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Article

Spatial social effects on the decision to participate in the youth labor market in a developing country

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Abstract:

Globally, many public policies seek to improve the results in participation, employment, and unemployment of the youth in the labor market. Evidence shows that education, age, sex, income conditions of the household, and working conditions affect labor market participation. However, how the behavior of the closest individuals affects the decision of the younger individuals to labor participation in a developing country is a matter of discussion. Using GPS location for 1094 young people, I estimate a spatial model for individual decisions to participate in the labor market in Colombia. Results show that the nearby individual's similar decision regarding labor participation affects the youth's decision to participate or social effects in youth labor participation.

Keywords: Spatial econometrics; labor force participation; spillover effects.
JEL Classification: C21; J21; J38; J46.

Efectos sociales espaciales sobre la decisión de participar en el mercado laboral de los jóvenes en un país en desarrollo

Resumen:

A nivel mundial, muchas políticas públicas buscan mejorar los resultados en participación, empleo y desempleo de los jóvenes en el mercado laboral. La evidencia muestra que la educación, la edad, el sexo, los ingresos del hogar y las condiciones laborales afectan la participación en el mercado laboral. Sin embargo, la forma en que el comportamiento de otros jóvenes afecta la decisión por participar en el mercado de trabajo, en un país en desarrollo, es un tema de discusión. Utilizando la ubicación (GPS) para 1094 jóvenes, se estima un modelo espacial para las decisiones individuales de participar en el mercado laboral en Colombia. Los resultados muestran que la decisión de un joven cercano con respecto a su participación laboral afecta la decisión individual por participar en el mercado laboral de otro joven, es decir, existen efectos sociales en la participación laboral juvenil.

Palabras clave: Econometría espacial; participación en la fuerza laboral; efectos de desbordamiento.
Clasificación JEL: C21; J21; J38; J46.

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1. Introduction

The labor participation of young people is a great concern in the world. The Agenda 2030 for Sustainable Development show the global importance of increasing the youth link to the labor market. Differences between regions, countries, sex, race, and age for youth labor participation are persistent along time. According to International Labor Organization (ILO, 2020), the youth labor force participation rate (LFPR) was 48.9% for Latin America and the Caribbean, with 57.9% LFPR for men and 39.6% for women.

However, over the last years, labor participation has lowered in Latin America due to "greater investment in education throughout the countries in the region, which motivates people to further invest in their human capital" (Viollaz, 2014). However, the percentage of youth who are not in employment, education, or training (NEET) has steadily increased over time (Tornarolli, 2017; Ham et al., 2020).

The decision to participate in the labor market is a dichotomous choice that includes employment and unemployment over inactive status. Of course, increasing youth employment is the goal. However, the other side of the problem is the unemployment of youth. United Nation's ILO (2019) stated that the problem of unemployment among young people ages 15–24 years in Latin America is so serious that one in five young people who seek employment fails to find a job, causing them to be discouraged and frustrated. The panorama of young people in Latin America does not seem to have changed because unemployment rates have remained around 20% for many years; furthermore, inequality between men and women has also persisted (ILO, 2019). Weller (2006) believed that high unemployment and informality rates in Latin America affect the labor insertion of young people. In 1990, the unemployment rate of young people aged 15–29 years was 12.8%; however, by 2002, the rate had skyrocketed to 16.1%. Increased unemployment unevenly affected young women, whose unemployment rate went from 15.9% to 20% over the period.

The youth labor force participation in Colombia does not show the same trends in Latin America.[1] It has increased in 2019. The findings of Ham et al. (2020) suggested that "although the transition into the labor market remains challenging for Colombian youth, young people are now participating more in the labor market" (p. 16). However, substantial regional differences exist in rural/urban or group ages or cities in Colombia (Mora & Muro, 2017; Ham et al., 2020). Colombia's unemployment and employment rates in 2018 for young people ages 14–28 years were 17.2% and 46.2%, respectively (Dane, 2018). The unemployment and employment rates of young people in Buenaventura, a modest-sized Colombian city with a population of roughly 250,000, were 22.5% and 26.85%, respectively, whereas those of the youth in the entire city were 17.5% and 35.9%, respectively (Mora & Sandoval, 2019).

To our knowledge, no other studies in Colombia have analyzed individual youth labor participation using a spatial approach. In these ways, this article mainly discusses whether the youth's individual decision regarding participating in the labor market is affected by the nearby individual's similar decision regarding the same. The influence of social group behavior on an individual's decisions has been known in the literature as social effects. Our results show positive spatial dependence in individual's decision regarding participation in the labor market, and thus, nearby youth individual exhibits similar decision outcomes regarding labor participation; that is, results show a social effect in the youth labor market. In a similar vein, how the household characteristics of the individual and the neighborhoods affect the decision to participate in the labor market is worthy of discussion. To discuss the idea, spatial probit models of labor participation for all youth, women, and men are estimated. Results show differences in the effects of the neighborhood individuals on labor participation between women and men. Our results are critical for public policy on youth labor participation. Are there enough policies oriented to the individual youth? Our response is not. Policies must be oriented toward the direction of how the youths interact with other youths in their neighborhood and how social behavior affects the youth labor market participation in developing countries.

[1] According to the HDI index Colombia, Colombia is a developing country. The HDI for Colombia in 2020 was 0.747, and most developed countries have a score above 0.80.

2. Literature review

2.1. Youth labor participation

Andrews et al. (2004) discussed youth labor participation in Australia. They found that youths who live in poorer quality neighborhoods face an increased likelihood of being unemployed at the ages of 18 and 21 years. Andrews et al. (2004) include included aggregate variables of the neighborhood of income, the proportion of the neighborhood with skilled vocational qualifications, and the proportion of the affluent neighborhoods are a substantially more likely neighborhood that has degree qualifications or higher to have attended a non-government school. Results show that neighborhood socioeconomic status has an important role in explaining the labor market outcomes of Australian youth (p. 22).

