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Urban structure, labor market, informal employment and gender in Mexico City

Tesis para optar por el grado

Doctor en Economía

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Contents

List of Figures

List of Tables

Chapter I

Introduction

I.1 Motivation

There is a significant portion of the literature that identify the way the urban structure can affect labor market outcomes by means of two factors. The former is the spatial disconnection between workers and job opportunities, and the latter is residential segregation.

At present, it is common for people to live far away from the place they work. Additionally, it is well known that individuals with similar socioeconomic characteristics, such as income, tend to reside in the same neighborhood. Hence, residential segregation and the spatial disconnection between jobs' location and individuals' residence may have an influence on the labor market outcomes of individuals, and producing an impact on as the rate of employment, informal employment, and the level of wages. Moreover, if so, the geographic patterns of those labor market outcomes become less random and, then, involving the presence of spillover effects. The existence of spillovers means that spatial disconnection and residential segregation have a key role in determining the previous outcomes. In other words, the spatial concentration of either socio-economic disadvantages or advantages entails spillover effects both for individuals and for the neighborhoods in which they live.

Under this perspective, Mexico City is an interesting case study, as we discuss extensively in this dissertation. Empirical evidence witnesses that this city suffers from spatial disconnection and residential segregation that affects the labor market outcomes of its residents. This is the core idea in which the discussion of this thesis will be built around.

This dissertation targets two main objectives. The former is to analyze the relationship between urban structure, such as spatial disconnection and residential segregation, and labor market outcomes in Mexico City in 2010. We deal with this topic in Chapters II and III. The latter is to study the observed spatial patterns of selected labor marker outcomes from 1990 to 2010 (Chapter IV).

Addressing these research questions is relevant because the residential choices of individuals affect an individual's labor market outcomes through access to jobs, residential segregation, or neighborhood effects. Space turns to be an important economic factor. It can heighten either positive or negative effects of the spatial concentration of advantageous or disadvantageous opportunities, respectively. For instance, the spatial concentration of disadvantageous labor conditions may generate greater inequality and worse labor market outcomes than in other areas without such concentration.

I.1.1 Metropolitan Area of Mexico City

According to the National Institute of Statistics and Geography, the Metropolitan Area of Mexico City (MAMC) is located in an endorheic basin surrounded by volcanic mountains, on a high volcanic plateau at about 2,240 m. above sea level.[1] It is comprised of 16 boroughs (*delegaciones*) in the Federal District, 59 municipalities in the State of Mexico and one municipality in the state of Hidalgo (see Figure I.1). Chapters II and III only cover 16 boroughs of the Federal District and 40 municipalities of the State of Mexico because of available data concerning time and distance between boroughs/municipalities. Empirical analysis of both chapters assesses the 97 percent of the total 2010 population of the MAMC. The population of the metropolitan area is about 20 million people, according to the 2010 Population and Housing Census. However, the total area of the MAMC is 7,864 km^2, whereas the study area of Chapters II and III is 5,600 km^2: our selection is not creating a relevant distortion as for the degree of significance of our results. Finally, Chapter IV includes all of the MAMC, except the municipality in the state of Hidalgo.[2]

Before discussing the contents of the thesis, it is important to clarify a key definition. In this thesis, we refer to the "central city" as the historical city center and the central business district (CBD) of MAMC. This area is comprised of four boroughs in the Federal District (see Figure I.1). As it is proven in this thesis, most of the jobs and the wealthiest households are concentrated in this part of the city.

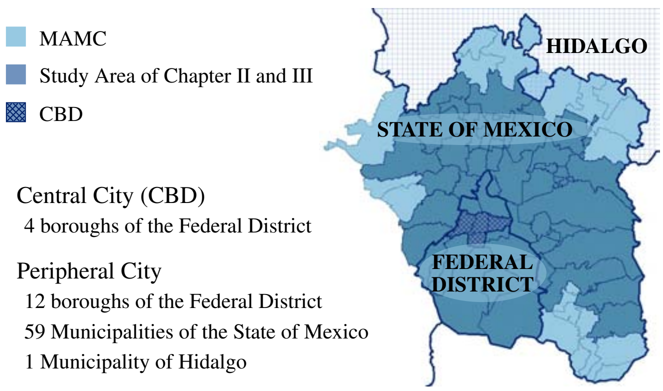

Figure I.1: Metropolitan Area of Mexico City

I.1.2 Main characteristics of study area

The rapid urbanization of Latin American cities has resulted in severe suburbanization, and Mexico City is no exception. Sobrino (2006) and Suárez-Lastra and Delgado-Campos (2007) highlight a process of suburbanization

[1]Endorheic basins have no drainage systems to major oceans or rives. Rather, the system is sustained and seasonally regulated via connections with swamps or lakes.

[2]The limitations of time and distance data do not affect the analysis in this Chapter.

and decentralization of economic activities in the MAMC. For the last 30 years, the central city has been losing both population and jobs. In 1980, 18 percent of the population of the metropolitan area lived in the central city, and in 2010 this share was 8.6 percent (see Table I.1). In 1980, manufacturing, commercial, and service employment in the central city comprised 40 percent of the total employment in the area we are taking into consideration. In 2008 this percentage dropped to 29 percent.

Table I.1: Urbanization and decentralization process in the MAMC

	Percentage of population				Percentage of jobs			
	1980	1990	2000	2010	1980	1989	1998	2008
Central city	17.96	12.40	9.20	8.56	39.70	36.20	32.80	29.36
Peripheral city	82.04	87.60	90.80	91.44	60.30	63.80	67.20	70.64

Sources: The Population and Housing Census 1980, 1990, 2000 and 2010 and the Economic Census 1980, 1989, 1999 and 2009.

There are two main types of spatial or residential segregation: racial or ethnic segregation and socioeconomic segregation. Most studies of residential segregation in North American and European cities have focused on racial or ethnic segregation. However, in most Latin American cities racial (or ethnic) segregation does not appear to be predominant (Rodríguez 2001 and 2008; Sabatini, 2006; Groisman and Suárez, 2006). In Latin America, particularly in Mexico, there are clear patterns of residential segregation in socioeconomic terms. Graizbord et al. (2003), Rodríguez (2008), Vilalta-Predomo (2008), Pérez and Santos (2011), and Monkkonen (2012), among others, point out the importance of patterns of socioeconomic residential segregation in the MAMC.

Residential segregation has a key role in increasing the separation between residences and places of employment, and also worsen the social networking of (unemployed) individuals living in poor areas, that *de-facto* decreases their employment opportunities as well as quality of their jobs. In this respect, the suburbanization of the population and the decentralization of employment could produce a spatial mismatch by increasing the physical distance between workplaces and workers' residence.

The MAMC is a good example of an area with a large percentage of suburbanized population but a lower degree of employment decentralization. This has generated spatial disconnection in the metropolitan area and an increase in commuting time. The average commuting time was 58 minutes in 1994, and rose to 67 minutes in 2007 (Casado, 2014). Furthermore, the spatial disconnection has worsened due to the effect of both the residential segregation and the poor access to public transport in the MAMC. The inferior access to public transport and transportation infrastructure decreased the mean traveling speed. In 1990, traveling speed was 38.5kpm; this speed reduced to 21kpm in 2004. In 2007 the estimated speed was 17kpm according to the Government of the Federal District.

Additionally, another key feature of the urban landscape in Latin America is the high levels of labor informality. Less than 50 percent of workers are covered by social-protection schemes (ILO). In Mexico, informal employment accounts for 28.8 percent of the employed population, according to the 2010 National Survey of

Occupation and Employment (*Encuesta Nacional de Ocupación y Empleo*, ENOE).[3] In MAMC, informal employment covered 28.4% of employed population in 1990, but it increased to 34.8% in 2010. In general, informal employees are more concentrated in the peripheral part of the city (see Table I.2).[4]

Table I.2: Percentage of informal workers in the MAMC

	Total			Central city			Peripheral city		
	1990	2000	2010	1990	2000	2010	1990	2000	2010
Informal workers	28.45	31.97	34.82	25.15	27.02	22.84	29.16	32.59	35.95

Source: 1990 and 2000 National Survey of Urban Employment (*Encuesta Nacional de Empleo Urbano*, ENEU), and 2010 National Survey of Occupation and Employment (*Encuesta Nacional de Ocupación y Empleo*, ENOE)

In the current literature, the effects of spatial disconnection and residential segregation in labor market outcomes have been studied theoretically and empirically. There are a large number of articles focusing on the empirical evidence about the effects of urban structure on labor market outcomes for North American and European cities; however, there is very little evidence of this relationship in Latin American cities. One of the goals of this thesis is to fill up this gap, partially. To the best of our knowledge the relationship between urban structure and the effects of informal employment has not been empirically studied, considering both access to jobs and residential segregation. And Mexico City is a particularly interesting case to study as it presents patterns of spatial disconnection and residential segregation with informal employment representing around one third of salaried employment.

On the technical side, this dissertation is also proposing a novel empirical control for the common endogeneity problem in estimating residential sorting. Here, we follow two strategies to address this problem. In Chapter II, we select a sample of individuals who cannot choose their residential location, such as members of households that are neither the head of the household nor the spouse. The individuals in this sample are not expected to take part in the location decision of the household. Instead, in Chapter III, we use instrumental variable estimation to control for residential sorting, again. The selected instrumental variables include urban and topographical characteristics, socioeconomic composition, and type of housing variables lagged ten years. As far as we know, there are no papers that use topographical characteristics as instrumental variables of job accessibility and residential segregation variables in an intraurban context. This is a typical feature distinguishing Mexico City because it covers an extensive area and has a large variety of climates, soils and rocks.

As for the identification of spillovers effects, this dissertation brings interesting novelties. There are few studies that prove the existence of spillover effects on labor market outcomes in an intraurban context. As mentioned above, Mexico City covers an extensive area; it is therefore possible to have a large number of spatial units with high socioeconomic homogenenity. This allows us to have enough variability to estimate several

[3] According to the ILO, informal employment accounts for 54% of total employment in Mexico, and the informal sector represents 34% of total employment. Informal employment includes informal employees, the self-employed and employers who are either inside or outside the informal sector.

[4] The possible causes of this fact are investigated in this thesis. For instance, the concentration of informal workers in the periphery could be a result of labor market conditions, such as high cost of commuting that increases the job search cost. This constraints the job search area to close neighborhoods where the informal jobs also predominate.

spatial econometric models and identify the existence of global or local spillovers effects.

I.2 Structure of the thesis

The dissertation is organized into three chapters beyond this introduction and final conclusions. Chapter II and III cover the relationship between urban structure and labor market outcomes on an individual level with data from 2010, whereas Chapter IV focuses on the way spillover effects influence the labor market outcomes within urban structure at aggregate level from 1990 to 2010.

In Chapter II we deal with the relationship between access to jobs and employment. We contribute to the literature by studying the effects of access to informal jobs on employment. In order to prove this relationship, we estimate a probability model of being employed, including different types of job accessibility indices by level of education (namely, basic and post-basic education) and labor status (namely, formal and informal). We also estimate the decay parameter of the accessibility index (instead of assuming this parameter equal to -1 as in most of the literature). This decay parameter takes different values depending on the mode of transport and labor status. This condition indicates that job accessibility by labor status could affect the probability of being employed differently. Our results assess that the most affected by closest job opportunities were women, less educated workers and informal workers.

In Chapter III, we investigate the relationship between residential segregation and two probabilities: the probability of being employed and the probability of being a formal worker. In this chapter, our contribution is to identify to which extent the effects of the urban structure impact on job opportunities according to the workers' gender. We found that residential segregation has negative effects on labor-force participation for married women and that living in a deprived neighborhood decreases the probability of being a formal worker for men.

In Chapter IV, we study the spatial patterns of three labor markets outcomes, namely non-employment rates, informal employment rates, and wages. We use different spatial econometric models to explain the spatial patterns of those variables, identifying endogenous and contextual effects (or global and local spillover effects, respectively). The major contribution of our analysis is studying the different kinds of labor market outcomes by gender, instead of limiting the scope to unemployment only.

In the appendices of this dissertation, we include the program in R we exploited to estimate several spatial panel data model with unknown heteroskedasticity such as SEM, SAR, SARAR/SAC, SLX, SDEM, SDM and GNM (see Appendix B). The common software systems used to estimate these kinds of models do not cover spatial panel data models with unknown heteroskedasticity. In addition, the originality of this R scrip allows working with sparse matrices in order to handle the size of the database and reduces the time spent on calculations, such as the inversion of a big spatial weight matrix (our database requires the calculation of the inverse of spatial weight matrix of 13716×13716).

I.3 Definitions

To conclude this introduction, we provide some clarifying definition of our key variables that have been exploited in the next chapters.

I.3.1 Job accessibility

One of the key variables of this research is job accessibility. It is defined as the opportunity to get a workplace. This concept involves to take into account the spatial distribution of jobs and the cost of having access to jobs (measured by distance or time). Therefore, the accessibility index is identified by two components: the transport or resistance factor (time or distance) and the motivation or activity factor.

Throughout this thesis we employ several versions of job accessibility indices. In Chapter II, we devote a complete subsection to explain this variable and how to calculate it. The first part of this chapter estimates the decay parameter of the job accessibility index. This parameter unveils that it is costly to commute in Mexico City; therefore, access to jobs is costly. We also estimate different models using various accessibility indices, and we obtain better results with a power function of the accessibility index. Therefore, in Chapters III and IV we only consider this index. Both chapters include this variable in the analysis because having access to jobs has important effects on employment, informal employment and wages. Moreover, the distinction between formal and informal jobs is relevant because each type of job affects the labor market outcomes differently, not only in sign but also in magnitude.

I.3.2 Residential segregation

Another key variable in this research is residential segregation, which refers to a spatial agglomeration of population groups defined in terms of socioeconomic status and ethnicity. This agglomeration generates unequal distribution of these groups in a selected area.

There are different measures of residential segregation in the literature. When residential segregation occurs along racial lines as in North American cities, the most widely used method is the one proposed by Massey and Denton (1988). The authors identify five dimensions of segregation: evenness, concentration, centralization, exposure, and clustering. These dimensions are usually included in different indices.

The most common indices are the dissimilarity index, which measures the uneven distribution of a population group and the isolation index, which measures a group's exposure. Other measures of residential segregation include those built on either one-dimensional or multidimensional poverty measures, or a combination of both methodologies, known as the Integrated Method. These measures target to capture residential segregation in socioeconomic terms. One-dimensional measures of poverty are calculated via household income. This method classifies a household as poor if the cost of a basket of goods and services at market price exceeds its income, that is, if its income is below a consumption poverty line.[5] Multidimensional measures of poverty are calculated with the unmet basic needs method (UBNM). This method measures those basic needs. The degree to which these needs are unmet, is considered an indicator of deprivation or poor living conditions (such as insufficient quantity and quality of dwelling services, lack of durable goods, and insufficient education).

Another type of analysis exploited to identify residential segregation in the literature is the exploratory spatial data analysis (ESDA). ESDA focuses on the analysis of data with a spatial or geographic component and includes many techniques and tools (Symanzik, 2013). It is common to use ESDA in the exploration of spatial autocorrelation. In general terms, positive autocorrelation occurs when observations within a specific geographic area are on average more similar than those with a random assignment. Negative spatial autocorrelation occurs when nearby observations are on average more distinct than what a random assignment would yield. Throughout the thesis, we employ many choropleth maps to highlight some features of Mexico City that provide evidence of the possible relationship between urban structure and labor market outcomes. These maps provide some hypotheses to contrast or show us the correct variable to use. For instance, most of the empirical studies use the unemployment rate and/or the percentage of whites, black or other ethnicities as an indicator of residential segregation. However, the ESDA technique allows concluding that the unemployment rate is not a good indicator of residential segregation in the case of Mexico City. For this reason, we replaced it with the percentage of individuals with incomplete basic education in Chapter II, a social deprivation index in Chapter III and IV (both as indicators of residential segregation).

I.3.3 Informal employment

The different views of informality could be categorized into three main schools of thought: the dualist school, the structuralist school, and the legalist school (Bacchetta et al., 2009).[6] The first school consider as informal workers those who queue to access to the formal sector. These workers are informally salaried. This definition corresponds to the traditional view of informality, namely the dualist's view. Under this perspective, informality acts as a buffer for the formal sector, shrinking in the upturn and expanding in the downturn.

In the structuralist view, informal individuals supply cheap labor and input to large, capitalist firms. Under this perspective, modern enterprises react to the globalization by introducing more flexible productive systems and by outsourcing as a strategy to cut their costs. Setting up such a global production network results in a steady demand for flexibility that only the informal economy is assumed to be capable of supplying.

Finally, a third type explanation of informality focuses on workers or firms who enter the informal sector voluntarily. This approach mostly refers to the self-employed individuals and/or small firms. From a legal standpoint, these individuals prefer to operate informally to avoid the costs associated with registration, such as taxation and regulation (Maloney, 2004).

[5] The consumption poverty line is the cost of a basket of goods and services at market prices.

[6] The terminology, however, is not standardized. Different authors give different names to the main approaches or group into different categories.

Additionally, there are two approaches defining informality or informal sector/employment: the enterprise-based approach and the job-based approach. The former defines the informal sector as being comprised of economic units that are not registered (i.e, they do not pay taxes), operate on a small scale, and rarely have an accounting system to separate the cost of the economic activity from household expenses. There are two types of informal economic units: those headed by self-employees and those headed by employers with or without family workers. Instead, the job-based approach confers informal status to the lack of payment and/or social security benefits for the worker. This approach classifies employees as formal or informal, whereas the first approach sorts independent workers (such as self-employees and employers).[7]

According to the first definition, any job in the informal sector cannot be formal. An individual who works in the informal sector does not sign a legal contract and, therefore, is not registered with social security. On the other hand, the second definition allows for the existence of informal jobs within the formal sector.

In this dissertation, we adopt the job-based approach and we identify a formal employee as any worker with a positive income and hired by an employer that guarantees to him/her with the social protection scheme (as social security). Instead, an informal worker is an individual not benefitting from social security and employment benefits.

I.3.4 Non-employment

In this dissertation, we adopt an ad-hoc definition of unemployment, namely non-employment. We understand non-employment as the situation of those individuals who do not work, nevertheless they have the possibility to do it. In this sense, this definition excludes students, retirees, and disabled persons.[8]

We use this alternative definition of unemployment because some peculiarities of the Mexican labor market. For instance, the official figure of unemployment rate is very low (less than 10 percent). This is due to the fact that the Mexican labor market is adjusted more via prices or wages and less via quantities or changes in the total employment (Negrete-Prieto, 2011). In addition, among the individuals that lose their jobs, some of them turn to the informal sector as informal workers in order to have an income, while others are underemployed because the unemployment benefits are not extended to the whole population in Mexico.

Therefore, we ground our choice of an ad-hoc definition on the evidence for the case of Mexico City. In this context, the unemployment rate is not representative of the true labor market conditions. Some inactive persons would work if they had the opportunity to do so, as housewives, for instance

[7] These definitions are taken from *La informalidad laboral. Encuesta Nacional de Ocupación y Empleo. Marco Conceptual-Metodológico* developed by the National Institute of National Institute of Statistics, Geography, and Informatics of Mexico.

[8] In other words, the definition of non-employment includes unemployed and inactive persons and excludes students, the disabled and retirees.

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Chapter II

Job accessibility, informal employment and gender

Abstract

In this chapter we estimate the effect of job accessibility on the probability of being employed in the labor force as a whole and by level of education in the Metropolitan Area of Mexico City. In this city the spatial distribution of jobs and individuals is very uneven and informal employment accounts for 29 percent of total employment. We have found that job accessibility increases the participation of women and that this empirical relationship is robust. We analyze how formal and informal job accessibility affects the probability of being employed. Informal job accessibility is relevant to informal workers, whereas formal job accessibility is relevant to formally employed female workers but not to formally employed male workers. Informal job accessibility has a higher effect on female workers than formal job accessibility. These results show that job location is a critical factor for gaining employment both for informal workers and women.

Key words: Job accesibility, informal employment, gender.
JEL-Code:

II.1 Introduction

There are two factors explaining how the urban structure could affect labor-market outcomes. The first is the spatial disconnection between workers and job opportunities. If job accessibility is low, spatial disconnection is high. The second is residential segregation, which could generate negative externalities in neighborhoods that reduce job opportunities for their residents.

Suburbanization of population, decentralization of employment and residential segregation could produce spatial disconnection or spatial mismatch by increasing the (physical and/or social) distance between jobs and workers. Spatial disconnection increases job search costs, commuting costs and/or worsens social networks. It affects the employment opportunities of individuals, especially less educated or poor individuals. Access to jobs depends on both spatial distribution of job opportunities and spatial flexibility (the capacity to move around and/or commute inside the city). These features cause some population groups to be more sensitive to local labor market conditions than others. For instance, high-skilled workers are less sensitive to local labor market conditions, than low-skilled workers.

The rapid urbanization of Latin American cities has resulted in severe suburbanization. Several studies point out that some of these cities are highly residentially segregated (Graizbord et al. 2003, Vignoli 2008, Vilalta-Pedromo 2008). These factors may increase the distance between jobs and workers. The Metropolitan Area of Mexico City (MAMC) is a good example of an area with a large percentage of suburbanized population but a lower degree of employment decentralization. This has generated spatial disconnection in the metropolitan area (Suárez-Lastra y Delgado-Campos, 2007). Furthermore, the spatial disconnection has worsened due to the effect of both the residential segregation (Graizbord et al., 2003; Rodríguez, 2008; Vilalta-Pedromo, 2008) and the poor supply of public transport in the MAMC.

In addition, there are high levels of labor informality in Latin America; less than 50 percent of workers are covered by social-protection schemes (ILO). In Mexico, informal employment accounts for 28.8 percent of the employed population, according to National Survey of Occupation and Employment (*Encuesta Nacional de Ocupación y Empleo*, ENOE 2010). The spatial distribution of formal and informal employment inside the city may also have effects on individuals' access to job opportunities.

Indeed, informal workers may be more sensitive to local labor market conditions than formal workers. This could be explained by the following facts. Most informal workers have a low level of education. In Mexico City, approximately 73 percent of informal workers have only a basic education (the 2010 Population and Housing Census). These workers generally find their jobs through informal job search methods. Around 60 percent of informal workers find their jobs through friends, relatives and/or acquaintances (ENOE 2010). The distribution of formal and informal jobs is spatially uneven. Formal jobs are more concentrated in the center of the city while informal jobs are spread out. According to the 2010 Population and Housing Census and the 2009 Economic Census, seven central municipalities have 57 percent of total formal employment and 41 percent of total informal employment. Informal workers have shorter commuting distances than formal workers. Informal workers commute on average 7km, while formal workers commute 11km (Origin-Destination Survey, *Encuesta Origen y Destino* – EOD-2007 –).

The effects of spatial disconnection on employment outcomes have been analyzed in a number of American cities and in several European cities. But to date, there are very few studies that analyze the relationship between accessibility and employment in Latin American cities, in spite of their rapid suburbanization and high level of segregation. In the case of Bogotá, Olarte-Bacares (2012) finds that improvements in public transport increase employment. As regards Mexico City, Suárez-Lastra and Delgado-Campos (2007) find a relationship between productivity and job accessibility.

Most of these studies consider only accessibility in terms of education or skill level (Immergluck, 1998; Detang-Dessendre and Gaigne, 2009; Matas et al., 2010). There are very few studies that analyze job accessibility by labor status, namely formal or informal. This is due to two reasons. Firstly, informal employment is not relevant in developed countries, whereas it is substantial in developing countries such as Mexico. The second is a shortage of databases that enable the identification of both informal employment and where it is located. Several Latin American databases facilitate the identification of informality status. Nevertheless, most of these databases do not have information about the location of informal jobs.

As spatial disconnection between job opportunities and workers exists in Mexico City, it is possible that accessibility is affecting employment. Furthermore, the distinction in terms of accessibility between formal and informal employment could be particularly significant in the case of Latin American cities like Mexico City. The aim of this paper is to analyze the relationship between accessibility and employment by labor status in the MAMC. Firstly, we estimate the effect of job accessibility on the probability of being employed. Secondly, we calculate two job accessibility indices by level of education and two job accessibility indices by labor status. Finally, we analyze the effects of job accessibility by level of education and by labor status on the probability of being employed.

We use mainly three databases: the Origin-Destination Survey 2007 (EOD-2007), the 2010 Population and Housing Micro-census and the 2009 Economic Census. The availability of the EOD-2007 for Mexico City allows us to estimate a decay parameter in the accessibility index (most of the papers assume this parameter equals -1). These decay parameters are different depending on mode of transport and labor status. This indicates that job accessibility by labor status could affect differently the probability of being employed. We have estimated a probit model using the Population and 2010 Housing Micro-census for the Federal District and the State of Mexico. This database provides a large number of socioeconomic variables and we can associate spatially aggregated variables to this database. We have used the 2009 Economic Census and the 2010 Population and Housing Census to calculate the accessibility indices and other spatially aggregated variables.

We have found that job accessibility increases the participation of women in the labor force. In addition, informal job accessibility increases the probability of being employed. In the case of men, formal job accessibility is not significant. In the case of women the effect of formal job accessibility is lower than informal job accessibility. Therefore, informal workers consider the job opportunities that are nearer to them to be more relevant. These results show that the location of job opportunities is an important factor in informal workers and women gaining employment.

Finally, the empirical literature points out that there are endogeneity problems with the accessibility variables (Ihlanfeldt and Sjoquist, 1990). We have tried to solve these problems through a subsample of individuals who do not choose their residential location such as members of households that are neither the head of the household nor the spouse. We have obtained robust results in the case of women, while the results for men are not significant.

The rest of the chapter is organized as follows. In Section II.2, we present a brief literature review of the spatial mismatch hypothesis and the mechanisms which generate it. We describe some empirical papers that try to prove the spatial mismatch hypothesis. Section II.3 presents the patterns of spatial disconnection and residential segregation of study area. Section II.4 defines the variables and the different accessibility indices that we have used to estimate the model. In Section II.5, we present the probit model and the results. In this section we show that there is a relationship between job accessibility and labor force participation in the MAMC. We also analyze job accessibility in terms of level of education and employment status. Section II.6 addresses the endogeneity problems of the accessibility index by using a subsample of individuals whose residential location is exogenous. Finally, conclusions are given in Section II.7.

II.2 Literature review

Urban structure can affect employment via job accessibility and/or residential segregation. The relationship between employment and accessibility has been studied since the theorization of the spatial mismatch hypothesis introduced by Kain (1968). This hypothesis states that there is a relationship between spatial disconnection and adverse labor market outcomes (such as high unemployment and low wages) especially as regards minorities. This spatial mismatch is due to the fact that residential location decision-making cannot adjust to geographic changes in employment opportunities. The relationship between employment and residential segregation has been studied by neighborhood effects literature (Durlauf, 2004). These studies analyze the effects of deprived neighborhoods on employment.

From a theoretical standpoint, there are several mechanisms that explain how spatial disconnection could affect employment opportunities, summarized in Ihlanfeldt (2005) and Gobillon et al. (2007). These mechanisms can be grouped into three categories, the mechanisms of supply, demand and social networks. They have been explained mainly by general equilibrium models of job search, search and matching models and efficiency wage models (Zenou, 2009). These models assume that distance (social or physical) affects various costs associated with one's job search. For example, distance can affect job search intensity, productivity or social networks.

Supply mechanisms explain that efficient job searching, job search intensity and/or willingness to accept a job decrease with distance (Brueckner and Martin, 1997; Arnott, 1998; Coulson, et al. 2001; Wasmer and Zenou, 2002, Brueckner and Zenou, 2003, Smith and Zenou, 2003). An individual has less incentive to seek or to accept a job that is far from home, because he/she has less information on these jobs as well as higher commuting and search costs. Ellwood (1986), Ihlanfeldt (1993), Holzer et al. (1994) and Zax and Kain (1996) find a positive relationship between the employment prospects of the black population and employment accessibility. Rogers (1997) and Immergluck (1998) find that the greater the job accessibility or proximity to work, the shorter duration of unemployment is. Ihlanfeldt and Sjoquist (1990) show that proximity to work increases the probability of being employed for young people.

Additionally, if there are not adequate modes of transport in the area, then search intensity and willingness to accept a job decline. For example, Kawabata (2003) finds that better access to public transport increases the probability of work and the work-hours of individuals who do not have a car. Ong and Miller (2005) and Baum

(2009) show that access to a car increases job opportunities and work-hours. In the case of England, Patacchini and Zenou (2005) find that individuals who live far from work or have worse job accessibility search less for a job, whereas those individuals who have access to a car increase their search intensity. In the case of Barcelona and Madrid, Matas et al. (2010) show that the probability of being employed for women increases with job accessibility and access to public transport.

