots, for each two-digit occupation code, the use of referrals against the skill requirements of different occupations measured by the Nam-Powers-Boyd (NPB) occupational index. Points are weighted by the number of immigrant workers in each industry or occupation. Sample is restricted to Venezuelan-born immigrants aged 15 to 64 years. In panel (a), estimates are averaged over the period 2015-2021. In panel (b), I use data only for 2021 because of substantial changes in the occupational classification and to capture information at the 4-digit occupation level. *Source:* 2015-2021 GEIH.

Figure 4: Probability of finding a job and network size



(a) UPZs (b) Sectors

Notes: The Figure plots the predicted probability of finding a job for different network sizes. Network size is defined as the immigrant density (working-age population per km2). Panel (a) presents results at the UPZ-level while panel (b) shows results using sectors as the neighborhood definition. Estimates are based on a logistic regression where the dependent variable is a dummy taking a value of 1 if a worker lost his/her job due to Covid-19 or arrived to the country in the previous year and is employed at the time of the survey, and 0 otherwise. The sample is restricted to Venezuelan-born workers aged 15 to 64 years living in Bogotá. Regressions control for the unemployment rate in the neighborhood, the number of other household members in the labor force, sex, age groups (15-19, 20-29, 30-39, 40-49, 50-59, 60-64), educational attainment groups (less than HS, HS degree but no college degree, college graduate or above), marital status, head of household, and work authorization status. I also include borough (*localidad*) fixed effects. Standard errors are clustered at the neighborhood level. *Source:* 2021 EMB.

Table 1: Descriptive statistics across samples

Variable	Sample GEIH	EMB
Demographics		
Male	.482	.469
Age: 15 to 24 years	.330	.277
Age: 25 to 40 years	.490	.532
College or vocational education	.193	.331
Arrived in the last 12 months	.113	.091
Working permit		.506
Labor Market		
Labor force participation	.736	.750
Employment rate	.623	.650
Referrals	.794	.648
Informal job	.885	.850
Observations	30,242	9,701

Notes: Summary statistics for working-age immigrants in the GEIH and EMB samples. To allow comparisons among samples, only data for 2021 is used. An informal job is one in which the worker has no social security coverage.

Table 2: Use of referrals (relatives, friends, or acquaintances) in job search

	Employed (%)	Unemployed (%)
Panel A. Country of origin		
Colombia	66.0	37.3
Venezuela	79.4	50.2
Ecuador	68.6	31.7
United States	53.1	14.2
Spain	53.0	27.5
Other	51.1	26.2
Panel B. Venezuelan-born immigrants		
Cohort of arrival		
Short-term (< 1 year)	83.5	51.2
Mid-term (1-5 years)	79.2	49.5
Long-term (> 5 years)	71.0	49.8
Sex		
Male	79.6	57.1
Female	79.0	46.2
Age		
Youth (15-24)	83.7	49.8
Adult (25-64)	77.6	50.3
Education		
High school dropouts	89.3	63.4
High school graduates	81.2	50.4
Some college	73.2	37.5
College graduates	64.0	28.4
Sector of employment		
Public sector	18.7	–
Private formal sector	51.1	–
Private semi-formal sector	56.5	–
Private informal sector	87.2	–
Agricultural sector	90.9	–

Notes: The Table reports the share of workers aged 15 to 64 employed or looking for a job that use relatives, friends, or acquaintances to find a job, averaged over the period 2014-2021. Referral-use for employed workers captures only information for wage and salary workers. Following Wahba & Zenou (2005), formal employment is defined as having a written job contract and social security coverage (both health and pension); semi-formal employment as having either a written job contract or social security coverage; and informal as having none. *Source:* 2014-2021 GEIH.

Table 3: Descriptive statistics by referral status

Characteristic	Referral	SE	No referral	SE	Difference	t-stat
Male	0.631	0.010	0.602	0.015	0.029	1.62
Age: 15 to 24 years	0.206	0.008	0.161	0.011	0.046	3.29
Age: 25 to 34 years	0.463	0.010	0.485	0.015	–0.022	–1.20
Age: 35 to 44 years	0.225	0.009	0.254	0.013	–0.028	–1.79
Age: 45 to 54 years	0.083	0.006	0.079	0.008	0.003	0.34
Age: 55 to 64 years	0.023	0.003	0.022	0.004	0.001	0.19
High school dropouts	0.230	0.009	0.140	0.010	0.090	6.63
High school graduates	0.392	0.010	0.339	0.014	0.053	3.03
Some college	0.186	0.008	0.206	0.012	–0.020	–1.34
College graduates	0.191	0.008	0.315	0.014	–0.124	–7.64
Married	0.571	0.010	0.584	0.015	–0.013	–0.75
With children (0–14 years)	0.441	0.010	0.460	0.015	–0.019	–1.05
Short-term (< 1 year)	0.085	0.006	0.063	0.007	0.022	2.36
Mid-term (1-5 years)	0.651	0.010	0.594	0.015	0.057	3.19
Long-term (> 5 years)	0.181	0.008	0.223	0.013	–0.042	–2.86
Working permit	0.563	0.010	0.673	0.014	–0.110	–6.28
Informal job	0.822	0.008	0.568	0.015	0.254	15.03
Observations	2,340		1,105			

Notes: The table reports descriptive statistics by referral status for working-age immigrants. Source: 2021 EMB.

Table 4: Immigrants' referral-use and the quality of the match

	A. Without firm fixed effects			
		Referral-use		
Dependent variable	Observations	Coefficient	S.E.	Model
(*log*) Starting hourly wage	1,011	–.089	.023	OLS
Starting wage bracket (*formal jobs*)	526	.105	.212	Ordered Logit
Wage growth	526	–.151	.067	OLS
Job tenure	3,373	.078	.049	Negative Binomial
Occupational downgrading	3,445	.046	.009	OLS
Occupational downgrading (*distance*)	1,020	.080	.023	Poisson
	B. With firm fixed effects			
		Referral-use		
Dependent variable	Observations	Coefficient	S.E.	Model
(*log*) Starting hourly wage	–	–	–	–
Starting wage bracket	526	.105	.239	Ordered Logit
Wage growth	526	.098	.248	OLS
Job tenure	641	–.171	.093	Negative Binomial
Occupational downgrading	650	.144	.099	OLS
Occupational downgrading (*distance*)	220	–.150	.026	Poisson

Notes: The Table reports results of a single regression for each of the six labor market outcomes on a dummy indicating whether the immigrant worker obtained his current job through a referral. I use two measures for starting wages. The first measure corresponds to the (*log*) hourly wage, excluding overtime pay, of workers with tenure ≤ 6 months. Using a lower threshold does not significantly change the coefficient but reduces considerably the sample size. The second measure uses only administrative information for formal jobs which is reported in brackets. Wage growth is defined as the probability of moving up the 'job ladder' for those migrants that have worked for a firm for more than one year, *i.e.*, moving up between income brackets as reported in the RELAB data. I use job tenure of all currently employed workers for at least a month at the time of the survey. Immigrants' occupational downgrading is measured using the median education level of natives in each 4-digit level occupation. All regressions include as individual controls age groups, sex, educational attainment, head of household, marital status, number of household members in the labor force, work authorization status, and sector of employment (informal vs. formal). Standard errors are clustered at the municipality level. *Source:* EMB–RELAB.