Meanwhile, using data from Argentina, Costa Rica, and Venezuela's respective household surveys, Weller (2006) analyzed the impact of different socio-demographic variables on youth labor participation in those countries. He performed a dynamic analysis incorporating elements of the career paths of age-specific cohorts. He concluded that education and training play an important role in young people's ability to successfully join the labor market and that fluctuations in workforce supply and demand are not the main cause of the high level of young unemployment.

Doiron and Gørgens (2008) analyzed the magnitude and type of state dependence in terms of being employed, unemployed, or outside the workforce for low-skilled Australian youth, (those without any post-secondary education). They used longitudinal data from the Australian Youth Survey for the period 1989–1994 and found evidence of dependence for occurrence, but they did not find dependence for the lagged duration. People who had employment experience were more likely to find a job in the future, regardless of the time they had spent in previous jobs. This was also shown to apply to periods of unemployment, meaning that it was easy to undo the benefits of previous work experiences given periods of unemployment.

Painter et al. (2007) examined the effects of location and race on labor force participation among minority youth and immigrants in the Los Angeles metropolitan areas using Public Use Microdata Sample (PUMS) data from the 2000 U.S. census. They found that both space and job accessibility play important roles in labor force participation for young people. Additionally, they found that first- and second-generation immigrants experience higher unemployment; however, young adult Latinos born in the U.S. were as likely to work as white youths.

Hernández and Montero (2011) analyzed the employment situation for young people in Europe and Spain for the period between 2005 and 2009, using data from the Labor Force Survey and the Active Population Survey, respectively. They concluded that although education and employment have a positive relationship, a mismatch exists between educational training and occupation. Additionally, young people have relatively high employment rates in the service sector, including a high proportion of women.

Using dynamic panel data with regional variables in 234 regions of 19 EU countries, Perugini and Signorelli (2010) found strong persistence over time of youth labor market performance and spatial dependence. Through the generalized method of moments (GMM), they found spatial autocorrelation. Their results showed that "supraregional aspects do matter in shaping labor market performance and that policy design should carefully consider the true spatial extent and interactions that occur at a regional level" (p. 179).

Spatarelu (2015) analyzed the youth unemployment rate, activity rate, and the NEET indicator for Romania using Eurostat data. He found that Romania's youth unemployment rate is fairly average, given that countries such as Italy, Greece, and Spain have high youth unemployment. However, he highlighted a concern about the high rate of NEET for the country.

Morissette et al. (2015) estimated the elasticity of labor force participation and school enrollment for after-tax wages for young men, considering the variation in wage growth that is induced by changes in world oil prices. The results indicate that in the 2000s, an increase in wages had a double impact on the labor markets. First, increasing wages reduced full-time university tuition and fees. Second, they brought individuals who were not enrolled in school or employed elsewhere into the labor market. However, they found little evidence that young men without a high school diploma would drop out of school in response to higher pay rates.

Caliendo and Schmidl (2016) analyzed the effectiveness of active labor market programs for youth based on studies conducted in Europe. They found that job search assistance (with and without monitoring) had positive effects, whereas public work programs have negative effects. Alternatively, the authors found mixed effects regarding training and salary subsidies.

Dorsett and Lucchino (2018) examined labor market transitions among young people in the United Kingdom at the end of their schooling. They used an econometric model of transitions that allows for an unobserved influence of heterogeneity. The data were obtained from the British Longitudinal Survey from 1991 to 2008. Among their main results, the authors highlight the importance of distinguishing between temporary unemployment and being out of school and economically inactive, given that the latter has a more damaging long-term impact on the probability of entering the workforce for both men and women. The results indicate the positive impact of work experience on men; however, for women, work experience loses its importance.

In Colombia, Pedraza (2008) examined the effectiveness of the legislature and operating policies around the youth labor market in Colombia. Using the Continuous Household Survey, the author found that the average number of hours young people worked was greater than what is allowed by the Code of the Minor that wages are unfair and that individuals under 18 years of age perform work activities that involve risks to their health and safety. Finally, the author indicates that despite various incentives offered by the government to employers in terms of labor cost reductions, the youth employment rate remained constant during the analysis period, 2001–2005.

Moreover, Farné (2009) examined the main policies and programs aimed at promoting labor participation for vulnerable youth and women in Colombia. The main findings showed that providing childcare services for children helped women gain employment and that the effectiveness of entrepreneurship programs for vulnerable populations is questionable. Additionally, the inappropriate design of employment subsidies has compromised their occupational impact and public employment services have proved to be of little use to young people and women.

De La Hoz et al. (2012) analyzed advances in the theory and measurement of the causes of youth unemployment. They surveyed scientific publications on the subject and found that the phenomenon is a consequence of demographic dynamics, incongruities between labor supply and demand, minimum wage, and economic dynamics.

Bustos and Carrasquilla (2013) analyzed the participation of young people in the labor market in Cartagena, Colombia using data from the Large Integrated Household Survey (GEIH) for the third quarter of 2011. They estimated a binomial logit model and concluded that the probability of participating in the labor market increases as young people reach higher levels of schooling. By contrast, being male increases the probability of participating in the labor market, as does being a head of household.

Mora et. al (2017) found that in Cali (Colombia), the longer is the job search time, the lower is the probability of leaving unemployment. They also found that young women are more likely to remain unemployed than young men.