Demand mechanisms explain that employers refuse to hire workers who live far away and in deprived areas (Zenou and Boccard, 2000; Zenou, 2002; Gobillon et al., 2007; Ross and Zenou, 2008). These workers may be less productive when they have to commute long distances to their jobs because they are absent more often, arrive late or are more tired. Van Ommeren and Gutierrez-i-Puigarnau (2011) find that absenteeism is higher for workers who commute long distances. Moreover, if they live in marginalized areas, they may have bad work habits. Certain ethnic groups could be discriminated against by customers (i.e. they do not want to be served by these individuals), so that employers are more reluctant to hire them. However, it seems that in many cases, companies do not consider the residence of individuals when they decide to hire them or not (Rogers, 1997). Moreover, even when knowing the location of residence, firms can have difficulty in determining the true job commute (Ross and Zenou, 2008).

The third mechanism is social networks. This mechanism is closely associated with residential segregation. Social segregation may deteriorate the quality of social networks (Gobillon et al., 2010). The spatial concentration of unemployed people can generate a negative externality which decreases the likelihood of being employed. It can be worse for low-skilled workers, youth and ethnic minorities, who rely more on informal job search methods (Holzer, 1987, 1988, O'Regan and Quigley, 1993; Ihlanfeldt, 2005). For example, Wahba and Zenou (2005) point out that the probability of finding a job through informal search methods such as friends and relatives decreases with the local unemployment rate. Bayer et al. (2008) show that when the quality of social networks is good (defined as similarity among neighborhoods or individual characteristics), they have positive impacts on hours or days worked, income, labor force participation and employment.

Nevertheless, residential segregation not only affects employment opportunities, but also deteriorates social networks. Residential segregation can generate other negative externalities (such as decreasing human capital, school dropouts, teen pregnancy and crime) if the area is deteriorated and socially marginalized. It causes individuals residing in such neighborhoods to receive fewer job offers and to be discriminated against by employers (Ihlanfeldt, 2005; Gobillon et al., 2010; Korsu and Wenglenski, 2010). However, Dujardin and Goffette-Nagot (2010) find that living in a poor or deteriorated neighborhood does not affect the probability of unemployment when they address endogeneity and it does affect it when they do not take endogeneity into account.

The relationship between accessibility, segregation and employment has been studied empirically in the case of several cities in the United States and some cities in Europe. The first studies about the relationship between job accessibility and employment had the aim of proving the spatial mismatch hypothesis for the black and young population in the United States. Some of these original studies found evidence of the existence of this relationship. Nevertheless, others found no conclusive or significant results (Jencks and Mayer, 1990; Holzer, 1991; Ihlanfeldt and Sjoquist, 1998). This was primarily due to methodological problems, such as inadequate job accessibility measures, endogeneity problems, small samples and aggregate data.

Later studies extended the analysis to European cities and other ethnic minorities. Some of these studies focused on women, because they have stronger spatial barriers than men. Largely responsible for domestic work or childcare, women find that the competing demands of home and paid work often restrict their job searches to the local neighborhood.

These studies introduced better job accessibility measures (Rogers, 1997; Shen, 1998, Immergluck 1998; Johnson, 2006) and measures of availability or access to public or private transport (Kawabata, 2003; Ong and Miller, 2005; Baum, 2009). They addressed the endogeneity problem of residential location (Weinberg, 2000 and 2004; Gurmu et al., 2008; Aslund et al., 2010).

Most of these studies concluded that there was a relationship between job accessibility and employment and this relationship was more important to ethnic minorities and less educated or low wage workers. Nevertheless, some studies showed that the effect of job accessibility on employment disappeared when they addressed the endogeneity problem or improved job accessibility measures. Sanchez et al. (2004), Gurmu et al. (2008) and Bania et al. (2010) did not find a relationship between job accessibility and employment among poor households who received *Temporary Assistance to Needy Families* (TANF) in the United States. They used many job accessibility measures and addressed endogeneity problems (they used a subsample of individuals who received public housing). In the case of Brussels, Dujardin et al. (2008) showed that job accessibility did not have an effect on unemployment probability. They used a subsample of individuals whose residential location may be exogenous (such as youths who lived with their parents).

These studies have analyzed the relationship between accessibility and employment using linear regression models where the dependent variable is the unemployment rate, employment, hours worked or wages (Kain, 1968; Ellwood , 1986). It has also been estimated using discrete choice models of labor force participation or unemployment (Ihlanfeldt and Sjoquist, 1990; Matas et al., 2010). Other studies analyze these results using unemployment duration models (Holzer et al., 1994; Rogers, 1997; Dawkins et al., 2005; Johnson, 2006; Gobillon et al., 2010). Finally, there are studies that explore these connections through structural equation models that include equations on employment, wages, commuting time and choice of residence to solve endogeneity problems (Ihlanfeldt, 2005).

These estimations include one or more variables that measure job opportunities in a neighborhood, such as the job accessibility index, commuting time or distance. Other proxies to measure accessibility are the ratio of jobs to workers in the area, the percentage of households owning a car, employment densities in a certain radius in minutes or distance on public and private transport, among others. In this paper we have used a probability model to analyze whether such relationships exist in the Metropolitan Area of Mexico City, using different job accessibility indices as proxies for access to employment opportunities.

II.3 The study area

These study covers 56 of 76 municipalities that are shown in Figure I.1. These municipalities have 5,758 *estratos* and 156 *distritos*.[1] Within the 56 municipalities there are about 8 million employed and 420,000 unemployed. In the metropolitan area (including the city center) there are approximately 5 million jobs.[2] In this central city there are 2 million jobs.

Approximately 3 million workers live in six of these 56 municipalities (see Figure II.1). Furthermore, jobs are concentrated in the center and west of the metropolitan area (see Figure II.2). The eastern and northern zones, areas away from the center, are those with higher unemployment rates as shown in Figure II.4. These facts are consistent with Suárez-Lastra and Delgado-Campos (2007). They suggest that the metropolitan area is characterized by an increasingly strong center and a disjointed periphery with sprawling jobs.

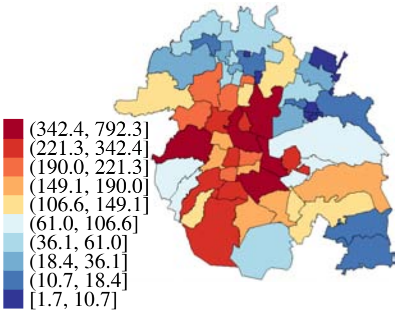


Figure II.1: Workforce per municipality (thousand)

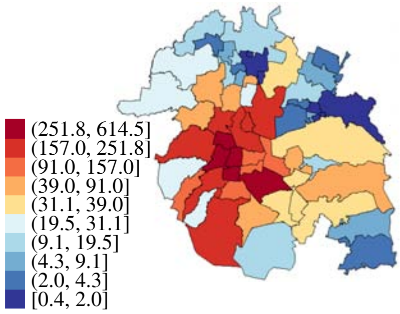


Figure II.2: Jobs per municipality (thousand)

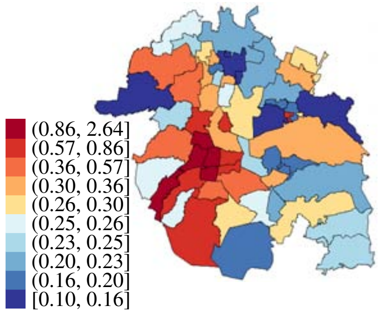


Figure II.3: Jobs ratio per municipality

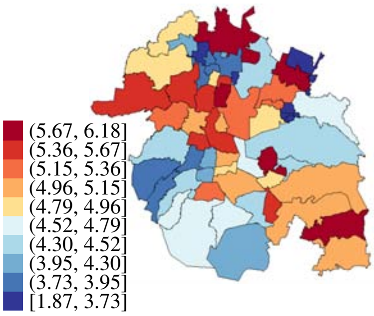


Figure II.4: Unemployment rate per municipality

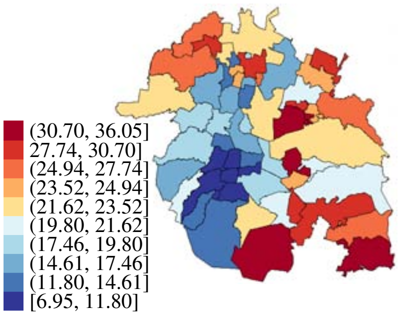


Figure II.5: Percentage of poor households per municipality

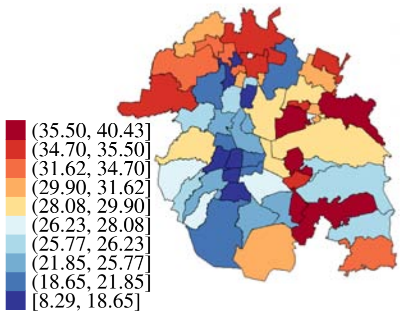


Figure II.6: Percentage of adults with incomplete basic education per municipality

Source: The Population and Housing Census 2010 and The Economic Census 2009.

As shown in Table I.1, there was a process of suburbanization and decentralization of economic activities in

[1]The '*distrito*' is a transport or traffic zone and is the territorial unit of EOD-2007. The '*estrato*' is a census tract or a set of census tracts that is set up by the National Institute of Statistics and Geography and is the smallest territorial unit of the Population and Housing Micro-Census.

[2]Data obtained from the Population and Housing Census 2010 and the Economic Census 2009. This number of jobs includes formal and informal jobs.

the MAMC. According to Suárez-Lastra and Delgado-Campos (2007), the share of employment located in the central city has declined in recent decades, despite its significant growth from 1990 to 2000. It has generated a discussion about whether the metropolitan area is monocentric or polycentric. Some studies consider it to be a central city extended through the main transport nodes (Sobrino, 2006; Suarez-Lastra and Delgado-Campos; 2009). Other studies conclude that the metropolitan area is polycentric or is in a process towards polycentrism (Graizbord and Acuña, 2005).

In addition, the distribution of modes of transport is not equitable in the territory. There is a concentration of both public and private transport in the center of the city, whereas there is a lack of important modes of transport in the periphery of the city. The public transportation system (such as Metro, Bus and Trolebus) is available in the center of the city. To date, only one rail system goes from the central city to the northwest metropolitan area. So the rest of the city only has *colectivo* buses as public transport.[3]

In the area of study the most used mode of transport is the *colectivo* with a share 46 percent, followed by the car with 21 percent and the metro with 14 percent. In terms of work trips 36 percent are made with private transport while 63 percent are made with public transport and the rest in other ways, according to the EOD-2007.

According to the Population and Housing Census 2010, in the central city approximately 52 percent of households have access to a car, and in the rest of the city this percentage is 43 percent, however in the most peripheral zone this percentage is 38 percent. In addition, 74 percent of households owning a car have one car, 20 percent have two and 6 percent have three or more, according to the EOD-2007.

Finally, some authors have identified patterns of socioeconomic residential segregation in the MAMC (Rodriguez, 2008; Vilalta-Predomo, 2008). Figures II.5 and II.6 depicts this residential segregation. There was a concentration of high levels of education in the center of the city, whereas there was a concentration of low levels of education in the periphery. This segregation is increasing the distance (social or physical) between employment centers and workers (see Figure II.4). In conclusion, suburbanization, decentralization and residential segregation result in poor workers being further away from jobs or in spatial disconnection. This disconnection worsens when workers depend more on public transport and social networks to find a work.

II.4 Data

II.4.1 The database and variables

The database that we have used is the Population and Housing Micro-Census 2010 for the Federal District and the State of Mexico.[4] The micro-census is approximately a 5 percent sample of the Population and Housing Census. This database has several advantages such as the greater number of observations and covariates that can be obtained. Another advantage is that variables can be obtained at a lower level of territorial aggregation,

[3] The *colectivo* buses are medium capacity buses

[4] The Population and Housing Micro-Census 2010 is the most recent Census of Mexico.

such as municipal, *distrito* and *estrato* level. Finally, we can use the micro-census and the Economic Census to approximate the number of jobs in the municipality, *distrito* or *estrato*. This is possible because the micro-census has information about place of work and residence of the individual, and the Economic Census has information about the employed population that work in the census tract that can be aggregate at municipal, *distrito* or *estrato* level.

The sample includes working-age men and women, between 25 and 65 years old (ages at which the majority of individuals have completed their studies and have not retired respectively). The sample includes employed individuals, unemployed individuals and housewives, and excludes students, retirees, and disabled persons.[5] The total sample is 399,877 individuals. However, we have eliminated from the sample individuals who have not specified their level of education, so the sample size is 399,484 individuals; 46.36 percent of which are males and 53.64 percent are females.

The variables that we have used in the econometric model include socioeconomic, accessibility and residential segregation (or deprivation) variables. The socioeconomic variables include age, age-squared (Age^2), dummy variables of education (incomplete elementary school, complete elementary school, secondary school, high school, some college, bachelor's degree and graduate school), if an individual is the head of his/her household, if she is married, the number of workers in the household (*Number workers*), the number of children under 12 years old in the household ($Child_{12}$) and family income.

The number of workers within the household is a proxy of the close contacts that people have to get a job (Wahba and Zenou, 2005). Most job seekers use their friends and relatives to find a job as empirical evidence shows (Holzer, 1998).

The analysis included the presence of children at home because the time spent at work competes with time spent on childcare. This variable is particularly important to women. Neoclassical theory of labor supply and household production model predicts that the presence of children is negatively related to female participation in the labor force. The presence of children raises women's reservation wage or price of non-market time. The latter depends on the age composition of the children. Younger children are particularly time intensive. Therefore, younger children are expected to have positive effects on raising the price of non-market time and lowering women's probability of being employed.[6]

As a proxy of residential deprivation or segregation, we include the percentage of individuals with incomplete basic education per *estrato* (*%IBE*).[7] In Mexico, basic education includes secondary school, i.e. nine years of education. Finally, the accessibility variable is the accessibility index (*AI*). The descriptive statistics of the

[5] In Mexico the unemployment rate is very low. One reason is that wages are flexible. Another reason is that cultural attitudes towards labor force participation are not homogeneous. Culture still matters for female employment rates and for hours worked. In Mexico, approximately 60 percent of working-age women are housewives.

[6] However, the impact of this variable on the probability of being employed could be overestimated due to endogeneity problems. The decision to have children may be a function of women's labor force participation.

[7] Other papers use the unemployment rate as a proxy of segregation or deprivation because more segregated zones are those with more unemployed workers. However, in the case of Mexico City the unemployment rate does not indicate residential segregation.

variables are presented in the Appendix, Table II.A.1.

II.4.2 Job accessibility index

In the literature there are several ways of measuring job accessibility. One way is through isochronic measures (Cervero et al., 1995, Rogers, 1997, El-Geneidy and Levinson, 2006). These measures are calculated using the number of jobs or jobs ratio within a given radius in terms of distance or time. Another way is the gravity-like measures, which are calculated as follows:

$$AI_{imk} = \sum_{j} O_{jk} f(C_{ijmk}) \tag{II.1}$$

where AI_{imk} is the job accessibility index for the residential zone i, the mode of transport m (private or public) and job type k (low-skilled or high-skilled/formal or informal); O_{jk} are opportunities in zone j for type k (these opportunities are the number of jobs or the jobs ratio in zone j by type k); and $f(C_{ijmk})$ is the impedance function, which depends on the cost of transportation from zone i to zone j. This cost can be approximated by distance (d), time (t) by mode of transport m and job type k, and generalized transport-costs. This employment accessibility is measured for a determined urban or regional area with N zones.

The impedance function can assume different functional forms. In the empirical literature, the most used functions are the power function, $f(C_{ijmk}) = C_{ijmk}^{-\delta}$, and the exponential function $f(C_{ijmk}) = \exp(-\delta C_{ijmk})$, where δ is the decay parameter. This parameter measures the relationship between observed interaction patterns (commuting trips) and distance (time) when other determinants of interaction are constant. A very negative decay parameter, δ, indicates that distance or time discourages the interaction more.

We have estimated the decay parameter of the impedance function for distance and time, δ, through a zero-inflated negative binomial regression model using the data from the Origin-Destination Survey 2007 (EOD-2007). We have followed the gravity equation that was proposed by Johnson (2006):

$$T_{ijmk} = K O_{ik}^{\alpha} E_{jk}^{\beta} A_j^{\gamma} f(C_{ijmk}) \tag{II.2}$$

where T_{ijmk} is the total workers of type k (low-skilled and high-skilled/formal and informal) who live in zone (*distrito*) i, work in zone (*distrito*) j and commute by mode of transport m (private and public); O_{ik} is the labor supply of the origin zone i; E_{ik} is the labor demand of the destination zone j; and A_j reflects competition between zone j and all alternative job zones l for commuting flows. When $(C_{ij} = d)$, $A_j = \sum_l \frac{E_l}{d_{jl}}$ and when $(C_{ijm} = t_m)$, $A_j = \sum_l \frac{E_l}{t_{mjl}}$. If the impedance function is exponential the model is:

$$T_{ijmk} = \exp[\ln(K) + \alpha \ln(O_{ik}) + \beta \ln(E_{jk}) + \gamma \ln(A_j) + \delta C_{ijmk} + \epsilon_i]. \tag{II.3}$$

If the impedance function is power the model is:

$$T_{ijmk} = \exp[\ln(K) + \alpha \ln(O_{ik}) + \beta \ln(E_{jk}) + \gamma \ln(A_j) + \delta \ln(C_{ijmk}) + \epsilon_i]. \tag{II.4}$$

We have estimated a zero-inflated negative binomial regression model because 53.61 percent of 24,336 origin destination pairs do not have commuting flows. The zero-inflated negative binomial regression model is used when there are excessive zeros and overdispersed count outcome variables. It assumes that the excess zeros are generated by a separate process from the count values, and that those excess zeros can be modeled independently. The results of these models are presented in Tables II.A.2 and II.A.3 of the Appendix. These Tables show that the parameter δ is very negative. This indicates that there are considerable intra-zone commutes because commuting costs are very high in terms of distance or time. In addition, commuting cost of public transport is higher than the commuting cost of private transport . The parameter δ of public transport time is more negative than the δ of private transport time.[8]

Due to the available data we have calculated job accessibility indices at *estrato* level in terms of Euclidean distance, centroid to centroid, and at *distrito* level in terms of average commuting time by mode of transport. We have substituted the decay parameter in each accessibility index. In addition, we have calculated job accessibility indices by level of education (basic and post-basic) and by labor status (formal and informal). We have assumed that low-skilled and high-skilled jobs are filled by workers with basic and post basic education, respectively.[9] Therefore, the calculated accessibility indices are:

$$AI_i(d) = \sum_j \frac{E_{jk} f(d_{ij})}{\sum_s EAP_{sjk} f(d_{sj})} \tag{II.5}$$

$$AI_i(t) = \alpha_i AI_i(t_{\text{private}}) + (1-\alpha_i) AI_i(t_{\text{public}}) \tag{II.6}$$

where

$$AI_i(t_{\text{private}}) = \sum_j \frac{E_{jk} f(t_{ij\text{private}})}{\sum_s \left[\alpha_s EAP_{sjk} f(t_{sj\text{private}}) + (1-\alpha_s) EAP_{sjk} f(t_{sj\text{public}})\right]}, \tag{II.7}$$

$$AI_i(t_{\text{public}}) = \sum_j \frac{E_{jk} f(t_{ij\text{public}})}{\sum_s \left[\alpha_s EAP_{sjk} f(t_{sj\text{private}}) + (1-\alpha_s) EAP_{sjk} f(t_{sj\text{public}})\right]}; \tag{II.8}$$

the impedance function, $f(\cdot)$, can have the following functional forms:

$f(d_{ij}) = d_{ij}^{-1}$	or	$f(t_{ijm}) = t_{ijm}^{-1}$	power impedance function with $\delta = -1$,
$f(d_{ij}) = d_{ij}^{\delta}$	or	$f(t_{ijm}) = t_{ijm}^{\delta}$	power impedance function with $\delta \neq -1$,
$f(d_{ij}) = \exp(\delta d_{ij})$	or	$f(t_{ijm}) = \exp(\delta t_{ijm})$	exponential impedance function;

where d_{ij} is distance in kilometers and t_{ij} is time in minutes by mode of transport (public or private) from zone i to zone j; E_{jk} is total employment or employment by type k (low-skilled or high-skilled/formal or informal) in zone j; EAP_{sjk} is total workforce or workforce by type k that could commute from zone s to zone j. Finally, α is the percentage of individuals that commute from zone i to zone j by private transport and $(1-\alpha)$ is the percentage of individuals that commute by public transport. These accessibility indices consider two factors of friction. One factor is distance or time and the other is job competition weighted by the distance or time that this workforce supply has to travel to reach their potential job.[10] In other words, these indices consider both labor

[8] Johnson (2006) estimates the decay parameter which is -0.0728 in Atlanta, -0.0626 in Boston, and -0.0459 in Los Angeles. These parameters are lower than the parameter that we have obtained in Mexico City. The decay parameter in miles is -0.1392 in Mexico City.

[9] In Mexico basic education includes secondary school, i.e. nine years of education. Post-basic education includes high school and more.

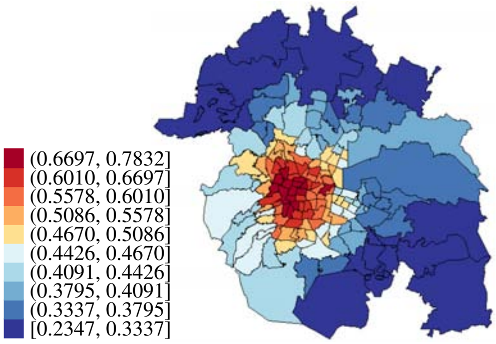
[10] In the empirical literature, there are other types of indices that consider only one friction term which is distance or time.

demand and supply, as well as modes of transport (Shen, 1998).

We have calculated accessibility indices using data from the Economic Census 2009 and the Population and Housing Census 2010. The total workforce is obtained from the Census of the Federal District and the State of Mexico. We have assumed that the distribution of the formal and informal workforce is the same as the distribution of the formal and informal employed population. In other words, the probability of a worker being formal or informal is the same as unemployed individual being formal or informal.

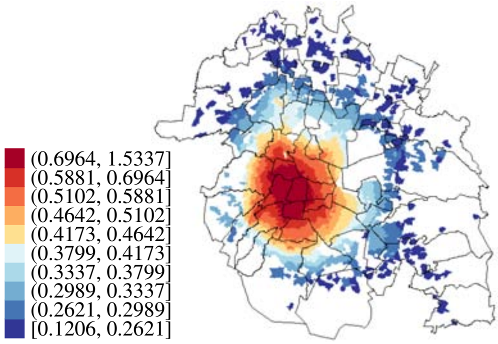
Total, low-skilled, high skilled, formal and informal employment is calculated using data of the Micro-Census of the Federal District, the State of Mexico, Hidalgo, Morelos, Queretaro, Puebla and Tlaxcala and the 2009 Economic Census. We approximate formal and informal employment in the census tract assuming that the distribution of formal and informal employment by economic sector in the census tract is the same as in the municipality. We have obtained the formal and informal municipal employment by economic sector from the Micro-Census, and total census-tract employment by economic sector from the Economic Census 2009.[11] We have calculated the low-skilled and high-skilled employment using the same approach and database, with which we have determined the formal and informal jobs. We have assumed that the distribution of low-skilled and high-skilled employment by economic sector in the municipality is the same as in the census tract.

The mean time is obtained from the Origin-Destination Survey 2007 (EOD-2007). We have calculated Euclidean distances between centroids from the Population and Housing Census 2010.[12] The descriptive statistics of accessibility indices are presented in the Appendix Table II.A.4.



$\text{AI}_{\text{power},\delta=-1}(\text{t})$

Figure II.7: Job accessibility index in time per *distrito*



$\text{AI}_{\text{power},\delta=-1}(\text{d})$

Figure II.8: Job accessibility index in distance per *estrato*

Source: Author's own calculation based on 2010 Population and Housing Census, 2009 Economic Census and the EOD-2007. Job accessibility index in time at *distrito* level are calculated using equation (II.5) with $f(t_{ij}) = t_{ij}^{-1}$. Average time in public transport is approximately 68 minutes and in private transport is 45 minutes. Job accessibility index in distance at *estrato* level are calculated using equation (II.6) with $f(d_{ij}) = d_{ij}^{-1}$

In Figures II.7 and II.8 and Table II.A.4 of the Appendix, we observe that accessibility indices by mode

[11] We use municipal commuting flows from the Federal District, the State of Mexico, Hidalgo, Morelos, Queretaro, Puebla and Tlaxcala to the Federal District and the State of Mexico in order to approximate formal and informal municipal employment by economic sector. Hidalgo, Morelos, Querétaro, Puebla and Tlaxcala are the nearest municipalities to the Federal District and the State of Mexico.

[12] The centroids were selected taking the most densely populated census tract.

of transport and labor status are different. The mean of the private transport accessibility index is higher than the mean of the public transport accessibility index. The mean of the formal accessibility index is higher than the mean of the informal accessibility index. These differences in terms of labor status may be due to formal employment being concentrated mainly in the center of the city, while informal employment is less concentrated. Seven central boroughs have 57 percent of the total formal employment and 41 percent of the total informal employment.[13] In Figures II.7 and II.8, we observe that the highest accessibility indices are concentrated in the central city.

In 2010, we see that the results obtained by Suárez-Lastra and Delgado-Campos (2007) in the early 90's have been maintained. They found that job accessibility is higher in the central city and lower in the periphery. They conclude that the MAMC has a spatial mismatch, as job accessibility has decreased in the inner periphery and in areas of the greatest population growth, although these areas are those with a greater proportional increase in employment. Moreover, this loss of employment access particularly affects low-income individuals. In Figures II.5, II.7 and II.8, we show that the lower-income municipalities match with the less accessible municipalities.

II.5 Econometric model and results

The MAMC presents patterns of residential segregation and spatial disconnection that could affect the probability of their residents being employed. Furthermore, in the case of Latin American cities, the spatial disconnection between formal and informal job opportunities and workers could be different. In order to analyze these facts, we have estimated the following probit model:

$$\Pr(Employment = 1 \mid \mathbf{X}) = \Pr(\beta\mathbf{X} + \epsilon > 0 \mid \mathbf{X}) = \Phi(\beta\mathbf{X}) \tag{II.9}$$

where $\Pr(Employment = 1 \mid \mathbf{X})$ is the conditional probability of being employed given the explanatory variables $\mathbf{X}$, β is the effects of changes in explanatory variables on the likelihood, ϵ is the error term, and Φ is the distribution function.

Firstly, we test whether the relationship between job opportunities and workers exists in Mexico City and whether the effects of accessibility are different in magnitude by gender. Afterwards, we analyze these effects by level of education. We estimate the equation (II.9) introducing two job accessibility indices by level of education. Finally, as the distinction in terms of accessibility between formal and informal employment could be important in the case of Latin American cities, we analyze the effects of job accessibility by labor status on the probability of being employed.

We only present in the main text the results obtained with the job accessibility index that is calculated using equation (II.6) with the decay parameter of power function equal to -1. The estimations with others decay parameters are in the Appendix. The models with this decay parameter have the smallest Akaike's Information Criterion (AIC) among almost all models. In some cases, due to the fact that the coefficients and marginal effects

[13] These boroughs are Azcapotzalco, Gustavo A. Madero, Iztapalapa, Alvaro Obregon, Benito Juarez, Cuauhtemoc and Miguel Hidalgo.

of socioeconomic variables do not vary with different accessibility indices, we present only the average marginal effects of the variables of interest.

II.5.1 General estimations

In this subsection we present the results of the probit model by gender (Table II.1 and Tables II.A.5 and II.A.6 of the Appendix). We observe that the coefficients of socioeconomic variables (*Age*, Age^2, dummies of education, *Head of household* and *Married*) are significant and with expected effects (see Table II.1). The average marginal effects are more significant and higher for women than for men. More experience and more education increase the likelihood of working. The head of the household as the breadwinner of the family is more likely to be employed. The probability of working increases when a man is married, and decreases when a woman is married, since a woman is more likely to dedicate herself to housework when she gets married. As expected, there is a positive correlation between the probability of being employed and the number of workers at home. The presence of young children decreases the probability of women participating in the labor market, because women have to spend time caring for their children, and this variable is not significant for men. The coefficient of family income has the expected sign in the case of women. However, in the case of men this variable has a positive effect. This may be explained by the fact that wealthy households have more job contacts. In other words, family income is a proxy of the close contacts that people have to get a job. If we estimate the model (II.9) restricting the sample to the head of the household, the coefficient of family income is not significant. The positive effect of this variable is due to other members of the household.