Table 5: Extent of sorting within neighborhoods

Variable	R^2 Method		Residual Method	
	Unconditional (1)	Conditional (2)	Unconditional (3)	Conditional (4)
Age	.006	.000	.080	.012
Male	.001	.001	.024	.028
Married	.002	.000	.043	.011
With children aged 0-14	.003	.000	.053	.016
High school graduate or lower	.163	.024	.403	.154
College graduate	.265	.046	.515	.214
Immigrant	.070	.039	.264	.197

Notes: The Table reports the extent of sorting within census blocks by comparing a series of individual characteristics for a randomly selected worker with the corresponding average characteristics in the block (not including the individual or someone in the same household). Only blocks with five or more workers are kept in the sample. Columns 2 and 4 condition on block group fixed effects. The first two columns report the R^2 from a regression of the individuals' characteristics on the block-level average. The last two columns report the pairwise correlation of the residuals of a regression of the individuals' characteristics and the block-level average on the block group fixed effect. *Source:* EMB–RELAB.

Table 6: Propensity of neighbors to work in the same block or establishment

	A. Block Group Controls							
	Working in the same Block				Working in the same Establishment			
	(1)		(2)		(3)		(4)	
Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Reside on same block (R)	1.28	0.06	1.12	0.09	.008	.002	.004	.003
R × Both male			0.21	0.14			.011	.005
R × Both household heads			–0.24	0.15			.004	.005
R × Both married			0.09	0.16			.001	.005
R × Both with children (0–14 years)			–0.14	0.22			–.007	.004
R × Both no children			–0.12	0.27			.002	.008
R × Both same age group			–0.27	0.13			.001	.005
R × Both HS graduates			0.91	0.17			.009	.009
R × Both college graduates			–0.83	0.13			–.004	.003
R × Both immigrants			4.63	1.65			2.57	3.13
R × Both immig. allowed to work			–4.61	2.08			–	–
R × Both long-term immigrants			–5.05	1.48			–2.57	3.12
R × Job switcher arrived recently			7.63	4.22			–2.57	3.13
Sample size	423,497				3,882,031			
	B. Individual Controls							

Variable	Working in the same Block (1) Coeff.	S.E.	(2) Coeff.	S.E.	Working in the same Establishment (3) Coeff.	S.E.	(4) Coeff.	S.E.
Reside on same block (R)	1.31	0.26	1.16	0.31	.009	.002	.004	.003
R × Both male			0.16	0.22			.010	.007
R × Both household heads			–0.27	0.19			.002	.005
R × Both married			0.10	0.21			.000	.006
R × Both with children (0–14 years)			–0.14	0.21			–.006	.005
R × Both no children			–0.24	0.35			.001	.009
R × Both same age group			–0.22	0.16			.001	.005
R × Both HS graduates			0.81	0.21			.012	.009
R × Both college graduates			–0.84	0.22			–.004	.004
R × Both immigrants			5.01	2.03			2.68	2.84
R × Both immig. allowed to work			–4.70	2.39			–	–
R × Both long-term immigrants			–5.65	2.14			–2.67	2.84
R × Job switcher arrived recently			8.22	4.30			–2.69	2.85
Sample size	422,956				3,882,031			

Notes: The Table reports results of linear probability models in which an observation is a pair of currently employed, working-age (15–64) individuals who reside in the same census block group (*sector*) but not in the same household within Bogotá in 2021. The first worker in the pair (job switcher) changed jobs in the last 12 months, transitioned from unemployment, or is a first-time employee. The second worker in the pair did not change jobs in the last 12 months. In columns 1 and 2, the dependent variable equals one if both individuals work in the same census block and zero otherwise. In columns 3 and 4, the dependent variable equals one if both individuals work in the same establishment (defined as block of employment × firm code). All specifications are for a sample that drops blocks with fewer than five workers, block groups with a single sampled block, and workers that moved to another neighborhood in the last year. I include workers living in another country one year before. Panel A reports results using block group fixed effects. Panel B include individual fixed effects. The coefficients have been multiplied by 100 to reflect percentage point changes. Standard errors in all cases are estimated by pairwise bootstraps. *Source:* EMB–RELAB.

Table 7: Immigrants' industrial and occupational clustering in the neighborhood

A. Average over all 4-digit industry and occupation classification

	Industry Coefficient	S.E.	Occupation Coefficient	S.E.
Observed clustering (NI^O)	.981	.256	.810	.126
Simulated random clustering (NI^R)	.546	.127	.500	.116
Difference ($NI^O - NI^R$)	.435	.244	.310	.133
Sample size (pairs)	1,544,025		1,588,656	

B. Top 5 industries and occupations by observed clustering

	Industry ISIC Code	NI^O	Occupation ISCO Code	NI^O
Canvas and related products	2394	60.7		
Residential construction	1522	16.7		
Retail sale of dairy products	4722	11.1		
Support activities for road transportation	5221	6.3		
Vegetable and melon farming	0113	5.6		
Shoe and leather workers			7536	10.0
Farmworkers and laborers			9211	9.1
Psychologists			2634	6.7
Garbage and recycling collectors			9611	5.6
Hand packers			9321	4.8

Notes: The Table shows estimates of clustering at industries and occupations from immigrants living in the same neighborhood (*sector*). Panel A presents results at the 4-digit industry and occupation classification, averaged over all industries and occupations. Panel B presents the observed clustering for the top five industries and occupations. NI^O is the average share of coworkers in the same industry or occupation (excluding other members of his household) with whom each worker is co-resident. NI^R is the average share that is simulated to occur randomly, ensuring that we generate the same size distribution of industries and occupations (in terms of matched workers) in the city as we have in the sample for immigrants. The sample consist of currently employed immigrants aged 15 to 64 years living in Bogotá. Pairs are constructed matching recently arrived immigrants with more established immigrants. The sample is restricted to industries or occupations with at least two observed immigrant workers. Both ISIC Rev. 4 and ISCO-08 codes correspond to the adapted version for Colombia. Reported standard errors are estimated by bootstrapping the entire sample of all possible pairs of workers with replacement. *Source:* 2021 EMB.