Serna et al. (2019) analyzed the labor participation of young people for the thirteen main metropolitan areas of Colombia find that young women had greater difficulty accessing employment compared to their male counterparts. Alternatively, the number of those who were employed under an employment contract, and the number of young people who focused on self-employment or entrepreneurship increased over the study period. Finally, the authors found high levels of unemployment for young people in low-income families and low levels of education.

Ham et al. (2020), analyzed the trends of young people in Colombia. They found that young people have systematically higher informality rates than adults between 2008 and 2017. Young women compared with young men have a lower labor LFPR (48% vs. 66%) and lower employment rate (37% vs. 57%).

Skilled (vs. unskilled) youth have more labor force participation (90% vs. 62%), more employment rates (75% vs. 50%), and less unemployment rate (16.3% vs. 19.8%) in the period.

2.2. Spatial labor force participation

Participation in the labor market at the regional level usually implies the estimation of the spatial model. Some estimation analyzes unemployment or employment aggregate rates in the spatial context. For example, Kalenkoski and Lacombe (2008) estimated the spatial autoregressive model (SAR) of the aggregate youth employment in 3065 counties in the United States of America, to discuss the effects of the minimum wages over employment. Their results show as 10% of the increase in the minimum wage reduces the youth population ratio by 2.5%.

Kalenkoski and Lacombe (2011) used a data panel to estimate the SAR model for 705 counties, and they found that controlling for spatial dependence through estimation of the SAR model indicates a 2.11% decrease in teen employment resulting from a 10% increase in the real effective minimum wage. This is a larger estimate because it includes both direct and indirect effects. Thus, studies that ignore the spatial dependence may underestimate the negative effect of minimum wages on teen employment" page 17. Lopez et al. (2017) also estimated this relationship in Spain using data for 46 Spanish provinces (NUTS-3) and their estimate from the Spatial Durbin Model (SDM), SAR, and dynamic panel model (DPM). Results of estimation showed a negative impact of minimum wages on the youth employment rate. However, the effects are minimum when they are controlled by spatial spillovers.

Other works have directly discussed labor participation in a spatial context. However, they did not estimate employment and unemployment rates separately. The dependent variable is the ratio of the individuals that belong to the workforce in a specific age range over the total population. Alternatively, Elhorts (2008) pointed out that if regional data are used first instead of individual data, "the observed variable consists of a proportion Lj of individuals belonging to the working-age population in region j (j = 1,…,N) who decides to participate" pp 169).

Elhorst and Halleck (2017) showed the main publications using LFPR. Table 1 summarizes this strand of literature. I elaborate on the analysis of Elhorst and Halleck (2017) and Martin-Roman et al. (2020) using main co-variables, specific information over regions, and include the last publications in Table 1.

Table 1 shows the main co-variables used in the regressions are unemployment, wages, and education. Most articles use spatial error model (SEM) (70%), followed by the spatial autoregressive model (SAR) (30%), and few estimations using spatial lag model, geographically weighted regressions (GWR) time-space recursive models (TRA), panel data, and ordinary least square (OLS).

TABLE 1.
Articles in spatial labor force participation

Study(Author)	Regions	Dependent Variable	Independent Variables	Population	Period	Specification
Moller and Aldashev (2006)	Germay, NUTS-3 West German: 327, East German: 111; N=438	Labour Force Participation Rate	Unemployment rate, Logarithm of the wages, wage dispersion in the lower and upper tail of the wage distribution, Daycare capacities per 1000 children below six years of age in each region, Dummies for eight regions	Male, Female	1998	SAR, SEM
Elhorst and Zeilstra (2007)	European Union (Belgium, Denmark, Germany, Greece, Spain, France, Ireland, Italy, Luxembourg, Netherlands, Austria, Portugal and UK) N=1825, 157 regions across 13 countries	Labour Force Participation Rate	LFPR(-1), Wage rate, Unemployment rate, Industry mix(Ratio of female employment to total employment within agricultural, manufacturing and service sectors), pension wealth accrual rate, Unemployment benefits, Education, Population age under 15.	Male, Female	1983 - 1997	SEM ,GLS
Ellhorst (2008)	European Union (Belgium, Denmark, Germany, Greece, Spain, France, Italy, Luxembourg, Netherlands, Austria, Portugal and UK) - NUTS 1 N=1825, 154 regions across 10 countries	Labour Force Participation Rate	LFPR(-1), Wage rate, Unemployment rate, Lower education, Medium education, Higher education,Birth rate, Industry Mix	Male and Female by Cohort (Age categories)	1986 and 1996	SEM, MESS
Cochrane and Poot (2008)	New Zealand, N= 58 Areas	Labour Force Participation Rate, Unemployment benefit rate, Sickness benefit rate, Invalids benefits rate, domestic purposes benefit rate	Private dwellings owned by the occupant in the area, Unemployment rate, Old working age, Solo parent families, Employment in service, Percentage of Maori, Unemployment benefit, Sickness benefits, Invalids benefits, domestic purposess benefits,	Total	1991, 1996, 2001, 2006	SAR, SEM, GWR

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TABLE 1. CONT.
Articles in spatial labor force participation

