CAF - WORKING PAPER #2020/10

First version: December 14, 2020

This version: September 5, 2024

Local shocks in labor markets: competition and information flow among peers

Lucila Berniell[1] | **Dolores de la Mata**[2] | **Federico Juncosa**[3]

[1]CEDLAS - Centro de Estudios Distributivos, Laborales y Sociales.
luberniell@gmail.com

[2]CAF - Development bank of Latin America and the Caribbean.
mdelamata@caf.com

[3]CAF - Development bank of Latin America and the Caribbean.
cjuncosa@caf.com

We present causal evidence of the effect of local labor supply shocks on labor outcomes of young job seekers in a developing country. We study a large-scale internship program in Argentina that randomly alters job seekers' local labor environment. Exposure to areas with high program saturation results in adverse effects on labor market outcomes following program completion, while having a nearby individual who participated in the program improves labor outcomes. These results are compatible with the coexistence of a mechanism of transmission of valuable labor market information among peers and a competition mechanism.

KEYWORDS

Local labor market shocks, Labor market frictions, Spacial frictions, Information frictions, Networks, Externalities, Displacement effects

CAF - DOCUMENTO DE TRABAJO #2020/10

Primera versión: 14 de Diciembre de 2020

Esta versión: 5 de septiembre de 2024

Shocks locales en mercados laborales: competencia y transmisión de información entre pares

Lucila Berniell[1] | **Dolores de la Mata**[2] | **Federico Juncosa**[3]

[1]CEDLAS - Centro de Estudios Distributivos, Laborales y Sociales.
luberniell@gmail.com

[2]CAF - Development bank of Latin America and the Caribbean.
mdelamata@caf.com

[3]CAF - Development bank of Latin America and the Caribbean.
cjuncosa@caf.com

Presentamos evidencia causal del efecto de shocks de oferta laboral local en resultados laborales de jóvenes que buscan empleo en un país en desarrollo. Estudiamos un programa de pasantías a gran escala en Argentina que altera el entorno laboral local de los demandantes de empleo de forma aleatoria. La exposición a áreas con alta saturación del programa resulta en efectos adversos en los resultados laborales luego de la culminación del programa, mientras que tener cerca un individuo que participó del mismo mejora los resultados laborales. Estos resultados son compatibles con la coexistencia de un mecanismo de transmisión de información valiosa entre pares sobre el mercado laboral y un mecanismo de competencia.

KEYWORDS

Shocks en mercados laborales locales, Fricciones en mercados laborales, Fricciones espaciales, Fricciones de información, Redes, Externalidades, Eectos de desplazamiento

1 | INTRODUCTION

Labor markets are significantly affected by spatial and informational frictions. Spatial frictions refer to the role that distances within cities and transit options play in determining the spatial distribution of vacancies and the candidates filling them. These spatial frictions imply a local aspect to labor markets, as people tend to restrict their job search to small, more accessible areas of the city where they perceive less competition from other job seekers (Manning and Petrongolo, 2017). Importantly, spatial frictions mean that labor market supply and demand shocks may not have uniform effects across different areas of the same city. Informational frictions are also a crucial aspect of equilibrium outcomes in labor markets. When information is scarce, job seekers often rely on their networks of contacts, family, and friends to learn about available job opportunities and use referral mechanisms to convey information about their productivity to potential employers (Montgomery, 1991; Calvó-Armengol and Jackson, 2004).

Both spatial and informational frictions can be more severe for young job seekers, specially those in developing countries. Young workers often have little or no previous contact with employers, so their nearly empty CVs provide limited information to prospective employers about their potential productivity (Pallais, 2014). If they have experience, much of it is in the informal labor market, which may not provide sufficient verifiable credentials to potential future employers (Berniell and de la Mata, 2017).[1] Additionally, they are more likely to be unaware of many relevant aspects of the labor market, such as the wages they can aspire to, the quality of potential employers, and the location of better job opportunities beyond those close to their residency. Moreover, the residential choices of young individuals are largely tied to those of their parents, conditioning the accessibility to job opportunities within the city. Altogether, these restrictions compel young job seekers to rely more on social networks to find employment and navigate more localized labor markets (eg. see Kramarz and Skans (2014) for the role of parents on the first job). These challenges are exacerbated in developing countries by the uneven distribution of formal, high-quality jobs within cities, the lack of extensive, affordable public transport options, and pronounced residential socioeconomic segregation.

In this paper, we present causal evidence of the effect of local labor market shocks on employment and wages of young job seekers in the context of a developing country. We leverage the implementation of a large-scale internship program in Argentina, called the First Step Program (PPP, for its Spanish acronym), which randomly alters young job seekers' local environments by changing the average job experience of potential competitors in their relevant local labor markets (competition shock), as well as that of peers connected through a neighborhood-based social network (information shock). Focusing on the sample of program applicants in the largest city where it was implemented, we first calculate each individual's exposure to these shocks, proxied by the share of treated individuals in their local labor market (competition shock) and their closest neighbor's program treatment status (information shock).[2] Then, by merging the program records of applicants with employer-employee longitudinal administrative data, we estimate the competition and information shock effects on individuals' probability of being employed in the formal

[1] A formal job is characterized by being registered with tax authorities and offering regulated and stable working conditions, while an informal job lacks these characteristics.

[2] For the effect of the closest neighbor's program participation status to be interpreted as an information transmission effect through networks, we need to assume that spatial proximity increases the likelihood of two applicants being connected through a social network. This type of assumption is frequent in studies analyzing the role of neighborhood-based networks on labor outcomes (Bayer et al., 2008; Hellerstein et al., 2011, 2014; Schmutte, 2015). As we show in the data section, on average, the closest neighbour applicant resides less than 60 meters away.

sector, the number of months employed, and the cumulative wage in the 12-month period following the program completion. In our specifications, we also estimate the direct effect of the program, although it is not the main objective of this paper.

The PPP targets individuals between 16 and 25 years old and consists of a 12-month paid internship in a firm within the formal sector. Due to excess demand, benefits are assigned randomly among applicants. Take-up rates are very high, with almost all program beneficiaries completing at least 9 months and 85% completing the full 12-month internship. Work experience and credentials derived from formal experiences provided by the PPP can be crucial in improving young people's job prospects in the Argentine context, as job quality in the formal sector is considerably better than in the informal sector but access to these jobs is elusive. Typically, individuals in this age group in the country are unemployed (19%), working in a salaried informal job (41%), or self-employed (6%).[3] During the 12-months period of the program, only a negligible fraction of non-beneficiaries worked in a formal firm.[4] Hence, when the program ends, the mean job experience that can be credited is greater for treated individuals than for control individuals.

Identification works as follows. The PPP is a large-scale, mostly untargeted program where the main eligibility restriction is based on age. As a result, applicants are scattered throughout the city. Due to random assignment, beneficiaries are also distributed throughout the city, resulting in areas that, by chance, have higher saturation than others. From the point of view of any applicant, the introduction of the PPP randomly alters the mean job experience of relevant competing candidates for job vacancies, increasing competition. At the same time, the mean job experience of a candidate's peers may increase randomly, potentially increasing the flow of relevant labor market information received from them.

We find evidence compatible with both competition and information effects. Having a neighbor who benefited from the PPP program—the information effect—positively affects the probability of ever being employed by 2 pp. The number of months of employment and the cumulative wage also display positive coefficients, although not statistically significant. On the other hand, a 10 percentage points increase in the saturation of the program within the relevant local labor market for each youth—the competition effect—negatively affects the probability of ever being employed, the number of months of employment and the cumulative wage. These outcomes are robust to the inclusion of individual and firm controls, and neighborhood fixed effects. Additionally, the significance of our estimates is preserved when considering randomization inference p-values, built by random permutations over candidates locations. Finally, our results are robust to varying sizes for the local market considered.

We perform heterogeneous effects analysis that provides further support for the proposed mechanisms. First, we analyse heterogeneous effects of the information effect by neighbors' characteristics (age, gender, and education). Previous evidence suggest that individuals who share characteristics such as age, gender, or race are more likely to transmit labor market information (Cingano and Rosolia, 2012; Jahn and Neugart, 2020; Glitz, 2017; Hellerstein et al., 2014). We find evidence of homophily by age: the information effect is primarily driven by treated neighbour that belongs to the same age group, while it becomes close to zero for individuals of different age groups. Finally, we find evidence that the competition effect mostly occurs on the periphery of the city center, where job seekers can access less job opportunities within a low commuting time.

[3]These percentages are computed using the Argentine Household Survey (*Encuesta Permanente de Hogares*, EPH for its acronym in Spanish), and correspond to the year 2012, which is the year in which the PPP was first assigned through lottery. The figures have not changed much throughout the last decade.

[4]Control individuals might have been either unemployed, worked in the informal sector or self-employed during this period, but this information is unobserved.

Our results provide three main contributions to the existing literature. First, we present novel empirical evidence supporting the existence of spatial frictions that make local labor conditions relevant for young people, especially in the context of a developing country. By examining an exogenous change in the labor supply that impacts job seekers' work history and information sets, we underscore the importance of these frictions, as highlighted in related studies from various fields (Manning and Petrongolo, 2017; Tsivanidis, 2023; Baum-Snow et al., 2017; Baum-Snow, 2020; Abebe et al., 2021). Our study contributes to the limited research on local externalities in labor markets from the labor supply perspective, using a reduced-form experimental approach.

Second, this work contributes to the empirical literature that emphasizes the importance of information transmission through networks of contacts for labor outcomes. Specifically, our paper relates to the empirical studies examining the relevance of neighborhood -based social networks for individual labor outcomes. Very close neighbours are more likely to work in establishments nearby (Bayer et al., 2008) and even in the same establishment (Hellerstein et al., 2011). Moreover, these papers show that neighborhood-based networks increase the probability of employment for job seekers experiencing a mass layoff, produce more productive job matches, reduce turnover, and increase wages (Hellerstein et al., 2014, 2019; Jahn and Neugart, 2020; Schmutte, 2015). This literature attributes these effects to the existence and use of connections between neighbors to seek employment.[5] Neighbourhood-based networks are specially relevant for youth. However, the evidence of the effects of this type of networks for this group are scant and our paper helps to fill this gap.

More broadly, this work also contributes to the impact evaluation literature of youth employment programs, particularly those focused on developing countries, which has been recently summarized in McKenzie (2017), Card et al. (2018) and Carranza and McKenzie (2024). A general concern in this literature are the displacement effects generated by this active labor market policies (Crépon et al., 2013; Marinescu, 2017; Abebe et al., 2021). In particular, Berniell and de la Mata (2017) found no aggregate displacement effects of the PPP program. Our study finds that, even if there is no evidence of aggregate displacement effects, both negative and positive externalities arise at local levels within the city.

2 | INSTITUTIONAL CONTEXT

The PPP is an internship program administered by the Secretariat of Equity and Employment in the province of Cordoba (Argentina), whose main objective is to facilitate youth entry into the labor market.[6] The Secretariat randomly selects beneficiaries among eligible candidates and provides them with 12 months of salaried employment. Young beneficiaries to the program receive the stipulated amount payed by the Secretariat, conditional on working 20 hours per week. The amount of the subsidy for the 2012 edition, analyzed in this paper, was around 90% of the legal minimum hourly wage.[7] A distinctive aspect of the program is that it seeks to improve the employability of young people through work experience in the formal sector of the economy, but does not require an instance of classroom training, apart from the one employers may impart at the time of incorporating the young intern to the firm. As in most developing markets, informality is a prevalent problem in our setting, where the informality rate reached 36% for the working-age population and 55% for the

[5] See Hellerstein and Neumark (2020) for a detailed review summarizing this evidence.

[6] The province of Cordoba is the second largest province in terms of population. The province represents 8.2% of the population of Argentina in the Census 2010, and 6.4% of the country's labor income. Additionally, average incomes are 90.4% of the country's average.