The accessibility variable, the accessibility index, is significant and with an expected effect in all estimates for women. However, this variable is less significant or not significant in almost all estimations for men, depending on the impedance function and the measure of cost of commuting (distance and time).[14] In the literature, there are diverse explanations of why women are more sensitive to local labor market conditions than men, summarized in MacDonald (1999). One explanation is that women earn less than men and female average wages vary less in the territory. Women receive less salaried compensation for greater commutes than men; therefore the net income-returns do not justify excessive commutes for women. Another explanation is that in most cases women are not the main breadwinners of the family, hence they search for partial, seasonal or temporary jobs which are less well-paid than full-time jobs. These kinds of jobs generally do not justify long commutes. Moreover, the dual role as worker and housewife/mother restricts commuting. Short commutes are easier to combine with the time demands of housework and/or childcare.

In addition, job distribution throughout the territory could affect the conditions of local labor markets. For example, if female-dominated jobs are uniformly distributed across the territory, it is easier for women to find a job near where they live. If the local labor market is spatially segmented, there are fewer job opportunities for women. Not all jobs can be reached by women because some of them may be far away. Finally, if there is

[14] We present the average marginal effects of the rest of the accessibility indices in the Appendix, Tables II.A.5 and II.A.6.

spatial segregation and a lack of modes of transport in the neighborhood, accessibility to nearby jobs may be more relevant. For example in Mexico City, time traveling on public transport is excessive; therefore the decay parameter is very negative. Due to this fact, the nearest jobs are relevant when individuals, such as women, depend on public transport. In the case of women, accessibility in terms of time in public transport has a larger effect on the probability of employment than accessibility in terms of time in private transport, when the decay parameter is different to -1 (see columns six and eight of Table II.A.5 and Table II.A.6 of the Appendix).

Finally, the percentage of individuals with incomplete basic education has the expected effect. Individuals who live in the most deprived areas have less probability of being employed. However the effect of this variable

Table II.1: Employment probability estimation and average marginal effects by gender
$-Pr(Employment = 1)-$

	Men		Women	
	Employment (1)	Average Marginal Effects (2)	Employment (3)	Average Marginal Effects (4)
Age	0.0270*** (7.24)	-0.0005*** (-7.43)	0.1036*** (45.89)	-0.0034*** (-30.15)
Age^2	-0.0004*** (-9.04)		-0.0014*** (-53.34)	
Incomplete elementary school				
Complete elementary school	0.0978*** (5.11)	0.0131*** (4.96)	0.0435*** (4.04)	0.0151*** (4.04)
Secondary school	0.2020*** (10.79)	0.0252*** (9.87)	0.1174*** (10.89)	0.0409*** (10.92)
High school	0.2297*** (10.95)	0.0281*** (10.28)	0.2856*** (23.97)	0.0999*** (24.05)
Some college	0.3039*** (11.52)	0.0353*** (11.58)	0.5380*** (36.30)	0.1868*** (36.87)
Bachelor's degree	0.3254*** (14.56)	0.0372*** (13.51)	0.7692*** (56.83)	0.2616*** (58.19)
Graduate school	0.5737*** (13.23)	0.0548*** (16.55)	1.2139*** (41.98)	0.3831*** (53.05)
Head household	0.4074*** (31.04)	0.0480*** (27.78)	0.3952*** (44.26)	0.1335*** (44.72)
Married	0.2332*** (18.69)	0.0269*** (17.25)	-0.7743*** (-103.56)	-0.2721*** (-107.48)
Number workers	0.0429*** (8.45)	0.0046*** (8.44)	0.0157*** (5.58)	0.0052*** (5.58)
Child$_{12}$	0.0055 (0.87)	0.0006 (0.87)	-0.1360*** (-38.70)	-0.0454*** (-39.10)
AI	0.0921 (1.95)	0.0098 (1.95)	0.6403*** (23.18)	0.2137*** (23.25)
%IBE	-0.1591** (-3.15)	-0.0169** (-3.15)	0.0068 (0.23)	0.0023 (0.23)
Family income	0.0013* (2.24)	0.0001* (2.24)	-0.0005** (-3.05)	-0.0002** (-3.05)
Constant	0.5220*** (6.27)		-1.7004*** (-33.07)	
LR	3063.73		45220.49	
N	185,209		214,275	

t statistics in parenthesis. * p <0.05, ** p <0.01, *** p <0.001. LR likelihood ratio. Standard errors of average marginal effects are calculated using Delta-Method.

is weak in the case of men and it is not significant in the case of women. We have made an estimation including an interaction term of high-level of education and incomplete basic education. This estimation indicates that less educated women living in a deprived neighborhood are less likely to participate in the labor market. In contrast, highly educated women living in a deprived neighborhood participate more frequently in the labor market. This result may be due to the fact that correlation between the percentage of individuals with incomplete basic education and job accessibility is higher in highly educated women than in less-educated women. The former is -0.39 and the latter is -0.43. The positive effect of the deprivation variable may capture part of the effect of job accessibility in the case of highly educated women.

II.5.2 Job accessibility by educational level

Job accessibility determines the employment outcomes in different ways. Some mechanisms are more relevant to some population groups than others (Gobillon and Selod, 2011). Access to jobs depends on both the geographical distribution of job opportunities and the spatial flexibility of individuals. Spatial flexibility means the willingness or ability of an individual to commute or move house. In other words, it is the possibility of adapting residential location (Van Ham et al., 2001). For example, if individuals are highly qualified, it is more likely that they are more spatially flexible, and consequently they are less sensitive to the local labor market. Simpson (1992) points out, through a residential mobility and commuting model, that highly qualified workers respond less to local employment conditions, unlike less-qualified workers. The wages offered to highly qualified workers are less sensitive to local labor demand conditions. Moreover, the search strategies of highly qualified workers are more spatially extensive and formal. Low-skilled jobs are rare in the neighborhood and low-skilled workers live far from the employment centers (Korsu y Wenglenski, 2010). For these reasons, the spatial barriers affect highly qualified workers less than less-qualified workers (Immergluck, 1998).

In order to determine whether accessibility affects the probability of being employed differently depending on educational level, we have estimated the equation (II.9) including two job accessibility indices by level of education. We have assigned each index to the corresponding educational level of individuals. The first index, $AI_{Basic\ Education}$, measures access to low-skilled jobs and it is approximated by the educational level of individuals. We consider low-skilled jobs to be those that are filled by workers with a basic education or less. The second index, $AI_{Post\text{-}basic\ Education}$, captures to what extent access to high-skilled job opportunities is relevant. High-skilled jobs are filled by highly educated individuals, i.e. individuals with a post-basic education.[15]. The results of these estimations are in Table II.2 and Table II.A.7 of the Appendix.

In Table II.2, we observe that socioeconomic variables, such as age, education, head of household and married, have the expected signs. However, the average marginal effects of education increases with respect the estimation of previous subsection. Access to low or high-skilled jobs reinforce the relevance of education as regards gaining employment.

Less-educated workers are more likely to be employed if they are near low-skilled job opportunities regardless of their sex (see Table II.2 and II.A.7 of the Appendix). This is consistent with several studies which conclude that there is a relationship between accessibility and employment, and this relationship is especially important to less-educated workers and low-paid workers (Kawabata, 2003; Korsu and Wenglenski, 2010; Matas

[15]In Mexico, post-basic education includes high school and more

Table II.2: Effects of job accessibility by educational level on the probability of being employed by gender
$-Pr(Employment = 1)-$

	Men		Women	
	Employment (1)	Average Marginal Effects (2)	Employment (3)	Average Marginal Effects (4)
Age	0.0270*** (7.26)	-0.0005*** (-7.45)	0.1039*** (46.01)	-0.0034*** (-30.16)
Age^2	-0.0004*** (-9.07)		-0.0014*** (-53.47)	
Incomplete elementary school				
Complete elementary school	0.0963*** (5.03)	0.0137*** (4.87)	0.0408*** (3.78)	0.0140*** (3.79)
Secondary school	0.1997*** (10.66)	0.0264*** (9.62)	0.1131*** (10.48)	0.0391*** (10.52)
High school	0.3173*** (7.32)	0.0386*** (7.21)	0.4944*** (19.38)	0.1728*** (19.70)
Some college	0.3937*** (8.36)	0.0454*** (8.44)	0.7501*** (27.38)	0.2588*** (28.61)
Bachelor's degree	0.4176*** (9.08)	0.0474*** (9.00)	0.9867*** (36.06)	0.3314*** (38.99)
Graduate school	0.6693*** (11.09)	0.0636*** (12.55)	1.4362*** (37.82)	0.4434*** (49.00)
Head household	0.4082*** (31.10)	0.0481*** (27.82)	0.3960*** (44.36)	0.1338*** (44.83)
Married	0.2332*** (18.69)	0.0269*** (17.25)	-0.7747*** (-103.63)	-0.2723*** (-107.55)
Number workers	0.0425*** (8.35)	0.0045*** (8.34)	0.0152*** (5.41)	0.0051*** (5.41)
Child$_{12}$	0.0055 (0.87)	0.0006 (0.87)	-0.1366*** (-38.86)	-0.0456*** (-39.27)
AI $_{\text{Basic Education}}$	0.1935** (2.96)	0.0206** (2.95)	0.7732*** (20.57)	0.2581*** (20.63)
AI $_{\text{Post-basic Education}}$	0.0011 (0.02)	0.0001 (0.02)	0.3458*** (9.22)	0.1154*** (9.23)
%IBE	-0.1565** (-3.11)	-0.0167** (-3.11)	-0.0254 (-0.86)	-0.0085 (-0.86)
Family income	0.0013* (2.32)	0.0001* (2.32)	-0.0005** (-2.84)	-0.0002** (-2.84)
Constant	0.4739*** (5.51)		-1.7679*** (-33.30)	
LR	3068.73		45163.28	
N	185,209		214,275	

t statistics in parenthesis. * p <0.05, ** p <0.01, *** p <0.001. LR likelihood ratio. Standard errors of average marginal effects are calculated using Delta-Method.

et al., 2010).

Regardless of the level of education, women are more sensitive to job accessibility. This result supports the conclusions of the previous subsection. Women have important spatial barriers or are less spatially flexible; therefore they are more sensitive to local labor market conditions.

II.5.3 Formal and informal job accessibility

Most of the empirical literature about job accessibility or spatial mismatch deals with developed countries, where the informal sector is not relevant. Few studies have focused on developing countries due to a shortage of databases. Among these studies, analysis of job accessibility distinguishing formal and informal sectors is rare. This is because although several Latin American databases enable the identification of informal workers; there are few databases that have information regarding informal job location.

In Mexico, as well as in other developing countries, the informal sector is an important part of total employment. In 2010, 28.8 percent of the employed population worked in an informal job. In the third quarter of 2011 this percentage increased to almost 30 percent, according to the ENOE. In the metropolitan area it represents approximately 31 percent of total employment and 43 percent of salaried employment.[16] According to Escamilla-Herrera (2002), the urban labor market in Mexico City has lost dynamism in some formal sectors such as manufacturing and the public sector due to the decentralization of economic activities and the suburbanization of the population. In other words, the formal sector has lost the capacity to absorb the labor force. As a result unemployment, the tertiarization of economic activity and the informal labor market have increased.

Amaral and Quintin (2006) and other authors point out that informal workers are in general less-qualified than formal ones. According to the ENOE-2010, in Mexico a high proportion of informal employment is not qualified; approximately 72 percent of informal workers have less than basic or secondary school education. In addition, the decay parameter of the impedance function and the accessibility indices by labor status are different (see Tables II.A.3 and II.A.4 of the Appendix). The latter indicates that the distribution of formal and informal employment is uneven among zones and within zones. Therefore, we expect that formal job accessibility has less impact on the probability of being employed than informal job accessibility.

In order to prove that accessibility by labor status has different effects on the probability of being employed, we have estimated the model (II.9) restricting the sample to salaried workers and assigning labor status to unemployed individuals. In other words, the subsample only considers individuals who are neither employers nor self-employed. Because we do not know whether an unemployed individual will be informal or formal, we have assigned labor status through the estimation of a logit model of the probability of being a formal worker. The variables of this model are sex, age, education, being the head of a household and being married.[17] In addition, in order not to have a single estimate of the probability of being formal, we use the logit imputation method. This method, generally used to impute missing values (Rubin, 1987), replaces missing values from m>1 Markov Chain Monte Carlo simulations. Subsequently, the final estimate is calculated as an average of the replaced m values. In this case, as the variable is dichotomous, we assign one if the average is greater than 0.50 and zero otherwise.

We present the results of the probability of being employed including both accessibility indices, formal and informal in Table II.3 and Table II.A.8 of the Appendix. We can observe that the coefficients of socioeconomic variables are significant and have expected effects. In the case of women the only variable that becomes insignificant is the number of workers in the household. With regard to the accessibility variable, it is significant and positive for informal workers regardless of sex. This may be due in part to the fact that a large proportion of informal workers are less-qualified (approximately 72 percent of informal workers have less than basic or

[16] Data obtained from the Population and Housing Census 2010.

[17] We estimated the probability of being formal for men and women separately. Although the coefficients of the two estimates are different from the joint estimation, the final results are not altered, after assigning the accessibility indices between formal or informal status.

secondary education). This is consistent with several studies which conclude that accessibility especially affects less-skilled workers (Kawabata, 2003; Matas et al., 2010). Additionally, the search methods of informal workers are in most cases informal methods, such as relatives, acquaintances or advertisements in the neighborhood, as opposed to formal workers. According to the ENOE 2010, 60 percent of informal workers get his/her job through friends, relatives and acquaintances, and 34 percent go to the establishment or offer employment. Informal workers are more reliant on their environment, such as contacts and being nearer to vacancies. Therefore informal job accessibility is very relevant to informal workers.

Table II.3: Effects of job accessibility by labor status on probability of being employed
–$Pr(Employment = 1)$–

	Men		Women	
	Employment (1)	Average Marginal Effects (2)	Employment (3)	Average Marginal Effects (4)
Age	0.0277*** (6.83)	-0.0013*** (-14.09)	0.1114*** (43.44)	-0.0041*** (-34.54)
Age^2	-0.0005*** (-9.80)		-0.0015*** (-51.68)	
Incomplete elementary school				
Complete elementary school	0.1323*** (6.28)	0.0245*** (6.06)	0.1016*** (8.01)	0.0309*** (8.08)
Secondary school	0.2851*** (13.72)	0.0483*** (12.25)	0.2373*** (18.33)	0.0741*** (18.78)
High school	0.3369*** (14.31)	0.0553*** (13.13)	0.5023*** (34.35)	0.1627*** (35.32)
Some college	0.4247*** (14.54)	0.0661*** (14.37)	0.7853*** (44.67)	0.2594*** (45.68)
Bachelor's degree	0.4609*** (18.28)	0.0702*** (16.51)	1.0461*** (63.96)	0.3458*** (67.54)
Graduate school	0.7505*** (16.13)	0.0953*** (19.90)	1.5031*** (47.49)	0.4788*** (57.26)
Head household	0.4173*** (29.26)	0.0629*** (26.78)	0.3703*** (37.13)	0.1196*** (36.53)
Married	0.2741*** (20.23)	0.0412*** (18.64)	-0.8662*** (-106.05)	-0.2989*** (-106.93)
Number workers	0.0342*** (6.20)	0.0047*** (6.20)	0.0050 (1.57)	0.0016 (1.57)
Child$_{12}$	0.0005 (0.07)	0.0001 (0.07)	-0.1667*** (-42.02)	-0.0520*** (-42.59)
AI$_{\text{Formal}}$	-0.0079 (-0.17)	-0.0011 (-0.17)	0.5556*** (19.53)	0.1734*** (19.59)
AI$_{\text{Informal}}$	0.2587*** (4.77)	0.0358*** (4.77)	0.9897*** (29.58)	0.3088*** (29.77)
%IBE	-0.1976*** (-3.69)	-0.0274*** (-3.69)	-0.1117*** (-3.37)	-0.0349*** (-3.37)
Family income	0.0013* (2.15)	0.0002* (2.15)	-0.0008*** (-4.00)	-0.0003*** (-4.00)
Constant	0.3451*** (3.83)		-2.0420*** (-35.17)	
LR	3319.90		48777.97	
N	130,426		180,668	

t statistics in parenthesis. * p <0.05, ** p <0.01, *** p <0.001. Standard errors of average marginal effects are calculated using Delta-Method. The subsamples are unemployed individuals or salaried workers.

Formal job accessibility is only significant for women. Its average marginal effect is smaller than that of informal job accessibility. Accessibility to formal employment for men is irrelevant as shown in Table II.3 and Table II.A.8 of the Appendix. These facts may be due to male formal worker commuting longer distances on average than any other individual (approximately 11km in a straight line). That is, his reserve distance is very high. In contrast, the average distance for male informal worker and female workers is 7km. Moreover, recently the informal sector has been more dynamic than the formal sector, i.e. more jobs have been created in the informal sector than in the formal sector, according to the National Institute of Statistics and Geography of Mexico. In the short run, this means that are more informal vacancies than formal ones, or there are more informal job opportunities than formal ones.

In conclusion, accessibility is more relevant depending on whether the individual is seeking formal or informal employment. Job accessibility is not relevant to male formal workers, whereas it is relevant to female formal workers. Job accessibility is important to informal workers regardless the sex. These facts may be due to formal employment being highly concentrated at the center (as mentioned above, seven central delegations have 57 percent of formal employment and 41 percent of informal employment). Instead, informal employment is spread out or local. However, as this analysis is static, it does not consider the fact that individuals can switch from formal to informal and *vice versa*. Nor can it show how different job accessibility affects such changes between employment statuses.

II.6 Endogeneity problems

The empirical literature of spatial mismatch has emphasized the endogeneity problem of job accessibility. There is a simultaneity problem between the probability of being employed and commuting distance or time, or in other words between the probability of being employed and job accessibility. Residential location and labor market outcomes are jointly determined (Ihlanfeldt and Sjoquist, 1990). For example, if the most productive workers attract the firms where they live, accessibility indices of these zones will be high (Aslund et al., 2010). Residential location is endogenous; individuals choose the place where they live. In other words, residential location is not random. The most productive workers can choose their residential location, because they are more spatially flexible. They may choose to live near their job; consequently accessibility indices capture differences in productivity. As standard urban model predicts, workers can select a residence with poor access, so that they consume more amenities or housing units at lower price (Ihlanfeldt, 2005).

Several studies have attempted to solve the simultaneity problem through structural models (Johnston et al., 2007) or by instrumental variables. However, it is difficult to envisage a structural model that adequately captures residential location decisions, and it is also difficult to find good instruments. On the other hand, there are papers that have used samples derived from housing programs (Aslund et al., 2010) or subsamples where the choice of residential location may be exogenous, for example household members who are not heads of the household such as young adults living with their parents (Dujardin et al., 2008). Nevertheless, these subsamples could not address the selection bias if parents and children share the same unobserved heterogeneity, for example in terms of productivity (Aslund et al., 2010). However, the literature is not conclusive about the importance and the direction of the bias. Some authors find no effects of access to jobs when they address endogeneity issues (Dujardin and Goffette-Nagot, 2010). Meanwhile, other authors find that the effects of access to jobs are underestimated if they do not take into account endogeneity issues (Aslund et al., 2010).

Table II.4: Effect of accessibility on the employment probability controlling for endogeneity
$-Pr(employment = 1)-$

	Men		Women	
	Employment (1)	Average Marginal Effects (2)	Employment (3)	Average Marginal Effects (4)
Age	0.0337*** (4.95)	0.0008*** (3.75)	0.1127*** (24.86)	0.0013*** (4.94)
Age^2	-0.0004*** (-4.88)		-0.0015*** (-27.26)	
Incomplete elementary school				
Complete elementary school	0.0629 (1.49)	0.0114 (1.46)	0.0956*** (3.53)	0.0340*** (3.51)
Secondary school	0.1397*** (3.53)	0.0241*** (3.30)	0.1878*** (7.25)	0.0661*** (7.16)
High school	0.1445*** (3.48)	0.0249** (3.28)	0.3753*** (13.81)	0.1286*** (13.48)
Some college	0.2367*** (5.00)	0.0385*** (4.75)	0.5734*** (18.17)	0.1892*** (18.06)
Bachelor's degree	0.2383*** (5.56)	0.0387*** (5.09)	0.8141*** (28.06)	0.2536*** (26.56)
Graduate school	0.4014*** (5.15)	0.0587*** (5.74)	1.1063*** (17.37)	0.3168*** (22.52)
Married	0.3312*** (18.11)	0.0477*** (19.38)	-0.8890*** (-68.40)	-0.3049*** (-68.61)
Number workers	0.0708*** (9.81)	0.0109*** (9.79)	0.0175*** (3.69)	0.0054*** (3.70)
AI	0.0951 (1.23)	0.0147 (1.23)	0.5191*** (9.17)	0.1598*** (9.18)
%IBE	0.2023* (2.30)	0.0312* (2.30)	-0.2401*** (-3.70)	-0.0739*** (-3.70)
Family income	0.0022** (2.91)	0.0003** (2.91)	0.0028*** (6.76)	0.0009*** (6.76)
Constant	0.2235 (1.57)		-1.8129*** (-18.59)	
LR	661.81		9527.80	
N	50,054		54,696	

t statistics in parenthesis. * p <0.05, ** p <0.01, *** p <0.001. LR likelihood ratio. Standard errors of average marginal effects are calculated using Delta-Method. The subsamples are household members who are not head of household or spouse.

We have used a subsample to address the endogeneity issue. This subsample excludes heads of households and spouses in order to control the problem of residential choice and the possible correlation between job accessibility index and employment probability. The descriptive statistics of variables for the subsample are presented in the Appendix, Table II.A.1. We have used a subsample because we do not have appropriate instrumental variables to address the endogeneity problem. Moreover, in the literature there is no consensus on how to set up a structural model that adequately captures the decision behind an individual's choice of residence. It is possible that the obtained results are not generalized to the whole population, because we have used a subsample.

Table II.4 and Table II.A.9 of the Appendix show the results after addressing the endogeneity problem. As in Section 5, the coefficients of socioeconomic variables have the expected signs and are significant. However, the coefficient of family income has a positive sign. This may be explained by the fact that wealthy households have more job contacts. In this case, family income is a proxy of the close contacts that people have to get a job. The coefficient of segregation variable (*%IBE*) changes the sign in the case of men. Nevertheless, its effect is slight.

This result may be explained by the fact that young men have to work in order to increase the family income.

With regard to job accessibility, in all cases, this variable is not significant for men, while it remains significant for women. However, this significance and the average marginal effects decrease. Therefore we obtain robust results. Job accessibility is relevant only to women and is not relevant to men.

II.7 Conclusions

The MAMC presents important patterns of spatial disconnection and residential segregation that affect labor force participation, especially of women and less educated individuals. Employment opportunities measured by the accessibility index are very important in the case of women in general and less educated men. However, the results are robust in subsamples only for women because these remain significant. Moreover, less-educated women are the most sensitive to local labor market conditions.

Access to different modes of transport has different effects on the participation of women in the labor force. Access to a mode of public transport is more relevant than access to a mode of private transport. In the case of men, the distinction of the access to modes of transport is not relevant.

A prominent result of this paper is the finding that the informal job accessibility index has a greater impact than the formal job accessibility index. The latter index is not significant for men. This result is explained by the fact that the informal sector absorbs a significant proportion of less skilled workers and accessibility for this type of worker is more important.

The spatial barriers are not equal for the whole population in the case of Mexico City. Women, especially less-educated women are the most sensitive to local labor market conditions. Access to informal or formal job has different effects on the probability of being employed. This distinction is relevant. An informal worker is more sensitive to the local labor market conditions than formal worker. The spatial barriers matter in the cases of women and informal workers.

The disconnection between the core and the periphery of Mexico City has caused the rise of unemployment and of the informal sector especially in the periphery. This spatial disconnection explains the importance of accessibility to informal employment. Moreover, this disconnection affects households with lower level of education more, households which are generally of lower incomes, those with highest levels of social segregation and higher unemployment, and are furthest away from employment opportunities.

The policy implications of the disconnection between workers and job opportunities depend on the context and mechanisms that generate this disconnection. Among the policies that could be implemented, are the facilitation of residential mobility, neighborhood regeneration policies, the development or subsidization of public and private transport, the spatial dissemination of information on available jobs, and the implementation of anti-discriminatory laws, among others.

Mexico City needs greater public transport infrastructure that connects remote residential areas with employment centers, especially those offering formal employment. The average commuting time is very long, which implies high costs that are generally absorbed by workers. These costs are often very high, especially for unskilled and female workers who prefer the informal sector which is more accessible to them given their qualifications and is closest in physical terms.

Therefore, public transport infrastructure investment that connects the sources of employment with labor supply may reduce effects of residential segregation, informality and unemployment. In recent years there has been investment in transport infrastructure in Mexico City. However, it is still lacking especially in the periphery of the city, where most people have only the bus as mode of transport.

In addition, policies can also be developed to create formal job subcenters close to the most densely populated areas, through the formalization of informal jobs or the creation of formal jobs. One of the causes of informality is the lack of formal credit. The formalization of informal employment could be achieved through the programs that give some credit to informal firms on the condition that within a fixed term they become formal.

In Mexico City, there have been central city repopulation policies which were aimed to low income households. However, the result of market was a very high price of housing, hence low income households have no access. The facilitation of the residential mobility of low income households implies subsidizing the land prices or the price of housing which could be very costly.

Further studies could suggest a better solution to the endogeneity problem of accessibility, through the availability of good instruments and the estimation of structural equations. Although in the literature there is still no consensus on the proper way to raise these structural equations and how to model the decisions behind residential location and place of work.

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Appendix II.A Tables

Table II.A.1: Descriptive statistics of sample and subsample

	General		Subsample[1]		Subsample[2]	
	Men	Women	Men	Women	Men	Women
Dependent						
Employment	94.55	52.58	92.27	43.76	91.36	67.48
Socioeconomic						
Age	40.71	41.16	39.61	40.87	34.60	36.08
	(10.42)	(10.68)	(10.15)	(10.72)	(8.62)	(9.83)
Education						
Incomplete elementary school*	7.74	11.40	7.00	11.20	4.39	6.36
Complete elementary school*	17.67	20.49	16.65	20.34	12.97	13.63
Secondary school*	31.79	28.58	32.52	28.62	32.95	29.09
High school*	16.76	17.05	17.22	17.31	19.71	19.99
Some college*	6.88	7.20	7.05	7.22	8.65	9.21
Bachelor's degree*	16.25	13.38	16.55	13.47	19.54	19.82
Graduate school*	2.91	1.89	3.01	1.83	1.81	1.89
Head of household*	68.95	19.71	66.86	17.77	-	-
Married*	75.54	67.09	74.73	68.44	37.10	30.87
Number of workers	1.10	1.44	1.07	1.44	1.86	1.94
	(1.20)	(1.14)	(1.19)	(1.13)	(1.42)	(1.42)
Number of children under 12 (Child_{12})	0.66	0.62	0.68	0.63	-	-
	(0.97)	(0.95)	(0.98)	(0.96)	-	-
Family income (thousand of pesos)	5.71	8.89	5.57	8.88	9.79	10.78
	(13.25)	(18.09)	(12.65)	(17.27)	(19.57)	(21.16)
Segregation						
% Incomplete basic education (%IEB)	26.56	26.30	26.58	26.32	26.05	25.56
	(11.97)	(11.89)	(11.98)	(11.88)	(11.02)	(10.97)
N	185,209	214,275	130,426	180,651	50,054	54,696

* Percentages. Standard deviation in parentheses. The subsamples[1] are workers who are neither employers nor self-employed. The subsamples[2] are household members who are not head of household or spouse.