Study(Author)	Regions	Dependent Variable	Independent Variables	Population	Period	Specification
Falk and Leoni (2010)	Austria, Districts N=121	Labour Force Participation Rate	Ratio of female to male wages, log net wage of females, Share of children aged 0-3 years in day care facilities in %, Fertility indicator, Log population density	Female	2001, 2002	SAR, SEM
Liu and Noback (2011)	Netherlands, Municipalities N=278	Labour Force Participation Rate	Women 35-45 as a percentaje of the toal female population Demographic Pressure (children and elders over active population) Unemployment jobseekers as a percentage of the professional population Female-dominated sector structure Disposable income, Education, Proportion owned houses, Duration conmute to work, Day care facilities, After school care facilities	Female	2002	SEM
Fogli and Veldkamp (2011)	United States, Counties N=3074	Labour Force Participation Rate	County's demographic characteristics, industrial composition and occupational data	Female	1940-2000	TSR
Elhorst and Halleck (2017)	European Regions (Belgium, Denmark, France, West Germany, Italy, Luxemburg, The Neatherlands, Spain), NUTS-2, N=108	Labour Force Participation Rate(LFPR)	LFPR(-1), Unemploument rate, Employment growth rate, Average compensation level (Wage), Percentage of people with higher level of education Percentage share of the population (age 15-24) to the total working age, Density, Spending levels as a pencentage of GDP, Measuring regulations and cost of dismissing and hiring workers	Total Male Female	1986-2010, decenial - census	Panel data, GMM-SYS, Pools, LSDV

TABLE 1. CONT.
Articles in spatial labor force participation

Study(Author)	Regions	Dependent Variable	Independent Variables	Population	Period	Specification
Kawabata and Abe(2018)	Tokio metropolis and (Chiba, Kanagawa and Saitama), Municipalities, N=243	Labour Force Participation Rate	Conmute time (for men), Log of residential land Price, Unemployment rate (men), Household with two or more children, Availability of childcare centers	Married men Unmarried women Marriend women without children Married women with children under 6 Married women with children, none under 6	2010	SDM, SLX
Mansour (2018)	Oman Villages, N=18	Labour Force Participation Rate	Employed females in rural areas, Female jobs in public sector Females with postgraduate educatio Female jobs in education sector Female jons in health and social sector	Female	2010	OLS, GWR
Martin-Roman, Cuellar-Marin and Moral (2020)	Spain Provicens (NUTS 3), N=50	Labour Force Participation Rate	Cyclical component of LFP, Cyclilcal component of unemployment, Dummys for Years,	All	1997-2015	SDM, SAR

Source: Elhorst and Halleck (2017), Martin-Roman et al. (2020) and own revision.

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3. Methodology

The decision to participate in the labor market, at a micro-level, is a dichotomous choice with a value of 1 if the market wage rate exceeds the individual's reservation wage and 0 if it does not. A person participates in the labor market if (s) he is employed or if (s) he is unemployed but available for work and actively seeking a job. This definition implies that both employed and unemployed people participate. People who do not participate are inactive." Ellhorst (2008) and Mora et al. (2017).

Following individual participation, I discuss the effects of the social group on an individual's decisions overall in the labor market. To discuss this idea, let us consider an individual discrete spatial labor participation model.

Let a latent variable Pi* be the unobservable utility associated with spatial individual participation in the labor market:

$$P_i *= \rho W_i P_i * + X_i\beta + \gamma W_i X_i + \epsilon_i; \epsilon_i \sim N(0, \sigma_\epsilon^2 I_n); \text{i=1,..,N} \quad (1)$$

I define LP_i as a dummy variable representing individual í's labor participation status. It takes a value of 1 if the individual is employed or is unemployed but is actively seeking work (market wage exceeds the reservation wage), and zero if the individual becomes inactive; that is, LPi=1 if Pi*>=0, and LPi=0 if Pi*<0. Model (1) is also called the "Spatial Durbin probit model" (LeSage & Pace, 2009; Lacombe & Lesage, 2018).

In equation (1), ***W*** is a spatial social matrix building over individual neighborhood participation in the labor market and allows us to analyze the effect of the behavior of the closest individuals on the decision of the younger individuals to participate in the labor market.[23] The influence of social group behavior on an individual's decisions has been known in the literature as social effects, or in some cases, peer effects (Dietz, 2002; Manski, 1993, 2000). There are many "words" to denote the effect of interactions with others on behavior." Such interactions may be called "social norms," "peer influences," "neighborhood effects," "conformity," "imitation," "contagion," "epidemics," "bandwagon," or "herd behavior" (Manski, 2000, p.127). Vendrik (1998, 2003) discussed the social norm and bandwagon effects on labor supply. In particular, how a woman's preferences are reinforced by experiences of other women in her social reference group. I follow Martín-Román et al.'s (2020) explanation of the effects of the individual neighborhood on the labor market that "labor supply decisions depend on individual determinants and on and individual neighbors' decisions. The spatial neighborhoods affect individual choices related to the labor supply." (p. 1612). However, I did not use neighborhood areas, a difference from Martín-Román et al.'s (2020) work. I exploit individual neighborhood differences to consider spatial social effects.

X_i is a vector of co-variables and $\epsilon_i$is the error model.

To select a specific spatial model, I follow the Hendry methodology (Florax et al. 2003; Angulo & Mur, 2011). Hendry's methodology implies starting with an SDM (Lesage & Page, 2009). SDM "provides a general starting point for discussion of spatial regression model estimation since his model subsumes the spatial error model and the spatial autoregressive model" (Lesage & Page, 2009, p. 46). Angulo and Mur (2011) showed an interesting picture of the relationship between different spatial models for cross-sectional data (Figure 1, p.41). The likelihood ratio test (LRT) is a common test to select SDM, SEM, or SAR.

In equation (1) setting both $\rho \neq 0$ and $\gamma \neq 0$ results in the spatial Durbin model (SDM). The SDM allows for a spatially lagged dependent variable and spatially lagged independent variables. When $\rho = 0$ and $\gamma = 0$ model (1) is a Probit model. In spatial probit models, marginal effects are different from the standard probit model due to the spatial matrix. LeSage and Pace (2009) found the average marginal effects for (1) as

[2] I appreciate the comments from the anonymous referees on the effects of bandwagon in the labor market.
[3] W is a weighted matrix. W could be contiguity, inverse distance, or K nearest neighbors.

$$\frac{\partial LP_i}{\partial X'_k} = (I_n - \rho W_i)^{-1} I_n \beta_k; k = 1,.,K; i = 1,.., \qquad (2)$$

The average marginal effects are divided into direct, indirect, and total effects. Direct effects have their own partial derivatives. Indirect effects are commonly thought of as spatial spillover impacts. According to Lacombe and Lesage (2018), "changes in the value of an explanatory variable for a single observation/county i can (potentially) influence all n -1 other observation/counties." Finally, total effects are defined as the sum of direct and indirect effects and represent the total cumulative effects associated with a change in a given observation for the explanatory variable.