[7] The gross monthly minimum wage was equivalent to \$ 585 in June 2012.

population aged 16 to 25 in Cordoba city in 2012.[8]

Firms that incorporate a worker through the PPP program are exempt from the non-salary and administrative costs that formally hiring and/or dismissing a worker normally entail, in addition to the employee salary subsidy the program provides. These costs can be significant, as social security contributions for a worker with the average country salary in Argentina amount to around 35 cents per dollar of salary payed to the employee (Álvarez et al., 2019). In addition, firms are not required to continue with the employment relationship after the end of the 12-month program, thus eliminating firing costs.

Eligibility conditions for young candidates consist of being between 16 and 25 years of age at the time of applying to the program, having a legal address in the province of Cordoba and not having been registered as a formal worker in the six months prior to the application deadline.[9] Eligibility conditions for firms require them to be formally registered with the tax authority and to have at least one registered employee.

The PPP was launched for the first time in 1999 and kept repeated editions every year until 2007. During that period, the program maintained characteristics similar to the edition under study, with the main difference that the selection of beneficiaries was made in a fist-come first-served basis until the available quotas were filled. The PPP was suspended after 2007 and remained inactive until it was relaunched in 2012.

From the 2012 edition onwards, beneficiaries were selected at random from a pool of applicants that outnumber available quotas by about 3 to 1.[10] The selection of the beneficiaries is made through a public draft in the Lottery of the Province of Cordoba, which occurs annually in the month of May. To participate in the draw, applicants must submit an enrollment form collecting their personal data and that of the firm where they intend to work. This form must also be supported by the firm where the candidate would perform its functions if selected.

3 | DATA

This article uses data from three sources. First, administrative data of the program, provided by the Secretariat of Equity and Employment Promotion (former Employment Promotion Agency of Cordoba). This government agency collects data from the program registration forms, including sociodemographic characteristics of the applicants, such as sex, age, marital status, number of children, educational level, enrollment at educational institutions, among others. It also includes information about the firm that supports the candidate's application, such as their legal name, activity sector and number of formally registered employees. We keep all records corresponding to individuals and firms in the province's capital, the city of Cordoba, which is the second largest city in Argentina.[11]

[8] This values are similar to the country-wise informality rate.

[9] Table A.1 shows descriptive statistics from the household survey data for the subset of the population who may be eligible to the program, which shows that the education rates among program applicants closely follows those observed for applicants to the program.

[10] The allocation mechanism includes quotas that imply that the probability of selection is not uniform among applications. First, there is a limit to the maximum number of beneficiaries per firm depending on the number of formally registered employees at the time of registration. Second, candidates can apply to multiple positions although they can be a PPP beneficiary in only one of them. Since these dimensions affect the selection probability, they are included as controls in all the specifications reported in the following sections.

[11] The city of Cordoba, the province's economic powerhouse, had a population of 1.39 million at the time of the implementation of the edition under study (INDEC, 2010). We consider the province's largest city, where the spatial frictions on information flows and commuting are more salient. Cordoba city metropolitan area spans across 576 squared kilometers, an order of magnitude larger than the province's second city, Rio Cuarto, with 64 sq. km.

A distinctive feature of the program's administrative records is that they include the residential address reported by the applicants and the address of the establishments where they applied. From these data, and making use of the Google Maps Application Programming Interface (API), we obtained the geographic coordinates of place of residence and place of intended work detailed in each file, as well as the distance and travel-time between them. This process had a high level of success: out of 8887 individuals who filled eligible forms in the city of Cordoba, we obtained 7,339 geolocations.[12] Following the same procedure, we obtained the coordinates of 2,998 firms, which amounts to 84% of firms in the city of Cordoba that received one or more PPP applications.

Table 1 presents the socioeconomic characteristics of the sample. Of the 7339 individuals who presented a valid form and who were successfully geolocated, 51% are women, and their average age is 21. In addition, 95% are single, 69% of those over 18 have completed high school while 8% of those over 21 have completed higher education at the time of registration. Although it was possible to apply to the program online, around 51% of applicants completed their application manually. The rate of registered employment in the months prior to the start of the program is close to zero, consistent with the eligibility criteria. The table also shows the chosen firm size among applications, displaying a higher incidence of large firms among applications relative to the one observed in household survey data for employed workers (see A.1). There are 36 and 29% of applications in firms with 10-100 workers and 101+ workers, respectively, whereas the observed rates among household survey responding employees are 12 and 6%.

Table 2 shows that, out of the 7,339 individuals in this sample, 2,604 (35.5%) were selected in the draft to receive the benefit. Compliance with the program assignment is notoriously high: 84.4% of those selected complete at least 2/3 of the internship, while 79% complete it fully.[13]

Figures 1 and 2 show the locations of individuals and firms applying to the program, respectively. In Figure 1, the beneficiary youngsters are marked in blue, while those who were not selected are marked in white. This figure shows that applicants and beneficiaries are scattered throughout the urban area of the city due to random assignment. Figure 2 shows a salient agglomeration of applications to establishments located in the center of the city, while another important fraction of such establishments are located along the main roads. This pattern reflects the monocentric structure of economic activity in the city.

An important message of Figure 1 is that there is a high density of applicants in the city. Table 3 summarizes this fact, showing the distribution of distances between each candidate's residential address and that of its first, tenth and fiftieth nearest program candidate. The nearest one lives 62 meters away on average, while 75% of candidates have their nearest applicant less than 90 meters away from their place of residence. Even considering the fiftieth nearest applicant of each candidate, the average distance between them is 709 meters. Table 4 shows the density of applicants and beneficiaries in radii of 100, 500 and 1,000 meters away from the residential address of each applicant. The exposure of candidates to nearing beneficiaries of the program in their vicinity is notorious: on average, each applicant to the program has about 16 beneficiaries within a radius of 500 meters from their place of residence.

[12]Table A.3 in the appendix shows the number of geolocated individuals and the differences in observable characteristics relative to non-geolocated individuals.

[13]Among candidates not initially selected by the draft, a small percentage (less than 3%) managed to become beneficiaries of the program, presumably by appealing their rejection.

4 | EXTERNALITY AND LOCAL LABOR MARKETS

The high density of PPP candidates and beneficiaries described in the previous section draw attention to the externalities that may result from implementing an active labor market policy in the scale of this program.[14] This is because the program acts upon agents that interact with each other across a social network of friends and acquaintances, and who face significant spatial and informational frictions when accessing employment opportunities. These observations lead us to depart from a canonical labor market framework and consider the presence of positive and negative externalities.

First, there may be negative externalities due to displacement. Within a job-matching framework, we can think of the PPP as causing a reduction on the costs of exerting search intensity for job-seekers who benefited by the PPP—directly or through their peers—which results in a higher optimal search intensity (Pissarides, 2000). The resulting increase in job-search intensity by a fraction of the population leads to a higher level of employment in equilibrium or, equivalently, in a higher probability of employment for the average worker. In turn, a higher level of employment carries an efficiency improvement in the matching function that leads to a tighter labor market, which bounds the creation of new employment (we refrain form considering changes in firms' choices at this point). If a fraction of workers chooses a higher search intensity in a tight labor market, their improved labor outcomes could partly come at the expense of the remaining workers.

Second, there may be positive externalities due to the social links between candidates and informational frictions in the labor market. Previous evidence on the direct effects of the PPP suggests that one main mechanism for its positive impact on employment is by a reduction in informational barriers (Berniell and de la Mata, 2017). The program may act upon informational barriers by providing beneficiaries with relevant information regarding the returns to salaried employment and job-search strategies. In turn, the signal of having held 12 months salaried employment in a formal-sector firm may be informative for potential employers on candidate types. However, both of these channels may also occur by the action of peers: a friend may be a relevant source of information on salaried employment opportunities for her peers (Calvó-Armengol and Jackson, 2004) and how to secure one more effectively. As PPP beneficiaries themselves are more likely to be employed after the program's conclusion, they might even provide referrals for their peers to their current employers (Montgomery, 1991). Consequently, by relaxing informational barriers to employment for PPP beneficiaries, the program can also improve labor outcomes for beneficiaries' friends who receive a second-hand treatment.

The potential for externalities as described above is magnified by the presence of spatial frictions. Even though cities, or metropolitan areas, are usually considered as a single labor market, the spatial structure of a city together with non-negligible pecuniary and non-pecuniary transportation costs have important consequences for the labor market. These affect the flow of information—labor-related or otherwise—, job-search patterns, social relationships, among others. Table 5 and Figures 3 and 4 present evidence on the role of space on job search.

Table 5 summarizes distances and commuting time between candidates' residential address and their proposed establishment. The median distance and the median commuting time in public transportation is 5.9 kilometers and 38 minutes, respectively. Figure 3 shows that candidates' applications are strongly biased towards more accessible firms, as the cumulative distribution of commuting time in public transit of worker-firm pairs is moved

[14] Using estimations from official household survey data, there were approximately 128,000 people economically active in the 16-25 age group, of which approximately 83,000 were eligible for the program (i.e., not salaried workers in the formal sector). This places the scale of the program at around 4% of the eligible population.

to the left relative to a cumulative distribution between pairs of workers and firms linked at random. The median of the observed commute in public transit between candidates' residential address and their proposed establishment is 27% lower (38 minutes versus 52 minutes) than that for worker-firms pairs assigned at random.

Additional evidence consistent with the role of space on job search is presented in Figure 4, showing that the odds of applying to the same firm are higher for a group of candidates that live nearby than for a group of candidates taken at random. The line shows the ratio between the observed frequency of same-firm pairs in groups of the K nearest applicants and the frequency of same-firm pairs in groups of K applicants taken at random. The probability of same-firm applicants among groups of five closest neighbors is about ten times greater than among candidate pairs taken at random.[15] This pattern may be due to significant transportation costs within the city, leading candidates to favor nearby vacancies. However, it is also consistent with a similarity in personal characteristics among individuals who live nearby that leads them to apply to firms of the same category or type.

Given the potential important role of spatial frictions, we propose to study the workings of both externalities—positive informative externality and negative competitive externality—using them as labor market shocks in a local environment. To this aim the randomness of the PPP assignment and its detailed geographic data provides a valuable setting. Its draw of beneficiaries among applicants to the program results in an exogenous source of variability that acts upon a social network and alters the spatial equilibrium of the labor market. First, it randomly assigns a 12-month work experience. Berniell and de la Mata (2017) show that the program causes a 25% increase in the probability of employment of beneficiaries after the end of the program, on aggregate for the whole province. Second, the program acts upon a social network, affecting beneficiary and non-beneficiary job-seekers by means of their mutual connections in the network. Third, the PPP randomly affects the competitive environment of candidates, altering the average work experience among their close competitors. In what follows, we will call these three channels *direct effect*, *information effect* and *competition effect*, respectively.

5 | IDENTIFICATION

We evaluate the positive and negative local external effects of the PPP program that arise from the locality of labor markets within the city. We exploit the random assignment mechanism that exogenously changes the local spatial equilibrium, relying on two types of variation. First, from the perspective of any applicant, the program randomly alters the mean job experience of competing candidates for job vacancies. For each individual in our sample, we construct a measure of the degree of competition in the local labor market as the share of PPP beneficiaries among the nearest K applicants, denoted as S^K.

The parameter K determines the breadth of the environment considered relevant for job-seekers. To inform the choice of K for our main specification we resort to Figure 4, since it shows how the probability of young neighbors postulating to the same firm decreases as the neighborhood considered expands, which is the basis for the existence of displacement. We choose $K = 15$, where the slope flattens.[16] Figure 5 shows the distribution of the variable S^K, for parameter values 10, 15 and 20, and Table 6 provides key descriptive statistics of the distributions. For our chosen value of $K = 15$, the observed fraction of beneficiary candidates among closest neighbors in the 10th and 90th percentiles is 0.20 and 0.53, respectively.

[15] The baseline probability that a random pair of individuals from the sample apply to the same firm is 0.37%.