Table 8: Urban mismatch and immigrants' labor outcomes

A. All Venezuelan-born immigrant workers					
		Job Accessibility		*Isolation Index*	
Dependent variable	Observations	Coefficient	S.E.	Coefficient	S.E.
Labor force participation	7,695	.0071	.0022	.0010	.0004
Unemployment	5,848	–.0065	.0028	–.0008	.0005
Employment: informal	5,098	–.0073	.0041	.0025	.0007
(*log*) Hourly wage	2,568	.0255	.0075	–.0047	.0010
Employment tenure (months)	5,089	.9463	.2378	–.1164	.0520
Unemployment spell (weeks)	714	.7457	.2880	–.0549	.0740
B. Immigrant workers who lost their job one year before					
		Job Accessibility		*Isolation Index*	
Dependent variable	Observations	Coefficient	S.E.	Coefficient	S.E.
Labor force participation	1,793	.0058	.0030	.0007	.0006
Unemployment	1,569	.0051	.0057	–.0015	.0010
Employment: informal	1,256	–.0050	.0085	.0021	.0012
(*log*) Hourly wage	581	.0072	.0137	–.0028	.0030
Employment tenure (months)	1,256	.1061	.3428	.1906	.1066
Unemployment spell (weeks)	313	1.1751	.4787	–.1724	.1155

Notes: The Table reports results of a single regression for each of the six labor market outcomes on both a measure of neighborhood job accessibility and immigrants' residential segregation (isolation index). Job accessibility and isolation index are measured as percentages (0 to 100). The unit of observation is the individual. Panel A reports results for the sample of all Venezuelan-born immigrant workers aged 15 to 64 years living in Bogotá. Panel B restrict the sample to immigrants that lost their job due to the Covid-19 restrictions and were living in the same neighborhood the year before. All regressions include as controls age groups, sex, educational attainment, head of household, marital status, number of household members in the labor force, and work authorization status. Regressions for employment and wages include also dummies for sector of employment (agriculture, manufacturing, retail, food, other). Wages include earnings of wage and salary workers and independent contractors. Standard errors are clustered at the neighborhood level. *Source:* 2021 EMB.

Table 9: Effect of neighborhood quality on formal employment

	(1)	(2)	(3)	(4)
Dependent variable				
(a) Prob. of being employed formally 1 year after (end-2019)	.072	.086	.107	.103
	(.036)	(.041)	(.052)	(.051)
(b) Prob. of ever being employed formally (2018-2021)	.063	.067	.078	.076
	(.038)	(.045)	(.057)	(.056)
(c) Prob. of being employed formally at the end of 2021	.028	.034	.039	.037
	(.019)	(.021)	(.026)	(.024)
Individual characteristics		✓	✓	✓
Neighborhood characteristics:				
– Share of referrals in 2017			✓	✓
– Distance to formal jobs				✓
Observations	642	552	528	528

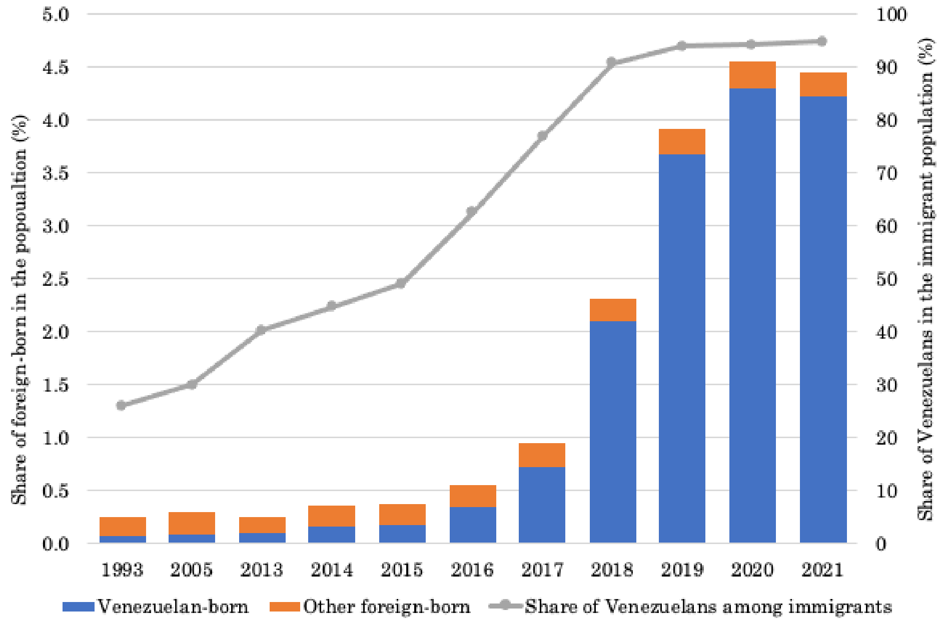
Notes: The Table reports results of linear probability models for each of the three labor market outcomes indicating whether a worker is employed in the formal sector on a measure of neighborhood quality that ranges between 0 and 100. The sample includes all working-age (15–64) immigrants who report having a PEP-RAMV and did not changed neighborhood in the last year or moved from a different municipality. All specifications are for a sample that drops census block groups (*sectors*) with fewer than five sampled workers. Individual characteristics include as controls age groups, sex, educational attainment, head of household, and marital status. Distance to formal jobs is constructed as a gravity-based job accessibility measure. The coefficients have been multiplied by 100 to reflect percentage point changes. Clustered standard errors are shown in parenthesis. *Source:* EMB–RELAB.