4. Data and Results

This study's data come from young people who live in Buenaventura. Buenaventura (Colombia) is Special District (industrial, port, biodiverse, and ecotourism) and the main seaport of Colombia and one of the ten most important ports in Latin America, moves more than 40% of the international trade of Colombia (La Republica, 2020). Buenaventura has a 6078 km^2 and the density of population is 69.75 hab/km^2. Buenaventura is located in the pacific area of Colombia and the coordinates are Latitude: 3.883, Longitude: -77.067; 3° 52′ 59″ North, 77° 4′ 1″ West. Most of the people are recognized as Afro-descendant,[4] 51.3% of the population are women, 39% are under 18 years old, and the average households in the urban area of the district are made up of 3.3 people. Moreover, according to the Colombian household stratification system, 76% of them belong to strata 1 and 2, 23% to strata 3 and 4, and 1% to strata 5 and 6[5]. (Propacifico, 2019, p. 21–23).

However, the economic benefits of seaport do not extend to the population. Socioeconomic indicators of Buenaventura City show higher unemployment (17.5%), higher poverty (64%), unsafety, and criminality (Propacifico, 2019, p.20).

In 2017, low life conditions in Buenaventura go to important protests (120 organizations and civil movements) and stop the Colombian trade by the seaport (El Tiempo, 2017). Protest reveals "unknown socioeconomic information" about Buenaventura and was the main determinant to realize the survey used here. Data are obtained from the survey "Employment and Quality of Life Survey for Buenaventura" conducted by the Fundación para el Desarrollo Integral del Pacífico (ProPacifico) in 2018.

The survey uses GPS technology to capture latitude and longitude information at the household level and collects data on individual participation in the labor market and socioeconomic variables. I selected the subset of the survey data that focused on young people[6]. In each household, I select randomly only one young person in the household with more than one young. The final data were 1094 young people between 14 and 28 years old.

Concerning the variables to explain the youth labor participation, I include dummies for age groups (18–24 years and 25–28 years old)[7], education (dummy for completed high school and a dummy for completed University), race (Dummy if the individual recognized as Afro descent), a proxy of the low income of the household (Dummy to take 1 if the household Colombian Stratification is between 1 to 2), unemployment (Dummy to take 1 if other people at the household are in unemployment situation, excluding himself), informality (Dummy to take 1 if other people at the household are in informality

[4] In the survey, "88% of the population of the urban area of Buenaventura is Afro-descendant (included are those who identify themselves as blacks or mulattos" (Propacifico, 2019, pp. 20). According to the Official Statistical Department (DANE), 88.7% of people recognized themselves as afro descendants (2015).

[5] The socio-economic stratification system in Colombia was created in 1994. Stratification system classifying households into six categories numbered 1 to 6. Strata 1 households correspond to those of lesser quality and strata 6 to the best conditions.

[6] By Colombian Law, people are considered young if they are between 14 and 28 years old (Colombian Law 1622 de 2013, Article 44).

[7] Age majority begins at 18 years old in Colombia.

situation, excluding himself)[8] and a proxy of commute time (less than 10 minutes to get public transport from the household).

Age differences are important in youth labor participation.[9] Fernandes-Alcantara (2018) showed differences between ages 16–19 and 20–24 years of youth labor participation in the United States (youth are between 16 and 24 years old). When the youth reach the majority age (20 years), labor force participation increases from 35.2% to 71.3% in the United States. I divided young people into three groups: (0) less than 18 years old, (1) the majority age (18 years) and before 24 years old, and (2) individual age between 25 and 28 years old. This difference is selected because once the youth reaches 25 years of age in Colombia, they cease to be a legal part of the family nucleus for access to social security (Article 163 of Colombia Law 100 of 1993 and Article 218 of Colombia Law 1753 of 2015). Segun and expected the labor participation increase to cover social security after 25 years old.

Andrews et al. (2004) discussed the effects of education in youth unemployment "much of the observed differences in unemployment probability in Table 4 can be explained in terms of individual's attributes such education." Education affects the probability to participate in different ways because if there is uncertainty regarding returns of high school or post-compulsory schooling or labor participation then maybe "optimal for an individual make inferences based on a previous decision of their peers" (Andrews et al., 2004; Bikhchandani et al., 1992).

The race is introduced in the labor market by Kain (1968, 1992) in the spatial mismatch model, and Stoll and Raphael (2000) discussed spatial job search patterns and quality of workers by race/ethnicity and proposed the hypothesis of a "geographical skills mismatch" between the skills required of jobs in workers' search areas and their skill sets.

The unemployment variable is usually including in LFPR models (Elhorst, 2007, 2008). Mora & Muro (2017) showed a positive correlation between informality on participation in labor in Colombia. Andrews et al. (2004) remark that personal connections are a successful job search method and show the relationship between neighborhoods and informal job networks.

Cantillo et al. (2019) found a positive correlation between socioeconomic stratification system, SES, and income that is "households in SES 1 and 2 were more likely to have low-income levels, those in SES 3 and 4 were more likely to have a middle-income range and high-strata households were more likely to have a high income." That is, in Colombia, low income is correlated with socioeconomic stratification 1 to 2.