[16] The choice of the number of neighbors does not significantly alter the results. As a robustness exercise, we run every specification for parameter values between 5 and 30 in Section 6.

Second, the program randomly alters the mean job experience of individuals who belong to the same social network, such as friends and family members. We infer a link between candidates based on spatial proximity using their residential address at the moment of application to the program. The relevant peer in our analysis will be the closest neighbour applicant.[17] As shown in Table 3, for most individuals applying to the PPP program, their nearest applicant is less than 100 meters away from their place of residence. For each individual in our sample, we construct a variable T^{vec}, that indicates closest neighbour's PPP beneficiary status.

These two sources of variation allow to address the issue of common factors affecting simultaneously the employment outcomes of an individual and her social network, as discussed in Manski (1993) and the typical concerns related to workers' self-selection into specific neighbourhoods for reasons that are related to employment-relevant characteristics of the neighborhood.

We estimate the following model:

$$E_i = \alpha + \gamma_1 T_i + \gamma_2 T_i^{vec} + \gamma_3 S_i^K + \delta_1 Q_i + \delta_2 Q_i^{vec} + \delta_3 \overline{QN}_i + u_i \tag{1}$$

where E_i is the outcome variable of individual i (ever employed in the formal sector, cumulative months in formal employment and cumulative wage in the 12 month period after the end of the PPP program), T_i is the PPP beneficiary status of individual i, T_i^{vec} is the PPP beneficiary status of individual i's nearest neighbour, S_i^K is the share of treated individuals among individual i's K nearest applicants. We include in all regressions a vector of stratification variables Q_i, that affect the individual's likelihood of being selected as beneficiary in the draft: number of files submitted, number of employees of the company to which she applies and the ratio between the number of applicants and the number of employees in the firm. Likewise, vectors Q_i^{vec} and $\overline{QN}_i$ correspond to these quota variables of the nearest neighbor and the averages of the nearest K applicants, respectively. The parameters of interest are γ_2 and γ_3, that we call for simplicity the information effect and the competition effect, respectively. Although it is not the main interest of our study, in all our tables we will also report parameter γ_1, which refers to the direct effect of the program.

Table 7 shows the correlation of several individual and neighbourhood characteristics with our three variables of interest, after conditioning for the vector of stratification variables. As expected, given the random assignment of the program, the individual, the neighbour's treatment status, and the program saturation among the nearest K neighbours do not show any specific pattern of selection. Only a small systematic imbalance seems to appear considering neighbourhood characteristics. We present all our specifications also controlling for observed individual characteristics and neighbourhood fixed effects, and show that results are robust to their inclusion.

[17] In the absence of information on the applicants' social network, the strategy of inferring them using geographic proximity is common in studies of social networks and labor markets (Bayer et al., 2008; Hellerstein et al., 2014; Schmutte, 2015; Jahn and Neugart, 2020). The identification strategy in these papers relies on the assumption that individuals can sort into neighborhoods but cannot sort into small areas Jahn and Neugart 2020 or blocks Bayer et al. 2008 within neighborhoods due to thin housing markets, so that the share of employed neighbours within small areas is exogenous, conditional on the employment of a larger encompassing area. Our identification strategy differs because we don't focus on the relation between a job seeker's labor outcomes and its neighbours' current employment status, which is endogenous in our context. Instead, we focus on the relation between job seeker's labor outcomes and the PPP treatment status of their neighbour, which is determined by the random assignment mechanism.

6 | RESULTS

Table 8 presents the estimated coefficients of Equation 1 for the three key variables of interest: the direct program effect (γ_1), the information effect (γ_2), and the competition effect (γ_3), on three outcomes —having ever been employed in a formal job in the 12 months following program completion ("ever employed"), the cumulative months of employment in that period, and the cumulative wage. The direct effects of the program on the three outcomes, shown on the first row, are positive and statistically significant, aligning with previous findings by Berniell and de la Mata (2017).[18]

Rows 2 and 3 in Table 8 show the externality effects. The results are consistent with the existence of both information and competition externalities, as both effects have the expected signs. Having a neighbor who benefited from the PPP program—the information effect—positively affects the three outcomes, increasing the probability of ever being employed by 2 pp, the number of months of employment by 0.18 months, and in the cumulative wage by 679 pesos, though the last two effects are not statistically significant. On the other hand, a 10 percentage points increase in the saturation of the program within the relevant local labor market for each youth—the competition effect—, negatively affects the three outcomes. It reduces the probability of ever being employed by 1.5 pp, decreases the number of months of employment by 0.9 months, and lowers the cumulative wage by 500 pesos.[19] The magnitude of the positive and negative externalities are substantially lower than the direct effect. The addition of a set of controls for observable individual (measured before the start of the program) and neighborhood fixed effects do not substantially change the estimated effects.

A placebo analysis offers additional support for our proposed causal links. First, we perform permutations on the residential locations of PPP candidates by randomly assigning a placebo residential address to each candidate from the list of all addresses, without replacement. Then, with the new assignment of (placebo) neighbors, we compute the values T^{vec} and S^{K} and estimate equation 1. We repeat the random permutations 1,000 times. Figures 6 to 8 display the distribution of the placebo OLS estimates together with the value of the effects of our main specification. The results indicate that the chances of observing placebo estimates of the magnitudes or larger (in absolute terms) than that obtained with the observed data are slim. Considering the ever employed outcome, the placebo informative effect is larger than our estimated informative effect only 7.4% of the times, while the placebo competitive effect is larger (in absolute terms) 0.1% of the times (see Table 9 for a summary of these results).

[18] Individuals who benefited from the PPP apprenticeship program experienced, in the 12 months after program completion, an increase in the probability of ever being employed by 7.7 percentage points (pp), an increase in the number of months of employment by 0.6 months, and an increase in the cumulative wage earned by 4,212 thousand pesos. We observe that the employability of PPP beneficiaries increased consistently throughout the period. The effects on the 'ever employed' outcome and the 'number of months employed', as presented in Table 8, are not driven by any specific anomalous month during the 12-month period. Table A.4 in the Appendix shows the direct effect on the probability of being employed in each month. Being a beneficiary of the PPP increases the probability of being employed in a given month by 4 to 6 pp, depending on the month considered.

[19] Just as with the direct effects, the magnitude of the external effects on the probability of being employed is consistently uniform across most individual months during the 12-month post-PPP period, as shown in Table A.4 and Figure A.1 in the Appendix. With the exception of the first month following the program's conclusion, having a neighbor who benefited from the PPP program increases the probability of being employed by 0.8 to 2 percentage points, depending on the month considered. The effects are statistically significant between the fourth and eighth months after PPP's conclusion. On the other hand, a 10 percentage points increase in the program's saturation reduces the probability of being employed in any of the months considered, although the effects are relatively larger from the fourth month onwards.

Our results are robust to alternative choices of the relevant K competitors considered to calculate the program saturation variable, S^K. Figures 9, 10, and 11 show the estimated effects when considering different values for the parameter K. The competition effects are stable for values of K between 8 and 30.

For values of K approaching 5, the coefficient γ_3 tend to be lower in magnitude and not statistically significant for the last two outcomes. This is consistent with neighbors that are likely to belong to the same social network of individual i. On the other hand, when considering high values of K, the measure of competition includes more noise and loses statistical significance, as the program saturation is computed with a group of individuals some of which are less likely to be competitors of individual i, as they are located further away.

6.1 | Homophily patterns in information transmission

As discussed in section 4, the informative effect of the PPP apprenticeship program may lift several informational barriers. Individuals are more likely to establish links with similar peers due to shared activities, local infrastructure, and preferences, so that the effectiveness of the information transmission though peers may vary depending on their characteristics. In particular, previous evidence suggest homophily patterns in information transmission based on age, gender, or race (Cingano and Rosolia, 2012; Jahn and Neugart, 2020; Glitz, 2017; Hellerstein et al., 2014).

We explore homophily patterns in the informative effect by considering whether this effect is different when individuals share or not specific characteristics with their closest neighbor. Specifically, we estimate the following model:

$$E_i = \alpha + \gamma_1 T_i + \gamma_2 T_i^{vec} + \gamma_3 S_i^K + \gamma_4 D_i^{j,vec} \times T_i^{vec} + \gamma_5 D_i^{j,vec} + \delta_1 Q_i + \delta_2 Q_i^{vec} + \delta_3 \overline{QN}_i + u_i \quad (2)$$

where $D_i^{j,vec}$ takes the value 1 if individual i does not share characteristic j (age group, sex, or level of education) with her closest neighbour. If information transmission were subject to homophily patterns, we would expect coefficient γ_2 to be positive and coefficient γ_4 to be negative, although not necessarily of the same magnitude.

Table 10 shows the case for age groups. The age groups considered are two: equal or below 21 and above 21 years old at the moment of registering for the program. The informative effect for those who share the same age group with their neighbor is much larger than for those who do not share age group. In fact, the interaction term $T^{vec} \times D^{j,vec}$ is negative for the three outcomes, and statistically significant for the ever employed outcome. The magnitude of this term for the ever employed outcome indicates that the information effect is null for those of opposite age group. The magnitude of the interaction terms for the remaining variables are also large and negative, but under-powered and not statistically significant.

Table 11 shows the case for gender and table 12 for educational attainment groups. Educational attainment group are two: those who did and didn't complete high school at the moment of registering for the program. In both cases, the interaction terms of the information effect with the dummy variable indicating that individuals do not share the same sex and educational attainment level, respectively, are not statistically significant.

Overall, these results highlight that most of the informative effect on the ever-employed outcome observed for the whole sample comes from individuals who share the same age group. Homophily by age reflects that for the youth, shared activities and local infrastructure, especially schools, play a major role in shaping social networks.

6.2 | Further evidence on the spatial frictions: geographic patterns

The salience of spatial frictions within a city, ie. economically significant costs to information and commuting flows, result in network formation and job matching patterns that reflect a bias for proximity (Manning and Petrongolo, 2017). These patterns are expected to be more marked in neighborhoods with lower connectivity to the rest of the city, in turn, resulting in local externality effects of larger magnitude. We explore heterogeneous effects by city zone, considering that areas closer to the Central Business District (CBD) are better connected to the rest of the city. We partition the city in two by choosing the midpoint of all candidates' places of residence and building a circle of radius chosen such that individuals within comprise half of the sample. Individuals in the sample who are among the 50% closer to the midpoint are categorized as *center*.

Specifically, we estimate the following model:

$$E_i = \alpha + \gamma_1 T_i + \gamma_2 T_i^{vec} + \gamma_3 S_i^K + \gamma_4 C_i \times T_i^{vec} + \gamma_5 C_i \times S_i^K + \gamma_6 C_i + \delta_1 Q_i + \delta_2 Q_i^{vec} + \delta_3 \overline{QN}_i + u_i \quad (3)$$

where C_i is a dummy variable that takes value 1 if individual i is classified as centre.

Table 13 shows the direct, information, and competition effects, as well as the interaction of the information and competition effects with the center dummy variable. The magnitude of the interaction terms goes in the expected direction in all cases (negative for the information effect and positive for the competition effect). However, the only statistically significant term appears for the ever-employed outcome. This result is consistent with a competition effect that is more prevalent in the periphery of the city. The city's urban form, concentration of economic activity in the CBD, and radial structure of its transit network likely result in less accessibility to job opportunities for residents in the periphery.

7 | CONCLUSION

Labor markets are significantly affected by spatial and informational frictions. Spatial frictions impose additional search costs for job opportunities, leading individuals to seek employment in smaller and more accessible areas of the city, making them more vulnerable to local labor market shocks. In turn, informational frictions push them to rely on their networks of contacts. These frictions are particularly severe for young job seekers.

This paper provides causal evidence of the effect of local labor market supply shocks on the employment and wages of young job seekers, in the context of a developing country. We show that a random labor market shock that alters young job seekers' local environments by changing the average job experience of potential competitors in their relevant local labor markets has a negative effect on their probability of ever being employed in the subsequent 12-month period, the total number of months employed, and cumulative wages. At the same time, when a close neighbor randomly increases their job experience, it has a positive effect on all three outcomes, consistent with an information effect. Our placebo analysis and sensitivity of the size of the relevant local labor market reassure that the local labor market shock—and not that in other parts of the city—is what matters for individual outcomes.