Table II.A.2: Estimations of the decay parameter of impedance function

	Power Gravity Model			Exponential Gravity Model		
	Distance – km –	Private Time – minutes –	Public Time – minutes –	Distance – km –	Private Time – minutes –	Public Time – minutes –
T_{ij}						
δ	-1.2265***	-0.7476***	-1.0504***	-0.0881***	-0.0114***	-0.0119***
	(-68.84)	(-30.45)	(-45.15)	(-52.80)	(-28.69)	(-26.44)
$\ln(O_i)$	1.3736***	0.8776***	0.9721***	1.2224***	0.8479***	0.9223***
	(37.58)	(26.34)	(42.84)	(21.44)	(23.81)	(37.32)
$\ln(E_j)$	0.5879***	0.3470***	0.5144***	0.4739***	0.3107***	0.4933***
	(31.54)	(20.35)	(38.60)	(16.98)	(17.19)	(35.88)
$\ln(A_j)$	-0.4403***	-0.4443***	-0.2154***	-0.5138***	-0.5114***	-0.3305***
	(-5.82)	(-5.63)	(-3.75)	(-6.98)	(-5.97)	(-4.98)
Constant	-6.2681***	1.5478	-2.6560***	-4.0754***	0.6844	-4.1843***
	(-5.56)	(1.71)	(-4.04)	(-3.78)	(0.71)	(-5.47)
Inflate						
δ	1.9781***	2.0730***	1.0778***	0.1051***	0.0283***	0.0096***
	(56.40)	(53.95)	(28.75)	(50.84)	(39.05)	(21.08)
$\ln(O_i)$	-0.6134***	-0.4812***	-0.7587***	-0.6002***	-0.4465***	-0.6948***
	(-14.42)	(-11.65)	(-25.00)	(-14.19)	(-11.13)	(-23.40)
$\ln(E_j)$	-1.3279***	-1.1434***	-1.0209***	-1.3167***	-1.0869***	-0.9880***
	(-44.06)	(-39.37)	(-39.94)	(-43.88)	(-38.41)	(-39.23)
$\ln(A_j)$	-1.0058***	-1.4967***	-2.5090***	-0.9940***	-1.5119***	-2.5517***
	(-20.29)	(-18.87)	(-34.44)	(-19.96)	(-19.41)	(-35.21)
Constant	26.7444***	23.9578***	40.5499***	29.9153***	29.8584***	43.9068***
	(35.03)	(24.94)	(47.96)	(39.03)	(31.74)	(53.03)
ln(alpha)	-0.3445***	-0.3563***	-0.4525***	0.0628*	-0.3188***	-0.4236***
	(-12.33)	(-18.22)	(-27.83)	(2.45)	(-15.62)	(-24.90)
Log-Likelihood	-87728.64	-51354.87	-74181.69	-90693.83	-51884.04	-74519.19
N	24,336	24,336	24,336	24,336	24,336	24,336

t statistics in parenthesis. * p <0.05, ** p <0.01, *** p <0.001. The power gravity model is estimated using equation (II.4). The exponential gravity model is estimated using equation (II.3). These estimations are in *distrito* level.

Table II.A.3: Estimations of the decay parameter of impedance function by labor status

	Power Gravity Model						Exponential Gravity Model					
	Distance		Private Time		Public Time		Distance		Private Time		Public Time	
	Formal	Informal	Formal	Informal	Formal	Informal	Formal	Informal	Formal	Informal	Formal	Informal
T_{ij}												
δ	-1.0527***	-1.0981***	-0.5825***	-0.5957***	-0.8204***	-0.8430***	-0.0762***	-0.0851***	-0.0092***	-0.0091***	-0.0097***	-0.0100***
	(-63.04)	(-54.46)	(-24.40)	(-17.62)	(-35.88)	(-32.67)	(-47.32)	(-36.76)	(-23.83)	(-15.18)	(-23.35)	(-28.94)
$\ln(O_i)$	1.0323***	1.1609***	0.7188***	0.7513***	0.8212***	0.9668***	0.9419***	0.9447***	0.7048***	0.7407***	0.7908***	0.9251***
	(23.64)	(34.15)	(27.40)	(20.49)	(34.59)	(43.04)	(19.43)	(17.03)	(25.88)	(18.91)	(33.06)	(39.26)
$\ln(E_j)$	0.4647***	0.3818***	0.2956***	0.1867***	0.4175***	0.3273***	0.3721***	0.2320***	0.2753***	0.1544***	0.4042***	0.3034***
	(26.00)	(17.54)	(19.54)	(6.45)	(33.55)	(20.16)	(15.45)	(6.61)	(17.57)	(5.13)	(31.75)	(18.42)
$\ln(A_j)$	-0.5088***	-0.5807***	-0.4040***	-0.6901***	-0.3171***	-0.4880***	-0.5460***	-0.6704***	-0.4247***	-0.8020***	-0.3753***	-0.5948***
	(-7.46)	(-7.71)	(-5.51)	(-7.33)	(-5.20)	(-7.42)	(-7.80)	(-8.31)	(-5.50)	(-7.93)	(-5.63)	(-8.25)
Constant	-0.2536	0.1060	2.7296***	6.4746***	0.5733	1.6557*	0.6586	3.3208***	1.5191*	6.1488***	-1.1430	0.5028
	(-0.24)	(0.13)	(3.65)	(6.63)	(0.90)	(2.57)	(0.70)	(3.41)	(1.98)	(5.84)	(-1.66)	(0.72)
Inflate												
δ	1.9214***	1.8063***	2.0263***	1.8607***	1.2740***	1.3895***	0.1094***	0.1203***	0.0291***	0.0325***	0.0131***	0.0151***
	(55.70)	(54.30)	(50.46)	(34.64)	(31.34)	(29.65)	(50.21)	(46.96)	(38.08)	(24.12)	(25.11)	(22.89)
$\ln(O_i)$	-0.3467***	-1.2625***	-0.5320***	-0.6912***	-0.6271***	-1.0580***	-0.3203***	-1.2339***	-0.5011***	-0.6984***	-0.5849***	-0.9887***
	(-8.03)	(-35.39)	(-15.13)	(-16.48)	(-20.33)	(-30.39)	(-7.62)	(-35.17)	(-14.60)	(-17.16)	(-19.33)	(-29.00)
$\ln(E_j)$	-1.0707***	-0.9646***	-0.9505***	-0.7170***	-0.8410***	-0.8557***	-1.0605***	-0.9433***	-0.9106***	-0.6831***	-0.8162***	-0.8278***
	(-46.05)	(-32.46)	(-40.68)	(-18.25)	(-40.91)	(-31.33)	(-45.62)	(-32.53)	(-40.09)	(-17.90)	(-40.12)	(-30.79)
$\ln(A_j)$	-0.6936***	-0.6297***	-1.0598***	-1.1641***	-2.1166***	-1.7297***	-0.6354***	-0.5553***	-1.0642***	-1.1192***	-2.1433***	-1.7449***
	(-14.41)	(-10.65)	(-13.14)	(-9.96)	(-27.49)	(-20.03)	(-12.96)	(-9.33)	(-13.41)	(-9.70)	(-28.00)	(-20.38)
Constant	16.1649***	23.7491***	16.3703***	17.1898***	29.7784***	28.8960***	18.4330***	25.2128***	22.1340***	21.9804***	33.8549***	32.9123***
	(23.82)	(30.53)	(18.47)	(13.26)	(36.85)	(33.39)	(27.62)	(32.35)	(25.84)	(17.44)	(43.26)	(38.99)
ln(alpha)	-0.3652***	-0.4112***	-0.4984***	-0.6348***	-0.6104***	-0.7247***	-0.0044	0.0301	-0.4754***	-0.5855***	-0.5915***	-0.6949***
	(-12.48)	(-14.97)	(-24.29)	(-18.77)	(-34.06)	(-33.39)	(-0.17)	(1.01)	(-22.51)	(-16.68)	(-32.20)	(-31.42)
Log-Likelihood	-74750.78	-47324.12	-44612.43	-18198.64	-59602.17	-41517.44	-77035.61	-49022.06	-44972.93	-18367.88	-59830.76	-41746.38
N	24336	24336	24336	24336	24336	24336	24336	24336	24336	24336	24336	24336

t statistics in parenthesis. * p <0.05, ** p <0.01, *** p <0.001. The power gravity model is estimated using equation (II.4). The exponential gravity model is estimated using equation (II.3). These estimations are in district level..

Table II.A.4: Descriptive statistics of accessibility indices

	General		
	Power $\delta = -1$	Power $\delta \neq -1$	Exponential
AI(d)	0.4754 (0.1690)	0.4787 (0.2172)	0.4766 (0.1659)
AI(t)	0.4872 (0.1238)	0.4956 (0.168)	0.4837 (0.1067)
AI($t_{private}$)	0.5565 (0.1373)	0.9545 (0.1795)	0.5324 (0.1073)
AI(t_{public})	0.4517 (0.1141)	0.2323 (0.0614)	0.4600 (0.1057)

	By Educational level					
	Basic education			Post-basic education		
	Power $\delta = -1$	Power $\delta \neq -1$	Exponential	Power $\delta = -1$	Power $\delta \neq -1$	Exponential
AI(d)	0.5033 (0.1592)	0.5119 (0.1938)	0.5024 (0.1554)	0.4527 (0.1795)	0.4543 (0.1697)	0.4606 (0.1509)
AI(t)	0.5056 (0.1148)	0.5031 (0.1092)	0.4977 (0.0957)	0.4770 (0.1302)	0.4748 (0.1036)	0.4792 (0.084)
AI($t_{private}$)	0.5898 (0.1339)	1.0898 (0.1733)	0.5622 (0.0976)	0.5381 (0.1432)	0.6585 (0.0975)	0.4945 (0.0861)
AI(t_{public})	0.4817 (0.1144)	0.3132 (0.0704)	0.4790 (0.0983)	0.4344 (0.1168)	0.3391 (0.0614)	0.4702 (0.084)

	By labor status					
	Formal			Informal		
	Power $\delta = -1$	Power $\delta \neq -1$	Exponential	Power $\delta = -1$	Power $\delta \neq -1$	Exponential
AI(d)	0.4900 (0.2074)	0.4896 (0.2204)	0.4918 (0.1808)	0.4624 (0.1477)	0.4663 (0.1664)	0.4628 (0.1421)
AI(t)	0.5104 (0.1448)	0.5103 (0.154)	0.5066 0.1035)	0.4666 (0.1075)	0.4612 (0.1122)	0.4573 (0.0818)
AI($t_{private}$)	0.5812 (0.1608)	0.8665 (0.1442)	0.5483 (0.1028)	0.5408 (0.1226)	0.9200 (0.1306)	0.5109 (0.0823)
AI(t_{public})	0.4684 (0.1296)	0.2830 (0.0646)	0.4834 (0.101)	0.4416 (0.1049)	0.2903 (0.0587)	0.4394 (0.0838)

Standard deviation in parentheses. Distance, d, in kilometres and time, t, in minutes. The job accessibility index in distance is calculated using equation (II.5) at *estrato* level. The accessibility index in time is calculated using equation (II.6) at *distrito* level. The accessibility indices in private and public time are calculated using equations (II.7) and (II.8), respectively.

Table II.A.5: Effects of the accessibility on the probability of being employed considering different job accessibility indices

–Average Marginal Effects–

	Distance		Time		Private Time		Public Time	
	Men (1)	Women (2)	Men (3)	Women (4)	Men (5)	Women (6)	Men (7)	Women (8)
$AI_{power,\delta=-1}$	0.0047 (1.43)	0.1412*** (23.27)	0.0098 (1.95)	0.2137*** (23.25)	0.0087* (2.09)	0.1764*** (22.89)	0.0080 (1.46)	0.2260*** (22.50)
%IBE	-0.0181*** (-3.39)	-0.0020 (-0.21)	-0.0169** (-3.15)	0.0023 (0.23)	-0.0174*** (-3.32)	-0.0135 (-1.39)	-0.0181*** (-3.41)	-0.0074 (-0.75)
$AI_{power,\delta\neq-1}$	0.0052 (1.95)	0.1128*** (22.94)	0.0104* (2.37)	0.1483*** (18.73)	0.0054 (1.71)	0.1312*** (22.76)	0.0153 (1.49)	0.4196*** (22.43)
%IBE	-0.0171** (-3.19)	-0.0009 (-0.09)	-0.0146** (-2.60)	0.0071 (0.69)	-0.0181*** (-3.45)	-0.0154 (-1.59)	-0.0181*** (-3.40)	-0.0078 (-0.80)
$AI_{exponential}$	-0.0001 (-0.02)	0.1237*** (21.49)	0.0046 (0.86)	0.2212*** (22.47)	0.0035 (0.72)	0.1982*** (21.85)	0.0038 (0.69)	0.2236*** (22.23)
%IBE	-0.0208*** (-3.94)	-0.0147 (-1.51)	-0.0192*** (-3.61)	-0.0073 (-0.74)	-0.0197*** (-3.79)	-0.0224* (-2.32)	-0.0196*** (-3.71)	-0.0127 (-1.30)

t statistics in parenthesis. * p <0.05, ** p <0.01, *** p <0.001. Standard errors are calculated using Deltha-Method. The average marginal effects of socioeconomic variables are very similar to those obtained in Table II.1. The accessibility index in distance is calculated using equation (II.5) at *estrato* level. The accessibility index in time is calculated using equation (II.6) at *distrito* level. The accessibility index in private time is calculated using equation (II.7) at *distrito* level. The accessibility index in public time is calculated using equation (II.8) at *distrito* level.

Table II.A.6: Effects of the accessibility by transport modes considering different impedance functions
–Average Marginal Effects–

	$AI_{power,\delta=-1}$		$AI_{power,\delta\neq-1}$		$AI_{exponential}$	
	Men (1)	Women (2)	Men (3)	Women (4)	Men (5)	Women (6)
AI($t_{private}$)	0.0182	0.1076***	0.0066	0.0788***	0.0031	0.0725**
	(1.83)	(5.86)	(0.86)	(5.54)	(0.21)	(2.62)
AI(t_{public})	-0.0137	0.0987***	-0.0044	0.1859***	0.0005	0.1477***
	(-1.05)	(4.12)	(-0.18)	(4.02)	(0.03)	(4.81)
%IBE	-0.0183***	-0.0076	-0.0183***	-0.0091	-0.0197***	-0.0145
	(-3.44)	(-0.78)	(-3.43)	(-0.93)	(-3.72)	(-1.48)

t statistics in parenthesis. * p <0.05, ** p <0.01, *** p <0.001. Standard errors are calculated using Deltha-Method. The average marginal effects of socioeconomic variables are very similar to those obtained in Table II.1. The accessibility index in private time is calculated using equation (II.7) at *distrito* level. The accessibility index in public time is calculated using equation (II.8) at *distrito* level. Both indices, private and public are included in the estimation. This table, unlike Table II.A.5, reports the average marginal effects when in the estimation it is included two accessibility indices by transport mode.

Table II.A.7: Effects of job accessibility by education level on probability of being salaried worker by gender considering different impedance functions and commuting cost
–Average Marginal Effects–

	Distance		Time		Private Time		Public Time	
	Men (1)	Women (2)	Men (3)	Women (4)	Men (5)	Women (6)	Men (7)	Women (8)
$AI_{power,\delta=-1}$								
$AI_{\text{Basic Education}}$	0.0119**	0.1786***	0.0206**	0.2581***	0.0152**	0.1953***	0.0178*	0.2700***
	(2.63)	(22.08)	(2.95)	(20.63)	(2.77)	(19.62)	(2.49)	(20.99)
$AI_{\text{Post-basic Education}}$	-0.0005	0.0700***	0.0001	0.1154***	0.0021	0.1213***	-0.0028	0.1303***
	(-0.13)	(8.55)	(0.02)	(9.23)	(0.36)	(10.89)	(-0.38)	(9.19)
%IBE	-0.0175**	-0.0090	-0.0167**	-0.0085	-0.0173**	-0.0188	-0.0180***	-0.0117
	(-3.27)	(-0.91)	(-3.11)	(-0.86)	(-3.29)	(-1.94)	(-3.37)	(-1.19)
$AI_{power,\delta\neq-1}$								
$AI_{\text{Basic Education}}$	0.0118**	0.1543***	0.0323***	0.1887***	0.0097*	0.1461***	0.0277*	0.4329***
	(3.03)	(22.25)	(4.29)	(13.88)	(2.40)	(19.78)	(2.41)	(20.93)
$AI_{\text{Post-basic Education}}$	-0.0008	0.0752***	-0.0059	0.0453**	-0.0022	0.1596***	-0.0092	0.2394***
	(-0.17)	(8.68)	(-0.66)	(2.72)	(-0.26)	(9.92)	(-0.65)	(9.00)
%IBE	-0.0168**	-0.0060	-0.0147**	-0.0330**	-0.0184***	-0.0223*	-0.0184***	-0.0129
	(-3.14)	(-0.61)	(-2.67)	(-3.26)	(-3.52)	(-2.30)	(-3.46)	(-1.32)
$AI_{exponential}$								
$AI_{\text{Basic Education}}$	0.0048	0.1547***	0.0149*	0.2742***	0.0103	0.2361***	0.0122	0.2788***
	(1.16)	(20.64)	(2.01)	(20.32)	(1.56)	(19.54)	(1.66)	(20.83)
$AI_{\text{Post-basic Education}}$	-0.0084	0.0674***	-0.0115	0.1432***	-0.0109	0.1412***	-0.0128	0.1491***
	(-1.62)	(6.96)	(-1.16)	(7.74)	(-1.14)	(7.95)	(-1.27)	(7.94)
%IBE	-0.0212***	-0.0228*	-0.0196***	-0.0193*	-0.0204***	-0.0309**	-0.0202***	-0.0198*
	(-4.03)	(-2.35)	(-3.70)	(-1.98)	(-3.92)	(-3.21)	(-3.83)	(-2.04)

t statistics in parenthesis. * p <0.05, ** p <0.01, *** p <0.001. Standard errors are calculated using Deltha-Method. The average marginal effects of socioeconomic variables are very similar to those obtained in Table (II.2). The accessibility index in distance is calculated using equation (II.5) at *estrato* level. The accessibility index in time is calculated using equation (II.6) at *distrito* level. The accessibility index in private time is calculated using equation (II.7) at *distrito* level. The accessibility index in public time is calculated using equation (II.8) at *distrito* level.Both indices, formal and informal, are included in the estimation.

Table II.A.8: Effects of job accessibility by labor status on probability of being salaried worker by gender considering different impedance functions and commuting cost
–Average Marginal Effects–

	Distance		Time		Private Time		Public Time	
	Men (1)	Women (2)	Men (3)	Women (4)	Men (5)	Women (6)	Men (7)	Women (8)
$AI_{power,\delta=-1}$								
AI_{Formal}	-0.0039	0.1033***	-0.0011	0.1734***	0.0006	0.1460***	-0.0038	0.1879***
	(-0.93)	(17.93)	(-0.17)	(19.59)	(0.11)	(19.52)	(-0.52)	(19.13)
$AI_{Informal}$	0.0314***	0.2236***	0.0358***	0.3088***	0.0311***	0.2558***	0.0346***	0.3244***
	(5.99)	(30.90)	(4.77)	(29.77)	(5.02)	(29.70)	(4.28)	(29.16)
%IBE	-0.0269***	-0.0359***	-0.0274***	-0.0349***	-0.0271***	-0.0486***	-0.0283***	-0.0421***
	(-3.64)	(-3.49)	(-3.69)	(-3.37)	(-3.72)	(-4.79)	(-3.84)	(-4.10)
$AI_{power,\delta\neq-1}$								
AI_{Formal}	-0.0035	0.0949***	-0.0051	0.1137***	0.0003	0.1644***	-0.0066	0.3762***
	(-0.89)	(17.45)	(-0.73)	(12.09)	(0.05)	(20.78)	(-0.47)	(19.65)
$AI_{Informal}$	0.0318***	0.2116***	0.0341***	0.2460***	0.0175**	0.2135***	0.0512***	0.5565***
	(6.40)	(30.96)	(4.34)	(22.87)	(3.17)	(27.90)	(3.60)	(28.50)
%IBE	-0.0260***	-0.0338**	-0.0296***	-0.0537***	-0.0287***	-0.0526***	-0.0288***	-0.0435***
	(-3.52)	(-3.28)	(-3.87)	(-5.04)	(-3.96)	(-5.19)	(-3.92)	(-4.24)
$AI_{exponential}$								
AI_{Formal}	-0.0107*	0.1014***	-0.0084	0.2164***	-0.0095	0.2014***	-0.0101	0.2182***
	(-2.42)	(16.56)	(-1.04)	(19.40)	(-1.26)	(19.10)	(-1.23)	(19.25)
$AI_{Informal}$	0.0225***	0.2125***	0.0271**	0.3589***	0.0212*	0.3211***	0.0265**	0.3635***
	(4.26)	(29.12)	(2.93)	(28.07)	(2.53)	(27.54)	(2.82)	(28.11)
%IBE	-0.0304***	-0.0468***	-0.0304***	-0.0452***	-0.0310***	-0.0601***	-0.0305***	-0.0492***
	(-4.16)	(-4.59)	(-4.13)	(-4.41)	(-4.29)	(-5.96)	(-4.18)	(-4.82)

t statistics in parenthesis. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Standard errors are calculated using Deltha-Method. The subsamples are unemployed individuals or salaried workers. The average marginal effects of socioeconomic variables are very similar to those obtained in Table II.3. The accessibility index in distance is calculated using equation (II.5) at *estrato* level. The accessibility index in time is calculated using equation (II.6) at *distrito* level. The accessibility index in private time is calculated using equation (II.7) at *distrito* level. The accessibility index in public time is calculated using equation (II.8) at *distrito* level. Both indices, formal and informal, are included in the estimation.

Table II.A.9: Effect of accessibility on the employment probability controlling for endogeneity and considering different job accessibility indices
–Average Marginal Effects–

	Distance		Time		Private Time		Public Time	
	Men (1)	Women (2)	Men (3)	Women (4)	Men (5)	Women (6)	Men (7)	Women (8)
$AI_{power,\delta=-1}$	0.0071	0.1166***	0.0147	0.1598***	0.0135	0.1315***	0.0063	0.1574***
	(0.91)	(10.13)	(1.23)	(9.18)	(1.36)	(9.02)	(0.48)	(8.33)
%IBE	0.0292*	-0.0690***	0.0312*	-0.0739***	0.0305*	-0.0891***	0.0268*	-0.0862***
	(2.17)	(-3.48)	(2.30)	(-3.70)	(2.32)	(-4.60)	(2.00)	(-4.37)
$AI_{power,\delta\neq-1}$	0.0088	0.0936***	0.0244*	0.1654***	0.0069	0.1005***	0.0120	0.2882***
	(1.40)	(10.08)	(2.32)	(10.91)	(0.92)	(9.21)	(0.50)	(8.19)
%IBE	0.0319*	-0.0682***	0.0414**	-0.0311	0.0285*	-0.0885***	0.0269*	-0.0875***
	(2.37)	(-3.43)	(2.88)	(-1.47)	(2.17)	(-4.58)	(2.01)	(-4.44)
$AI_{exponential}$	-0.0041	0.1073***	-0.0002	0.1787***	-0.0020	0.1681***	-0.0045	0.1676***
	(-0.54)	(9.78)	(-0.02)	(9.56)	(-0.17)	(9.76)	(-0.34)	(8.80)
%IBE	0.0217	-0.0777***	0.0243	-0.0759***	0.0236	-0.0877***	0.0227	-0.0856***
	(1.63)	(-3.96)	(1.81)	(-3.85)	(1.81)	(-4.56)	(1.70)	(-4.37)

t statistics in parenthesis. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Standard errors are calculated using Deltha-Method. The subsamples are household members who are not head of household or spouse. The average marginal effects of socioeconomic are very similar to those obtained in Table II.4. The accessibility index in distance is calculated using equation (II.5) at *estrato* level. The accessibility index in time is calculated using equation (II.6) at *distrito* level. The accessibility index in private time is calculated using equation (II.7) at *distrito* level. The accessibility index in public time is calculated using equation (II.8) at *distrito* level.

Chapter III

Neighborhood effects and informal employment

Abstract

Residential segregation may affect access to labor market opportunities as well as job quality for individuals living in poor neighborhoods. We found that in the Metropolitan Area of Mexico City, residential segregation has negative effects on labor force participation for married women, while living in a deprived neighborhood decreases the probability of being a formal worker for men. Formal and informal job accessibility only affects less educated workers. Social interaction effects and strong social network ties (family network) have different effects on job formality depending on the composition of the members of neighborhood or household in terms of their job status, namely formal or informal. If the majority of members are formal workers, the probability of being a formal worker increases, but if the majority of members are informal employers, this probability decreases.

Key words: Neighborhood effects, informal employment.
JEL-Code: R23, J46.

III.1 Introduction

Residential segregation refers to the territorial agglomeration of households that belong to the same social group defined in terms of socioeconomic status and ethnicity, among other factors. Segregation per se is not a problem in the urban development of a city; it has both advantages and disadvantages. Some disadvantages of residential segregation appear when it increases the physical separation between residences and job places, worsens social networks or generates negative neighborhood effects in poor areas. The agglomeration of poor individuals in some neighborhoods may decrease their job opportunities and determine the quality of employment and/or social networks as well as their human capital. For these reasons, it is difficult for these individuals to access the labor market and good jobs. There is both theoretical and empirical evidence of the negative effects of living in poor neighborhoods on individuals' economic and social outcomes. The reason behind these negative effects is the existence of what are called neighborhood effects, which are defined as the influences of social interaction on the behavior or outcomes of individuals Dietz (2002). The mechanisms behind neighborhood effects are summarized in Jencks and Mayer (1990), Dietz (2002), Durlauf (2004) and Galster (2012).

Most studies of residential segregation in American and European cities have focused on racial or ethnic segregation. However, in most Latin American cities this kind of segregation does not appear to be predominant (Rodríguez 2001 and 2008; Sabatini, 2006; Groisman and Suárez, 2006). In Latin America, particularly in Mexico, there are clear patterns of residential segregation in socioeconomic terms (Graizbord et al., 2003; Rodríguez, 2008; Vilalta-Predomo, 2008). However, very few studies have analyzed the relationship between residential segregation and labor market outcomes in Latin American cities. Gray-Molina et al. (2003) found that living in a segregated neighborhood decreases individual income in Bolivian cities. Sánchez-Peña (2008) found an association between residential segregation and job instability, but she found no relationship between residential segregation and informal employment in Mexico City. Groisman and Suarez (2010) found that individuals living in segregated zones have a lower probability of being employed and working in a good-quality job in some peripheral zones of Greater Buenos Aires. They also observed that living in segregated zones has effects on wages. Those who reside in deprived neighborhoods earn less than those who live in non-segregated zones. Likewise, Pero et al. (2005) found that living in a favela diminishes wages in Rio de Janeiro. However, none of them attempted to disentangle or analyzed the mechanisms behind neighborhood effects that affect employment or informal employment. Furthermore, these papers did not consider or properly consider endogeneity issues.

This chapter attempts to fill these gaps for Mexico City. First, we analyze how the probability of being employed and the probability of being a formal or informal worker are affected by residential segregation. We take into account three mechanisms through which segregation and urban structure can affect those probabilities. The first mechanism is the contextual or exogenous effects of living in a segregated neighborhood. The second mechanism is the effect of job accessibility. The last mechanism is strong family ties and endogenous effects. Secondly, we examine the endogeneity problem that arises principally from sorting with a set of instrumental variables. Finally, we analyze neighborhood effects separately by gender and educational level because women and less educated workers have higher spatial constraints in terms of residential location and commuting.

We find that spatial variables such as a social deprivation index and a job accessibility index better explain women's probability of being employed, whereas these variables better explain men's probability of being a formal worker. Additionally, our spatial variables have stronger effects on less educated individuals. Social interaction effects, measured by formal and informal worker densities and strong social network ties (or family network ties), determine the job formality of both men and women. Meanwhile, job accessibility only determines the job formality of less educated individuals. There is a stronger negative relationship between job formality and residential segregation when endogeneity is controlled for in both men and women in Mexico City.

The rest of the chapter is organized as follows. In Section III.2, we present a brief literature review of neighborhood effects on labor market outcomes. In the next section, we briefly describe several measures of residential segregation and its patterns in Latin American cities, particularly in the Metropolitan Area of Mexico City (MAMC). Section III.4 presents the econometric model and discusses identification and endogeneity problems of social interaction models. Section III.5 displays the results of two probit models: the first is the probability model of being employed and the second is the probability model of being formal worker. Finally, conclusions are given in Section III.6.