Commuting time is explained by Giuliano and Small (1991). They discussed how, in polycentric urban areas like Los Angeles, a spatial analysis may have clear implications for concentrating poverty and joblessness, residential locations and commuting, and job search behaviors. Painter et al. (2007) found that space and job accessibility play a significant role in youth unemployment in Los Angeles.

Descriptive statistics for selected variables are presented in Table 2.

Table 2 shows that 32.3% of the individuals surveyed participated in the labor market in 2018 (LFP = 1, either employed or unemployed). The mean estimate of age is 21.08 years for all people; women were 1.34 years older on average. 90% of individuals are recognized as Afro descent. 78% of individuals have low income. 53% of the people in the household (excluding himself) work in informal labor. 26% of the people in the household are unemployment. 67.4% of the household spend more than 10 minutes to obtain public transportation (commute time). Finally, the latitude and longitude variables correspond to the GPS coordinates for the individual in Buenaventura City.

[8] Our definition of formality is based on whether the person contributes to pension and health care in their current job (Mora & Muro, 2017).
[9] I very much appreciate the referee comments on different age groups.

TABLE 2.
Descriptive Statistics (Mean)

Variable/Statistics	ALL	Women	Men
Age	21,08	21,68	20,34
Individual Participation Labor (LFP)	0,323	0,234	0,432
Afro-descendent	0,898	0,9055	0,888
Household Low Income	0,778	0,781	0,774
Informality	0,530	0,493	0,576
Unemployment	0,261	0,244	0,283
High School	0,574	0,441	0,593
University	0,180	0,226	0,124
Age 1: Age 18 to 24 years old	0,344	0,345	0,342
Age 2: Age 25 to 28 years old	0,205	0,242	0,159
Sex	0,449	-	-
Commute Time	0,674	0,661	0,688
Latitude	3,878	3,878	3,878
Longitude	-77,02	-77,02	-77,02
N	1094	603	491

Source: Own computations using ECCV -Buenaventura 2018.

To select a specific W matrix configuration, I use the following criteria:[10,11]

TABLE 3.
Criteria's to select a model

	AIC	BIC	BF -Bayes Factor
		All	
Contiguity 2	3,2138	3,3337	1,0617
Contiguity 3*	3,0940	3,2139	0,0000
Contiguity 4	3,1370	3,2569	1,0217
		Male	
Contiguity 2	1,4123	1,4584	0,9731
Contiguity 3*	1,3578	1,4039	0,0000
Contiguity 4	1,3704	1,4165	0,4925
		Female	
Contiguity 2	1,7361	1,7861	0,9748
Contiguity 3*	1,6851	1,7351	0,0000
Contiguity 4	1,6950	1,7450	0,4179

Source: Own computations using ECCV -Buenaventura 2018. Note: In the case of AIC for Men, I use second-order Akaike due n/k=24.55 (Hurvich and Tsai,1989). (*) Model selected.

[10] BF is used by Lesage (2008). However, Kass & Raftery (1995) considered BIC "may be used for reporting scientific results with other analysis omitted but serving as background support" (p. 792) and AIC "are asymptotically equivalent to those based on the Bayes factor" (p.790).

[11] I also run spatial regressions with inverse distance and k nearest neighborhoods with order 1 to 4. However, ρ was not statistically significant.

Table 3 show BF, AIC, and BIC for different weigh contiguity matrix in spatial estimations in the case of ρ is significantly different from zero.[12][13]

Lesage (1988) used BF values according to a scale developed by Jefrey (1961), differences in range of (0,1.15) provide <very slight> evidence in favor model 1 versus 2, differences between (1.15,3.45) provide <slight evidence>, whereas the range (3.45,4.60) represent <strong evidence> and the range (4.60, ∞) indicate <decisive evidence> in favor of model 1 versus 2" (p. 38)

BF shows slight evidence in models for all, male, and female youths. Finally, I use minimum AIC and BIC to select a specific weight matrix. Star (*) in Table 3 marks the selection of the final W matrix.

Estimations of the Spatial Probit models are presented in Table 4,[14]

TABLE 4.
SAR Probit model estimation

	ALL	Female	Male
Constant	-1,7610***	-1,5983***	-1,2963***
	[0,2151]	[0,3035]	[0,3035]
Afro-descendent	-0,2458*	-0,2743	-0,2561***
	[0,1456]	[0,2090]	[0,0210]
Sex	0,7803***		
	[0,0998]		
Informality	0,9575***	0,8062***	1,2713***
	[0,1012]	[0,1362]	[0,1489]
Unemployment	0,7628***	0,8431***	0,6149***
	[0,0853]	[0,1032]	[0,1250]
Household Low Income	0,3128***	0,4145***	0,2996***
	[0,1120]	[0,1511]	[0,1163]
Age 2 (25 to 28)	1,3393***	1,0064***	1,8608***
	[0,1287]	[0,1779]	[0,2260]
Age 1 (18 to 24)	0,8657***	0,6056***	1,0446***
	[0,1160]	[0,1587]	[0,1613]
High School	-0,5034***	-0,3456***	-0,6259***
	[0,1092]	[0,1648]	[0,1606]
University	0,4490***	0,3202*	0,5775***
	[0,1477]	[0,1520]	[0,2243]
Commute Time	0,03134	0,2372**	-0,1843
	[0,0966]	[0,1130]	[0,1391]
ρ	0,5566***	0,5460***	0,4527***
	[0,0757]	[0,1013]	[0,1179]

[12] When ρ is significantly different from zero probit estimates are biased and inconsistent

[13] I use xy2cont program development by Lesage (1998, pages 45-47) in Matlab to compute a contiguity matrix.