We provide further evidence that reinforces the argument that local labor market shocks operate through both information and local competition channels. First, we show that when the shock of job experience is experienced by a neighbor, the effects are larger in magnitude if individuals belong to the same age group. We argue that this homophily pattern aligns with previous literature that suggest that the effectiveness of information transmission through peers is greater for individuals who share certain characteristics, as these individuals are more likely to establish links due to shared activities, local infrastructure, and preferences. The finding of homophily patterns in information transmission by age, rather than by gender or educational level attained, may reflect the central role that schools play for the youth in shaping social networks. Second, we provide evidence showing that the competition effect is larger for individuals living in the periphery of the city, where spatial frictions are more acute. In the specific context of our study, these neighborhoods have lower connectivity to the rest of the city. The city's urban form, concentration of economic activity in the CBD, and radial structure of its transit network likely result in less accessibility to job opportunities for residents in the periphery.

Our results have direct implications for public policy. First, the information effect can be a valuable resource to enhance the impact of labor insertion programs, exploiting existing social networks. For example, the random allocation of benefits could be stratified by areas where lasting bonds of social interaction are usually built, such as the educational establishment attended by young people. In this way, the assignment could be designed so as to affect as many social nuclei as possible and thus exploit the transmission of information among peers.

On the other hand, there are policy instruments with the potential to avoid the observed negative displacement effects, by way of expanding the relevant labor market of the population targeted and reduce spacial frictions in labor markets. Examples of this could be targeted transport subsidy policies and the use of employment agencies that inform of job opportunities throughout the city. Finally, the existence of this competition effect demands caution when considering scaling up this type of programs.

8 | TABLES

TABLE 1 Descriptive statistics

	Mean	SD	p25	p50	p75	N
Individual characteristics						
Female	0.5093	0.4999	0	1	1	7,339
Age	21.1372	2.4358	19	21	23	7,338
Single	0.9509	0.2160	1	1	1	7,339
Children	0.0813	0.2734	0	0	0	7,339
High school (18+)	0.6944	0.4607	0	1	1	4,742
Higher education (21+)	0.0805	0.2722	0	0	0	2,148
Manual application	0.5051	0.5000	0	1	1	7,339
Individual formal employment before treatment						
Month -5	0.0139	0.1171	0	0	0	7,339
Month -4	0.0041	0.0638	0	0	0	7,339
Month -3	0.0083	0.0908	0	0	0	7,339
Month -2	0.0134	0.1148	0	0	0	7,339
Month -1	0.0258	0.1584	0	0	0	7,339
Firm-size in applications						
1-4 employees	0.2298	0.4208	0	0	0	7,201
5-10 employees	0.1376	0.3445	0	0	0	7,201
11-100 employees	0,3422	0,4745	0	0	1	7,201
101+ employees	0.2904	0.4540	0	0	1	7,201
Neighborhood characteristics (census data)						
UBI	0.0839	0.0744	0.0334	0.0639	0.1145	7,313
Informality	0.3107	0.1465	0.1852	0.2971	0.4064	7,313
Unemployment	0.0714	0.0205	0.0594	0.0693	0.0855	7,313

Notes: Data for individual characteristics and firm-size in applications are obtained from the program's administrative data. Data for formal employment in the months before program assignment are obtained from social security administrative data. Neighborhood characteristics are obtained from province census data 2008.

TABLE 2 PPP program take-up

	Non-beneficiary		PPP beneficiary	
	N	(%)	N	(%)
Full attendance	129	2.72	2,064	79.26
Partial+ attendance	140	2.96	2,198	84.41

TABLE 3 Distance to the 1st, 10th and 50th nearest neighbor (meters)

	1st nearest neighbor	10th nearest neighbor	50th nearest neighbor
Mean	62.49	284.22	709.26
SD	83.38	236.56	507.37
Skewness	12.98	9.09	6.06
p25	9.54	197.09	531.30
Median	49.27	252.72	603.39
p75	90.34	313.73	733.62
N	7,339	7,339	7,339

Notes: The statistics reported correspond to straight-line distances to the closest, 10th closest and 50th closest neighbor of each PPP candidate.

TABLE 4 Number of applicants and beneficiaries in radii of 100, 500 and 1000 meters

	Neighbors			Beneficiary neighbors		
	100m	500m	1000m	100m	500m	1000m
Mean	2.60	43.06	142.84	0.95	15.70	51.57
SD	3.07	38.65	103.39	1.37	15.12	39.36
Skewness	2.46	2.83	2.10	2.32	2.72	2.08
p25	1	23	87	0	8	30
Median	2	34	128	0	12	45
p75	3	45	155	1	17	56
N	7,339	7,339	7,339	7,339	7,339	7,339

Notes: The table reports the number of candidates and beneficiaries within 100, 500 and 1000 meters of straight-line distance.

TABLE 5 Residence-establishment commuting time and distance for all applications

	Distance walking	Distance in public transit	Time in public transit
Mean	5.39	6.78	39.72
SD	4.31	5.49	25.18
Skewness	1.06	1.08	0.95
p25	1.84	2.26	22.15
Median	4.68	5.90	37.57
p75	7.73	9.80	52.99
N	9,425	9,400	9,400

Notes: The table reports descriptive statistics on commutes from candidates' residence to their proposed establishment for all PPP applications, as reported by Google Maps API for regular business days at 8:30 am.

TABLE 6 Program saturation by number of nearest neighbors considered

	10 nearest neighbors	15 nearest neighbors	20 nearest neighbors
Mean	0.36	0.35	0.35
SD	0.16	0.13	0.11
Skewness	0.22	0.18	0.17
p10	0.20	0.20	0.20
Median	0.40	0.33	0.35
p90	0.60	0.53	0.50
N	7,339	7,339	7,339

Notes: The table shows descriptive statistics for the program saturation variable in K closest neighbors, for K values of 10, 15 and 20 PPP candidates.

TABLE 7 Balance statistics for direct program assignment, nearest neighbor assignment and program saturation

	Mean	T		T^{vec}		S^K	
	(1)	(2)		(3)		(4)	
Individual characteristics							
Female	0.5094	-0.0132		0.0000		0.0026	
Age	21.1376	-0.0325		0.0548	**	-0.1214	
Single	0.9509	0.0043	**	-0.0118		-0.0100	
Children	0.0814	-0.0142		-0.0011	**	-0.0256	
Highschool (18+)	0.6942	0.0117	***	0.0280		0.0713	
Higher education (21+)	0.0806	0.0368		-0.0020	*	-0.0172	
Manual application	0.5050	0.0064		0.0208		0.0664	
Individual formal employment before treatment							
Month -5	0.0139	-0.0009		-0.0007		0.0093	
Month -4	0.0041	0.0004		0.0022		-0.0014	
Month -3	0.0083	0.0016		0.0016		-0.0022	
Month -2	0.0134	0.0021		0.0014		-0.0039	
Month -1	0.0258	0.0027	***	0.0003	***	0.0112	***
Firm-size in applications							
1-4 employees	0.2300	-0.0064		0.0060		0.0486	
5-9 employees	0.1238	0.0038		0.0043		0.0250	
10-99 employees	0.3555	-0.0138	**	-0.0164		-0.0543	
100+ employees	0.2907	0.0164		0.0060		-0.0193	
Neighborhood characteristics (census data)							
UBI	0.0839	-0.0049	**	-0.0062	***	-0.0448	***
Informality	0.3108	-0.0080	**	-0.0111	**	-0.0899	***
Unemployment	0.0714	-0.0012		-0.0013		-0.0113	

Notes: The table shows the full sample mean of each characteristic and the difference relative to baseline value for variables direct program assignment, nearest neighbor assignment and share of beneficiaries in 15 nearest neighbors.

TABLE 8 Main specification. Direct and external effects of the PPP

	Ever employed		Cumulative months		Cumulative wage	
	(1)	(2)	(3)	(4)	(5)	(6)
Direct effect (T)	0.0772***	0.0741***	0.6240***	0.5989***	4,212.4***	3,966.6***
	(0.0120)	(0.0120)	(0.1112)	(0.1111)	(782.6)	(782.0)
Information effect (T^{vec})	0.0203*	0.0206*	0.1784	0.1747	678.6	712.5
	(0.0121)	(0.0121)	(0.1104)	(0.1100)	(763.0)	(763.5)
Competition effect (S^k)	-0.0147***	-0.0156***	-0.0932**	-0.0872**	-517.6*	-497.6
	(0.0045)	(0.0048)	(0.0405)	(0.0441)	(285.2)	(315.9)
Control group mean	0.3016	0.3016	2.2103	2.2103	12620.0	12620.0
Observations	7,334	7,275	7,334	7,275	7,334	7,275
Controls	No	Yes (FE)	No	Yes (FE)	No	Yes (FE)

Notes: this table shows the OLS estimates of coefficients γ_1 (direct effect of the PPP), γ_2 (information effect), andγ_3 (competition effect) of Equation 2. The outcome "ever employed" refers to the probability of being employed in the formal sector in the 12-month period following the end of the PPP program; "Accumulated months" and "Accumulated wage" refer to the number of months in formal employment and the sum of monthly wages, respectively, in the same 12-month period. All regressions include as control variables a set of stratification variables that affects the individual's likelihood of being selected as beneficiary in the draft (number of files submitted, number of employees of the company to which she applies and the ratio between the number of applicants and the number of employees in the firm), the same set of stratification variables of the nearest neighbor and the averages of the nearest K=15 applicants. Robust standard errors in parenthesis. Statistical significance is indicated as follows: $*$ $p < 0.1$; $**$ $p < 0.05$; $***$ $p < 0.01$.

TABLE 9 Robustness: placebo analysis

		Ever employed	Cumulative months	Cumulative wage
		(1)	(2)	(3)
Information effect	Coef	0.0203	0.1795	683.6
	P-value	(0.074)	(0.098)	(0.358)
Competition effect	Coef	-0.0148	-0.0943	-514.5
	P-value	(0.001)	(0.033)	(0.079)

Notes: The table shows the estimates to the information effect and competition effect resulting from 1 and their associated P-values calculated by 1000 location permutations.

TABLE 10 Homophily by age group

	Ever employed	Cumulative months	Cumulative wage
	(1)	(2)	(3)
Direct effect (T)	0.0765***	0.6200***	4,194.7***
	(0.0120)	(0.1113)	(783.4)
Information effect (T^{vec})	0.0415**	0.2978**	1,185.1
	(0.0161)	(0.1452)	(1,026.3)
Different age group $\times$ Information effect ($T^{vec} \times D^{j,vec}$)	-0.0464**	-0.2626	-1,103.6
	(0.0230)	(0.2094)	(1,457.8)
Competition effect (S^k)	-0.0147***	-0.0931**	-516.6*
	(0.0044)	(0.0405)	(285.1)
Control group mean	0.3016	2.2103	12,620.0
Observations	7,334	7,334	7,334
Controls	No	No	No

Notes: This table shows the OLS estimates of equation 2. Age groups considered are equal or below 21 and above 21 years old at the moment of registering for the program. The outcome "ever employed" refers to the probability of being employed in the formal sector in the 12-month period following the end of the PPP program; "cumulative months" and "cumulative wage" refer to the number of months in formal employment and the sum of monthly wages, respectively, in the same 12-month period. All regressions include as control variables a set of stratification variables that affects the individual's likelihood of being selected as beneficiary in the draft (number of files submitted, number of employees of the company to which she applies and the ratio between the number of applicants and the number of employees in the firm), the same set of stratification variables of the nearest neighbor and the averages of the nearest K applicants. Robust standard errors in parenthesis. Statistical significance is indicated as follows: $*$ $p < 0.1$; $**$ $p < 0.05$; $***$ $p < 0.01$.