Online Appendix

Immigrant Networks in the Labor Market

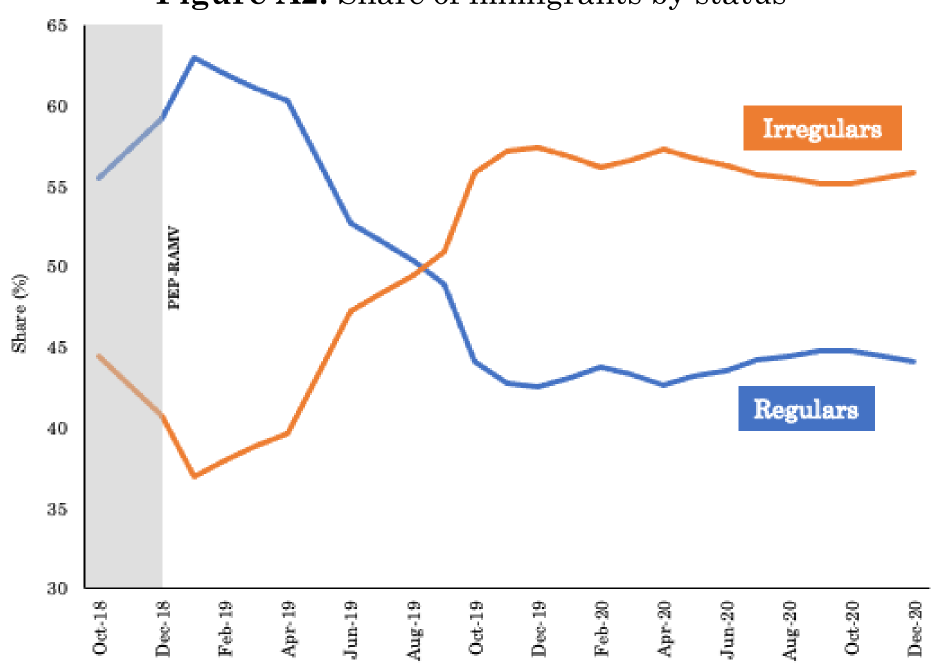
A Additional Figures and Tables

Figure A1: Immigration shock



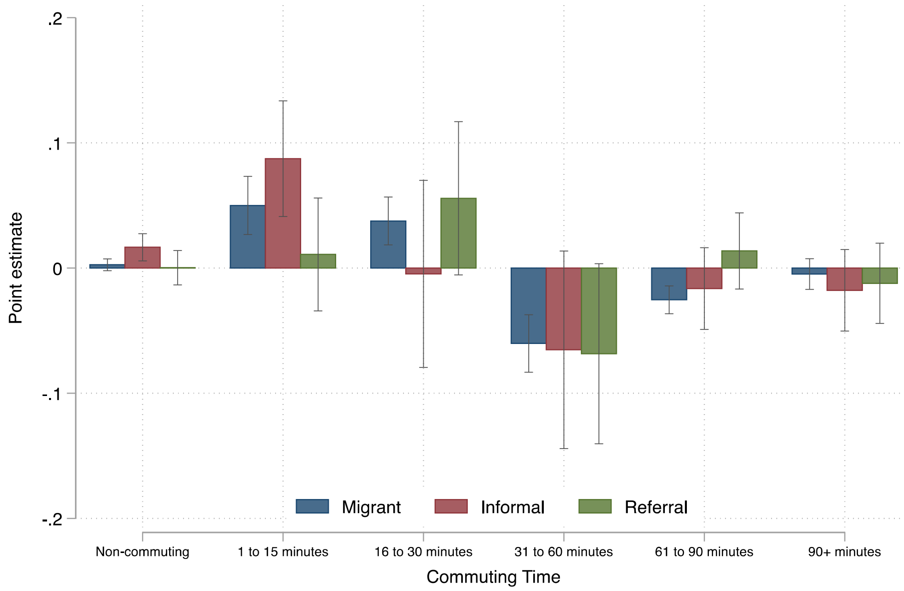
Notes: The Figure presents the foreign-born population as a percentage of the total population in Colombia (left axis) and the share of Venezuelan-born immigrants in the total foreign-born population (right axis) between 1993 and 2021. Shares are estimated using the population aged 15 to 64 years. Sample weights are based on the 2018 Population Census projections. *Source:* GEIH (2013-2020), Population Census (1993, 2005).

Figure A2: Share of immigrants by status



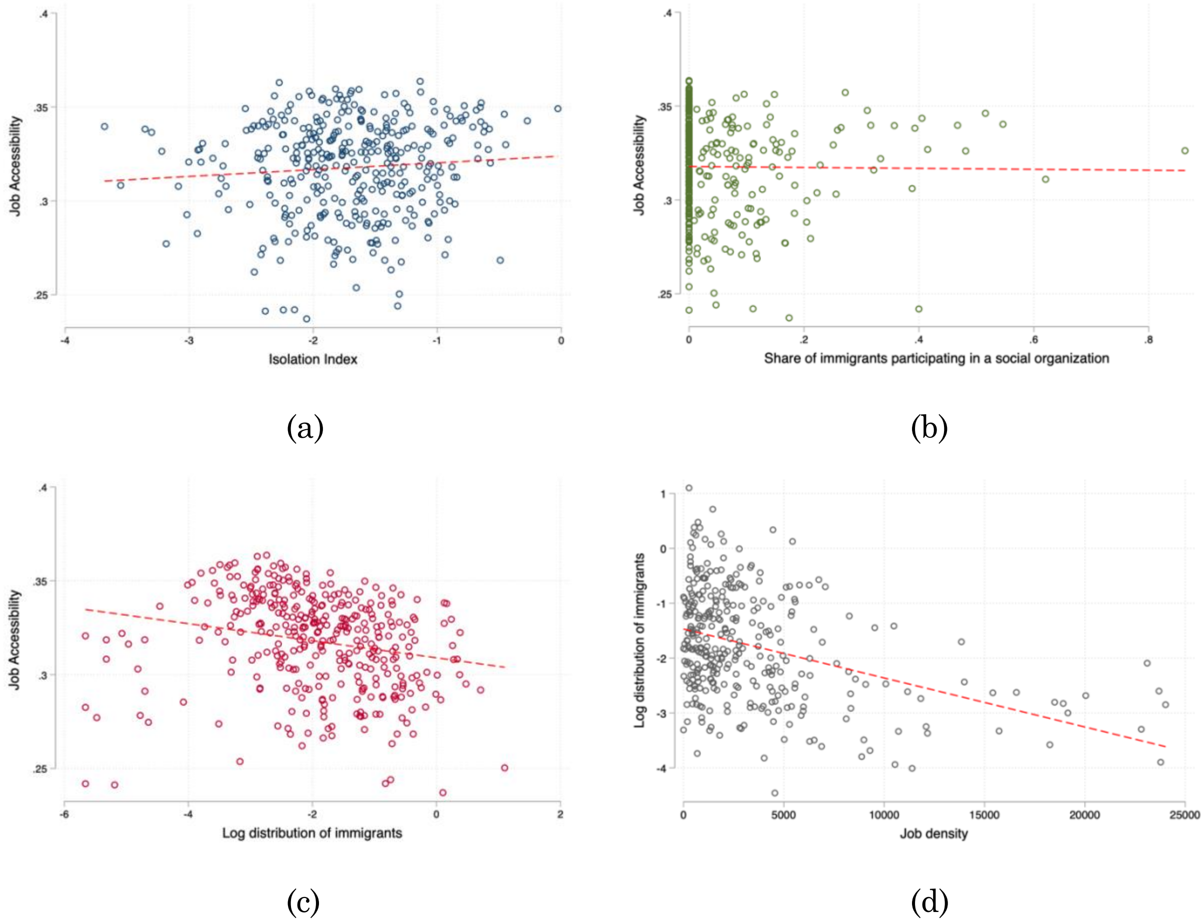
Notes: The Figure shows the share of immigrants with a regular and irregular status between October 2018 and December 2020. The shaded area indicates the first regularization period of undocumented immigrants, known as PEP-RAMV. *Source:* Migración Colombia; R4V.