III.2 Literature review

III.2.1 Theoretical background

The literature on neighborhood effects has studied the relationship between residential segregation and labor market outcomes. Neighborhood effects are defined as the impact of neighborhood characteristics and/or social interactions on individual behavior and/or results (Dietz, 2002). In other words, neighborhood effects are influences of the socioeconomic composition of a neighborhood on the individuals living in that neighborhood. In terms of the labor market, there are several mechanisms that explain how these effects may affect access to labor market as well as job quality.

The first mechanism states that neighborhood effects influence the acquisition and formation process of human capital (Arnott and Rowse, 1987; Wilson, 1987; Jencks and Mayer, 1990; Benabou, 1993). Peer group effects, social contagion, role models and the provision of social and educational services determine the acquisition of human capital. The lack or low quality of social and educational services in poor eighborhoods diminishes individuals' human capital. The second mechanism is attitudes and habits towards work (Wilson, 1987), which can be positive or negative and affect individuals' productivity. These attitudes are also guided by peer group effects, role models and access to opportunities. The third mechanism is the dissemination of and access to job opportunities (Ioannides and Loury, 2004; Topa, 2001; Bayer et al., 2008). Social networks, the availability of transportation modes and suitable jobs increase both dissemination and access to job opportunities. The last mechanism is employer discrimination, which reduces job opportunities because employers refuse to hire workers living in deprived neighborhoods (Zenou and Boccard, 2000; Permentier et al., 2007; Jacques and Walkowiak, 2009). That is, there is a stigmatization process of certain neighborhoods that decreases job opportunities and affects the attitudes of the individuals living in those neighborhoods.

The first and second mechanisms have been explained by role model or collective socialization and social interaction models. These models posit that not only do residents' good or bad influences or actions in a neighborhood affect the decisions or behaviors of the individuals living in the same neighborhood (Jencks and Mayer, 1990), but they also affect individuals' preferences, information and outcomes. In other words, these models explain why social decisions (such as educational attainment, marriage, childbearing and crime) are not only individual choices and have effects on an individual but also generate externalities. Likewise, others? actions influence individual actions via constraints, expectations and preferences (Manski, 2000).

The third and fourth mechanisms have been theoretically studied through the analysis of spatial disconnection and social networks. The literature related to spatial disconnection explains various mechanisms that relate job accessibility and labor opportunities, as summarized in Ihlanfeldt (2005) and Gobillon et al. (2007). These mechanisms are grouped into three types, namely supply, demand and social network mechanisms. Meanwhile, the literature specialized in social networks explains that the effect of social networks on job searches, wages, the length of unemployment and job quality depends on both the quality and quantity of the networks, as well as on the efficient use of contacts to obtain information, and individuals' socioeconomic, physical and ethnic proximity (Elliott, 1999; Ioannides and Loury, 2004; Pellizzari, 2010), as well as the type of ties (Granovetter, 1995; Montgomery, 1991).[1] Similarly, the shape or structure of the network determines the labor market outcomes because this shape explains how information is transmitted (Burt, 2000; Calvo-Armengol and Jackson, 2004). For instance, a redundant network does not generate more information.[2] Finally, labor status or type of occupation influences the information flow (Conley and Topa, 2002). For example, if one's personal contacts are unemployed, they will not have information about job vacancies. Moreover, if they are unemployed and have information about job vacancies, they will not have the incentives to share that information.

III.2.2 Empirical evidence and observational data studies

From a methodological standpoint, Manski (1993) identified three types of neighborhood effects: endogenous, exogenous or contextual, and correlated. These neighborhood effects explain why individuals who belong to the same group behave similarly. Endogenous effects are direct influences of average group behavior on individuals, also called social externalities or feedback effects. Exogenous or contextual effects refer to influences of exogenous group reference characteristics (such as racial or religious composition). Correlated effects arise from exposure to common or institutional factors through sorting or self-selection into a reference group. In a neighborhood, they originate from residential choice. Finally, Dietz (2002) incorporates other neighborhood effect related to public spillovers or public externalities. This effect arises from interaction among neighborhoods. All of these effects are methodologically difficult to disentangle.

Empirical studies of neighborhood effects on employment can be divided into four categories: observational, experimental or quasi-experimental, correlated, and aggregated data studies (Durlauf, 2004). In turn, these studies can be divided between those that analyze the long-term effects of growing up in a deprived neighborhood and those that investigate the current effects (Galster et al., 2008). This paper uses observational data and analyses the current effects of living in a deprived neighborhood.

Some empirical studies of neighborhood effects find a negative relationship between living in a poor or deprived neighborhood and labor market outcomes (O'Reagan and Quigley, 1998; Vartanian, 1999; Korsu and

[1] A tie is defined by a combination of time, emotional intensity, mutual confidence and reciprocity (Granovetter, 1973). According to this definition, these ties are classified into strong and weak. Strong ties include close friends and family, whereas weak ties comprise acquaintances, coworkers and neighbors, among others.

[2] A redundant network refers to a network in which everyone knows each other, and no one has a connection with members of other groups.

Wenglenski, 2010; Bayer and Ross, 2009; Bauer et al., 2011). However, other studies observe no neighborhood effects or very weak ones (Oreopoulos, 2003; Dujardin and Goffette-Nagot, 2010). With respect to social networks, the empirical evidence is no conclusive (Ioannides and Loury, 2004). Some authors detect positive impacts on wages (Marmaros and Sacerdote, 2002) and short periods of unemployment duration (Bentolila et al., 2010); whereas other studies suggest that one's social networks used may lead to either positive or negative results (Pellizzari, 2010). Some of these papers explain that the effect of a social network depends crucially on individual characteristics and the use of this network by firms or workers. The effect of a social network is significant when the network is made of individuals who are similar in terms of their educational level or income (Galster et al., 2008).

The studies that analyze the relationship between residential segregation and labor market outcomes in Latin American cities find negative neighborhood effects on wages, employment and job quality (Gray-Molina et al., 2003; Pero et al., 2005; Sánchez-Peña, 2008; Groisman and Suarez, 2010). Contreras et al. (2007) found that social networks increase the probability of being employed and being a salaried worker, in the case of Bolivia. However, none of these studies attempts to disentangle or analyze the mechanisms behind neighborhood effects that affect employment or job formality. These papers do not approach or do not properly approach endogeneity issues. For instance, Sánchez-Peña (2008) finds a positive relationship between residential segregation and precarious jobs in the case of Mexico City. However, she does not find a relationship between residential segregation and informal employment. This may be due to the fact that she does not control for sorting bias. The aim of this paper, unlike Sánchez-Peña (2008), is to identify some neighborhood effects, addressing endogeneity or sorting bias through a set of instrumental variables. Finally, we analyze these effects separately by gender and educational level.

As regards observational studies, they use individual samples and a wide range of neighborhood variables (Corcoran et al., 1992; Rivkin, 2001; Weinberg, 2004). These studies can be classified into those that exploit the variation of intra-city segregation to estimate neighborhood effects and those that exploit the variation of segregation across cities. This paper analyses intra-city neighborhood effects in Mexico City.

Some studies use average neighborhood measures such as the unemployment rate, poverty measures (poverty line), and social or racial composition indices as proxies of residential segregation. Other studies build indices with a principal component analysis or factorial analysis which combine several variables such as poverty rate, mean income, percentage of households that receive public or social assistance, percentage of adults with basic education, unemployment rate, and the percentage of housing with certain characteristics (such as overcrowding), among others. These proxies of residential segregation are included in linear regression or panel data models. The dependent variable can be the mean wage and labor hours, among others. Other papers estimate binary choice or unemployment duration models, while yet other papers apply multilevel, semi-parametric and non-parametric models (McCulloch, 2001). We use a social deprivation index (*SDI*) as a proxy of residential segregation, since socio-economic segregation is a multidimensional phenomenon that comprises poverty, lack of urban infrastructure and exclusion, among other factors. We estimate two probit models, one on labor force participation and other on job formality, because the relevant mechanisms behind neighborhood effects may be different in each probability.

Observational studies have identification problems between contextual and endogenous effects, as well as non-observed heterogeneity and self-selection (Durlauf, 2004). These problems have been approached by panel data estimation with fixed effects or variables in differences (Bolster et al., 2007). Another approach is instrumental variables (Vartanian, 1999). Some instrumental variables used frequently are intra-metropolitan variations, political factors and topographical variables (Cutler and Glaeser, 1997; Weinberg, 2000 and 2004; Ross and Zenou, 2008). Other authors estimate residential choice through structural equations or control functions (Ross, 1998; Bayer and Ross, 2009; Dujardin and Goffette-Nagot, 2010; Bauer et al., 2011). Structural equations are estimated with hedonic price models, or with dichotomous variables that measure the probability of living in a deprived neighborhood. On the other hand, samples of youth have been used to approach sorting. Residential relocation is expected to be less likely for youth than for adults (Cutler and Glaeser, 1997). Other samples include households that have not moved residence. Another method is to construct a counterfactual and compare the results of two workers that work in the same census track (same reference group), but one individual lives in this census track and the other lives in another census track (Bayer et al., 2008). Finally, some of these studies combine the literature of spatial disconnection with the literature on neighborhood effects (Dawkins et al., 2005; Dujardin et al., 2008; Korsu and Wenglenski, 2010). This paper accounts for spatial disconnection through the job accessibility index explained in Appendix A, which approaches endogenity issues through instrumental variables, because we have neither prices of dwellings to estimate structural equations nor panel data. Moreover, since Mexico City covers an extensive area, it is possible to have enough variability in topographical variables, which will be used as instruments of our neighborhood variables as explained later.

III.3 Residential segregation and labor informality

III.3.1 Latin America

In Latin America, both segregation indices and poverty measures have been used to identify residential segregation. Segregation indices are obtained not only in ethnic terms (Gray-Molina et al., 2003) but also in socioeconomic terms such as income, employment status, migratory status and educational level, among others (Kaztman and Retamoso, 2005; Groisman and Suárez, 2006; Monkkonen, 2012).[3] These indices and poverty measures indicate that most Latin American cities are highly residentially segregated. There are studies of residential segregation for several Latin American cities, such as the Metropolitan Area of Sao Paulo (Torres, 2004), Greater Buenos Aires (Groisman and Suárez, 2006), Cordoba (Tecco and Valdes, 2006), Greater Montevideo (Kaztman and Retamoso, 2005), Bogota (Aliaga-Linares and Alvarez-Rivadulla, 2010), the Metropolitan Area

[3] In Latin America, there is both socioeconomic and ethnic residential segregation. However, as indigenous and black individuals are usually the poorest individuals, they are also socioeconomically segregated in terms of residence. Moreover, the ethnic dimension is not the main determinant of residential segregation (Telles, 1994).

of Lima (Peters and Skop, 2007), and several cities in Mexico (Monkkonen, 2012) and Chile (Sabatini et al., 2001; Rodríguez, 2001), among others.

In general, this segregation is characterized by two patterns. The first is the concentration of high-income or wealthy households in city center and the closest peripheral zones that are well-connected to the central business district (*CBD*) through the road network. The second is the large share of poor households that are located in peripheral zones where there is a lack of urban infrastructure, whereas a lower percentage of them is concentrated in deprived zones near the center (Sabatini, 2003).

Some authors point out that the current patterns of residential segregation in some Latin American cities have their roots in the Colonial period (Roitman and Giglio, 2010; Sheinbaum, 2010). During the Colonial period, most affluent citizens lived in the city center, whereas the indigenous people were displaced towards the periphery. The Spanish Indies Code prohibited the indigenous and other castes from living in the city center. After the independence, this tendency remained unchanged. The same pattern persisted as cities expanded; that is, the wealthy households remained in the center whereas poor households occupied the new peripheries. The arrival of the railway and public transportation, the new industrial settlements and the new residential areas at the beginning of the 20th century transformed the cities. The wealthy households started to move to the best peripheral zones in terms of accessibility and amenities. Simultaneously, some places at the center became community residences, namely *vecindades* or *conventillos*, for poor households.

The fast growth of the main Latin American cities started during the import substitution period. Both the population and area of therse cities increased rapidly due to the rural migration. Most of these migrants had to settle illegally in places with poor conditions (steep, rocky slopes of volcanos and drained lakes, among others) because of publicly-subsidized dwellings and available land. In the last four decades, the growth of many Latin American cities can mostly be explained by the natural growth of the urban population rather than by rural migration. However, the residential location patterns of wealthy and poor households have not changed. The lack of effective housing policies and planning has left the market as the only mechanism to explain the location patterns in these cities.

There is no empirical evidence of the effects of residential segregation on informal employment in Latin American cities, despite of the fact that according to the International Labor Organization (*ILO*) around fifty percent of workers are not covered by social-protection schemes in Latin America. Moreover, some studies for Latin American cities show at a descriptive level that there may be a relationship between residential segregation and informal employment (Sabatini, 2003; Sánchez-Peña, 2008). Other papers find a relationship between individual poverty and informal employment (Devicienti et al., 2009). Finally, some authors posit that unemployment and informal employment determine residential segregation (Piedade-Morais et al., 2003; Kaztman and Retamoso, 2005).

III.3.2 Mexico City

We identified patterns of residential segregation in socio-economic terms by using a social deprivation index (*SDI*). This index indicates the zones with high levels of poverty or deprivation (high SDI). SDI is a multidimensional poverty measure calculated with the UBNM. We constructed this index at neighborhood level by using the methodology proposed by The National Council for Evaluation of Social Development Policy (*CONEVAL*) for the whole country. This methodology uses the proportions of different variables such as education, social security, dwelling characteristics and durables goods (detailed indicators are presented in Table A.1.1 of Appendix A). We calculated these proportions at *estrato* level using the 2010 Population and Housing Census data at census track level. The *estrato* is the smallest geographical unit that we can use to identify individuals' residence in the 2010 Population and Housing Micro Census. As an *estrato* can be a census track or a group of census

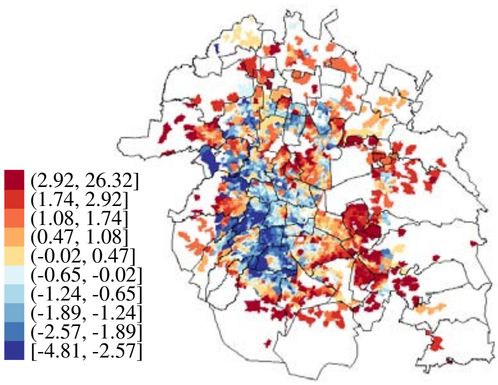

Figure III.1: Social deprivation index per *estrato*

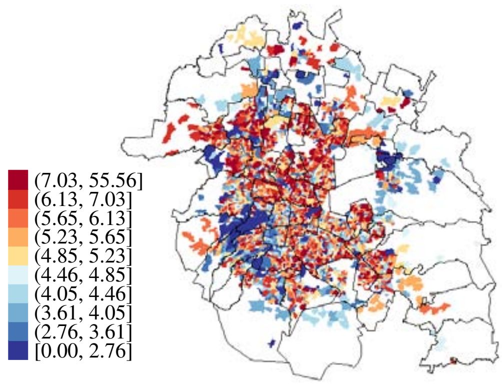

Figure III.3: Unemployment rate per *estrato*

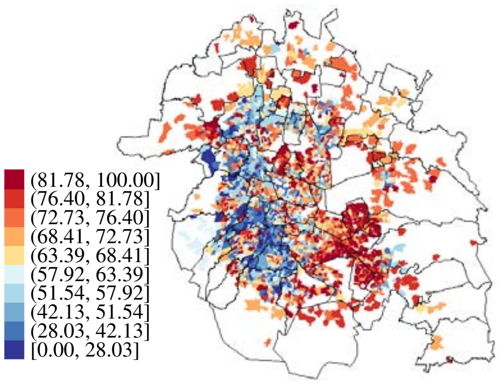

Figure III.2: Percentage of workers whose income is less than three minimum wages per *estrato*

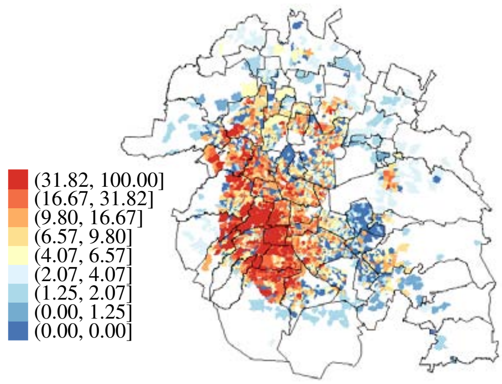

Figure III.4: Percentage of households whose per-capita income is 90 decile of income per *estrato*

Source: Elaborated with data of the Population and Housing Census 2010

tracks, we add these variables at census track level to build *estrato* measures.[4] The index was constructed using principal component analysis. In other words, the index is a weighted sum by the greatest eigenvalue associated with the eigenvector of the covariance matrix of variables.

Instead of using a poverty line to identify poor households, we prefer the SDI because it captures an important

[4]The estrato's mean area is 0.43 km^2 and its mean population is 4,103.

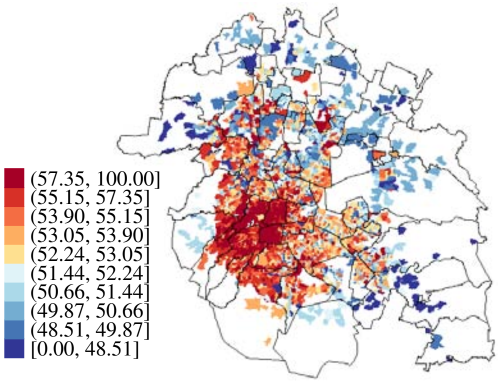

Figure III.5: Employment rate per *estrato*

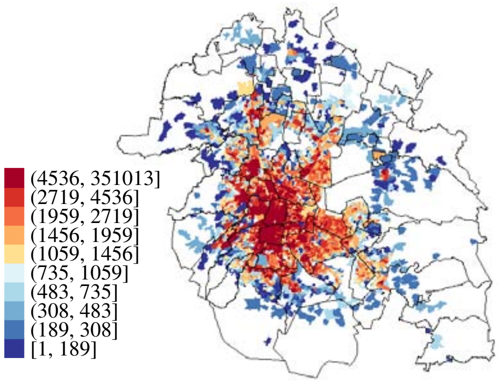

Figure III.6: Jobs density per *estrato* (km^2)

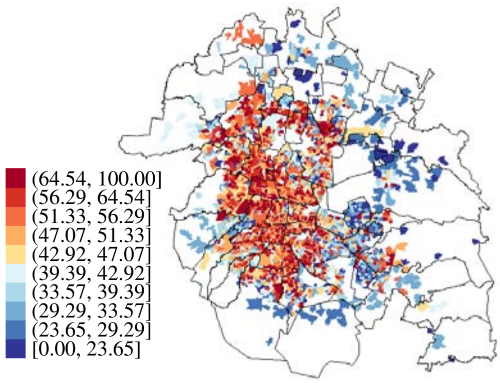

Figure III.7: Percentage of formal workers per *estrato*

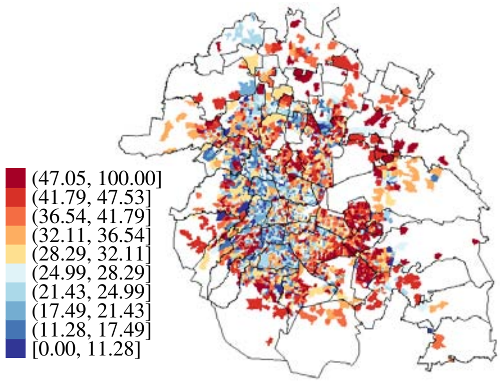

Figure III.8: Percentage of informal workers per *estrato*

Source: Elaborated with data of the Population and Housing Census 2010 and the Economic Census 2009

issue in Latin American cities, namely informal dwellings and settlements. Informal dwellings and settlements include those places that do not meet basic standards or safety norms in building and land use regulations, and land that is occupied illegally. Moreover, the SDI captures other socioeconomic characteristics that may indicate a zone's degree of deprivation. As explained in previous chapter, other authors use the unemployment rate as a proxy of residential segregation. However, in the case of Mexico City we did not use the unemployment rate to identify residential segregation because we did not observe a clear pattern of spatial concentration of unemployment rates. The only observed pattern is that the wealthiest areas have the lowest unemployment rates (see Figure III.3 and Figure III.4). This is confirmed by the low Moran's I of the unemployment rate for the study area (see Table III.B.2 of Appendix III.B).

Just like Rodríguez (2008), Vilalta-Predomo (2008), Pérez and Santos (2011), and Monkkonen (2012), among others authors, we concluded that there is a high level of residential segregation in Mexico City. Figure III.1 depicts the evident pattern of residential segregation. The most deprived zones (high SDI) are concentrated in the periphery of the city, whereas the wealthiest zones are located in the center and west of the city (Figure I.1 of Chapter I shows the MAMC and its central business district or CBD). The lowest indices correspond to zones with high-income households (see Figure III.4), whereas low-income households dwell in zones with high SDI (see Figure III.2). Moreover, the Moran's I clearly revels the existence of spatial correlation in our measure of residential segregation (see Table III.B.2 of Appendix III.B).

Higher employment rates are concentrated in the center and west of the city, where the wealthiest households reside (see Figures III.5 and III.4, respectively).[5] The lowest employment rates are located on the edge of the city where the highest deprivation scores are and where most of the poor households live (see Figures III.5, III.1 and III.2, respectively). These facts may give some initial descriptive evidence of a relationship between residential segregation and individual labor force participation.

In the study area informal workers account for 30% of total employed individuals, and most of these informal workers reside in the periphery of the city. As Figure III.8 shows, the highest proportion of informal workers is also located in the peripheral zones. Moreover, this concentration matches to the most deprived zones, as Figures III.1 and III.8 illustrate. Meanwhile, the highest proportion of formal workers is located in the center and west of the city (see Figure III.7). These facts clearly show a correlation between residential segregation and individual labor status (formal vs informal).

Another interesting fact that may affect both the probability of being employed and the probability of being formally employed is the spatially uneven distribution of jobs (see Figure III.6). It should be noted that the distribution of formal and informal jobs is also spatially uneven. Formal jobs are more concentrated in the city center while informal jobs are widely dispersed. Seven central municipalities account for 57% of total formal employment and 41% of total informal employment (2010 Population and Housing Census and 2009 Economic Census). The location pattern of employment and its strong relationship with our segregation measure raises a question that should be answered: What part of labor market outcomes is due to segregation effects and what part to job accessibility differentials across the metropolitan area?.

III.4 Model and variables

III.4.1 Empirical strategy

As we explained in the previous section, there may be evidence that residential segregation or urban structure affects both the probability of being employed and the probability of being a formal worker in the MAMC. To analyze the causal effects of living in a segregated neighborhood on both probabilities, we estimated a standard discrete choice model of social interaction for each probability, which has the following specification:

$$\begin{aligned} \Pr(y_i = 1 \mid \mathbf{x}_i, \mathbf{z}_{ig}) &= h(\beta \mathbf{x}_i + \theta \mathbf{z}_{ig} + \gamma m_{ig} + \epsilon_{ig} > 0) \\ &= \Phi(\beta \mathbf{x}_i + \theta \mathbf{z}_{ig} + \gamma m_{ig}) \end{aligned} \tag{III.1}$$

where i is an individual, g is a neighborhood, and $\Pr(y_i = 1 \mid \mathbf{x}_i, \mathbf{z}_{ig})$ is the conditional probability of being employed or being a formal worker given some explanatory variables $\mathbf{x}_i$ and $\mathbf{z}_{ig}$. $\mathbf{x}_i$ are observable individual characteristics, $\mathbf{z}_{ig}$ are observable neighborhood characteristics or contextual effects, m_{ig} is the average choice

[5]The employment rate is defined as the number of resident workers over the working age population.

of reference group that directly affects individuals or endogenous effects, and ϵ_{ig} is the error term. The error term follows a structure that includes three elements:

$$\epsilon_{ig} = \psi_i + \tau_g + u_{ig}, \tag{III.2}$$

where ψ_i captures unobservable individual characteristics, τ_g captures unobservable neighborhood characteristics, and u_{ig} is the idiosyncratic error term.[6]

In both models, we include several socioeconomic variables as individual characteristics. These variables are age and squared age (*Age*^{2}), years of education (*Education*), if the individual is head of household and marital status. We introduced the number of children under 12 years old in the household (*Child*$_{12}$) in the probability model of being employed, because the childbearing time competes with working time, especially for women. We also include the household income in this probability. Moreover, dummy variables on type of occupation and economic sector were introduced in the probability model of being a formal worker. Finally, we introduced the inverse Mills ratio in the probability of being a formal worker to control for the possibility of sample selection bias. The selection equation includes the same socioeconomic variables as the probability model of being employed. The number of children in the household under 12 and the household income are the exclusion restrictions. We exclude the spatial variables that we will refer to below for the selection equation.

Another group of variables that we included in both probabilities is strong social network ties or family network ties. We included the number of workers in the household (*WH*) in the probability of being employed. This variable is a proxy of the closest contact that an individual has to be hired (Wahba and Zenou, 2005). Meanwhile, we used the percentage of formal and informal workers in the household (*%WH*$_F$ and *%WH*$_I$, respectively) as proxies of strong social network ties or family network ties in the probability model of being a formal worker. The more formal workers are in the family, the higher the probability of being a formal worker because the individual has more information about formal jobs than about informal jobs. To the contrary, if there are more informal workers in the household, an individual will have less information about formal jobs and the likelihood of being formal will be lower.

Urban structure can affect employment and job formality via accessibility to job opportunities; therefore, we introduced an accessibility index (AI) in the probability of being employed and two accessibility indices by labor status, either formal or informal (*AI*$_F$ and *AI*$_I$, respectively), in the probability of being a formal worker. These indices measure the access to job opportunities and were calculated with an equation proposed by Shen (1998); the calculus of job accessibility is presented in Appendix A. We used the social deprivation index (*SDI*) as a proxy for residential segregation. Finally as a proxy of social interaction effects, we introduced two density measures in the probability of being a formal worker.[7] One is formal worker density (*Den*$_F$) and the other is

[6]However, we cannot identify the unobservable individual characteristics because we do not find a good instrument that varies by each individual.

[7]We do not introduce a proxy variable for social interaction effects in the probability of being employed, because the sample includes employees and self-employees. These individuals create their own jobs and they do not need other workers to obtain information on vacancies. These individuals are less likely to use neighborhood contacts such as employed neighbors to start a new business. Moreover, we introduced the employment rate as a proxy for social interaction effects in this probability, and this variable was not significant when

informal worker density (Den_I). These densities are the total number of formal or informal workers minus family members of the corresponding individual that work in formal or informal jobs, respectively, divided by *estrato*'s area in ha.[8] The descriptive statistics of the variables are presented in Table III.B.3 of Appendix III.B.

We simultaneously introduced formal and informal job accessibility to disentangle different effects by labor status effects on the probability of being a formal worker. The relationship between these variables is strong and non-linear (see Figure III.A.1 of Appendix III.A). This non-linearity allows the effects of job accessibility to be disentangled; otherwise, if we introduce only one job accessibily, for example formal job accessibility, we will simply observe the net effect of both kinds of accessibility, and this effect may be positive or negative. Actually we expect that the more formal jobs in a zone the higher the probability of being a formal worker, whereas the more informal jobs the lower is this probability. If the nearest formal jobs have a higher effect than the nearest informal jobs, the net effect of job accessibility will be positive, if not it will be negative.

In order to capture these opposite effects we introduced both kinds of accessibility simultaneously. Moreover, because each job accessibility index measures a different type of job, if we had simply introduced one of the kinds of job accessibility, the coefficient would probably be biased.

In the case of formal and informal worker densities, we did not have this same identification problem because the correlation between both densities is low and the relationship between them is non-linear (see Figure III.A.2 of Appendix III.A). It is expected that the higher the formal worker density, the higher the probability of being a formal worker, and the higher the informal worker density, the lower this probability. This is due to the fact that if there are more formal workers in a zone, the individual will have more information about vacancies in formal jobs, and if there are more informal workers she will have less information about vacancies in formal jobs and more information about vacancies in informal jobs. Because each density measures a different type of information, we can disentangle how social interaction effects act depending on the type of worker, namely formal or informal.

III.4.2 Instrumental variables

Methodologically, social interaction models have identification problems disentangling contextual, endogenous and correlated effects. The correlated effects generate two types of bias in estimated coefficients. The first bias is due to self-selection within the reference group; in this case it is due to residential choice. This produces a correlation between observable neighborhood characteristics, $\mathbf{z}_{ig}$ (III.1), and unobservable individual characteristics, ψ_i (III.2). The second bias occurs when there is a correlation between observable and unobservable neighborhood characteristics, that is, a correlation between $\mathbf{z}_{ig}$ (III.1) and τ_g (III.2), respectively.