[14] Estimation using 1000 MCMC iterations with 100 MCMC burn-in discard.

TABLE 4. CONT.
SAR Probit model estimation

	ALL	Female	Male
Log-likelihood	-1521,5134	-832,5570	-692,7740
Percent correctly predicted	74,49%	71,47%	76,57%
LRTest	20,0300	0,5010	2,464
N	1094	603	491

Note: ***Statistically significant at the 0.01 level; ** Statistically significant at the 0.05 level; *Statistically significant at the 0.1 level. Standard errors appear in brackets [ ].

The second column in Table 4 shows the estimate of a SAR Probit for All youth. The Lr-test between SDM and SAR models does not reject the null γ=0 (χ^2 (12) = 28.3). SAR Probit model predicts 74.49% correctly (ones and zeros).

Table 4 also shows a positive statistical significance of ρ (0.56 with SD equal to 0.075). That means a positive spatial dependence in an individual's decision regarding participation in the labor market, so nearby individuals exhibit similar decision outcomes regarding participating in the labor market. That is, results show the influence of the youth group behavior on an individual's decision or social effects in the youth labor market.

Age dummies, High School, University, Low Income, Informality, Unemployment, Sex, and Rho are statistically significant. However, commute time and race not statistically significant. Age, Afro-descendent, University, Low Income, Informality, Unemployment, and Sex increase labor participation. Race (Afro descent) and High School reduce the likelihood of labor participation.

The third column in Table 4 estimates a SAR probit for Woman because the Lr-test of γ=0 does not reject the null hypothesis and the model predicts 71.47% correctly. Age dummies, University, Low income, Informality, Unemployment, and Commute time are statistically significant and increase the likelihood of labor participation.

The fourth column of the results, Table 4, estimates a SAR Probit for Men because the Lr-test of γ=0 does not reject the null hypothesis and the model predicts 76.57% correctly. Afro-descendent, Age dummies, University, Low income, Informality, Unemployment is statistically significant and increase the likelihood of labor participation. High School reduces the likelihood of labor participation.

In nonlinear models, such as SAR probit models, the parameter magnitudes associated with the estimated coefficients do not have the same marginal effects interpretation as in standard regression models (Lesage & Page, 2009, p. 293). The estimate coefficients of SAR Probit only show the direction of the effect (increase or decrease). Table 5, show the marginal effects (total, direct and indirect) of the spatial estimation.

TABLE 5
Posterior Median Marginal effects.

Variable/Effects	DIRECT EFFECTS			INDIRECT EFFECTS			TOTAL EFFECTS		
	ALL	FEMALE	MALE	ALL	FEMALE	MALE	ALL	FEMALE	MALE
Afro-descendent	0,0348	-0,0631	-0,1148**	0,038806	-0,0756	-0,1003***	0,0736	-0,1387	-0,2151***
	[0,039]	[0,0506]	[0,0559]	[0,0530]	[0,0786]	[0,0463]	[0,0911]	[0,1228]	[0,1001]
Sex	0,3249***			0,3553***			0,6801***		
	[0,0331]			[0,1016]			[0,1082]		
Informality	0,7042***	0,1854***	1,1524***	0,7713***	0,2214***	0,9961**	1,4755***	0,4068***	2,1485***
	[0,0843]	[0,0429]	[0,1135]	[0,2341]	[0,0878]	[0,5004]	[0,2688]	0,1027	[0,5321]
Unemployment	0,3612***	0,1938***	0,4894***	0,3954***	0,2307**	0,4220***	0,7567***	0,4244***	0,9115***
	[0,0366]	[0,0373]	[0,0574]	[0,1131]	[0,0893]	[0,1172]	[0,1214]	[0,0984]	[0,2331]
Household Low Income	0,0812***	0,0952***	0,0748**	0,0881**	0,1134**	0,0641***	0,1693***	0,2086**	0,1388**
	[0,0255]	[0,0367]	[0,0351]	[0,0361]	[0,0505]	[0,0241]	[0,0557]	[0,0922]	[0,0637]
Age 2 (25 to 28)	0,1604***	0,2314***	0,0975**	0,1753***	0,2769**	0,0828***	0,3356***	0,5083***	0,1803***
	[0,0432]	[0,0510]	[0,0467]	[0,0668]	[0,1116]	[0,0159]	[0,1009]	[0,1441]	[0,0434]
Age 1 (18 to 24)	0,1490***	0,1395***	0,1113***	0,1630***	0,166**	0,0967***	0,3120***	0,3056***	0,2076**
	[0,0319]	[0,0396]	[0,0395]	[0,0592]	[0,0663]	[0,0338]	[0,0822]	[0,0973]	[0,0942]
High School	-0,3268***	-0,0798**	-0,5033***	-0,3583***	-0,0948***	-0,4352***	-0,6851***	-0,1746**	-0,9385***
	[0,0419]	[0,0393]	[0,0580]	[0,1147]	[0,0305]	[0,1294]	[0,1329]	[0,0842]	[0,2537]
University	0,0407***	0,0739**	0,0347***	0,0453***	0,0878**	0,0292**	0,0859***	0,1617***	0,0638***
	[0,0136]	[0,0278]	[0,0053]	[0,0136]	[0,0354]	[0,0138]	[0,0136]	[0,0464]	[0,0102]
Commute Time	0,000053	0,0546**	-0,043	-0,000056	0,0649***	-0,0364	-0,000003	0,1195***	-0,0794
	[0,0249]	[0,0221]	[0,0336]	[0,0277]	[0,0173]	[0,0395]	[0,05045]	[0,0374]	[0,0699]

Note: ***Statistically significant at the 0.01 level; ** Statistically significant at the 0.05 level; *Statistically significant at the 0.1 level. Standard errors appear in brackets [ ].