Figure A3: Differences in commuting time among immigrants



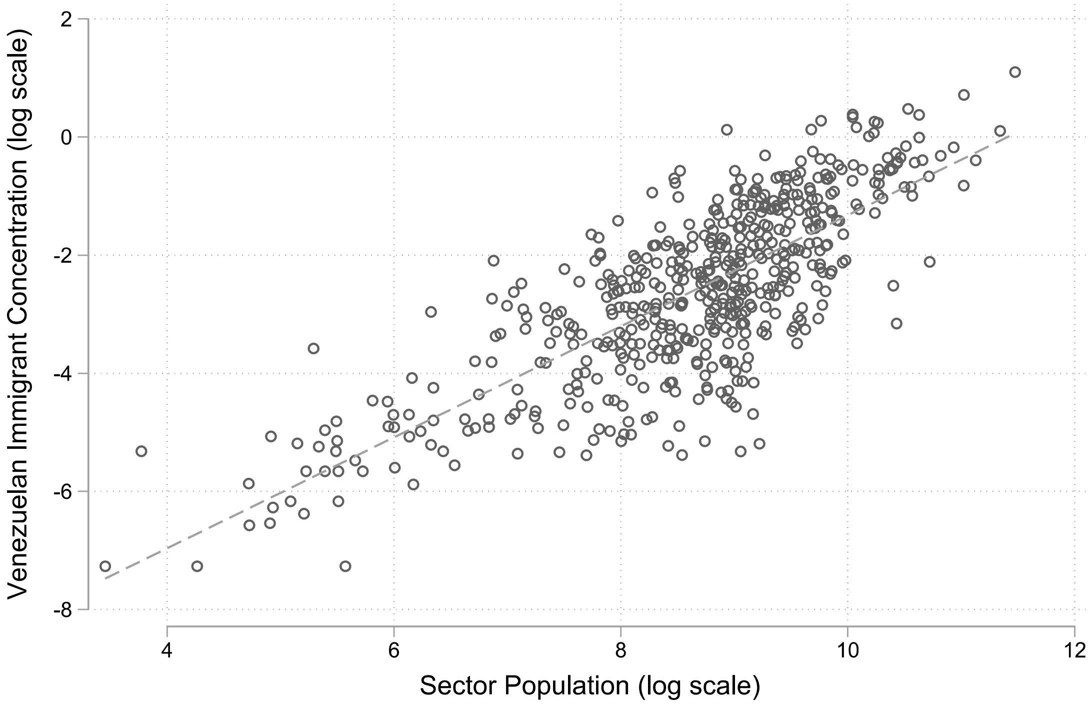
Notes: The Figure plots the point estimates and 95-percent confidence intervals of multiple regressions relating the probability of commuting within some window of time on a dummy variable for group membership (immigrant, informal worker, or finding a job through referrals). Sample is restricted to Venezuelan-born workers aged 15 to 64 years living in Bogotá. All regressions control for age and number of household members in the labor force, and include dummies for sex, marital status, head of household, educational attainment, work permit, residential neighborhood, and mode of transportation. Standard errors are clustered at the neighborhood level. *Source:* 2021 EMB.

Figure A4: Spatial vs. social mismatch



Notes: Panel (a) plots the relationship between the measure of job accessibility for each neighborhood (sector) and the (log) isolation index. Panel (b) plots the measure of job accessibility against the share of immigrants aged 15 to 64 years participating in a social, cultural, political, religious, productive, or union organization. Panel (c) plots the measure of job accessibility against the (log) distribution of immigrants across neighborhoods. Panel (d) plots the (log) distribution of immigrants across neighborhoods against the job density for high-wage jobs. High-wage jobs are defined as jobs paying above two-thirds of the median hourly wage (including self-employment labor income) for full-time, male workers in the city. All plots exclude neighborhoods with fewer than five sampled immigrant workers. *Source:* 2021 EMB.

Figure A5: Concentration of immigrants and size of the local population across neighborhoods



Notes: The Figure plots the distribution of immigrants across neighborhoods (sectors) in the y-axis and the size of the neighborhood population in the x-axis. Sample is restricted to Venezuelan-born workers aged 15 to 64 years living in Bogotá. *Source:* 2021 EMB.

Table A1: Job transition matrices

(a) Occupations

		Occupation in current job in Colombia											
		Armed forces	Managers	Professionals	Technicians and associate professionals	Clerical support workers	Services and sales workers	Skilled agricultural workers	Craft and related trade workers	Plant and machine operators	Elementary occupations	Not working	No information
Occupation in last job in Venezuela	Armed forces	0.0%	3.7%	0.0%	6.8%	0.8%	31.5%	0.0%	5.4%	0.4%	25.2%	24.9%	1.3%
	Managers	0.0%	2.4%	13.2%	1.0%	1.6%	23.4%	3.5%	3.1%	4.3%	11.3%	34.1%	2.2%
	Professionals	0.0%	3.2%	14.6%	3.1%	1.8%	21.3%	0.0%	9.3%	2.5%	8.1%	35.0%	1.1%
	Technicians and associate professionals	0.0%	1.5%	2.7%	10.5%	0.5%	22.4%	2.5%	8.6%	3.0%	17.7%	27.9%	2.7%
	Clerical support workers	0.0%	3.1%	0.0%	7.9%	6.0%	28.6%	0.0%	2.7%	2.2%	10.6%	36.8%	2.2%
	Services and sales workers	0.0%	0.7%	0.7%	6.7%	0.5%	31.4%	0.7%	8.1%	2.4%	15.5%	30.3%	3.0%
	Skilled agricultural workers	0.0%	0.7%	0.0%	1.2%	0.2%	16.3%	18.1%	19.0%	0.2%	29.9%	14.5%	0.0%
	Craft and related trade workers	0.0%	0.0%	0.1%	3.9%	0.4%	10.7%	1.7%	42.1%	2.7%	19.5%	17.2%	1.7%
	Plant and machine operators	0.0%	1.2%	0.4%	0.6%	0.9%	17.2%	4.4%	17.9%	16.4%	16.0%	19.8%	5.1%
	Elementary occupations	0.0%	1.3%	0.7%	0.3%	0.1%	14.5%	7.3%	10.0%	3.5%	30.7%	29.1%	2.7%
	Was not working before migrating	0.0%	0.3%	0.2%	0.4%	0.7%	15.7%	1.0%	4.1%	1.1%	11.5%	62.8%	2.1%
	No information	0.0%	0.0%	0.1%	0.0%	6.8%	18.8%	0.1%	14.6%	0.5%	13.7%	26.7%	18.7%

(b) Industries

		Industry classification of current job in Colombia														
		Ag.	Manuf.	Mining	Const.	Commerce	AFS	Transp.	Comm.	Finance	Real estate	Prof. serv.	Public admin.	Other services	Not working	No information
Industry of last job in Venezuela	Agriculture	41.7%	5.3%	4.0%	7.9%	10.2%	0.9%	1.5%	0.0%	0.0%	0.0%	3.7%	0.0%	6.0%	16.5%	2.4%
	Manufacturing	2.3%	20.5%	0.9%	7.0%	21.1%	1.9%	8.8%	0.0%	0.3%	0.0%	3.4%	0.3%	4.0%	25.9%	3.4%
	Mining and utilities	2.4%	6.7%	3.0%	1.0%	6.4%	5.5%	15.3%	0.0%	0.0%	0.0%	0.0%	0.0%	19.7%	32.6%	7.3%
	Construction	1.3%	5.4%	2.8%	42.1%	12.2%	4.5%	3.6%	0.0%	0.0%	0.0%	0.7%	0.2%	2.9%	20.9%	3.5%
	Commerce	2.4%	10.9%	7.7%	6.0%	23.7%	3.6%	7.7%	0.6%	0.2%	0.0%	2.0%	1.2%	3.7%	25.8%	4.7%
	Accommodation and food services	5.3%	5.2%	0.5%	15.4%	21.9%	17.6%	4.6%	0.9%	0.3%	0.5%	2.2%	0.8%	3.3%	16.6%	4.9%
	Transportation	1.1%	11.2%	0.8%	3.1%	16.9%	6.5%	19.5%	0.0%	0.6%	0.1%	3.6%	2.0%	4.8%	25.5%	4.3%
	Communications	0.0%	0.3%	0.2%	0.0%	16.0%	6.9%	0.8%	15.5%	0.0%	0.0%	2.7%	0.5%	15.2%	42.1%	0.0%
	Finance	0.7%	8.9%	0.2%	3.1%	24.0%	2.7%	3.1%	5.5%	4.3%	0.0%	11.7%	0.2%	5.0%	20.7%	9.9%
	Real estate	0.0%	0.0%	0.0%	0.0%	50.5%	2.3%	13.8%	0.0%	0.0%	0.0%	8.2%	4.2%	0.0%	15.0%	6.0%
	Professional services	0.9%	8.3%	0.9%	8.7%	11.0%	5.4%	8.4%	1.6%	0.0%	0.0%	8.3%	1.1%	1.5%	31.6%	12.1%
	Public administration	0.8%	8.2%	0.1%	3.3%	10.6%	4.8%	7.5%	1.4%	0.1%	0.9%	5.8%	10.1%	9.2%	36.2%	1.0%
	Other services	1.9%	7.0%	0.7%	2.5%	7.8%	1.1%	6.8%	0.6%	0.1%	0.0%	3.7%	1.8%	30.8%	31.9%	3.4%
	Was not working before migrating	1.2%	4.4%	0.8%	2.9%	10.3%	1.8%	5.8%	0.6%	0.0%	0.0%	1.4%	0.5%	4.8%	62.8%	2.7%
	No information	2.3%	14.0%	1.3%	9.4%	11.2%	1.9%	4.0%	1.1%	0.3%	0.0%	1.3%	0.4%	3.5%	36.8%	12.7%