The existence of correlated effects indicates that unobserved characteristics determine both the residential

we addressed endogeneity issues. This may be due to the fact that there is a multicollinearity problem between employment rate, SDI and AI.

[8] Other variables were tried, like the percentage of formal and informal workers and the employment rate of formal and informal employment, but the results were not satisfactory due to the high level of multicollinearity with the SDI variable.

choice and the probability of being employed or a formal worker. In other words, either individual unobserved characteristics affect the probability of being employed or being a formal worker, or unobserved neighborhood characteristics, such as institutions that promote employment or job formality, influence both probabilities. Therefore, estimated coefficients of contextual and endogenous effects are biased; that is, the effects of SDI or job accessibility indices are biased, as are the coefficients of social interaction variables such as formal and informal workers densities.

We deal with the bias due to correlated effects by estimating a probit model with instrumental variables. These instrumental variables partially control for the endogeneity caused by self-selection and attempt to approximate the correlation problem between observed and unobserved neighborhood characteristics. The instrumental variables used include urban and topographical characteristics, socioeconomic composition and type of housing variables lagged ten years. We use the following topographical characteristics: altitude, six types of rocks, five climate regions and 34 combinations of types of soils and subsoils (see Figure III.A.3, III.A.4, III.A.5 and III.A.6, and Table III.A.1).[9] The tests for these instruments prove that they are relevant and exogenous as will be shown in the next section.

In Mexico City and in other Latin American cities, the residential location patterns of poor and wealthy households have been partially determined by natural geographical conditions, such as climate and the type of soil or rocks. For instance, a neighborhood in Mexico City called *Jardines del Pedregal* was developed in a zone where there were volcaniclastic igneous rocks. These rocks were used as amenities to construct a garden city for wealthy households (see Figure III.A.4). The type of soil determines the kind and growth of vegetation, due to the different soil nutrients and the climate influencing its growth. Lush vegetation is another amenity that wealthy households value. The best types of soil and climate for lush vegetation are located in the west of the city, where wealthy households reside. For instance, leptosols, found on hill slopes, are generally more fertile, and this type of soil is located in the western part of the city (see Figure III.A.6), while the temperate climate, which also favors the growth of vegetation, is also located in this part of the city (see Figure III.A.5).

Poor households, on the other hand, live in the worst places in terms of natural geographical conditions. These zones have inexpensive housing prices or have been occupied illegally. They are located in the highest steep rocky places or drained lakes.[10] The soil of drained salt lakes is sodic subsoil, which is located at the east of the city (see Figure III.A.6, solonchaks soils and sodic subsoils).[11] This soil combined with igneous extrusive rocks generates a unique soil in terms of its mechanical properties. This soil contains considerable amounts of water, high plasticity and a high compression index (Carreón-Freyre et al., 2003; Díaz-Rodríguez , 2006; Díaz-Rodríguez et al., 2009). These properties generate strain effects which cause foundation problems for high-rise and/or heavy buildings. Moreover, this combination triggers other problems such as subsidence and subsoil

[9]Other authors that have used geological variables as instruments are Rosenthal and Strange (2008) and Combes et al. (2010).

[10]For instance, the highest steep rocky areas correspond to felsic igneous rocks (see Figure III.A.4).

[11]The valley of Mexico is located in an ancient lake complex of five interconnected bodies of water: Zumpango, Xaltocan, Texcoco, Xochimilco and Chalco. In the 17th century, the decision was made to eliminate this lake complex. In 1976 the drainage was completed.

fracture, which has been worsened by groundwater extraction from deep aquifers and directly affects the urban infrastructure. This can be observed in several buildings and streets, which have cracks. The subsidence also generates flooding problems in some zones. Since Mexico City is located in seismic zone, the soil mechanics is more relevant because, as some authors claim, there is a relationship between high amplification and duration of earthquakes and the presence of the lake bed, or more precisely the presence of lacustrine clays (Flores-Estrella et al., 2007).[12] The soils that contain lacustrine clays are located at the eastern part of the city.

The relationship between urban infrastructure and firms' location decisions is well-documented theoretically and empirically (Alonso, 1964; Ihlanfeldt and Raper, 1990; McDonald and McMillen, 2006). In Mexico City, the mechanical properties of the soils have important consequences on urban infrastructure and firms' location decisions. Soil mechanics is relevant in the foundation of buildings and earthworks (such as embankments, tunnels, dikes and levees among others). For instance, it is impossible to construct high-rise office buildings in some areas of the city, especially in the east. The mechanical properties of soils are related to the parental material (main composition of soil) that is used to classify soils. As we do not have the mechanical properties of soils by zones, we used the types of soils as instrument of the neighborhood variables (i.e. social deprivation index, job accessibility index,and workers densities), because the type of soil affects the location of both companies and individuals. Moreover, we used the type of rocks, climate and altitude because these natural geographical conditions are amenities or disamenities that influence individuals' residential location decisions as well as firms' location decisions (Gottlieb, 1995). In other words, types of rocks, climate and altitude are mainly used as instrument of SDI and workers densities. These variables are biased by residential sorting. Types of soil are mainly instruments for job accessibility indices that are biased by firms' location decisions. All the topographical instruments are exogenous. The soils that correspond to drained lakes could be endogenous, but the lake was drained to prevent the flooding of the CBD and the drainage was completed in its entirety at least fifty years ago.

Other instruments that we used are socioeconomic variables and type of housing variables lagged ten years. The types of housing are apartments, houses and others.[13] We expected to find a larger number of apartments in the city center than in the periphery. It is more likely that high- and medium-income households live in apartments than poor households. Additionally, the percentage of type of housing lagged ten years indicates the predominance of one type of housing that affects the individuals' location decision. Therefore, we use this variable as instrument of SDI and worker densities. We also use the percentage of individuals who were born in the Federal District and the percentage of individuals who do not work and do not study (both lagged ten years) as instrument of SDI and workers densities. We expect that individuals who were born in the Federal District have historically lived in better places in terms of amenities and accessibility, or in the city center, than those who were born in the State of Mexico. We also expect that most of individuals that do not work and do not study live in low-income households and thus live in worse places because their opportunities are limited. Finally, another instrumental variable for SDI and workers densities are the percentage of city blocks with named streets. Illegal

[12]Mexico City is located in the subduction zone of the Pacific Ocean, where the Cocos plate subducts the North America plate.
[13]Other types of housing include *vencindades* and buildings that are unsuitable to live in.

dwellings are located in zones where there are streets with no name; these are the most deprived zones. Moreover, high- and medium-income households reside on blocks with named streets. These instrumental variables could be endogenous. However, some of them are lagged ten years and there is a low likelihood that these variables directly affect both probabilities. These variables are used as exclusion restrictions for the possibility of reverse causality, because they indicate patterns of residential location, but there are no mechanisms that explain how these variables could affect the probability of being employed or the probability of being a formal worker.

The structural parameters of contextual and endogenous effects was not identified in the probability model of being a formal worker.[14] We partially disentangled these effects through the separation between exclusively contextual effects and those that may be capturing both effects. As purely contextual effects, we introduced the social deprivation index and the job accessibility indices (formal employment and informal employment). As social interaction variables, we used the density of formal and informal workers. We included densities and accessibilities simultaneously in the probability of being a formal worker in order to disentangle the endogenous effects from contextual effect. Therefore, part of the contextual effect of densities is captured via job accessibility indices. However, there may be other contextual effects of densities that cannot be properly identified.

III.4.3 Data base

We used the 2010 Population and Housing Micro-census for the Federal District and the State of Mexico to analyze the neighborhood effects on both probabilities. The Micro-census is a sample of approximately 5% of the Population and Housing Census. This sample has a large number of observations and variables that allows different population groups to be analyzed, such as married women or less educated individuals. Our neighborhood variables can be integrated into this data base at the *estrato* level.

We used a first sample of men between 25 and 65 years of age (we assume that individuals have completed their studies at age 25). A second sample includes working-aged married women who are not heads of household.[15] The individuals are located at *estrato* level. The *estrato* can be rural, rural-urban and urban.[16] We only included the urban estrato in the sample in order to have a more homogeneous sample within the 56 municipalities in study area. The sample size of men is 172,265 individuals and the sample size of women is 107,795 individuals. We used married women who are not heads of household because they are a more homogeneous population group in terms of time and spatial constraints. Additionally, less educated individuals have more spatial constraints than other population groups. They cannot easily move residential location or commute because they have income constraints. Therefore, we estimated both probabilities by educational level. We divided the samples into individuals with basic education or less and individuals with post-basic education.[17]

[14]Brock and Durlauf (2007) establish the conditions to identify the parameters of endogenous and exogenous effects in a discrete choice model of social interaction.

[15]The sample includes employed and unemployed and inactive workers and excludes students, the disabled and retirees.

[16]An urban *estrato* is an *estrato* within a county with a population of 5,000 or more. There are 4,756 urban *estratos*

[17]Basic education requires nine years of education.

III.5 Results

III.5.1 Exogeneity and relevance of instrumental variables

All instrumental variables are exogenous and relevant because they do not affect both probabilities, but they do determine the location of both individuals and firms, or indicates some patterns of residential location. Moreover, we did not reject the overidentification test (see Tables III.1 and III.2). In general, the topographic instruments had the expected signs and were significant in the first stage equation. For instance, the altitude increases the SDI and decreases the job accessibility. Volcaniclastic igneous rocks diminish the SDI because wealthy households live in these zones. This type of rock is hard/strong and it is difficult to construct with. Felsic igneous rock positively affects the SDI and is located in the north of the city where poor households live. This zone corresponds to the highest steep, rocky places that we referred to in the previous section. The combination of soils with solonchaks soil and sodic subsoils increases the SDI and decrease the job accessibility indices, as we previously explained, these soils may have mechanical properties that generate foundation problems for high-rise and/or heavy buildings.

Table III.1: Instrumental variables and first stage statistics of probability model of being employed $-Pr(employed = 1)-$

	Full sample		Education			
			Basic		Post-Basic	
	Men	Married Women	Men	Married Women	Men	Married Women
Topographical characteristics						
Altitude	x		x		x	
Rocks types (6)	x(4)	x(3)	x(4)	x(4)	x(4)	
Soil types (34)	x(24)	x(14)	x(27)	x(17)	x(25)	x(15)
Climate regions (5)	x(3)	x(2)	x(3)		x(3)	
Socioeconomic characteristics lagged ten years (2000)						
% born in F.D.	x		x		x	
Type of housing (2000)						
% Apartments	x	x	x	x	x	x
% Houses	x	x	x	x	x	x
SDI						
Shea R^2	0.25	0.12	0.28	0.15	0.16	0.14
F statistics	3302.41	1605.52	1996.91	1115.24	1135.13	724.73
AI						
Shea R^2	0.48	0.35	0.49	0.34	0.30	0.39
F statistics	15841.69	10933.42	8824.37	5065.16	3871.18	4500.10
Cragg-Donald Weak identification test	1632.97	718.41	947.32	511.26	380.14	374.21
Sargan Test	39.62	25.25	44.89	27.59	32.99	19.78
	(0.20)	(0.15)	(0.15)	(0.15)	(0.52)	(0.18)
ALN Test	40.44	25.08	45.76	29.05	33.33	19.87
	(0.17)	(0.16)	(0.13)	(0.14)	(0.50)	(0.18)

t statistics in parenthesis. ALN Amemiya-Lee-Newey test. F.D. the Federal District.
Source: Population and Housing Census 2000 and 2010, and cartographic maps of National Institute of Statistics, Geography, and Informatics of Mexico.

The other instruments (socioeconomic composition and type of housing variables lagged ten years and percentage of city blocks with named streets) are significant and have the expected effects on endogenous variables. For instance, the percentage of apartments decreases the SDI, whereas the percentage of houses increases it. The

Table III.2: Instrumental variables and first stage statistics of probability model of being a formal worker
$-Pr(formal\ worker = 1)-$

	Full sample		Education			
			Basic		Post-Basic	
	Men	Married Women	Men	Married Women	Men	Married Women
Urban characteristics						
% block with street name	x	x	x	x	x	x
Topographical characteristics						
Altitude	x	x	x	x	x	x
Rocks types (6)	x(2)	x(2)	x(3)	x(2)	x(4)	x(4)
Soil types (34)	x(15)	x(17)	x(11)	x(24)	x(28)	x(25)
Climate regions (5)	x(2)	x(2)	x(4)	x(4)	x(4)	x(4)
Socioeconomic characteristics lagged ten years (2000)						
% born in F.D.	x		x		x	x
% do not work	x	x	x	x	x	x
Type of housing (2000)						
% Apartments		x	x	x		
% Houses				x	x	x
SDI						
Shea R^2	0.13	0.12	0.13	0.19	0.16	0.16
F statistics	2052.51	467.52	1829.74	218.57	827.27	240.48
AI_F						
Shea R^2	0.42	0.35	0.52	0.55	0.39	0.32
F statistics	6557.80	2893.51	4591.45	1135.16	3912.37	1353.90
AI_I						
Shea R^2	0.38	0.32	0.43	0.47	0.36	0.28
F statistics	7051.68	2711.23	5141.66	989.95	4419.74	1574.82
Den_F						
Shea R^2	0.09	0.11	0.07	0.10	0.13	0.13
F statistics	1756.38	444.92	1513.97	187.01	765.11	261.89
Den_I						
Shea R^2	0.11	0.11	0.10	0.14	0.11	0.10
F statistics	1171.25	184.29	803.41	109.49	273.71	90.64
Cragg-Donald Weak identification test	393.10	84.49	193.13	36.49	105.82	28.98
Sargan Test	24.48	25.35	24.12	39.73	45.89	41.92
	(0.14)	(0.15)	(0.15)	(0.14)	(0.15)	(0.14)
ALN Test	22.40	17.60	22.23	38.00	39.48	33.55
	(0.21)	(0.55)	(0.22)	(0.18)	(0.36)	(0.44)

t statistics in parenthesis. ALN Test Amemiya-Lee-Newey Test.
Source: Population and Housing Census 2000 and 2010, and cartographic maps of National Institute of Statistics, Geography, and Informatics of Mexico.

percentage of individuals who were born in the Federal District diminishes the SDI score and the percentage of individuals who neither work nor study increases it. Finally, the percentage of city blocks with named streets negatively affects the SDI.

As shown in Tables III.1 and III.2, all the instruments were relevant. The Shea R^2 and F-statistics are high by the usual standards; thus, the instruments are not weak. We also reject the null hypothesis that the instruments are weak according to the Cragg-Donald Weak identification test. The instruments used in each sample are different because the location decisions or location patterns are different in each group (see Tables III.1 and III.2). Likewise, the effect of sorting bias on each probability is different, because the samples are different in each probability. For instance, the sample used in the probability of being a formal worker is more homogeneous in terms of employment status because this sample only includes salaried workers.[18] The samples by educational

[18]Unlike, the sample used in the employment probability model, and included employers and self-employed.

level also are more homogeneous. The consistency of all instruments measured by the overidentification test changes with each sample. In other words, the relevance of every instrument is different in each sample, just as the effect of the set of relevant instruments is different in each endogenous variable. For instance, the semi-arid temperate climate has a negative effect on SDI for men with basic education, whereas this climate has positive effect on SDI for men with post-basic education. This is due to the fact that men with basic education who live in that climate are not the poorest within this group. Meanwhile, men with post-basic education who live in that climate are the poorest within this group.

Finally, we only partially control for the sorting bias. There is individual unobserved heterogeneity that we cannot address. However, we use the instrumental variable approach of Bayer and Ross (2009) to address the unobserved heterogeneity. They group the individuals into homogeneous cells which are constructed with individual and family attributes. We used the following individual attributes: sex, age (aggregated into 3 categories), marital status, three categories of educational level and if the person was born in the Federal District. As family attributes, we use the presence of children under 12 and the relative position of a member inside the family such as a head of household, spouse or child, among others. According to these attributes, identical individuals are grouped into 2,016 cells. The mean of observed neighborhood characteristics by cells was used as instruments of SDI, job accessibilities and worker densities. The mean was obtained excluding the individual and family. In other words, we calculate the average of SDI, job accessibilities and worker densities by cells, and these averages are instruments of these variables. The results using these instruments are presented in Table III.B.7 of Appendix III.B. They indicate that the bias that we cannot address is low. However, we reject the overidentification test for these instruments.

III.5.2 Probability of being employed

Tables III.3 and III.4 present the estimations of the probability of being employed by gender and level of education. These tables show that socioeconomic variables are significant and have the expected effects, except for the household income among men. This variable may capture family networks among men, because if we omit this variable in the estimation the coefficient of the number of workers in the household increases. The SDI has a negative effect on the labor force participation for married women when we address the endogeneity issues. Moreover, this effect is higher on less educated women.

Job accessibility has a positive effect on the probability of being employed. When we address endogeneity issues, its effect diminishes among married women, whereas its effect increases among men. The positive effect of job accessibility among men disappears when we divide the sample by level of education. However, job accessibility has a significance level of 0.052 in the estimation of men with basic education. The fact, that the effect of job accessibility increases when we address endogeneity among men, may due to residential sorting bias. Some individuals, who live near to CBD and have less SDI, have high unemployment rates. Because, they may have family support or own sources that allows them to stay unemployed for a little longer. On the other hand, some individuals, who live far away from CBD and have high SDI, have low unemployment rates. Because, they have to work in order to have income; and most of them are informal workers. These facts may attenuate the effect of job accessibility among men. The decrease of job accessibility's effect among women, when we address endogeneity, may due to multicollinearity problems. That is, instrumental variable estimation reduces multicollinearity between SDI and job accessibility in the women's estimation. Less educated men and married women have more spatial constraints that make residential mobility and/or commuting difficult; that is, they are more sensitive to local labor market conditions. Less educated individuals live far away from high employment zones; thus, they have fewer job opportunities.

Table III.3: Estimation results of probability of being employed for men
–$Pr(employed = 1)$–

	Full sample		Education			
			Basic		Post-basic	
	Probit	IV Probit	Probit	IV Probit	Probit	IV Probit
SDI	0.0005	0.0142	-0.0068	0.0094	0.0165*	-0.0219
	(0.10)	(1.39)	(-1.17)	(0.86)	(2.39)	(-1.35)
AI	0.0913	0.1723*	0.1029	0.2015	0.0946	-0.1065
	(1.93)	(2.27)	(1.55)	(1.94)	(1.70)	(-1.17)
WH	0.0406***	0.0399***	0.0335***	0.0329***	0.0463***	0.0498***
	(6.80)	(6.84)	(4.31)	(4.17)	(4.99)	(4.78)
Age	0.0283***	0.0284***	0.0265***	0.0265***	0.0283***	0.0277***
	(7.32)	(7.08)	(5.29)	(5.26)	(4.50)	(4.65)
Age^2	-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.0004***
	(-9.16)	(-8.82)	(-6.81)	(-6.71)	(-5.45)	(-5.61)
Education	0.0263***	0.0281***	0.0289***	0.0309***	0.0358***	0.0320***
	(18.21)	(14.53)	(9.61)	(9.49)	(9.77)	(9.10)
Head of household	0.4165***	0.4163***	0.3771***	0.3756***	0.4809***	0.4776***
	(30.60)	(29.36)	(21.50)	(19.82)	(21.39)	(21.68)
Married	0.2453***	0.2460***	0.2365***	0.2364***	0.2482***	0.2454***
	(18.81)	(18.24)	(13.64)	(13.15)	(12.17)	(12.56)
Child$_{12}$	0.0042	0.0033	0.0034	0.0017	0.0036	0.0037
	(0.61)	(0.47)	(0.42)	(0.20)	(0.29)	(0.32)
H. Income	0.0015**	0.0016**	0.0020*	0.0021*	0.0017*	0.0014*
	(2.61)	(2.74)	(2.03)	(2.20)	(2.23)	(1.96)
Constant	0.3754***	0.3120**	0.4413***	0.3703**	0.1924	0.3425*
	(4.38)	(3.13)	(3.85)	(2.88)	(1.38)	(2.42)
LR	2709.96	2707.23	1275.49	1277.43	1402.85	1636.95
Wald test		6.07		6.54		8.69
N	172,265	172,265	95,732	95,732	76,533	76,533

t statistic in parenthesis. * p <0.05, ** p <0.01, *** p <0.001. *t* statistics are calculated with cluster standard errors. LR, likelihood ratio

Finally, strong social network ties or family network ties determine the probability of being employed. The more workers there are in the family, the higher the probability of being employed.[19] In Mexico, most of the unemployed individuals find their jobs through friends and family. According to the 2010 ENOE, 60% of salaried workers found their jobs through friends, family members and acquaintances. This indicates that strong social network ties help individuals to find a job.

III.5.3 Probability of being a formal worker

Tables III.5 and III.6 show the estimations of the probability of being a formal worker by gender and level of education. Socioeconomic variables are significant and have the expected effects. Likewise, the dummy variables

[19]Family network ties has a significance level of 0.054 in the estimation of women with post-basic education.

of type of occupation and economic sector are significant and have the expected effects. The predominantly formal economic sectors are manufacturing, finance, electricity, water and gas, and government. The inverse Mills ratio indicates that there is sample selection bias for married women, but there is no sample selection bias for men. When we divide the sample by level of education, the number of years of education is not significant for women with post-basic education, and neither the age nor the squared age are significant for women with basic education. In other words, age simply affects labor force participation but does not determine the job formality among women with basic education. Likewise, education encourages labor force participation but does not affect the job formality among women with post-basic education.

Residing in a deprived neighborhood has a negative effect on the probability of being a formal worker among men. SDI has a significance level of 0.059 in the estimation of women with basic education. Most of highly educated, married, female workers live in neighborhoods with low SDI or wealthy neighborhoods. This group has the lowest average deprivation score (see Table III.B.3 of Appendix III.B); thus, SDI does not affect their probability of being a formal worker. Individuals with basic education have stronger negative effects of living in a deprived neighborhood (see Table III.B.5 of Appendix III.B). When we control for endogeneity, the SDI coefficient becomes more negative, which may explain why Sánchez-Peña (2008) did not find a relationship between residential segregation and informal employment in Mexico City. She did not address the sorting bias of the variable that measures residential segregation or analyze the neighborhood effects separately by gender and educational level.

The coefficients of the formal and informal job accessibility indices show the expected signs. Highly ac-

Table III.4: Estimation results of probability of being employed for women
$-Pr(employed = 1)-$

	Full sample		Education			
			Basic		Post-basic	
	Probit	IV Probit	Probit	IV Probit	Probit	IV Probit
SDI	0.0098*	-0.0546***	-0.0056	-0.0509***	0.0400***	-0.0454**
	(2.42)	(-5.11)	(-1.25)	(-4.19)	(5.66)	(-2.78)
AI	0.4474***	0.2135**	0.4796***	0.2286*	0.3470***	0.2005*
	(10.49)	(3.09)	(8.53)	(2.39)	(6.18)	(2.41)
WH	0.0339***	0.0393***	0.0416***	0.0457***	0.0170	0.0256
	(6.20)	(6.89)	(6.53)	(6.43)	(1.34)	(1.93)
Age	0.0865***	0.0868***	0.0916***	0.0917***	0.1012***	0.1010***
	(24.50)	(26.16)	(21.33)	(22.03)	(15.74)	(16.07)
Age^2	-0.0011***	-0.0012***	-0.0012***	-0.0012***	-0.0014***	-0.0014***
	(-28.18)	(-30.38)	(-24.73)	(-25.72)	(-18.05)	(-18.75)
Education	0.0644***	0.0538***	0.0179***	0.0112***	0.1310***	0.1187***
	(41.70)	(23.14)	(7.58)	(4.32)	(37.67)	(28.11)
Child$_{12}$	-0.1552***	-0.1496***	-0.1156***	-0.1113***	-0.2191***	-0.2118***
	(-27.29)	(-25.03)	(-17.16)	(-14.98)	(-24.83)	(-23.36)
H. Income	-0.0012***	-0.0016***	-0.0022***	-0.0026***	-0.0014***	-0.0020***
	(-4.12)	(-5.07)	(-3.45)	(-3.98)	(-4.02)	(-5.47)
Constant	-2.5328***	-2.2930***	-2.3740***	-2.1752***	-3.4760***	-3.2532***
	(-30.57)	(-25.80)	(-23.56)	(-19.31)	(-22.88)	(-21.43)
LR	4104.99	3831.00	1537.61	1414.98	2598.63	2491.11
Wald test		121.70		40.91		117.25
N	107,795	107,795	68,356	68,356	39,439	39,439

t statistic in parenthesis. * p <0.05, ** p <0.01, *** p <0.001. *t* statistics are calculated with cluster standard errors. LR, likelihood ratio.

Table III.5: Estimation results of probability of being a formal worker for men
$-Pr(formal\ worker = 1)-$

	Full sample		Education			
			Basic		Post-basic	
	Probit	IV Probit	Probit	IV Probit	Probit	IV Probit
SDI	-0.0094*	-0.0835***	-0.0083	-0.0602**	-0.0016	-0.0624***
	(-2.08)	(-3.94)	(-1.35)	(-2.66)	(-0.26)	(-3.67)
AI_F	0.4258**	1.1257***	0.8947***	0.9953***	-0.0613	0.1316
	(3.29)	(5.53)	(5.30)	(4.70)	(-0.38)	(0.52)
AI_I	-0.9199***	-2.4061***	-1.4525***	-2.8240***	-0.1800	-0.5626
	(-5.11)	(-7.89)	(-6.13)	(-9.06)	(-0.83)	(-1.52)
Den_F	0.0102***	0.0065***	0.0120***	0.0143***	0.0076***	0.0032*
	(21.42)	(3.80)	(21.54)	(5.81)	(13.10)	(2.30)
Den_I	-0.0122***	-0.0035	-0.0129***	-0.0056*	-0.0122***	-0.0048
	(-21.55)	(-1.43)	(-20.45)	(-2.16)	(-14.60)	(-1.58)
$\%WH_F$	0.4172***	0.4221***	0.4846***	0.4751***	0.3205***	0.3293***
	(30.59)	(30.15)	(26.14)	(23.81)	(17.89)	(18.24)
$\%WH_I$	-0.3748***	-0.3895***	-0.3300***	-0.3370***	-0.4535***	-0.4693***
	(-28.15)	(-28.04)	(-20.13)	(-19.93)	(-20.48)	(-20.17)
Age	0.0382***	0.0382***	0.0332***	0.0318***	0.0458***	0.0461***
	(9.58)	(9.57)	(6.19)	(5.80)	(7.51)	(7.49)
Age^2	-0.0004***	-0.0004***	-0.0003***	-0.0002***	-0.0005***	-0.0006***
	(-7.57)	(-7.47)	(-3.78)	(-3.43)	(-7.31)	(-7.43)
Education	0.0699***	0.0675***	0.0873***	0.0831***	0.0391***	0.0349***
	(28.82)	(21.88)	(20.12)	(18.32)	(8.11)	(6.81)
Head of household	0.1737***	0.1728***	0.1337**	0.1077*	0.2405***	0.2501***
	(5.93)	(5.64)	(3.21)	(2.56)	(5.52)	(6.20)
Married	0.1585***	0.1471***	0.0951**	0.0709*	0.2135***	0.2154***
	(7.05)	(6.46)	(2.85)	(2.13)	(6.83)	(7.25)
Executives						
Experts	-0.2900***	-0.2720***	-0.8908***	-0.8703***	-0.1874***	-0.1685***
	(-11.44)	(-10.15)	(-9.16)	(-8.88)	(-7.40)	(-6.35)
Technician	-0.2316***	-0.2232***	-0.5359***	-0.5302***	-0.2342***	-0.2167***
	(-9.48)	(-8.80)	(-8.59)	(-8.34)	(-8.64)	(-7.42)
Supervisors	-0.0215	-0.0180	-0.2489***	-0.2529***	-0.1078**	-0.0945*
	(-0.66)	(-0.54)	(-3.47)	(-3.50)	(-2.81)	(-2.39)
Workers	-0.4806***	-0.4701***	-0.7474***	-0.7384***	-0.5277***	-0.5109***
	(-20.88)	(-19.68)	(-12.59)	(-11.98)	(-21.19)	(-18.88)
Apprentices	-0.5357***	-0.5161***	-0.8051***	-0.7838***	-0.5963***	-0.5763***
	(-21.00)	(-18.71)	(-13.36)	(-12.48)	(-15.81)	(-13.56)
Manufacturing						
Commerce	-0.2839***	-0.2825***	-0.3148***	-0.3044***	-0.2465***	-0.2520***
	(-13.47)	(-13.57)	(-13.30)	(-13.23)	(-8.92)	(-9.12)
Services	-0.2661***	-0.2601***	-0.2495***	-0.2361***	-0.2878***	-0.2876***
	(-12.34)	(-11.50)	(-9.99)	(-9.28)	(-11.27)	(-10.97)
Financial	0.2721***	0.2759***	0.3458**	0.3520***	0.2758***	0.2664***
	(6.17)	(6.00)	(3.27)	(3.36)	(5.86)	(5.47)
Construction	-0.8366***	-0.8296***	-0.8763***	-0.8660***	-0.6467***	-0.6423***
	(-31.48)	(-31.12)	(-28.79)	(-29.13)	(-17.54)	(-17.98)
Electricity	0.5236***	0.5410***	0.5827***	0.5743***	0.4498***	0.4618***
	(7.22)	(7.35)	(6.23)	(6.13)	(4.37)	(4.46)
Transport	-0.6908***	-0.6965***	-0.7486***	-0.7533***	-0.5747***	-0.5756***
	(-25.59)	(-26.83)	(-25.26)	(-25.24)	(-16.06)	(-15.95)
Government	0.6167***	0.6385***	0.9151***	0.9269***	0.3553***	0.3665***
	(19.35)	(19.27)	(22.07)	(22.08)	(9.90)	(9.85)
I Mills Ratio	0.3021	0.2505	-0.3378	-0.5716	0.8142	0.8387
	(0.88)	(0.71)	(-0.65)	(-1.11)	(1.66)	(1.89)
Constant	-0.7969***	-0.4751**	-0.5506*	-0.0871	-0.4701*	-0.3592
	(-5.23)	(-3.15)	(-2.42)	(-0.37)	(-2.16)	(-1.71)
LR	14586.55	14788.83	9719.40	9716.06	4586.19	4147.33
Wald test		245.66		153.19		36.35
N	109,900	109,900	59,065	59,065	50,835	50,835

t statistic in parenthesis. * p <0.05, ** p <0.01, *** p <0.001. *t* statistics are calculated with cluster standard errors.
LR, likelihood ratio.