Direct effects for ALL sample show that if the young are older than 25 years, then the probability of participating in the labor market increases by 16% compare with younger than 18 years. For women, if the youth is older than 25 years old, then the probability of participating in the labor market increases by 23%, whereas that for men increases by 9.7%. For all youth who are between 18 and 24 years of age, the probability increases but the increase is two-point percent lower. Meanwhile, women reduce in 10 p.p., and men increase in 2 p.p.

Afro descent was only significant for male young. In other studies and theory models, differences between races arise in both groups.

Education variables (High School and University) increase labor participation. The results are interesting: High School reduces the probability to enter the labor market and University education increases the probability. For all youth, high school reduces the probability to participate by 32%, and the university increases the probability of participating by 4%. For men, high school reduces the probability to 50% and 8% in the women's case. Colombian Policies such as Youth in Action (2015) supports young people in poverty and vulnerability, with money transfer so that they can continue their technical, technological, and professional studies (University), reduce the labor participation after high school, and explain the negative effects of the high school in the labor participation.

Low income increases the probability of participation in all estimations (all, male, and female youths) and is statistically significant. For ALL samples in 8%, for Women 9%, and 7% for Men. Women in less poor condition increase a 2 p.p. additional compare with Men.

Informal jobs are a significant problem in Colombia because the Colombian labor market is segmented (Mora & Muro, 2015, 2017). Ham et al. (2020) showed that the youths who have just entered the labor market are more likely to be employed than unemployed but in unsalaried and informal jobs. In this way, neighborhoods informal reinforce informal working jobs. That is, the more people involved in the informal jobs spatially near an individual, the more likely it that an individual will participate in the informal labor market. Results show more effects in the men case compared to women. Informal men have a 6.38 (1.15/0.18) more probability than informal women to participate in the labor market.

Unemployment in the household increases labor participation and the effect is between 36% in all youth. The pressure for male youth is more than women when unemployment affects the household. Male youths have 2.52 (0.4894/0.1937) more probabilities to participate in the labor market compared to women, when the household has more unemployed members. Unemployment in the household increases the labor participation, and the effect is between 36% in all youth.

Pressure for men youth is more than women when unemployment affects the household. Male youths have 2.52 (0.4894/0.1937) more probabilities to participate in the labor market than female youths when the number of unemployed people in the household is greater than the employed ones.

Commute time is only significant for Women. When public transportation is less than 10 minutes to the house the probability to participate in the labor market for women is 5.4%. Finally, the sex variable shows men have a 32% more probability to participate than Women in the labor market.

Indirect effects or “cumulative spatial spillovers” (Lacombe & LeSage, 2018) show that the effects of the spatial spillover impact more than the direct effects the participation in the labor market. Male estimation shows different behavior: indirect effects are smaller in magnitude than the direct effects and present “second-order effects” (Lacombe & LeSage, 2018, pp. 13). That is, results show that the spatial spillovers are different for females and males and spatial spillovers for females have more impacts on labor participation than males.

Concerning the co-variables, table 5 shows a positive spatial spillover of the age variables in young people. Young in neighborhoods older than 25 years compared with those younger than 18 years old and those between 18 and 24 years stimulate the labor participation of the other youths in the neighborhoods. The high school has a negative spatial spillover; that is, more individuals nearby other high school individuals reduce labor participation in all estimations.

For the university, women and men are considered separately to have positive spillover effects, that is, more individuals with university degrees increase participation in the labor market.

Low Income shows that more individuals in the neighborhood in poor conditions increase labor participation and the effects are more pronounced in male youths than female ones (7% vs. 11%).

Informality and Unemployment show a positive spatial spillover. In this way, informality jobs and unemployment in the neighborhood increase the probability to participate in the labor market. Spatial spillover effects of commute time are statistically significant in female estimation and show if the individual women live near public transportation then the labor participation increase.

5. Conclusions

This article analyzes spatial dependence at the individual level for labor force participation among young people in a developing country. Results show a spatial pattern exists in youth labor force participation. That is, young people are more likely to participate in the labor market if other young people in the neighborhood also participate in the labor market. In particular, the regional labor market in Buenaventura (Colombia) shows social effects in the youth spatial labor market.

In the last few years, the Colombian government enacted policies, such as Youth in Action (2015), First Job Act (2010), 40000 First Job (2015), and First Youth Act (2016), to increase the participation of young people in the labor market. The Youth in Action policy may explain the negative effect of high school education on labor participation. However, spillover effects vary between men and women (In men, the spillover effect reduces the probability to participate in the labor market three times more than women).

Meanwhile, spillover effects of the university on the female participants are higher in magnitude compared with that in male labor participation. More women who are university degree holders in neighborhoods cumulatively increase the participation of women with the same university educational attainment.

In terms of public transportation, for Women, commute time is important. Nearby locations for public transportation increase the probability to participate in the labor market. Hence, commute time may highlight the effects of neighborhoods on labor women participation and the distance to public transport is useful to reduce the probability of insecurity on the streets and increase female labor participation.

Youth public policies in Colombia have forgotten the role of the regional informal jobs in youth labor participation. Informal jobs in the household increase the probability to participate in the labor market; however, it may reproduce poor labor conditions if the youth do not exit the circle of informality. Mora and Muro (2017) found that in Colombia, workers who were employed in informal positions during the preceding period and who continued to be employed in the informal sector ranged from 20% to 30%.

Finally, in future research, the marginal effects (direct and indirect) of the interaction in variables must be discussed. Due to spatial nonlinearities, marginal effects of a change in both interacted variables are not equal to the marginal effect of changing just the interaction term because one must compute the spatial cross derivative of the expected value of the dependent variable.

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