Source: DANE, Encuesta Pulso de la Migración (round 2, Oct - Nov 2021).

Table A2: Wages and commuting time

A. All Venezuelan-born immigrant workers

	(log) Hourly wage				
	(1)	(2)	(3)	(4)	(5)
Commuting time (in minutes)	.0021	.0017	.0014	.0015	–.0006
	(.0006)	(.0005)	(.0005)	(.0006)	(.0020)
Demographic controls		✓	✓	✓	✓
Allowed to work dummy			✓	✓	✓
Sector of residence FEs				✓	✓
Sector of employment FEs					✓
Observations	2,023	2,023	2,023	2,023	1,118

B. Immigrant workers who lost their job one year before

	(log) Hourly wage				
	(1)	(2)	(3)	(4)	(5)
Commuting time (in minutes)	.0030	.0028	.0027	–.0006	–.0059
	(.0014)	(.0013)	(.0012)	(.0016)	(.0554)
Demographic controls		✓	✓	✓	✓
Allowed to work dummy			✓	✓	✓
Sector of residence FEs				✓	✓
Sector of employment FEs					✓
Observations	502	502	502	502	261

Notes: The Table reports results after regressing (log) wages on commuting time at the individual level. Panel A estimates results using all Venezuelan-born workers aged 15 to 64 years living in Bogotá. Panel B restrict the sample to immigrants that lost their job due to the Covid-19 restrictions and were living in the same neighborhood the year before. Wages include earnings of wage and salary workers and independent contractors. Demographic controls include age groups, educational attainment, number of household members in the labor force, and dummies for male, marital status, and head of household. Reported trips longer than 3 hours are excluded. *Source:* 2021 EMB.

Table A3: Descriptive statistics by immigrants' neighborhood concentration

Characteristic	High	SE	Low	SE	Difference	t-stat
Neighborhood conditions (issues faced)	0.230	0.007	0.172	0.005	0.058	6.65
Socioeconomic strata	2.351	0.059	2.884	0.052	–0.533	–6.76
Economic density (in millions)	0.160	0.008	0.340	0.036	–0.180	–4.83
Access to transportation (minutes)	10.60	0.276	10.59	0.201	0.011	0.03
Distance to jobs (minutes)	46.32	1.136	41.29	0.809	5.028	3.61
Observations	168		501			

Notes: The table reports descriptive statistics between neighborhoods (sectors) with a high concentration of immigrants and those with a low concentration. High concentration neighborhoods are defined as those above the 75^{th} percentile. Neighborhood conditions is a combine measure of some of the main perceived problems by residents (safety, contamination, odors, noise, etc.). Socioeconomic strata is a proxy of the socioeconomic condition of dwellings and determines the cost charged for public services. Economic density measures the number of jobs per squared kilometer. Access to transportation measures the time it takes residents to get to the nearest station. Distance to jobs measures the time it takes a worker to get to his job. Source: 2021 EMB.

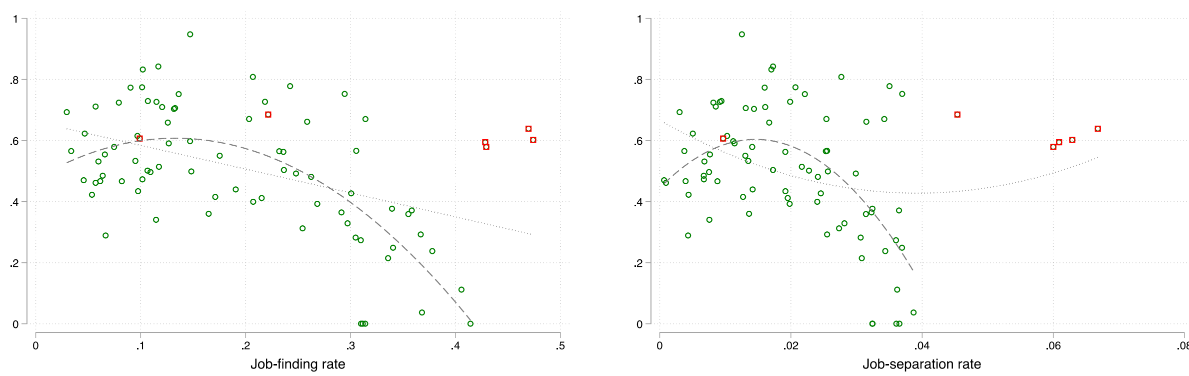
B Empirical Facts Appendix

B.1 Referral-use and Labor Market Conditions

Although immigrants display widespread use of social contacts to find jobs, the frequency by which workers rely on their social contacts to search for jobs is affected by labor market conditions. Previous work by Galenianos (2014) and Picard & Zenou (2018) suggest that when the rate at which workers find jobs increases, the incidence of referrals is lower.[38] Galeotti & Merlino (2014) find support for this fact by showing that there is an inverted U-shape relationship between the use of social contacts to search for jobs and the job separation rate across regions in the U.K.

The data for Colombia suggest some evidence of an inverted U-shape relationship for both the job-finding rate (Figure B1, panel (a)) and the job-separation rate (Figure B1, panel (b)). The use of personal networks is increasing when finding jobs is hard but decreases as labor market conditions improve. Similarly, workers invest more time on the use of personal contacts when jobs are split at a low rate but reduce their reliance on the network when matches break at an increasing rate. This suggest that when the labor market is loose, information through the network may be limited as the number of available jobs decreases and the pool of unemployed workers increases.