Table III.6: Estimation results of probability of being a formal worker for women
$-Pr(formal\ worker = 1)-$

	Full sample		Education			
			Basic		Post-basic	
	Probit	IV Probit	Probit	IV Probit	Probit	IV Probit
SDI	-0.0112	-0.0821***	-0.0260**	-0.0404	0.0138	-0.0290
	(-1.60)	(-4.21)	(-2.89)	(-1.89)	(1.36)	(-1.23)
AI$_F$	0.1982	0.5483	0.4715	1.1779**	0.1738	-0.6400
	(0.95)	(1.54)	(1.76)	(2.95)	(0.62)	(-1.38)
AI$_I$	-0.2233	-0.8305	-0.2105	-1.5650**	-0.2692	1.0346
	(-0.78)	(-1.63)	(-0.57)	(-2.76)	(-0.69)	(1.46)
Den$_F$	0.0111***	0.0052**	0.0125***	0.0109***	0.0093***	0.0040
	(14.63)	(2.92)	(12.35)	(3.59)	(10.14)	(1.86)
Den$_I$	-0.0131***	-0.0033	-0.0151***	-0.0052	-0.0125***	-0.0089
	(-12.77)	(-1.11)	(-11.34)	(-1.51)	(-8.43)	(-1.80)
%WH$_F$	0.4848***	0.4970***	0.5834***	0.5907***	0.3949***	0.4115***
	(21.23)	(20.88)	(16.88)	(15.34)	(13.02)	(12.87)
%WH$_I$	-0.3459***	-0.3649***	-0.2863***	-0.3064***	-0.3748***	-0.3838***
	(-12.63)	(-13.55)	(-7.14)	(-7.36)	(-9.17)	(-8.83)
Age	0.0410***	0.0421***	-0.0138	-0.0121	0.0821***	0.0853***
	(3.84)	(4.02)	(-0.74)	(-0.66)	(6.01)	(6.38)
Age^2	-0.0003**	-0.0004**	0.0003	0.0003	-0.0009***	-0.0009***
	(-2.77)	(-3.01)	(1.52)	(1.51)	(-5.30)	(-5.75)
Education	0.0571***	0.0538***	0.0800***	0.0841***	0.0092	0.0021
	(10.20)	(8.74)	(11.28)	(11.77)	(0.81)	(0.17)
Executives						
Experts	0.0226	0.0459	-0.2591	-0.2537	0.0226	0.0403
	(0.44)	(0.87)	(-1.22)	(-1.18)	(0.45)	(0.75)
Technician	0.0974	0.1249*	-0.2228	-0.2274	0.0271	0.0562
	(1.90)	(2.34)	(-1.39)	(-1.37)	(0.51)	(0.96)
Supervisors	-0.2752***	-0.2387**	-0.5815***	-0.5743***	-0.2818**	-0.2538**
	(-3.95)	(-3.27)	(-3.56)	(-3.53)	(-3.13)	(-2.69)
Workers	-0.3983***	-0.3741***	-0.7080***	-0.7197***	-0.4177***	-0.3934***
	(-8.24)	(-7.44)	(-4.81)	(-4.65)	(-8.23)	(-7.47)
Apprentices	-0.6665***	-0.6469***	-0.8284***	-0.8521***	-1.0603***	-1.0404***
	(-12.91)	(-12.27)	(-5.59)	(-5.59)	(-13.78)	(-12.74)
Manufacturing						
Commerce	-0.3823***	-0.3895***	-0.4702***	-0.4728***	-0.2480***	-0.2528***
	(-9.22)	(-9.76)	(-10.14)	(-10.58)	(-4.28)	(-4.03)
Services	-0.2453***	-0.2525***	-0.4183***	-0.4186***	-0.0376	-0.0438
	(-6.00)	(-6.36)	(-9.07)	(-9.43)	(-0.70)	(-0.81)
Financial	0.4654***	0.4640***	0.9824***	1.0380***	0.4939***	0.4815***
	(5.06)	(5.06)	(4.23)	(4.38)	(5.18)	(5.08)
Construction	0.0788	0.0763	0.1924	0.2098	0.1179	0.1211
	(0.74)	(0.71)	(1.26)	(1.35)	(0.89)	(0.86)
Electricity	1.1246***	1.1455***	1.4107***	1.4205***	0.9520**	0.9352***
	(3.74)	(3.57)	(3.70)	(4.54)	(2.64)	(3.33)
Transport	0.4087***	0.4180***	0.2209	0.2244	0.5660***	0.5564***
	(4.59)	(4.91)	(1.75)	(1.78)	(4.65)	(4.64)
Government	0.6241***	0.6343***	0.7437***	0.7579***	0.6265***	0.6199***
	(10.87)	(10.88)	(9.03)	(9.32)	(8.68)	(8.20)
I Mills ratio	-0.3855***	-0.4079***	-0.7021***	-0.6859***	-0.2011	-0.2317
	(-3.83)	(-4.13)	(-3.91)	(-3.97)	(-1.74)	(-1.90)
Constant	-0.7913*	-0.6483*	0.5934	0.6314	-0.9606*	-1.0062*
	(-2.34)	(-1.97)	(0.99)	(1.07)	(-2.21)	(-2.26)
LR	5209.17	5273.61	2182.99	2232.44	1667.95	1618.01
Wald test		28.23		21.50		19.56
N	26,638	26,638	12,067	12,067	14,571	14,571

t statistic in parenthesis. * p <0.05, ** p <0.01, *** p <0.001. *t* statistics are calculated with cluster standard errors. LR, likelihood ratio.

cessible formal job opportunities increase the probability of being a formal worker, whereas having access to informal job opportunities decreases this probability. These job accessibility indices do not determine the job formality of highly educated workers. There is weak evidence that informal job accessibility affects this probability negatively for highly educated male workers. Moreover, this negative effect is stronger in the probability of being a formal worker among less educated male workers than among highly educated male workers (see

Table III.B.5 of Appendix III.B). The effect of informal job accessibility is stronger than the effect of formal job accessibility. Therefore, the net effect of the job accessibility indices is negative. This may be due to the fact that formal jobs are highly concentrated in the center and west of the city, whereas informal jobs are less concentrated in the center and located near less educated workers who live in the periphery. This result suggests that a policy focusing on reducing informal employment should generate and/or decentralize large numbers of formal jobs in order to have positive net effects on the probability of being a formal worker.

Formal and informal worker densities have the expected effects. However, there is no evidence that the density of informal workers negatively affects the probability of being a formal worker among women. The effect of the density of both formal and informal workers is stronger among less educated workers. The net effect of densities is statistically significant among less educated workers, but it is not significantly different from zero among highly educated workers. If the number of formal and informal workers per hectare increases the same amount in a given neighborhood, the net effect will be positive on less educated workers and zero on highly educated workers. This means that increasing the number of formal workers in a neighborhood is enough to generate positive net effects on the probability of being a formal worker. The more formal workers reside in a neighborhood, the more information about formal job vacancies there will be. Correspondingly, the probability of being a formal worker will increase.

Strong social networks ties or family networks ties are relevant to job formality. A high percentage of formal workers in the household increases the probability of being a formal worker, whereas a high percentage of informal workers diminishes this probability.[20] Rodríguez-Oreggia et al. (2013) found that the presence of a formal worker in the household reduces the probability of being an informal worker in the case of the Mexican manufacturing industry. Our results for Mexico City are consistent with that result for the whole country. Moreover, the separation between formal and informal workers in the household allows us to distinguish how the preponderance of either group of workers in the household affects job information flows. A member of a household in which there are a high number of formal workers has more information about formal job vacancies. Meanwhile, an individual living with a high number of informal workers in the household has more information about informal job vacancies. Therefore, the labor status of the remaining members of the household influences the probability of being a formal worker in different directions. If we do not control for this fact, the net effect of strong social network ties may be positive or negative depending on the composition of the household members in terms of their labor status, either formal or informal. For instance, Mitra (2004) found that strong social network ties, such as relatives, diminish the probability of being a regular wage/salaried worker. This may be explained because he does not distinguish the labor status of relatives within this social network. If the composition of social network is mostly comprised of informal workers, the net effect on the probability of being a formal worker will be negative; otherwise it will be positive.

[20]Because many families only have one working member, we have performed an estimation for households with more than two working members. The results indicate that the effect of $\%WH_F$ and $\%WH_I$ are greater when there are more working members in a household.

Finally, the neighborhood effects are more relevant to less educated workers. However, the question is which effect is the strongest. In order to answer this question, we estimated the semi-elasticity of the neighborhood and social network variables. These semi-elasticities are presented in Table III.B.6 of Appendix III.B. This table shows that access to job opportunities primarily influences the probability of being a formal worker. Social interaction effects (weak ties) are more important than strong social networks ties or family nerwork ties; that is, the effect of the former is greater than the latter. Among men, the positive net effect of social interactions does not compensate for the negative net effect of access to job opportunities. However, among women, the positive net effect of social interactions is greater than the negative net effect of access to job opportunities. These last results are due to the fact that the nearest informal jobs largely condition the informal employment of less educated male workers. The difference in the semi-elasticity between formal and informal job accessibility for women is not as great as this difference is for men.

III.6 Conclusions

In the Metropolitan Area of Mexico City, residential segregation is affecting the employment probability of women and is determining the informal employment of men when we control for endogeneity bias. In other words, women living in deprived neighborhoods are less likely to be employed, whereas men living in deprived neighborhoods are less likely to be formal workers. Neighborhood effects measured by a social deprivation index and a job accessibility index better explain women's probability of being employed, whereas these effects better explain men's probability of being a formal worker. This is due to the fact that women have more spatial constraints than men. Married women have to combine several activities such as housework, work and commuting. Given the constraints of housework time and work time, commuting time is considerably restricted. Additionally, since there are no extended unemployment benefits in Mexico City, men have to work in order to support the household. The employment rate of men is higher than that of women (0.68 and 0.39, respectively).

Among women, living in a deprived zone negatively affects their probability of being employed, whereas high accessibility to job opportunities increases this probability. Among men, only the accessibility of job opportunities affects the probability of being employed. On the other hand, living in a deprived neighborhood decreases the probability of being a formal worker for both men and women. Formal and informal job accessibility is only relevant for less educated workers. Social interaction effects measured by the density of formal and informal workers in the neighborhood affect the probability of being a formal worker. The existence of strong social network ties or family network ties conditions the formality of workers. In summary, this paper found that neighborhood effects are relevant to both labor participation and job formality, and we observed differences between women and men and between less and highly educated individuals. Less educated individuals are affected by neighborhood effects more strongly than highly educated individuals.

It is important to disentangle the mechanisms behind neighborhood effects in order to design effective public policies. There are two types of public policies that have been implemented to improve the conditions of poor individuals living in deprived neighborhoods; the first is place-based policies and the second is person-based policies. The former have been implemented in the USA and Europe; however, these policies have more costs than benefits (Cheshire, 2009). Some of these policies consist of mixing neighborhoods or residential relocation to better neighborhoods, affecting mostly to ethnic minorities. Most of them do not have a significant impact in terms of employment. In the case of Latin America, this type of policy might not be effective because residential segregation is socioeconomic in nature and social interaction among individuals with different incomes is very unlikely, even if they live in the same neighborhood.

In Latin America, individuals who live in deprived zones have limited job opportunities because they are far from employment zones and are not well connected by urban infrastructure. In some cases, the urban infrastructure is unsuitable or insufficient, and this affects microenterprises' access to capital and technology and the formation of individual human capital. A substantial proportion of these individuals becomes informal workers in domestic microenterprises because it is the only option. The development and improvement of urban infrastructure may help to increase the productivity of both domestic microenterprises and workers located in deprived zones.

Since 2007, a program to improve the urban environment in Mexico City has been implemented, the *Programa Comunitario de Mejoramiento Barrial*. This program aims to facilitate the association and organization of individuals within a deprived neighborhood in order to improve the urban public spaces of this neighborhood. The goal is to strengthen the social network ties in these neighborhoods. This type of program should be implemented along with other job training programs for individuals and credit for micro-firms in order to integrate both firms and workers into the urban development of the neighborhood. This can help local firms to grow, develop and formalize, and it could thus increase productivity.

Social programs based on social interactions can strengthen social network ties or produce new networks. This generates a social multiplier that may increase the effects of macroeconomic policies, such as education, housing, employment and social security. Social networks and social interaction effects may be relevant, as shown by the results of this paper. The combination and integration of different public policies may yield stronger effects than non-integrated policies because the externalities of social interaction matter.

Finally, future studies can improve the empirical estimation of both probabilities of being employed and being a formal worker. As this paper only considers a static context, it assumes that today's informal workers will always be informal. However, in reality workers can switch from formal to informal jobs or vice versa, and the urban structure may affect these transitions. Future studies can identify the direct and indirect effects of social interactions and analyze social interaction effects on job transitions. Furthermore, they can better address the endogenity issues, especially individual unobserved heterogneneity, or extend the analysis to other Latin American cities.

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Appendix III.A Figures

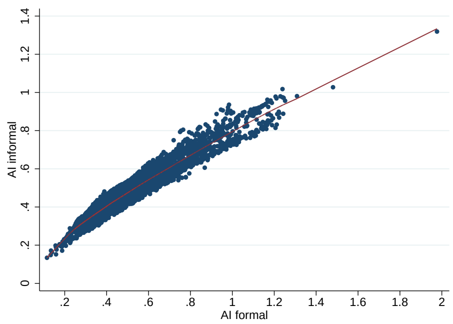

Figure III.A.1: Job accessibility indices

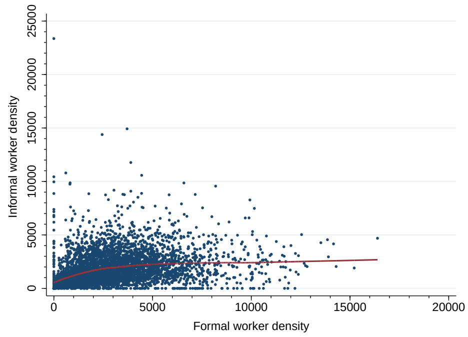

Figure III.A.2: Formal and informal densities

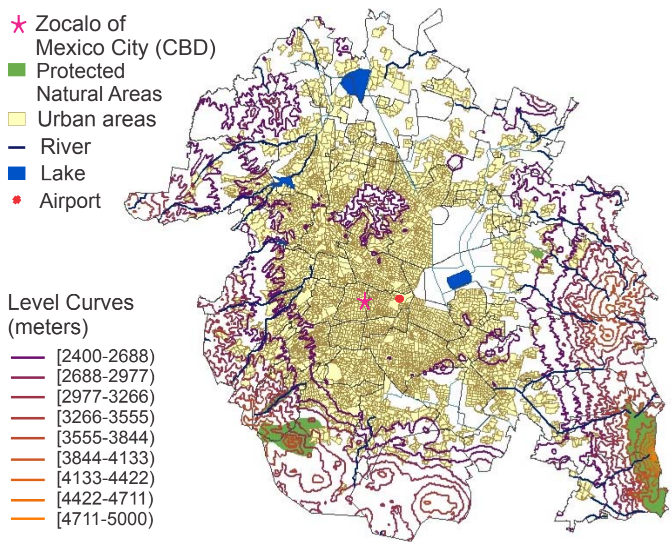

Figure III.A.3: Orography

Source: Elaborated with data of cartographic maps of National Institute of Statistics, Geography, and Informatics of Mexico.

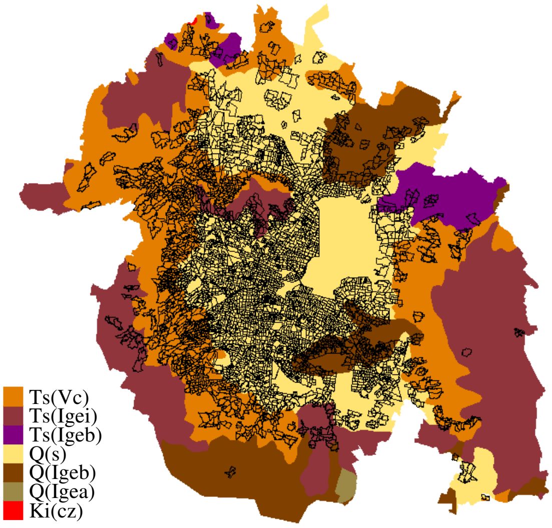

Figure III.A.4: Types of rock

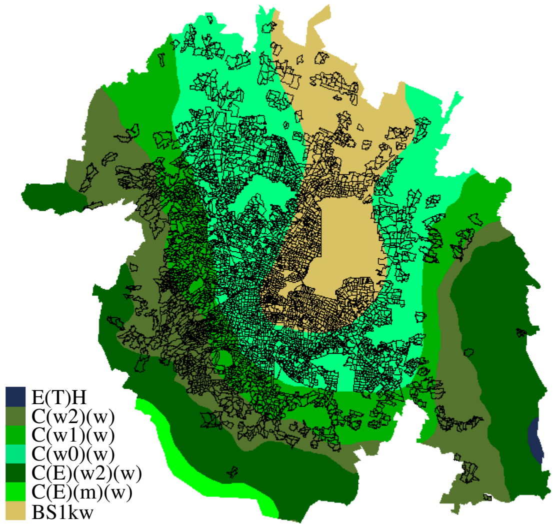

Figure III.A.5: Climate regions

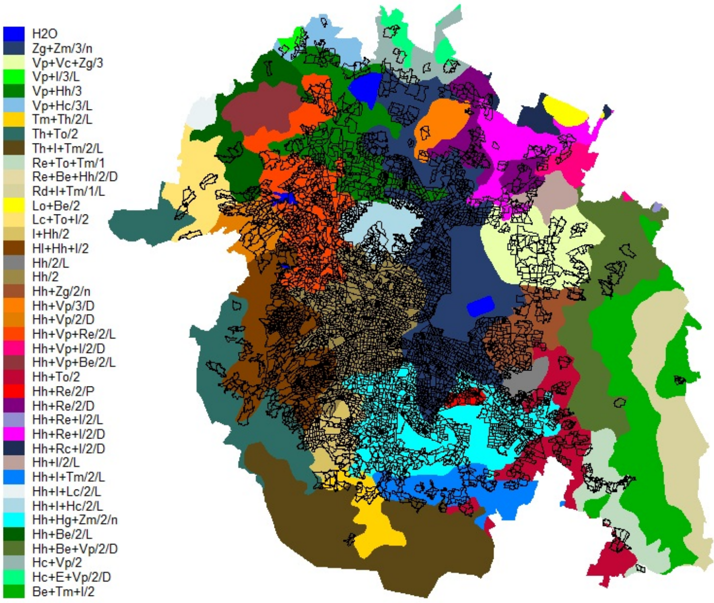

Figure III.A.6: Types of soil

Source: Elaborated with data of cartographic maps of National Institute of Statistics, Geography, and Informatics of Mexico.

Table III.A.1: Labels of Figures III.A.4, III.A.5 and III.A.6

Types of rock	
Ki(cz)	Sedimentary Mesozoic Cretaceous
Q(Igeb)	Extrusive Felsic Igneous Cenozoic Quaternary
Q(s)	Soil Cenozoic Quaternary
Ts(Igeb)	Extrusive Intermediate Igneous Cenozoic Neogene
Ts(Igei)	Extrusive Felsic Igneous Cenozoic Neogene
Ts(Vc)	Volcaniclastic Igneous Cenozoic Neogene
Climate regions	
BS1kw	semi-arid and temperate
C(E)(w2)(w)	semi-cold and sub-humid
C(w0)(w)	temperate and sub-humid (low humidity)
C(w1)(w)	temperate and sub-humid (medium humidity)
C(w2)(w)	temperate and sub-humid (high humidity)
Types of soil and subsoil	
Be+Tm+I/2	Eutric Cambiosols + Molic Andosols + Leptosols /medium texture
Hc+E+Vp/2/D	Calcaric Phaeozems + Rendzinas + Pellic Vertisols /medium texture/Duric
Hc+Vp/2	Calcaric Phaeozems + Pellic Vertisols /medium texture
Hh+Be+Vp/2/D	Halpic Phaeozems + Eutric Cambiosols + Pellic Vertisols/medium texture/Duric
Hh+Be/2/L	Halpic Phaeozems + Eutric Cambiosols /medium texture/Lithic
Hh+Hg+Zm/2/n	Halpic Phaeozems + Gleyic Phaeozems + Mollic Solonchaks/medium texture/Sodic
Hh+I+Hc/2/L	Halpic Phaeozems + Leptosols + Calcaric Phaeozems /medium texture/Lithic
Hh+I+Tm/2/L	Halpic Phaeozems + Leptosols + Mollic Andosols /medium texture/Lithic
Hh+I/2/L	Halpic Phaeozems + Leptosols /medium texture/Lithic
Hh+Rc+I/2/D	Halpic Phaeozems + Calcaric Regosols + Leptosols /medium texture/Duric
Hh+Re+I/2/D	Halpic Phaeozems + Eutric Regosols + Leptosols /medium texture/Duric
Hh+Re/2/D	Halpic Phaeozems + Eutric Regosols /medium texture/Duric
Hh+Re/2/P	Halpic Phaeozems + Eutric Regosols /medium texture/Stony
Hh+To/2	Halpic Phaeozems + Ochric Andosols /medium texture
Hh+Vp+Be/2/L	Halpic Phaeozems + Pellic Vertisols + Eutric Cambiosols /medium texture/Lithic
Hh+Vp+I/2/D	Halpic Phaeozems + Pellic Vertisols + Leptosols/medium texture/Duric
Hh+Vp+Re/2/L	Halpic Phaeozems + Pellic Vertisols + Eutric Regosols /medium texture/Lithic
Hh+Vp/2/D	Halpic Phaeozems + Pellic Vertisols /medium texture/Duric
Hh+Vp/3/D	Halpic Phaeozems + Pellic Vertisols /fine texture/Duric
Hh+Zg/2/n	Halpic Phaeozems + Gleyic Solonchaks/medium texture/Sodic
Hh/2	Halpic Phaeozems /medium texture
Hh/2/L	Halpic Phaeozems /medium texture/Lithic
Hl+Hh+I/2	Luvic Phaeozems + Halpic Phaeozems + Leptosols /medium texture
I+Hh/2	Leptosols + Halpic Phaeozems /medium texture
Lc+To+I/2	Chromic Luvisols + Ochric Andosols + Leptosols /medium texture
Re+To+Tm/1	Eutric Regosols + Ochric Andosols + Mollic Andosols /coarse texture
Th+I+Tm/2/L	Humic Andosols + Leptosols + Mollic Andosols /medium texture/Lithic
Th+To/2	Humic Andosols + Ochric Andosols /medium texture
Tm+Th/2/L	Mollic Andosols + Humic Andosols /medium texture/Lithic
Vp+Hc/3/L	Pellic Vertosols + Calcaric Phaeozems /fine texture/Lithic
Vp+Hh/3	Pellic Vertosols + Halpic Phaeozems /fine texture
Vp+I/3/L	Pellic Vertosols + Leptosols /fine texture/Lithic
Vp+Vc+Zg/3	Pellic Vertosols + Chromic Vertosols + Gleyic Solonchaks/fine texture
Zg+Zm/3/n	Gleyic Solonchaks + Mollic Solonchaks /fine texture/Sodic

Cartographic maps of National Institute of Statistics, Geography, and Informatics of Mexico.

Appendix III.B Tables

Table III.B.2: Moran's I

Social Deprived Index	0.1297*** (0.0005)
Unemployment rate (u)	0.0177*** (0.0005)
Percentage of workers whose income is less than three minimum wages	0.1025*** (0.0005)
Percentage of households whose per-capita income is 90 decile of income	0.0882*** (0.0005)

Standard deviation in parenthesis. The formula to calculate the Moran's I is in Appendix A equation A.3. The spatial weight matrix is the inverse of the distance between *estrato* i and *estrato* j, d_{ij}; $w_{ij} = 1/d_{ij}$.

Table III.B.3: Descriptive statistics of samples and subsamples

	Men			Married women		
	Full sample	Education		Full sample	Education	
		Basic	Post-Basic		Basic	Post-Basic
Employed*	94.57	94.00	95.28	38.88	31.60	51.49
Social Deprivation Index (SDI)	0.1119 (1.95)	0.7575 (1.88)	-0.6958 (1.71)	0.1933 (2.00)	0.7421 (1.92)	-0.7578 (1.75)
Accessibility Index (AI)	0.4477 (0.18)	0.4107 (0.16)	0.4941 (0.20)	0.4280 (0.17)	0.4005 (0.15)	0.4757 (0.19)
Number of workers in the household (WH)	1.11 (1.20)	1.15 (1.27)	1.05 (1.11)	1.4 (0.90)	1.5 (0.99)	1.23 (0.69)
Age	40.76 (10.45)	41.50 (10.68)	39.85 (10.06)	41.99 (10.18)	43.00 (10.52)	40.25 (9.30)
Education	10.68 (4.23)	7.56 (2.42)	14.58 (2.34)	9.63 (4.18)	7.04 (2.54)	14.12 (2.19)
Head of household*	68.69	71.59	65.07	-	-	-
Married*	75.10	79.70	69.35	-	-	-
Number of children in the household (Child_{12})	0.64 (0.95)	0.71 (1.02)	0.55 (0.86)	0.86 (1.03)	0.84 (1.07)	0.90 (0.95)
Household income (H. income)	5845.25 (13529.82)	4521.62 (11522.64)	7500.91 (15524.98)	9770.38 (19174.95)	7312.6 (11876.19)	14030.26 (27053.3)
N	172,265	95,732	76,533	107,795	68,356	39,439
Formal Worker*	63.90	50.82	79.10	62.45	41.00	80.21
Social Deprivation Index (SDI)	0.0918 (1.92)	0.7340 (1.87)	-0.6543 (1.70)	-0.1722 (1.91)	0.5837 (1.92)	-0.7981 (1.67)
Formal accessibility index (AI_F)	0.4593 (0.2170)	0.4142 (0.1856)	0.5118 (0.2381)	0.4761 (0.2269)	0.4277 (0.1947)	0.5161 (0.2432)
Informal accessibility index (AI_I)	0.4366 (0.1606)	0.4046 (0.1415)	0.4736 (0.1731)	0.4464 (0.1665)	0.4121 (0.1467)	0.4749 (0.1763)
Density of formal workers in ha. (Den_F)	28.83 (22.46)	25.55 (21.01)	32.64 (23.49)	30.33 (23.60)	26.53 (21.73)	33.47 (24.60)
Density of informal workers in ha. (Den_I)	17.55 (13.58)	19.19 (14.67)	15.64 (11.91)	16.69 (12.99)	19.08 (14.32)	14.72 (11.41)
% Formal workers in the household (% WH_F)	28.63 (41.89)	22.43 (38.05)	35.83 (44.90)	48.44 (47.10)	37.85 (44.60)	57.21 (47.31)
% Informal workers in the household (% WH_I)	19.09 (35.67)	24.27 (39.01)	13.08 (30.25)	22.77 (38.43)	33.01 (42.47)	14.30 (32.37)
Age	39.54 (10.04)	40.15 (10.3)	38.84 (9.69)	40.55 (8.93)	41.61 (9.25)	39.66 (8.56)
Education	10.90 (4.14)	7.73 (2.32)	14.59 (2.36)	11.39 (4.31)	7.41 (2.44)	14.69 (2.24)
Head of household*	68.07	71.14	64.51	-	-	-
Married*	75.57	80.46	69.89	-	-	-
N	109,900	59,065	50,835	26,638	12,067	14,571

* Percentages. Standard deviation in parenthesis.