TABLE 11 Homophily by gender

	Ever employed	Cumulative months	Cumulative wage
	(1)	(2)	(3)
Direct effect (T)	0.0766***	0.6205***	4,185.4***
	(0.0120)	(0.1112)	(782.7)
Information effect (T^{vec})	0.0244	0.2119	1,079.7
	(0.0165)	(0.1499)	(1,032.4)
Opposite sex × Information effect ($T^{vec} \times D^{j,vec}$)	-0.0089	-0.0708	-834.8
	(0.0230)	(0.2082)	(1,454.4)
Competition effect (S^k)	-0.0148***	-0.0939**	-524.1*
	(0.0045)	(0.0405)	(285.0)
Control group mean	0.3016	2.2103	12,620.0
Observations	7,334	7,334	7,334
Controls	No	No	No

Notes: This table shows the OLS estimates of equation 2, where $D^{j,vec}$ is a dummy that takes the value 1 if the nearest neighbor has opposite sex than individual i. The outcome "ever employed" refers to the probability of being employed in the formal sector in the 12-month period following the end of the PPP program; "cumulative months" and "cumulative wage" refer to the number of months in formal employment and the sum of monthly wages, respectively, in the same 12-month period. All regressions include as control variables a set of stratification variables that affects the individual's likelihood of being selected as beneficiary in the draft (number of files submitted, number of employees of the company to which she applies and the ratio between the number of applicants and the number of employees in the firm), the same set of stratification variables of the nearest neighbor and the averages of the nearest K applicants. Robust standard errors in parenthesis. Statistical significance is indicated as follows: $*$ $p < 0.1$; $**$ $p < 0.05$; $***$ $p < 0.01$.

TABLE 12 Homophily by educational level

	Ever employed	Cumulative months	Cumulative wage
	(1)	(2)	(3)
Direct effect (T)	0.0772***	0.6226***	4,191.6***
	(0.0120)	(0.1112)	(781.2)
Information effect (T^{vec})	0.0267	0.1751	598.3
	(0.0181)	(0.1633)	(1,128.9)
Different education $\times$ Information effect ($T^{vec} \times D^{j,vec}$)	-0.0114	0.0027	96.4
	(0.0232)	(0.2101)	(1,465.6)
Competition effect (S^k)	-0.0148***	-0.0934**	-520.1*
	(0.0045)	(0.0405)	(285.3)
Control group mean	0.3016	2.2103	12,620.0
Observations	7,334	7,334	7,334
Controls	No	No	No

Notes: This table shows the OLS estimates of equation 2. Education groups considered are Incomplete High-school and Complete High-school or more. The outcome "ever employed" refers to the probability of being employed in the formal sector in the 12-month period following the end of the PPP program; "cumulative months" and "cumulative wage" refer to the number of months in formal employment and the sum of monthly wages, respectively, in the same 12-month period. All regressions include as control variables a set of stratification variables that affects the individual's likelihood of being selected as beneficiary in the draft (number of files submitted, number of employees of the company to which she applies and the ratio between the number of applicants and the number of employees in the firm), the same set of stratification variables of the nearest neighbor and the averages of the nearest K applicants. Robust standard errors in parenthesis. Statistical significance is indicated as follows: $* \; p < 0.1$; $** \; p < 0.05$; $*** \; p < 0.01$.

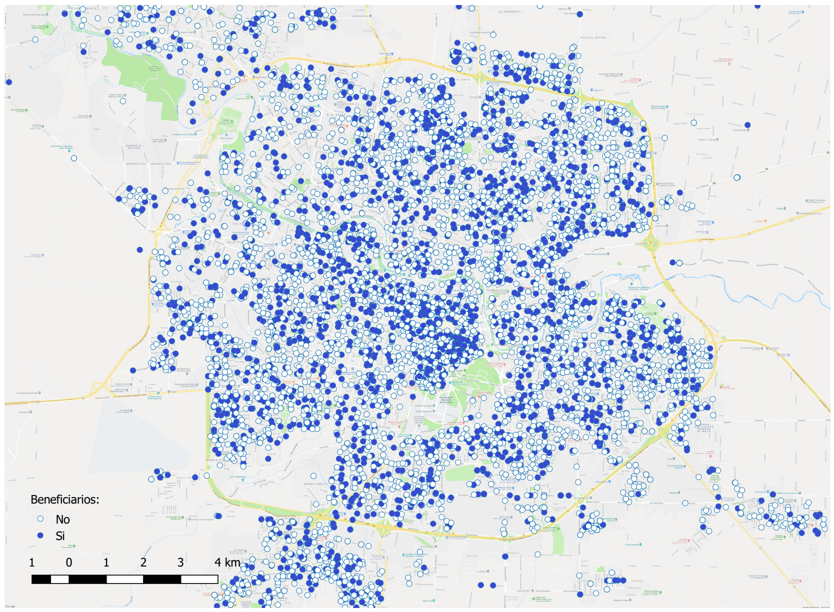
TABLE 13 Heterogeneity by city zone

	Ever employed	Cumulative months	Cumulative wage
	(1)	(2)	(3)
Direct effect (T)	0.0765***	0.6173***	4,182.6***
	(0.0120)	(0.1113)	(782.4)
Information effect (T^{vec})	0.0252	0.2126	1,075.7
	(0.0171)	(0.1538)	(1,087.6)
Centre x Information effect ($C \times T^{vec}$)	-0.0095	-0.0642	-771.1
	(0.0240)	(0.2193)	(1,514.8)
Competition effect (S^k)	-0.0258***	-0.1643***	-956.2**
	(0.0063)	(0.0563)	(405.9)
Centre x Competition effect ($C \times S^k$)	0.0196**	0.1177	776.3
	(0.0089)	(0.0814)	(574.3)
Control group mean	0.3016	2.2103	12,620.0
Observations	7,334	7,334	7,334
Controls	No	No	No

Notes: This table shows the OLS estimates of equation 3, where C_i is a dummy that takes the value 1 if individual i resides in the centre of the city. We partition the city in two by choosing the midpoint of all candidates' places of residence and building a circle of radius chosen such that individuals within comprise half of the sample. Individuals in the sample who are among the 50% closer to the midpoint are categorized as *center*. The outcome "ever employed" refers to the probability of being employed in the formal sector in the 12-month period following the end of the PPP program; "cumulative months" and "cumulative wage" refer to the number of months in formal employment and the sum of monthly wages, respectively, in the same 12-month period. All regressions include as control variables a set of stratification variables that affects the individual's likelihood of being selected as beneficiary in the draft (number of files submitted, number of employees of the company to which she applies and the ratio between the number of applicants and the number of employees in the firm), the same set of stratification variables of the nearest neighbor and the averages of the nearest K applicants. Robust standard errors in parenthesis. Statistical significance is indicated as follows: $* \ p < 0.1$; $** \ p < 0.05$; $*** \ p < 0.01$.

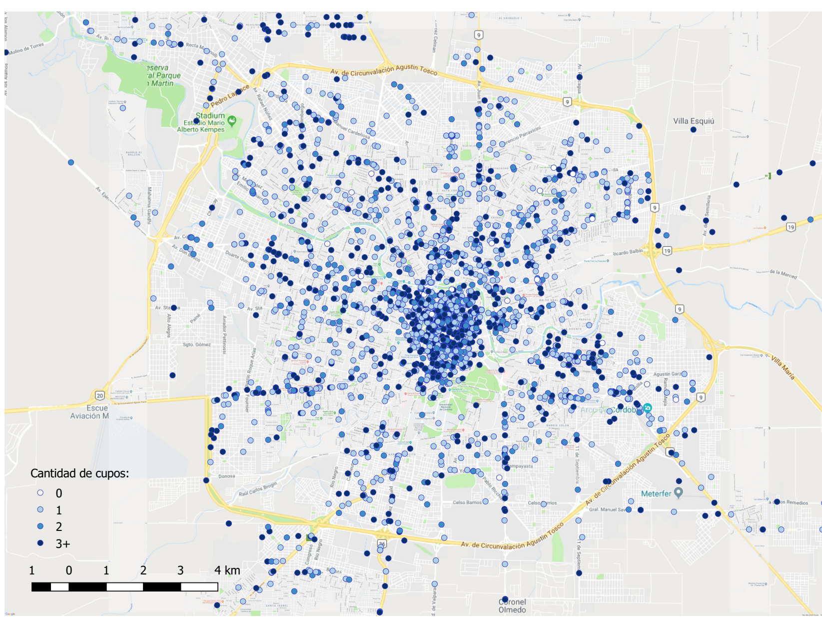
9 | FIGURES

FIGURE 1 Location of beneficiary and non-beneficiary candidates in Cordoba city



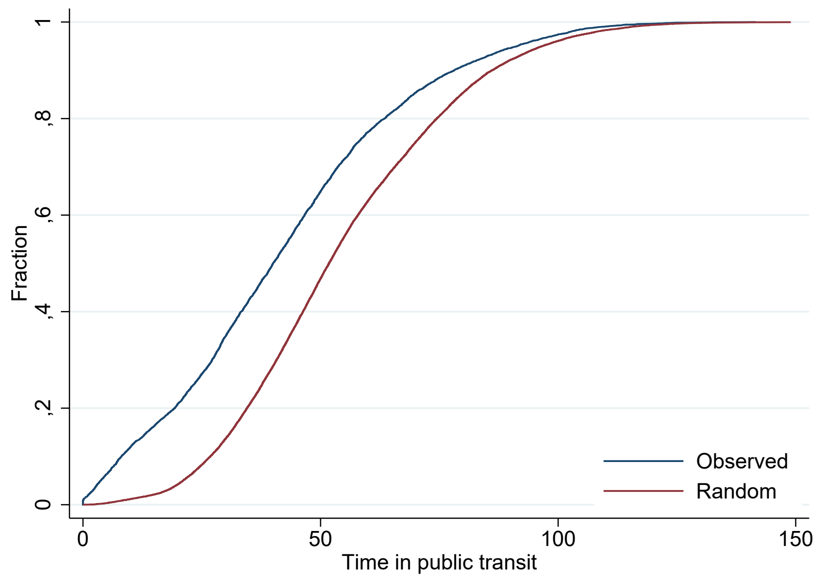
Note: The figure presents all applicants that presented a valid PPP application and were successfully geolocated. Beneficiary and non-beneficiary candidates appear in blue and white, respectively.

FIGURE 2 Location of eligible firms in Cordoba city



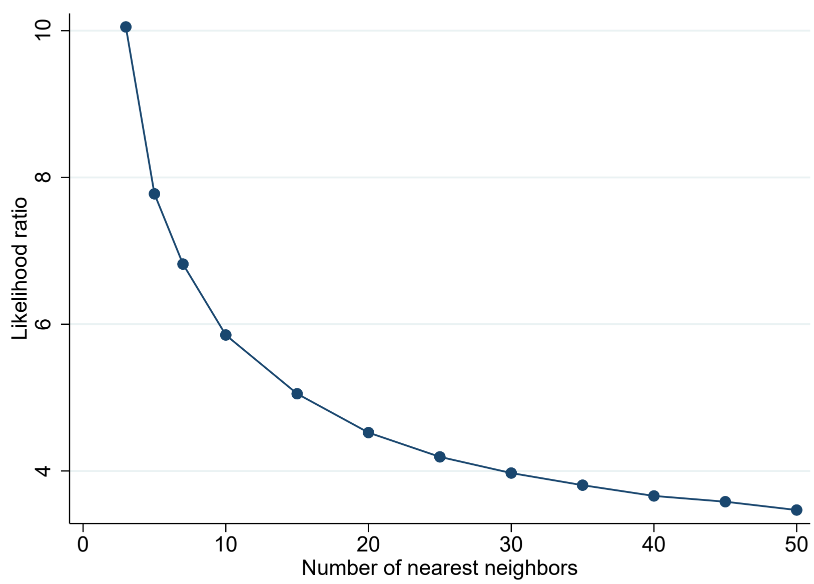
Note: the figure presents all firms that received valid PPP applications, by maximum allowed number of PPP beneficiaries.