Figure B1: Referrals and the business cycle



(a) Job-finding rate (b) Separation rate

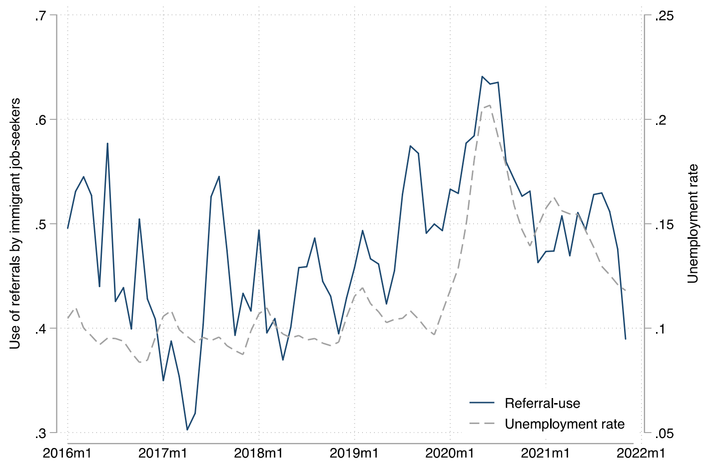
Notes: The Figure displays the average job-finding rate or separation rate (*x-axis*) and the proportion of immigrant jobseekers that use friends, relatives, or acquaintances as the main job search method (*y-axis*) for each year-MSA combination between 2016 and 2021. To reduce bias from low sample size, I exclude MSAs with an immigrant population below 5,000 active workers aged 15 to 64 years by 2021. Red boxes highlight data for Cúcuta, one of the main border municipalities and a large recipient of temporary immigrant inflows. The long-dashed line reports a quadratic fit excluding Cúcuta. *Source:* 2016-2021 GEIH.

Figure B2 looks at the evolution of the use of job referrals among immigrant job seekers and total unemployment rate in Colombia. There seems to be a stronger

[38] The ways in which aggregate labor market conditions affect the use of personal networks and how it affects our estimates of the effect of referrals on labor outcomes is still largely unknown.

relationship when facing negative economic shocks (e.g., shutdowns resulting from the Covid-19 pandemic). When unemployment is not too high, immigrant workers react to a swift increase in aggregate unemployment by relying more in their social contacts to search for jobs.[39]

Figure B2: Unemployment and the use of job referrals



Notes: The Figure displays the evolution between 2016 and 2021 of the use of job referrals among immigrant job seekers and total unemployment rate in Colombia. Each point in time corresponds to a 3-month moving average. Sample is restricted to workers aged 15 to 64 years. *Source:* 2016-2021 GEIH.

B.2 Effect of Network Strength on Labor Market Outcomes

I examine whether very local interactions (match strength) have an impact on labor market outcomes. Following Bayer *et al.* (2008), I construct a proxy of network strength at the individual level that intends to capture how likely are other workers in the block in helping an individual find a job.

I start by constructing a sample of all possible pairings of individual i with other individuals who reside in the same block $b(i)$ and do not belong to the same household, using all working-age individuals (aged 15 to 64 years).[40] For each pair (i,j), I compute a linear combination of the pair's covariates using the estimated parameters from the interaction of these variables with R_{ij} in Eq. (1) in the paper: $M_{ij} = \hat{\alpha}_1' X_{ij}$.[41] I then average M_{ij} over all matches for individual i, where $N_{b(i)}$ is i's number of neighbors, to get our network strength proxy, Q_i:

[39] This type of *substitution effect* has been explored by Picard & Zenou (2018). By embedding social interactions in an urban model with labor market frictions they show that there is a non-monotonic relation between the aggregate employment rate and the intensity by which workers search for jobs.
[40] Before constructing the pairs, I drop blocks with fewer than five observations and sectors with fewer than two blocks.
[41] In the computation, I only include parameters that are statistically significant at a minimum at the 10% percent level.

$$Q_i = \frac{1}{N_{b(i)}} \sum\nolimits_{j \in N_{b(i)}} M_{ij} \ . \tag{B.1}$$

Since the network strength measure does a better job of characterizing the referral effect for workers who are less attached to the labor market, I focus on the sample of immigrant workers that lost their job due to the COVID-19 pandemic or that were living in another country 12 months before. Taking as the unit of observation an individual rather than a pair, I estimate the following equation:

$$y_i = \theta_{b(i)} + \delta_1 Q_i + \delta_2' X_i + \mu_i \ , \tag{B.2}$$

where y_i is a labor market outcome; $\theta_{b(i)}$ is a block-level fixed effect; X_i is a vector of individual characteristics (see Table 3 in the paper); and μ_i is an individual error term. I standardize Q_i to express results as a one-standard-deviation increase in network strength on the corresponding labor market outcome. By including block-level fixed effects, δ_1 identifies the additional effect of network strength once we account for average outcomes and attributes of workers in the block. For all employment outcomes and the probability that a worker's commuting time is less than 30 minutes, I estimate a linear probability model. For hours worked and hourly wage, I estimate a linear regression.

All results are presented in Table B1. For the specifications using all origin-country groups (including natives), match strength has a positive and statistically significant effect on informality, hours worked, and commuting short distances. For instance, a one-standard-deviation increase in match strength rises the probability of finding an informal job by about 5.5 percentage points, average hours worked per week by about 0.7 hours, and the probability of commuting within 30 minutes by 1.6 percentage points.

Table B1: Effect of network strength on immigrant's labor market outcomes

	Origin-country group					
	All groups			*Venezuelan-born*		
Dependent variable	Obs.	Coefficient	S.E.	Obs.	Coefficient	S.E.
Employment	25,019	.001	.005	2,191	.000	.011
Employment: wage and salary workers	17,098	–.022	.007	1,757	.004	.013
Employment: informal	17,098	.055	.008	1,757	–.006	.012
Hours worked per week	17,098	.704	.232	1,757	.175	.515
(*log*) Hourly wage	9,285	–.120	.020	811	–.002	.030
Commuting time	12,546	–.376	.389	1,456	.193	.594
Pr(commuting ≤ 30 minutes)	12,546	.015	.006	1,456	.006	.013
Standard deviation of network strength (%)		.691			1.703	

Notes: The Table reports results of a single regression for each of the six labor market outcomes on a proxy for network strength (Q_i) and the full set of individual characteristics reported in Table 3. Block fixed effects are included in all regressions. The regression for commuting time includes, in addition, origin and mode of transportation fixed effects. Results are for a sample of workers aged 15 to 64 years that lost their job due to the Covid-19 pandemic or that were living in another country 12 months before. The coefficients reported in the table characterize the effect of a one-standard-deviation increase in match quality on the corresponding labor market outcome. Standard errors are clustered at the block level. *Source:* EMB–RELAB.

B.3 Estimation of Clustering at Industries and Occupations

To study whether workers employed in the same industry or occupation are likely to live in the same neighborhoods, I follow broadly Hellerstein *et al.* (2011) and compare the observed clustering of immigrants versus what a random clustering would yield. Using the 2021 EMB sample, I match recently arrived immigrants (those arriving in the las 12 months to the country) to immigrants arriving in earlier waves. The sample is restricted to Venezuelan-born immigrants living in Bogotá who are between 15 and 64 years of age.