FIGURE 3 Distribution of residence-workplace commuting times, observed vs. random worker-firm pairs



Note: the figure shows the distribution of commuting times in public transit between the residential and workplace addresses declared in all valid PPP applications, compared to residence-workplace pairs chosen at random. Time calculations based on Google Maps Directions API.

FIGURE 4 Likelihood ratio of same-same firm applicants by number of closest neighbors



Note: the figure shows the share of applicant pairs that choose the same firm for groups of closest neighbors of increasing size relative to pairs of applicants chosen at random.

FIGURE 5 Histogram of program saturation by number of closest neighbors considered

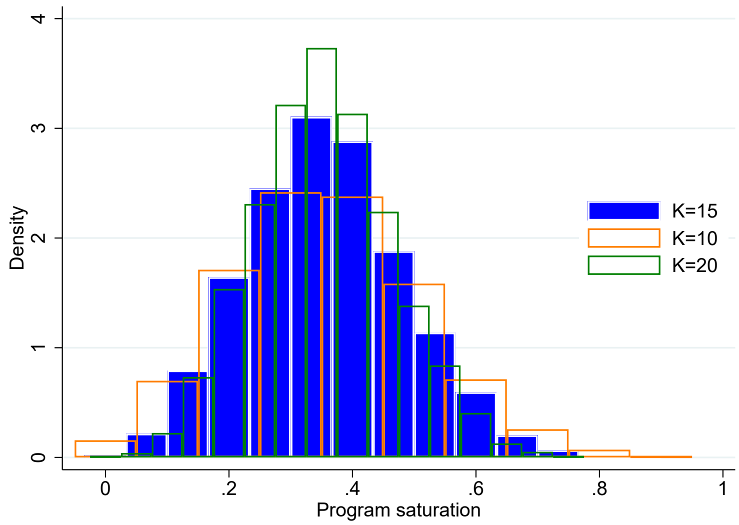
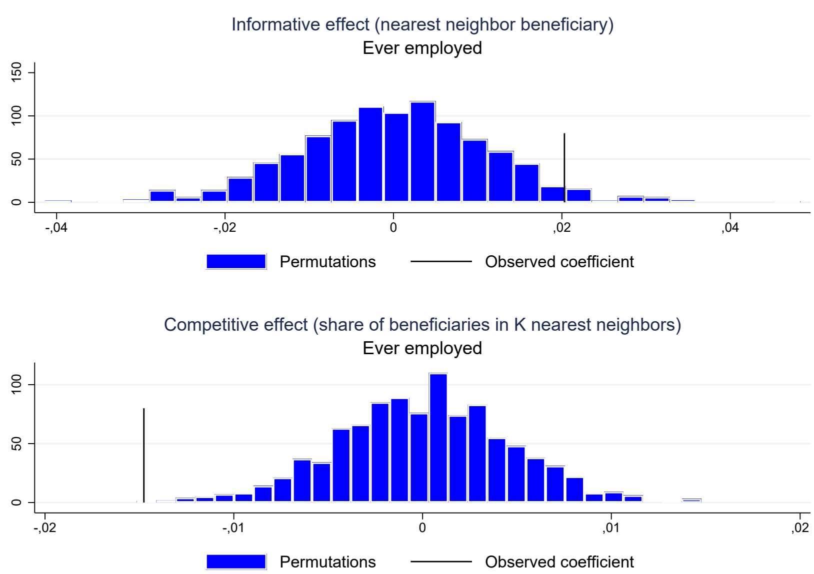
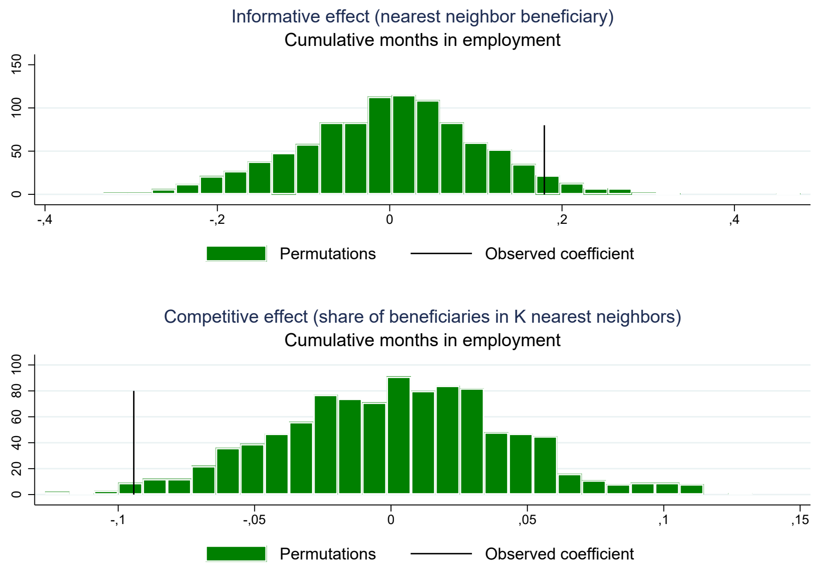


FIGURE 6 Observed vs. placebo locations



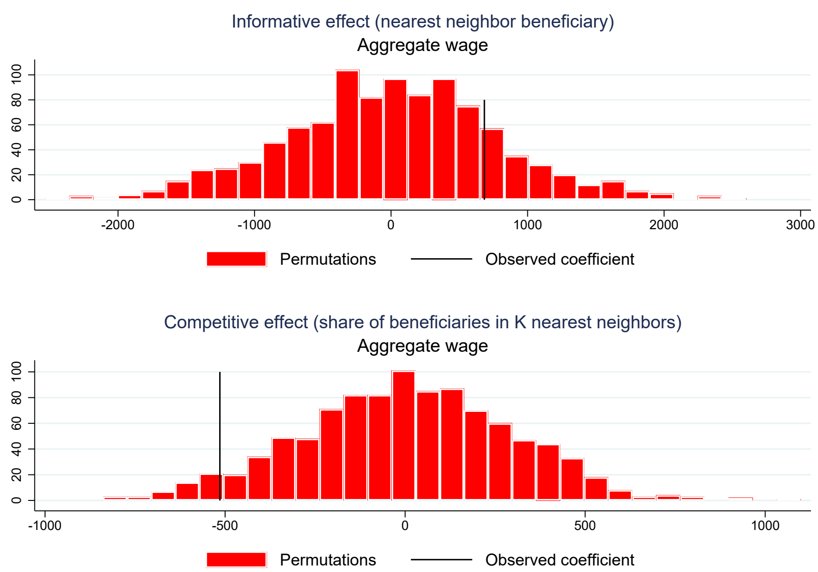
Note: The figure shows the distribution of coefficients from 1000 location permutations and the observed coefficient for the *direct effect*, the *information effect* and the *competition effect*, resulting from specification 1.

FIGURE 7 Observed vs. placebo locations



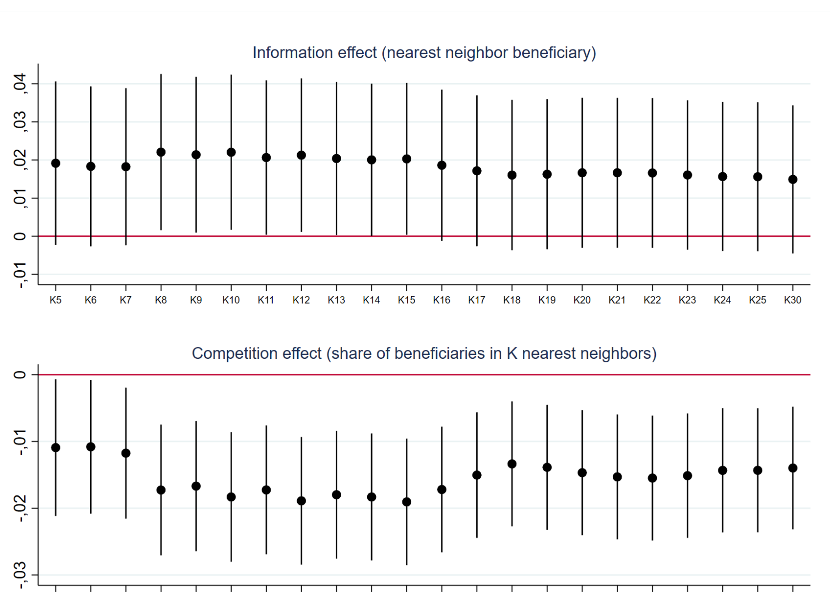
Note: The figure shows the distribution of coefficients from 1000 location permutations and the observed coefficient for the *direct effect*, the *information effect* and the *competition effect*, resulting from equation 1.

FIGURE 8 Observed vs. placebo locations



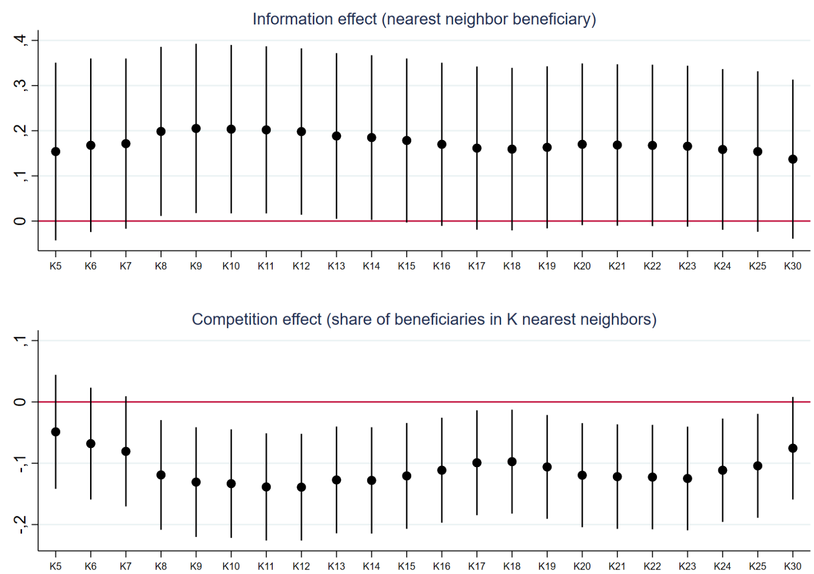
Note: The figure shows the distribution of coefficients from 1000 location permutations and the observed coefficient for the *direct effect*, the *information effect* and the *competition effect*, resulting from equation 1.

FIGURE 9 Information and competition effects on ever employed outcome for alternative values of parameter K



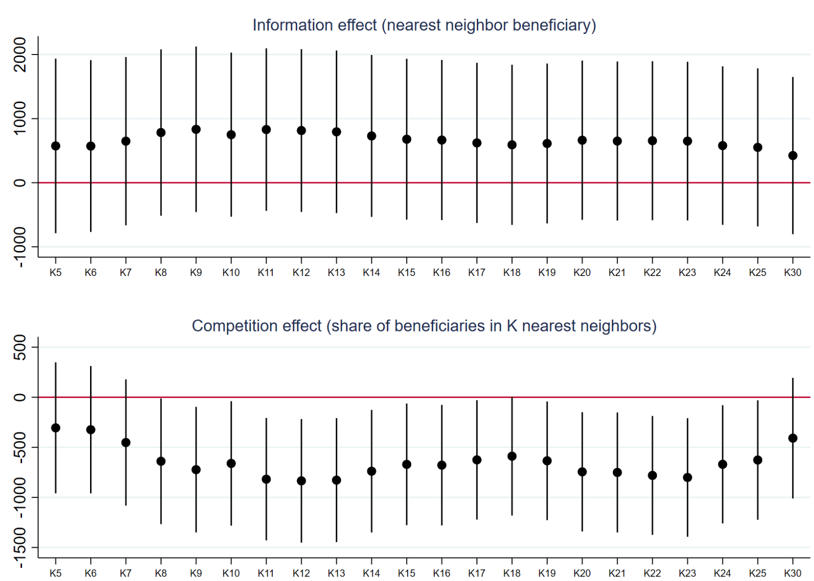
Note: The figure shows the *information effect* and the *competition effect*, resulting from equation 1, for different values of K.

FIGURE 10 Information and competition effects on cumulative months outcome for alternative values of parameter K



Note: The figure shows the *information effect* and the *competition effect*, resulting from equation 1, for different values of K.

FIGURE 11 Information and competition effects on cumulative wage outcome for alternative values of parameter K



Note: The figure shows the *information effect* and the *competition effect*, resulting from equation 1, for different values of K.

ACKNOWLEDGEMENTS

We thank the valuable comments from participants of conferences at LACEA, RIDGE, UEA North American Meetings, Asociación Argentina de Economía Política, and seminars at Universidad de San Andrés, Universidad Nacional de La Plata, Universidad de la República, Catholic University of Lisboa and the valuable comments received from colleagues at CAF research department across multiple interactions. We thank the Ministerio de Desarrollo Social y Promoción del Empleo for access to administrative data from the program. We also thank Victoria Castillo and Moira Ohaco from *Ministerio de Trabajo, Empleo y Seguridad Social* (Argentina) for their help in understanding the administrative records about formal employment trajectories. The views expressed are those of the authors and do not necessarily reflect those of CAF. We thank Belén Cañuelo for outstanding research assistance.

REFERENCES

Abebe, G., Caria, A. S., Fafchamps, M., Falco, P., Franklin, S. and Quinn, S. (2021) Anonymity or distance? job search and labour market exclusion in a growing african city. *The Review of Economic Studies*, **88**, 1279–1310.

Álvarez, F., Eslava, M., Sanguinetti, P., Toledo, M., Alves, G., Daude, C. and Allub, L. (2019) *RED 2018: Institutions for productivity: towards a better business environment*. CAF.

Baum-Snow, N. (2020) Urban transport expansions and changes in the spatial structure of us cities: Implications for productivity and welfare. *Review of Economics and Statistics*, **102**, 929–945.

Baum-Snow, N., Brandt, L., Henderson, J. V., Turner, M. A. and Zhang, Q. (2017) Roads, railroads, and decentralization of chinese cities. *Review of Economics and Statistics*, **99**, 435–448.

Bayer, P., Ross, S. L. and Topa, G. (2008) Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes. *Journal of Political Economy*, **116**, 1150–1196.

Berniell, L. and de la Mata, D. (2017) Starting on the right track? the effects of first job experience on short and long term labor market outcomes. *CAF Working Paper Series*.

Calvó-Armengol, A. and Jackson, M. O. (2004) The effects of social networks on employment and inequality. *American Economic Review*, **94**, 426–454. URL: https://www.aeaweb.org/articles?id=10.1257/0002828041464542.

Card, D., Kluve, J. and Weber, A. (2018) What works? A meta analysis of recent active labor market program evaluations. *Journal of the European Economic Association*, **16**, 894–931.

Carranza, E. and McKenzie, D. (2024) Job training and job search assistance policies in developing countries. *Journal of Economic Perspectives*, **38**, 221–44.

Cingano, F. and Rosolia, A. (2012) People i know: job search and social networks. *Journal of Labor Economics*, **30**, 291–332.

Crépon, B., Duflo, E., Gurgand, M., Rathelot, R. and Zamora, P. (2013) Do Labor Market Policies have Displacement Effects? Evidence from a Clustered Randomized Experiment. *The Quarterly Journal of Economics*, **128**, 531–580.

Glitz, A. (2017) Coworker networks in the labour market. *Labour Economics*, **44**, 218–230.

Hellerstein, J. K., Kutzbach, M. J. and Neumark, D. (2014) Do labor market networks have an important spatial dimensionα. *Journal of Urban Economics*, **79**, 39–58.

— (2019) Labor market networks and recovery from mass layoffs: Evidence from the great recession period. *Journal of Urban Economics*, **113**, 103192.

Hellerstein, J. K., McInerney, M. and Neumark, D. (2011) Neighbors and coworkers: The importance of residential labor market networks. *Journal of Labor Economics*, **29**, 659–695.

Hellerstein, J. K. and Neumark, D. (2020) Social capital, networks, and economic wellbeing. *The Future of Children*, **30**, 127–152.

INDEC (2010) Proyecciones Poblacionales en base al Censo 2010. Datos recuperados de Web INDEC, https://www.indec.gob.ar/nivel4_default.asp?id_tema_1=2&id_tema_2=24&id_tema_3=119,.

Jahn, E. and Neugart, M. (2020) Do neighbors help finding a job? social networks and labor market outcomes after plant closures. *Labour Economics*, **65**, 101825.

Kramarz, F. and Skans, O. N. (2014) When strong ties are strong: Networks and youth labour market entry. *Review of Economic Studies*, **81**, 1164–1200.

Manning, A. and Petrongolo, B. (2017) How local are labor markets? evidence from a spatial job search model. *American Economic Review*, **107**, 2877–2907.

Manski, C. F. (1993) Identification of endogenous social effects: The reflection problem. *The review of economic studies*, **60**, 531–542.

Marinescu, I. (2017) The general equilibrium impacts of unemployment insurance: Evidence from a large online job board. *Journal of Public Economics*, **150**, 14–29.

McKenzie, D. (2017) How effective are active labor market policies in developing countries? a critical review of recent evidence. *The World Bank Research Observer*, **32**, 127–154.

Montgomery, J. D. (1991) Social networks and labor-market outcomes: Toward an economic analysis. *The American economic review*, **81**, 1408–1418.

Pallais, A. (2014) Inefficient hiring in entry-level labor markets. *American Economic Review*, **104**, 3565–99.

Pissarides, C. A. (2000) *Equilibrium unemployment theory*. MIT press.

Schmutte, I. M. (2015) Job referral networks and the determination of earnings in local labor markets. *Journal of Labor Economics*, **33**, 1–32.

Tsivanidis, N. (2023) Evaluating the impact of urban transit infrastructure: Evidence from bogota's transmilenio. *University of California, Berkeley*.

A | APPENDIX

TABLE A.1 Descriptive statistics: potentially eligible population for PPP (household survey, representative at the city level, 2012)

	Mean	SD	p25	p50	p75	N
Female	0.4249	0.4948	0	0	1	83,330
Age	21.3015	2.4309	19	21	23	83,330
High school (18+)	0.5781	0.4943	0	1	1	78,914
Higher education (21+)	0.0901	0.2868	0	0	0	50,277
1-4 employees	0.5140	0.5008	0	1	1	38,704
5-10 employees	0.3024	0.4603	0	0	1	38,704
11-100 employees	0.1326	0.3399	0	0	0	38,704
101+ employees	0.0510	0.2205	0	0	0	38,704
Monthly wage	1758.7	1,262.7	1,000	1,600	2,400	47,789

*Notes:*The distribution of employees by firm size is reported only for those who responded the work in a firm with 1 or more employees.

TABLE A.2 Distribution of formal employees by firm size (household survey, representative at the city level, 2012)

	Mean	SD	p25	p50	p75	N
1-4 employees	0.1468	0.3548	0	0	0	33,691
5-10 employees	0.1989	0.4001	0	0	0	33,691
11-100 employees	0.2826	0.4513	0	0	1	33,691
101+ employees	0.3717	0.4844	0	0	1	33,691
Monthly wage	3,132.6	1,843.1	22,00	3,000	3,500	42,107

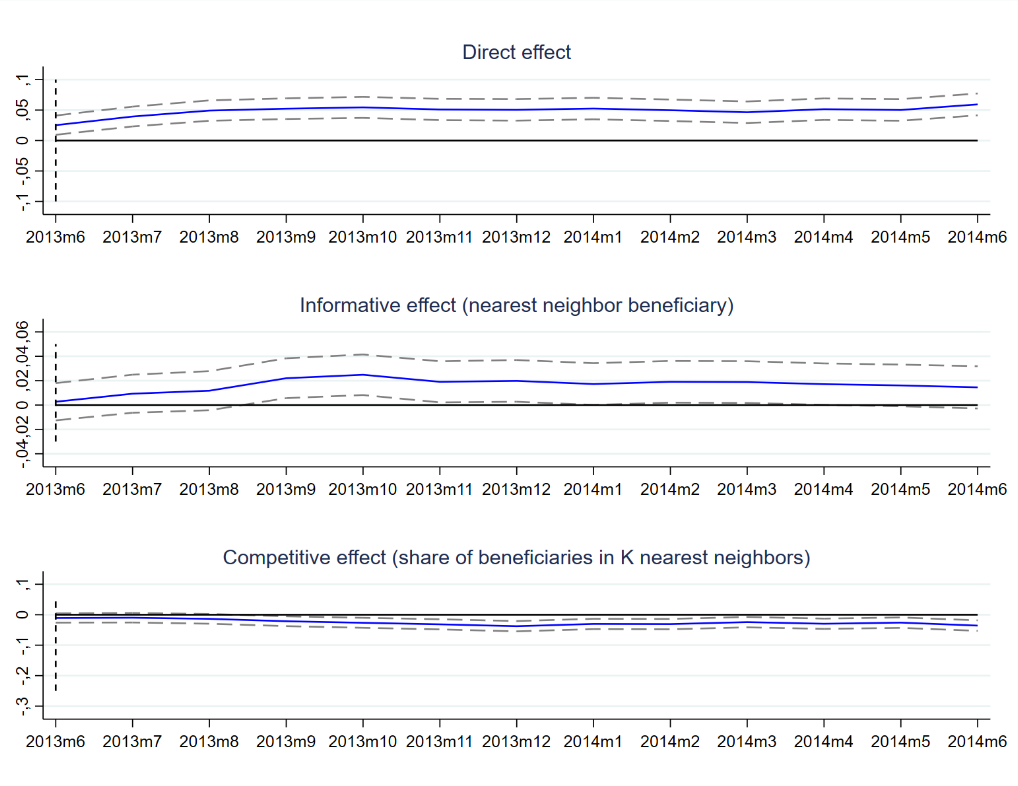
Note: The distribution of employees by firm size is reported only for those who responded with a value of 1 or more.

TABLE A.3 Sample selection. Descriptive statistics and balance tests of georeferenced candidates

		Non-georref. candidates				
	Mean	Difference		SE	Ratio	N
	(1)	(2)	***	(4)	(3)	(5)
Individual characteristics						
Female	0.5094	0.0210		0.0140	0.0411	8,882
Age	21.1376	-0.3534	***	0.0665	-0.0167	8,881
Single	0.9509	-0.0129	*	0.0066	-0.0136	8,882
Children	0.0814	0.0394	***	0.0089	0.4840	8,882
High school (18+)	0.6942	-0.0919	***	0.0173	-0.1323	5,686
Higher education (21+)	0.0806	-0.0127		0.0144	-0.1573	2,514
Manual application	0.5050	0.0589	***	0.0139	0.1166	8,882
Individual formal employment before treatment						
Month -5	0.0139	0.0022		0.0035	0.1612	8,882
Month -4	0.0041	0.0011		0.0020	0.2634	8,882
Month -3	0.0083	-0.0019		0.0023	-0.2233	8,882
Month -2	0.0134	-0.0056	**	0.0026	-0.4199	8,882
Month -1	0.0258	-0.0096	***	0.0037	-0.3733	8,882
Neighborhood characteristics (census data)						
UBI	0.0839	0.0376	***	0.0029	0.4477	8,839
Informality	0.3108	0.0778	***	0.0052	0.2504	8,839
Unemployment	0.0714	0.0075	***	0.0007	0.1053	8,839

Note: The table shows descriptive statistics for the candidates who were successfully georeferenced, together with balance tests between them and non-georeferenced candidates. We report OLS coefficients (column 2) for the non-georeferenced dummy variable taking each listed characteristic as dependent variable. Column 3 shows the ratio of columns 2 and 1, and column 4 shows standard errors in parentheses..