Let i (recent arrival) and j (earlier cohort) be a pair of immigrant workers; $I^R(i,j)$ is a dummy variable equal to one if i and j live in the same neighborhood (sector); and $I^W(i,j)$ is a dummy variable equal to one if i and j work in the same 4-digit industry or occupation, respectively.[42] Using the sample of pairs, I compute for each recent arrival the percentage of immigrant workers from earlier cohorts working in the same industry (respectively occupation) who live in the same neighborhood (sector)—excluding the individual worker. I average this share across all N recently arrived immigrants to create the *network isolation index*, NI^O:

$$NI^O = \frac{1}{N}\sum_{i=1}^{N} \frac{\sum_i I^R(i,j) \times I^W(i,j)}{\sum_i I^W(i,j)} \times 100\,. \tag{B.3}$$

Note that the sums in the numerator and denominator are taken over all pairs for worker i. Their ratio is the fraction of previous immigrants in the same industry or occupation that live in the same neighborhood as worker i. To do inference, I bootstrap the entire sample of pairs with replacement 100 times and compute NI^O with the corresponding standard deviation and sample size; then, I estimate the mean standard error and report it along the network isolation index.

Since some neighbors are likely to work in the same industries or occupations, even if workers are assigned randomly to industries or occupations, I compare the network isolation measure to the extent of clustering that occurs *randomly* and denote this measure as NI^R. I randomly assign immigrant workers to industries and occupations, ensuring that I generate the same size distribution of industries and occupations (in terms of matched workers) in the city as I have in the sample. This is basically assigning workers to industries or occupations holding constant every time the number of workers that end up employed in a given industry or occupation. For each simulation, I compute NI^O. I repeat this 100 times and compute NI^R as the mean over these simulations.

All results are presented in Table 7 in the paper.

[42] I restrict the sample to industries and occupations with at least two observed immigrant workers and drop pairs where both workers belong to the same household.

B.4 Urban Mismatch

To analyze if distance to jobs (spatial mismatch) and limited social connections (social mismatch) affect immigrants' labor market outcomes, I construct the following measures:

(i) *Social mismatch*. I start with a measure of residential segregation: isolation index. This measures the extent to which immigrants are exposed only to one another. Let M_n be the number of immigrants aged 15 to 64 years in block n, M_S the number of immigrants aged 15 to 64 years in neighborhood (sector) S, and L_n the total population aged 15 to 64 years in block n, then the isolation index $I_{S(n)}$ at the sector-level is constructed using the following formula:

$$I_{S(n)} = \sum_{n \in S} \left(\frac{M_n}{M_S}\right)\left(\frac{M_n}{L_n}\right).$$

As a second proxy of social mismatch, I estimate the share of immigrants in the neighborhood (sector) aged 15 to 64 years participating in a social, cultural, political, religious, productive, or union organization. This measures the membership to institutions that provide social capital, providing information about the degree of interactions with weak ties (*e.g.*, natives).

(ii) *Spatial mismatch*. I measure job-access using a gravity-based accessibility measure following Shen (1998). Let A_n be the accessibility to employment from residential neighborhood n; N represents the total number of residential and employment location; J_m is the number of jobs in neighborhood m (workplace location); T_{nm} is the average commuting time from residential neighborhood n to each workplace location m (one-way distance); C_m is the competition or potential demand for jobs in neighborhood m; and W_n is the number of workers (employed and unemployed) living in n. The job-access measure that incorporates the location of competing workers is estimated as follow:

$$A_n = \sum_{m=1}^{N} f(T_{nm})\frac{J_m}{C_m} \quad \text{where} \quad C_m = \sum_{n=1}^{N} f(T_{nm})W_n\,.$$

The term $f(T_{nm})$, also known as the "distance decay" effect, increases the spatial variation in the competition for jobs that is being driven by variation in population density across neighborhoods. I model the distance decay function an iceberg commuting cost such that $f(T_{nm}) = (e^{\nu T_{nm}})^{-1}$. I take $\nu = 0.012$, the rate of spatial decay or disutility from commuting, from Tsivanidis (2019) who estimated it for Bogotá using the 2015 Mobility Survey.

For a pair of residential (n) and workplace (m) locations where I do not observe in the data commuting flows, and therefore I cannot compute the average commuting time, I impute the average commuting time from residence n to workplace m using the STATA command *osrmtime* (Huber & Rust, 2016). The command uses the Open-Source Routing Machine (OSRM) and OpenStreetMap to find the optimal route by car.

B.5 Informal to Formal Employment Transitions

To estimate the effect of residence-based networks on immigrants' informal-to-formal job transitions, I leverage the expansion in 2018 of a two-year special permit (known as PEP-RAMV) that allowed irregular or undocumented immigrants to stay and work in Colombia. I use information in the 2021 EMB on Venezuelan-born immigrants aged 15 to 64 years living in Bogotá with a PEP. Because the information in the EMB does not distinguish between PEP (first wave) and PEP-RAMV (second wave), I rely on both the timing of when each policy was introduced and eligibility requirements to restrict the sample to those most likely to be holding a PEP-RAMV instead of the traditional PEP. The sample is constructed by excluding the following workers:

(i) Those living in Colombia for more than 5 years or less than 12 months. The PEP-RAMV targeted workers who arrived between 2017 and 2018.
(ii) Those holding only a Colombian ID and those with valid work visa. Because the PEP-RAMV targeted undocumented migrants, those with a Colombian ID or a work visa are less likely to have been part of the cohort of interest.
(iii) Those that show up in the RELAB before August 2, 2018. Immigrants employed in formal jobs before the introduction of the PEP-RAMV would not have had the irregular status.
(iv) Those workers that changed neighborhood in the last year or moved from a different municipality. I'm interested in looking at the effect for workers who did not changed neighborhood from the time the policy was introduced. The assumption made here is that the residential location of workers who report not moving in the past year has remained the same since 2018. Some evidence indicates that the fraction of movers on a yearly basis is small.

I measure the quality of social contacts in each neighborhood based on the extent to which information about formal (high-wage) jobs could potentially be diffused through the network, weighted by the size of the initial network. Using information on a previous wave of the EMB for 2017, I construct an index that ranks neighborhoods based on the unemployment rate, the share employed in the formal sector, and the share employed in low-income jobs for Venezuelan immigrants.[43] I begin by sorting neighborhoods by each measure. The share of formal employment is sorted from low to high, while the unemployment rate and share of low-wage jobs are sorted from high to low. I then create a cumulative percentile distribution of the total

[43] Low-income jobs are defined as immigrants earning lower than two-thirds of the median hourly income for full-time, male workers in the city. In the data, the threshold is slightly above the legal minimum wage which is the wage floor in the formal sector.

number of immigrant workers in each neighborhood based on the ranking for each measure. I average the three cumulative percentage distributions. Scores can range from 0 to 100.

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