FIGURE A.1 Dynamic effects: Specification 1, 15 nearest neighbors, no controls



Note: The figure shows coefficients and 90% confidence intervals for *direct effect*, *information effect* and *competition effect*, for 12 post-treatment months, resulting from specification 1. Competition effect corresponds to estimation on share of beneficiaries among 15 nearest neighbors.

TABLE A.5 Homophily by gender

	Ever employed		Cumulative months		Cumulative wage	
	(1)	(2)	(3)	(4)	(5)	(6)
Direct effect (T)	0.0751***	0.0730***	0.5950***	0.5938***	3,954.7***	3,946.4***
	(0.0120)	(0.0120)	(0.1105)	(0.1108)	(784.1)	(779.6)
Information effect (T^{vec})	0.0257	0.0273*	0.2116	0.2182	1,118.4	1,149.4
	(0.0163)	(0.0164)	(0.1478)	(0.1488)	(1,028.4)	(1,038.3)
Opposite sex $\times$ Information effect ($T^{vec} \times D^{j,vec}$)	-0.0136	-0.0145	-0.0910	-0.1020	-879.9	-924.7
	(0.0228)	(0.0229)	(0.2064)	(0.2077)	(1,452.9)	(1,466.8)
Competition effect (S^k)	-0.0146***	-0.0160***	-0.0971**	-0.0918**	-555.4*	-543.9*
	(0.0044)	(0.0048)	(0.0405)	(0.0440)	(286.8)	(314.7)
Control group mean	0.3016	0.3016	2.2103	2.2103	12,620.0	12,620.0
Observations	7,282	7,307	7,282	7,307	7,282	7,307
Controls	Yes	Yes (FE)	Yes	Yes (FE)	Yes	Yes (FE)

Notes: This table shows the OLS estimates of equation 2, where $D^{j,vec}$ is a dummy that takes the value 1 if the nearest neighbor has opposite sex than individual i. The outcome "ever employed" refers to the probability of being employed in the formal sector in the 12-month period following the end of the PPP program; "cumulative months" and "cumulative wage" refer to the number of months in formal employment and the sum of monthly wages, respectively, in the same 12-month period. All regressions include as control variables a set of stratification variables that affects the individual's likelihood of being selected as beneficiary in the draft (number of files submitted, number of employees of the company to which she applies and the ratio between the number of applicants and the number of employees in the firm), the same set of stratification variables of the nearest neighbor and the averages of the nearest K applicants. In addition, regression results shown in columns (1), (3) and (5) include controls for individual and neighborhood characteristics, while columns (2), (4) and (6) include controls for individual characteristics and neighborhood fixed effects. Robust standard errors in parenthesis. Statistical significance is indicated as follows: $* \; p < 0.1$; $** \; p < 0.05$; $*** \; p < 0.01$.

TABLE A.6 Homophily by educational level

	Ever employed		Cumulative months		Cumulative wage	
	(1)	(2)	(3)	(4)	(5)	(6)
Direct effect (T)	0.0752***	0.073***	0.5916***	0.5908***	3,934.2***	3,929.2***
	(0.0120)	(0.0120)	(0.1104)	(0.1108)	(782.1)	(777.8)
Information effect (T^{vec})	0.0207	0.0228	0.1201	0.1231	314.3	328.6
	(0.0180)	(0.0181)	(0.1622)	(0.1631)	(1,127.9)	(1,138.5)
Different education × Information effect ($T^{vec} \times D^{j,vec}$)	-0.0038	-0.0056	0.0689	0.0652	557.4	550.8
	(0.0231)	(0.0232)	(0.2080)	(0.2088)	(1,462.6)	(1,470.2)
Competition effect (S^k)	-0.0146***	-0.016***	-0.0972**	-0.0914**	-555.2*	-539.6*
	(0.0044)	(0.0048)	(0.0405)	(0.0440)	(286.8)	(314.8)
Control group mean	0.3016	0.3016	2.2103	2.2103	12,620.0	12,620.0
Observations	7,282	7,307	7,282	7,307	7,282	7,307
Controls	Yes	Yes (FE)	Yes	Yes (FE)	Yes	Yes (FE)

Notes: This table shows the OLS estimates of equation 2. Education groups considered are Incomplete High-school and Complete High-school or more. The outcome "ever employed" refers to the probability of being employed in the formal sector in the 12-month period following the end of the PPP program; "cumulative months" and "cumulative wage" refer to the number of months in formal employment and the sum of monthly wages, respectively, in the same 12-month period. All regressions include as control variables a set of stratification variables that affects the individual's likelihood of being selected as beneficiary in the draft (number of files submitted, number of employees of the company to which she applies and the ratio between the number of applicants and the number of employees in the firm), the same set of stratification variables of the nearest neighbor and the averages of the nearest K applicants. Robust standard errors in parenthesis. Statistical significance is indicated as follows: $* p < 0.1$; $** p < 0.05$; $*** p < 0.01$.

TABLE A.7 Homophily by age group

	Ever employed		Cumulative months		Cumulative wage	
	(1)	(2)	(3)	(4)	(5)	(6)
Direct effect (T)	0.0752***	0.0735***	0.5913***	0.5958***	3917.5***	3,954.2***
	(0.0120)	(0.0121)	(0.1107)	(0.1111)	(786.2)	(782.9)
Information effect (T^{vec})	0.038**	0.040**	0.2683*	0.2791*	1,153.1	1,198.5
	(0.0160)	(0.0161)	(0.1441)	(0.1445)	(1,024.3)	(1,022.8)
Different age group $\times$ Information effect ($T^{vec} \times D^{j,vec}$)	-0.0407*	-0.0425*	-0.2136	-0.2297	-1,006.6	-1,058.5
	(0.0229)	(0.0230)	(0.2074)	(0.2078)	(1,455.8)	(1,457.3)
Competition effect (S^k)	-0.0144***	-0.0155***	-0.0965**	-0.087**	-535.7*	-495.1
	(0.0045)	(0.0048)	(0.0405)	(0.0441)	(287.5)	(315.9)
Control group mean	0.3016	0.3016	2.2103	2.2103	12,620.0	12,620.0
Observations	7,255	7,280	7,255	7,280	7,255	7,280
Controls	Yes	Yes (FE)	Yes	Yes (FE)	Yes	Yes (FE)

Notes: This table shows the OLS estimates of equation 2. Age groups considered are equal or below 21 and above 21 years old at the moment of registering for the program. The outcome "ever employed" refers to the probability of being employed in the formal sector in the 12-month period following the end of the PPP program; "cumulative months" and "cumulative wage" refer to the number of months in formal employment and the sum of monthly wages, respectively, in the same 12-month period. All regressions include as control variables a set of stratification variables that affects the individual's likelihood of being selected as beneficiary in the draft (number of files submitted, number of employees of the company to which she applies and the ratio between the number of applicants and the number of employees in the firm), the same set of stratification variables of the nearest neighbor and the averages of the nearest K applicants. Robust standard errors in parenthesis. Statistical significance is indicated as follows: $* \, p < 0.1$; $** \, p < 0.05$; $*** \, p < 0.01$.

TABLE A.8 Homophily by city zone

	Ever employed		Cumulative months		Cumulative wage	
	(1)	(2)	(3)	(4)	(5)	(6)
Direct effect (T)	0.0754***	0.0740***	0.5908***	0.5979***	3,912.4***	3,959.6***
	(0.0120)	(0.0120)	(0.1106)	(0.1111)	(784.6)	(782.1)
Information effect (T^{vec})	0.0230	0.0261	0.2057	0.2292	1,094.8	1,227.9
	(0.0170)	(0.0170)	(0.1516)	(0.1515)	(1,078.3)	(1,070.2)
Centre x Information effect	-0.0069	-0.0111	-0.0668	-0.1080	-787.3	-1,019.8
($C \times T^{vec}$)	(0.0239)	(0.0240)	(0.2172)	(0.2187)	(1,509.8)	(1,523.3)
Competition effect (S^k)	-0.0244***	-0.0238***	-0.1539***	-0.1386**	-913.9**	-816.0*
	(0.0062)	(0.0067)	-0.056	(0.0611)	(406.5)	(438.9)
Centre x Competition effect	0.0178**	0.0165*	0.0981	0.0996	686.0	627.2
($C \times S^k$)	(0.0089)	(0.0096)	(0.0809)	(0.0874)	(576.6)	(629.9)
Control group mean	0.3016	0.3016	2.2103	2.2103	12,620.0	12,620.0
Observations	7,255	7,280	7,255	7,280	7,255	7,280
Controls	Yes	Yes (FE)	Yes	Yes (FE)	Yes	Yes (FE)

Notes: This table shows the OLS estimates of equation 3, where C_i is a dummy that takes the value 1 if individual i resides in the centre of the city. We partition the city in two by choosing the midpoint of all candidates' places of residence and building a circle of radius chosen such that individuals within comprise half of the sample. Individuals in the sample who are among the 50% closer to the midpoint are categorized as *center*. The outcome "ever employed" refers to the probability of being employed in the formal sector in the 12-month period following the end of the PPP program; "cumulative months" and "cumulative wage" refer to the number of months in formal employment and the sum of monthly wages, respectively, in the same 12-month period. All regressions include as control variables a set of stratification variables that affects the individual's likelihood of being selected as beneficiary in the draft (number of files submitted, number of employees of the company to which she applies and the ratio between the number of applicants and the number of employees in the firm), the same set of stratification variables of the nearest neighbor and the averages of the nearest K applicants. Robust standard errors in parenthesis. Statistical significance is indicated as follows: $* p < 0.1$; $** p < 0.05$; $*** p < 0.01$.

TABLE A.4 Probability of being employed: Dynamic effects. Specification 1, 15 nearest neighbors, no controls

			Direct effect (T)		Information effect (T^{vec})		Competition effect (S^k)	
			Difference	SE	Difference	SE	Slope	SE
	Baseline emp	N	(1)	(2)	(3)	(4)	(5)	(6)
Month 1	0.1744	7,339	0.0403 ***	(0.0099)	0.0037	(0.0097)	-0.0040	(0.0036)
Month 2	0.1867	7,339	0.0501 ***	(0.0102)	0.0086	(0.0100)	-0.0040	(0.0037)
Month 3	0.1942	7,339	0.0530 ***	(0.0103)	0.0151	(0.0102)	-0.0058	(0.0037)
Month 4	0.2036	7,339	0.0551 ***	(0.0105)	0.0189 *	(0.0104)	-0.0062 *	(0.0038)
Month 5	0.2130	7,339	0.0520 ***	(0.0106)	0.0173	(0.0106)	-0.0082 **	(0.0038)
Month 6	0.2207	7,339	0.0521 ***	(0.0107)	0.0186 *	(0.0107)	-0.0117 ***	(0.0039)
Month 7	0.2205	7,339	0.0543 ***	(0.0107)	0.0187 *	(0.0107)	-0.0104 ***	(0.0039)
Month 8	0.2188	7,339	0.0516 ***	(0.0107)	0.0216 **	(0.0107)	-0.0102 ***	(0.0039)
Month 9	0.2209	7,339	0.0485 ***	(0.0107)	0.0171	(0.0107)	-0.0072 *	(0.0040)
Month 10	0.2175	7,339	0.0533 ***	(0.0107)	0.0141	(0.0106)	-0.0075 *	(0.0039)
Month 11	0.2211	7,339	0.0522 ***	(0.0108)	0.0134	(0.0107)	-0.0077 *	(0.0039)
Month 12	0.2304	7,339	0.0616 ***	(0.0109)	0.0114	(0.0108)	-0.0102 **	(0.0040)

Note: The table shows the mean employment rate, direct, information, and competition effect coefficients and standard errors (in parenthesis) for 12 post-treatment months.