Table III.B.4: Estimation results of probability of being a employed: sample selection equation

	Men			Married women		
	Full sample	Education		Full sample	Education	
		Basic	Post-basic		Basic	Post-basic
WH	0.0400***	0.0329***	0.0483***	0.0326***	0.0391***	0.0186
	(7.58)	(4.59)	(5.51)	(6.75)	(6.66)	(1.89)
Age	0.0284***	0.0266***	0.0281***	0.0839***	0.0886***	0.0994***
	(7.38)	(5.42)	(4.36)	(24.93)	(20.22)	(17.63)
Age^2	-0.0004***	-0.0004***	-0.0004***	-0.0011***	-0.0011***	-0.0014***
	(-9.09)	(-6.86)	(-5.28)	(-28.86)	(-23.56)	(-20.52)
Education	0.0271***	0.0307***	0.0344***	0.0670***	0.0221***	0.1290***
	(21.31)	(11.14)	(9.53)	(64.95)	(10.32)	(42.23)
Head household	0.4152***	0.3732***	0.4796***			
	(30.43)	(21.33)	(21.82)			
Married	0.2416***	0.2316***	0.2472***			
	(18.84)	(13.73)	(12.29)			
$Child_{12}$	0.0032	0.0016	0.0039	-0.1596***	-0.1202***	-0.2210***
	(0.48)	(0.20)	(0.31)	(-32.22)	(-18.55)	(-27.66)
H. Income	0.0016**	0.0023	0.0015*	-0.0010***	-0.0018**	-0.0015***
	(2.78)	(1.94)	(2.17)	(-4.45)	(-3.27)	(-5.99)
Constant	0.4045***	0.4634***	0.2547	-2.3182***	-2.1705***	-3.2597***
	(5.06)	(4.45)	(1.82)	(-31.45)	(-21.82)	(-26.26)
LR	2950.65	1393.27	1458.26	7705.44	1530.62	3116.35
N	172,265	95,732	76,533	107,795	68,356	39,439

t statistic in parenthesis. * p <0.05, ** p <0.01, *** p <0.001. LR, likelihood ratio

Table III.B.5: Average marginal effects of IV Probit

	Men			Married women		
	Full sample	Education		Full sample	Education	
		Basic	Post-basic		Basic	Post-basic
Probability of being employed						
SDI	0.0015	0.0011	-0.0021	-0.0196***	-0.0177***	-0.0169***
	(1.39)	(0.86)	(-1.35)	(-5.11)	(-4.19)	(-2.78)
AI	0.0183*	0.0233	-0.0100	0.0768**	0.0793*	0.0747*
	(2.27)	(1.94)	(-1.17)	(3.09)	(2.39)	(2.41)
WH	0.0042***	0.0038***	0.0047***	0.0142***	0.0159***	0.0095
	(6.84)	(4.17)	(4.78)	(6.89)	(6.43)	(1.93)
Probability of being a formal worker						
SDI	-0.0245***	-0.0192**	-0.0158***	-0.0224***	-0.0124	-0.0069
	(-3.94)	(-2.66)	(-3.67)	(-4.21)	(-1.89)	(-1.23)
AI_F	0.3301***	0.3181***	0.0333	0.1496	0.3607**	-0.1517
	(5.53)	(4.70)	(0.52)	(1.54)	(2.95)	(-1.38)
AI_I	-0.7055***	-0.9025***	-0.1422	-0.2266	-0.4792**	0.2452
	(-7.89)	(-9.06)	(-1.52)	(-1.63)	(-2.76)	(1.46)
Den_F	0.0019***	0.0046***	0.0008*	0.0014**	0.0033***	0.0009
	(3.80)	(5.81)	(2.30)	(2.92)	(3.59)	(1.86)
Den_I	-0.0010	-0.0018*	-0.0012	-0.0009	-0.0016	-0.0021
	(-1.43)	(-2.16)	(-1.58)	(-1.11)	(-1.51)	(-1.80)
$\%WH_F$	0.1238***	0.1518***	0.0832***	0.1356***	0.1809***	0.0975***
	(30.15)	(23.81)	(18.24)	(20.88)	(15.34)	(12.88)
$\%WH_I$	-0.1142***	-0.1077***	-0.1186***	-0.0995***	-0.0938***	-0.0910***
	(-28.04)	(-19.93)	(-20.17)	(-13.55)	(-7.36)	(-8.83)

t statistic in parenthesis. * p <0.05, ** p <0.01, *** p <0.001.

Table III.B.6: Average semi elasticity of IV Probit
$-Pr(formal\ worker = 1)-$

	Basic education	
	Men	Married women
SDI	-0.0137	-0.0057
AI_F	0.1329	0.1548
AI_I	-0.3667	-0.1974
Den_F	0.1123	0.0895
Den_I	-0.0341	-0.0304
$\%WH_F$	0.0311	0.0742
$\%WH_I$	-0.0261	-0.0271

Table III.B.7: Estimation results with IV probit and IV cell-based approach

	Full sample		Education			
			Basic		Post-basic	
	IV Probit	IV cell-based	IV Probit	IV cell-based	IV Probit	IV cell-based
Probability of being employed						
Men						
SDI	0.0142*	0.0176**	0.0094	0.0112	-0.0219	-0.0058
	(2.22)	(2.77)	(1.25)	(1.48)	(-1.58)	(-0.43)
AI	0.1723***	0.1886***	0.2014**	0.2126**	-0.1066	-0.0152
	(3.67)	(4.03)	(3.03)	(3.20)	(-1.22)	(-0.18)
Married women						
SDI	-0.0546***	-0.0569***	-0.0523***	-0.0540***	-0.0454***	-0.0578***
	(-7.88)	(-8.39)	(-7.62)	(-7.91)	(-3.97)	(-5.19)
AI	0.2134***	0.2193***	0.2225***	0.2158***	0.2005**	0.1748**
	(4.86)	(5.03)	(3.68)	(3.57)	(3.27)	(2.86)
Probability of being a formal worker						
Men						
SDI	-0.0832***	-0.0787***	-0.0594***	-0.0588***	-0.0623***	-0.0618***
	(-10.14)	(-9.60)	(-5.54)	(-5.48)	(-5.01)	(-5.03)
AI_F	1.1373***	1.1031***	1.0040***	0.9526***	0.1313	0.1829
	(8.95)	(8.68)	(6.34)	(6.01)	(0.67)	(0.94)
AI_I	-2.4244***	-2.5340***	-2.8291***	-2.8509***	-0.5623*	-0.6661*
	(-13.14)	(-13.76)	(-12.00)	(-12.09)	(-1.98)	(-2.37)
Den_F	0.000065***	0.000086***	0.000142***	0.000154***	0.000032**	0.000033**
	(6.99)	(9.34)	(9.69)	(10.54)	(2.98)	(3.12)
Den_I	-0.000035**	-0.000038**	-0.000056***	-0.000062***	-0.000048*	-0.000039
	(-2.86)	(-3.18)	(-3.54)	(-3.89)	(-2.20)	(-1.79)
Married women						
SDI	-0.0822***	-0.0890***	-0.0404*	-0.0445*	-0.0290	-0.0375
	(-4.50)	(-4.92)	(-2.05)	(-2.25)	(-1.21)	(-1.58)
AI_F	0.5529	0.4644	1.1686***	1.0419**	-0.6225	-0.7224
	(1.93)	(1.62)	(3.45)	(3.07)	(-1.49)	(-1.75)
AI_I	-0.8386*	-0.9687*	-1.5534**	-1.5525**	1.0076	1.1540
	(-2.04)	(-2.35)	(-3.13)	(-3.12)	(1.61)	(1.87)
Den_F	0.000052**	0.000077***	0.000109***	0.000128***	0.000040*	0.000037
	(3.12)	(4.70)	(3.95)	(4.66)	(2.05)	(1.88)
Den_I	-0.000033	-0.000012	-0.000052	-0.000048	-0.000088	-0.000100*
	(-1.23)	(-0.46)	(-1.71)	(-1.55)	(-1.93)	(-2.22)

t statistic in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Chapter IV

Spatial spillover effects on labor market outcomes

Abstract

This chapter aims at assessing the determinants of the spatial distribution patterns of a few selected outcomes at urban level (non-employment rate, informal employment rate, and real wages). By referring to Mexico City we identify that the characteristics of neighborhoods, such as average education and the nearest job opportunities, help to understand the records of the level of these outcomes. In the same wake, we are able to isolate to which extent spillover effects impact on non-employment and informal employment rates, as well as the real wages. Furthermore, as a novelty in the literature, we are able to detect and quantify the direct influence that social interactions produce on the geographic location patterns of informal employment rates.

Key words: Spillover effects, labor market outcomes, spatial econometrics.

IV.1 Introduction

The existence of local factors bringing advantageous job or leisure opportunities for individuals is a clear agglomeration force that agglutinate resources spatially. When focusing on the side of job opportunities, one of the most recurrent consequences of the clustering effect of individuals is the creation (or consolidation) of social network that enhance the likelihood to find an employment or bettering the quality of job conditions (including wages), for instance.

In other words, the concentration of the distribution of population (and, as a direct consequence of employment) inside a selected area (such a neighborhood) certainly affects the labor market outcomes of this area. Furthermore, according to the degree of social connection among individuals, it is also possible to record important spillover effects not only inside a neighborhood, but also across neighborhoods. The presence of these types of spillovers generates positive externalities that each individual (or neighborhoods, if we refer to a more aggregate level) may take benefit from.

When talking about spatial spillovers, we are referring to the causal relationship between some features of a neighborhood or the effects of the action of one or more individuals settled in a specific neighborhood that impact on either the social or the economic outcomes of another neighborhood or the decisions taken by individuals of other neighborhoods. In their nature, spillovers can be local or global. When referring to local spillovers, we are considering the case in which the externality effect is generated only at the neighborhoods' level (namely, no individual transmission effect is effective). Instead, the existence of global spillover effects implies that not only neighborhood characteristics affect an individual's decision process but also individual-social interactions or the decision-process of individuals cross-fertilize. As a consequence, in the wide range of factors that determine the neighborhoods' features that give rise to the global spillovers it is also possible to include ad-hoc local public policies that have a direct effect in improving the individual welfare sphere. This is the case of public policies fueling the employment opportunities or bettering the wage treatment.

Under this perspective, the objective of this chapter is to analyze the role played by the spatial spillover effects in influencing three key labor market outcomes, namely non-employment rate, informal employment rate, and wages in the Metropolitan Area of Mexico City (MAMC). We adopt the definition of non-employment and informal employment that has been discussed in the Introduction. Our idea is to provide evidence that the neighborhood composition and/or spillover effects have an important role in the determination of the above mentioned labor market outcomes and their changes over time. Moreover, we discern the extent to which the differentiation between local and global spillover effects can be statistically relevant to understand the temporal evolution of those outcomes. This result is particularly important in a policy perspective. In case of assessing that the existence of global spillover matters for our three selected outcomes, we are implicitly assuming that there exist feedback effects possibly originated by social interactions. Then, any initiative aiming at improving the social-interaction action could also been considered as a welfare improving device.

Nevertheless, the positive impact issuing from the spillovers effects may suffer from the presence of spatial barriers, such as commuting and residential location constraints. Beyond of not being evenly distributed across Mexico City they impact in a different manner on the different groups of population of that city. Women have tighter spatial and time constraints than men, as we discuss in Chapter II and III. Therefore, it is relevant to distinguish between labor market outcomes for men and women and, as a novelty, we will take into account this discriminating feature in our analysis. This will turn to be a key strategy of analysis because the geographic distribution of female and male non-employment rates follow distinct patterns.

The novelty of this contribution stands in the target to deliver new evidence for a general question that has not been studied so extensively for the case of Latin American urban areas. There are few papers that investigate the spillover effects on several labor market outcomes in an intraurban context using spatial econometrics for the case of North American and European countries. Topa (2001) and Conley and Topa (2002) analyze local spillovers effects on unemployment rates using census tract data for Chicago. Bill (2005) studies the relationship between global spillovers and unemployment rate within metropolitan Sydney. Finally, only Valdivia-López

(2009) studies the spillover effects on self-employment in the central part of Mexico City. However, a part of self-employment is informal and the author does not control for this issue in his analysis since it is not possible to distinguish between the formal and informal sector in his database. Instead, we use a better proxy of informal employment, and extend the analysis to almost the whole area of MAMC, by which we enrich the range of results that can be delivered. In particular, one of our principal novelties is being able to analyze the importance of the spillover effects in determining the degree of informal employment in urban neighborhoods.

To the best of our knowledge, neighborhood effects on informal employment and wages have not been studied under the lens of aggregated data and/or gender issue. In this thesis, it is possible to tackle this question because Mexico City's extensive area is divided into several census tracts. These census tracts are heterogeneous, not only in terms of socioeconomic composition but also in terms of labor market outcomes. Therefore, we have enough variability to identify the existence of spillover effects in the way we previously described under a spatial-oriented perspective

The rest of the chapter is organized as follows. Section IV.2 proposes a brief review of the literature about spillover effects and their possible impact on labor market outcomes. The observed spatial patterns of non-employment, informal employment, and wages in Mexico City are presented in Section IV.3 along with the descriptive analysis of these patterns. Section IV.4 presents the empirical methodology that comprises the estimation of several spatial econometric models. The main results are summarized in Section IV.5. Finally, the discussion and conclusions are given in Section IV.6 and IV.7, respectively.

IV.2 Related literature

The literature on both social interactions and neighborhood effects examines the relationship between neighborhood characteristics and outcomes in terms of labor market, education, among others. The social interaction models emphasize that individual actions affect the preferences, information, choices and outcomes of other individuals. Theoretically, this can be modeled by introducing a dependence between each individual's utility function (or payoff function) and the actions of the other individuals. In this manner, the presence of local interactions generate spillovers, externalities, or social multipliers, which generate a positive benefit in the determination of the level of the final individual outcomes.

When thinking of the labor market dimension, the neighborhood effects can be generated by the existence of social networking among individuals, peer, or role effects among agents. These mechanisms are summarized in Jencks and Mayer (1990), Dietz (2002), Durlauf (2004) and Galster (2012). Neighborhood effects can be classified into endogenous, exogenous (or contextual), and correlated effects (Manski, 1993). Endogenous effects are measured by the direct influence of the average-group behavior on individuals' decisions or neighborhoods' features. Exogenous or contextual effects refer to influences exerted by the exogenous characteristics of a reference group on the individual decision-taking process. Finally, correlated effects arise from the exposure of each individual to common or institutional factors due to the sorting or residential choice.

In the literature, spatial spillovers arise when a causal relationship between some characteristic and/or action of a neighborhood or an individual located in a neighborhood entail a significant influence on the outcomes, decisions, or actions of individuals located in other neighborhood (LeSage, 2014). These spillovers can be local or global as we described in the introduction of this chapter.

Empirically, the presence of spatial spillovers effects can be analyzed exploiting either individual or aggregated data. The use of aggregated data has the advantage of simplifying the analysis of interactions among neighborhoods. This is the typical case of the analysis of intra-urban spatial spillover effects on labor market outcomes. Topa (2001) estimated a nonlinear regression model in which the unemployment rate in a given neighborhood depends on the unemployment rate of adjacent neighborhoods, finding an important spatial interdependence in the unemployment rate among neighborhoods. Conley and Topa (2002) analyzed the effect of social networks on employment, using different measures both physical and non-physical distances within the neighborhood. They found that there is a spatial correlation of unemployment at different distances. However, this correlation disappears when they controlled for observable characteristics of neighborhoods.

There is only one paper examining spillover effects in the case of Mexico City; its target is the study of the geographic patterns of self-employment rates and its spillover effects in the Federal District (Valdivia-López, 2009).[1] The author found the impact of the social interaction effects (or contagion effects, as he calls it) on self-employment rates by means of a spatial lag model. Even if this result is important, this author considers a very small part of Mexico City (the downtown area), accounting for 299 census tracts (namely, 6.5% of total census tracts,). Furthermore, he did not discern methodologically between local and global spillover effects because he estimated only one type of spatial dependence model.

In spite of the fact that the spatial econometrics has not been widely exploited to investigate the spillover effects at intra-urban level, there are several papers that analyze the inter-regional differences in labor market outcomes using spatial econometrics, in particular when focusing on unemployment rates and wages. These papers attempt to explain the existence and persistence of spatial disparities in unemployment at regional level within a country (some of these papers are summarized in Elhorst, 2003).[2] As for the spillover effects on regional unemployment rates, some papers asses their presence; that is, they found a significant degree of spatial dependence among regional labor markets in Europe (Overman and Puga, 2002; López-Bazo et al., 2002; Niebuhr, 2003; Patachini and Zenou, 2007; Cracolici et al., 2007; Halleck Vega and Elhorst, 2013).

Referring to the importance of spatial spillovers in the wage determination process, a few papers attempt to analyze the existence of a wage curve using spatial econometrics (Buettner, 1999; Longhi et al. 2006; Elhorst et al., 2007; Falk and Leoni, 2011; Fingleton and Palombi, 2013).[3] These papers found that spatial lag of

[1] Federal District is located in the central part of Mexico City as shown in Figure I.1 in the Introduction.

[2] There are two theoretical explanations of observed regional disparities in unemployment rates. The first one is related to a long-run equilibrium and the second one is related to a disequilibrium that may be persistent depending on the adjustement costs.

[3] There is an inverse relationship between wages and local unemployment rates, namely wage curve. There are several explanations for these phenomena, for instance efficiency wage or turnover cost explanations, theory of monopsony, explanations founded in urban economic and new geographic economics literature.

unemployment rates and/or wages is a proper framework to deal with this issue. Further, another group of papers exploit spatial econometrics (with data at individual level) in order to model the presence of a network structure among economic agents (Lee, 2007; Lee et al., 2010). In terms of empirical modeling, some of these papers adopt the spatial lag and spatial Durbin models where the network structure is introduced through the presence of a spatial weight matrix.

Overall, several papers have found evidence of regional spillover effects on unemployment rates and wages. By referring to this stream of literature, one of the aims of this chapter is to identify the existence of urban spillover effects on both wages and unemployment rates, as well as informal employment rates in a spatial econometric framework.

IV.3 Descriptive analysis of labor market outcomes in Mexico City

In Mexico City, the socioeconomic composition of neighborhoods and the correspondent labor market outcomes have been changing for the last two decades. There are few papers that tackle this issue: most of the current literature refer to the 90s (Dávila- Ibáñez et al., 2007; Ariza and Solís, 2009; Villareal and Hamilton, 2009; Valdivia-López, 2009; Sanchez-Peña, 2012). According to this strand of literature, residential segregation in terms of socioeconomic characteristics recorded a slight increase in the 90s; in other words, the spatial distribution of individuals or households was already uneven in terms of socioeconomic characteristics (like education or income), and it became slightly more uneven in the 90s.

By referring to several segregation indices, Ariza and Solís (2009), conclude that there is an increase in segregation in terms of income and education during the 90s, and this segregation decreased in terms of type of occupation. Dávila-Ibáñez et al. (2007), using a principal component analysis, and Sanchez-Peña (2009), using a segregation index,[4] found that residential location of the wealthiest and poorest households has been polarized; that is, the wealthiest and the poorest households are clustering throughout the space. Villareal and Hamilton (2009) corroborated this conclusion using segregation indices and Moran's I over wages and education. Finally, Valdivia-López (2009) found a spatial polarization between high and low values of self-employment rates in Federal District, using global and local Moran's I.

IV.3.1 Data

The data exploited in this study come from the 1990, 2000 and 2010 Population and Housing Censuses for the Federal District and the State of Mexico. Our unit of reference is the census tract. In Mexico, a census tract corresponds to an urban *Area Geoestadística Básica* (AGEB).[5]

An urban AGEB is a set from 1 to 50 census blocks. The size of census tracts varies widely depending on

[4]Theil index over head of househols' income and education.

[5]Before the 1990 Population and Housing Census the smallest geographic area to identify the individuals' residence was municipality.

the size of the census blocks. These census blocks are delimited by streets, avenues, sidewalks, or any other feature in the field that can be identified easily. Furthermore, the spatial size of census tracts also varies over time. The census tracts are often combined or divided over time. First, we identified the changes in the spatial structure of the AGEB between each census. Second, we refer to the spatial division of 2010 Population and Housing Census as georeferenced of 1990 and 2000. Because census tract boundaries change over time, in order to preserve the spatial comparability across time, we select the census tracts boundaries of 2010 as a benchmark and, then, we adjust the 1990 and 2000 variations (with respect to this benchmark) to fit these boundaries. Lastly, we combined the census-tract cells with less than 200 habitants. Overall, we deal with 4,572 census tracts.[6]

Given the scope of this analysis, we define non-employees as the individuals between 18 and 65 years old who do not have a job, excluding students, retirees and disabled persons. To the same extent, informal workers include working individuals who do not have social security and/or do not receive wages. The average real wages are the monthly wages deflated by consumer price index of Metropolitan Area of Mexico City.[7]

In the 1990 Population and Housing Census, there are no available official information about the social security status of an interviewed person. Therefore, we estimate a probability model of being an informal worker using the 1990 National Survey of Urban Employment (*Encuesta Nacional de Empleo Urbano* – ENEU –). We consider as a dependent variable the probability of being an informal worker in 1990 and as explanatory variables we include age, square age, education by levels, gender, marital status, kinship, economic sector, and type of occupation. With the estimated coefficients, we predict the probability of being an informal worker for working age population in the census. We consider an individual to be informal worker if the predicted probability was greater than 0.45.[8]

Finally, we calculate the informal employment rate as the ratio of the total informal workers over the total salaried workers. This is our proxy of the level of informal workers who live in a neighborhood.

IV.3.2 Changes in labor market outcomes

The distribution of non-employment rate, informal employment rate, and wages have changed significantly over time when compared to the geographic distribution of these variables as we will see in the next subsection (see Figures IV.1, IV.2 and IV.3). We remark a decrease of non-employment rates in a left-hand shift from 1990 to 2010 (see Figure IV.1). This shift is explained by the increase of female participation in the labor force. The average non-employment rate was 61.33% in 1990 and decreased to 47.62% in 2010. However, the male non-employment rate has risen during these two decades.

Informal employment rates were polarized between 1990 and 2010, especially among men (see Figure IV.2). We observe three peaks in the distribution: one around 20%, another around 40%, and a third around 60%. We

[6]The average census tract population was 3,195 in 1990, 3,761 in 2000 and 4,043 in 2010.

[7]The Consumer Price Index of Metropolitan Area of Mexico City (2010=100) comes from National Institute of Statistics, Geography, and Informatics of Mexico (INEGI).

[8]We chose the intersection of sensitivity and specificity curves as the probability cut-off. That point was 0.45.

also notice that the mean of informal employment rate increased during the overall period and that this increase is greater among men than women. Some authors posit that the informal employment has increased not only in Mexico City but also in the country in the last decades (Ariza and Solís, 2009).

Finally, the average real wages shifted to the left from 1990 to 2000 and to the right from 2000 to 2010. In other words, real wages increased from 1990 to 2000 but did not change from 2000 to 2010. However, the dispersion has been almost constant during the period. As we will discuss in the next section, the inequality among census tracts have not changed. The mean of average real wages is greater for men than for women. The Figure IV.3 shows that the inequality is greater among men than among women. This evidence anticipates that the gender composition is a crucial factor in explaining variations in labor market outcomes.

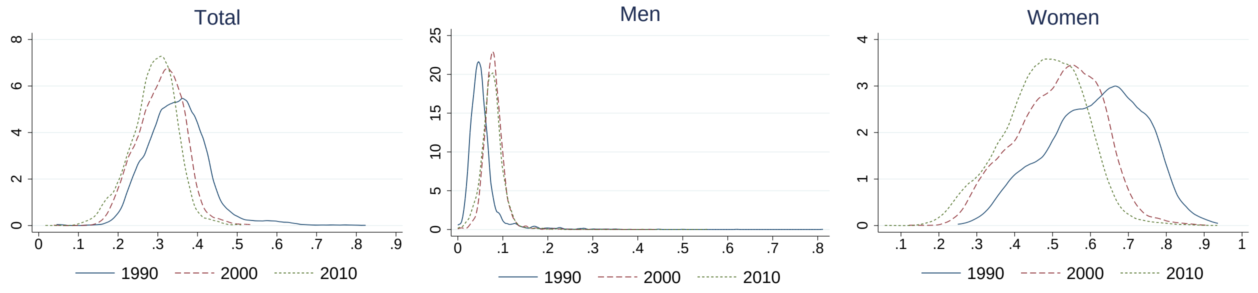

Figure IV.1: Kernel function of non-employment rate among tracts by gender

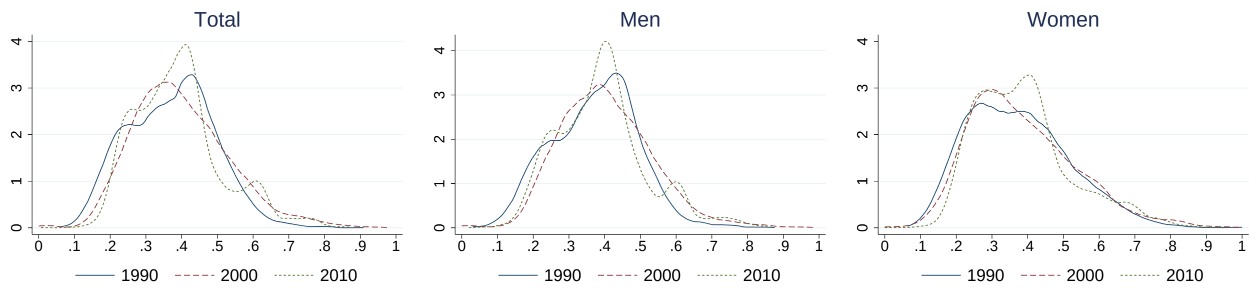

Figure IV.2: Kernel function of informal employment rate among tracts by gender

Figure IV.3: Kernel function of ln average real wages among tracts by gender

The changes recorded in the level of wages are due to local government actions and other important events as the trade liberalization and the decline of the size of the public-sector (Graizbord et al., 2003). It is worth noting that Mexico's entry into NAFTA meant an increase in Mexico City's service sector in contrast to a decrease in its manufacturing sector. In 1989, the manufacturing sector accounted for 42% of the total employment, while the service sector achieved 27.5% of the total employment. Ten years later, the manufacturing and service sectors represented 19.3% and 47.7% of total employment respectively. The increase of service and trade sectors, as well as the reduction of public and manufacture sectors implied that informal employees in Mexico City increased from 28% to 35% in just two decades (1990 ENEU and *the Encuesta Nacional de Ocupación y Empleo* – 2010 ENOE –).

Furthermore, most of the formal service sector and the public sector tended to be concentrated in the central business district and the west part of Mexico City. Meanwhile, informal service and commerce sectors clustered in the most peripheral part of the city. This dynamics increased the polarization of informal employment rates over time.

During the 80s and 90s, there was an important suburbanization process of the population and decentralization of the employment. This trend continued during the next decade but at a slower pace because of the local government intervention. During the 2000s, the local government of the Federal District implemented an urban policy to re-densify the inner city and control the peripheral sprawl. In the meanwhile, the government of the State of Mexico promoted the urban sprawl in the northwest of the city by increasing the availability of cheap renting or buying houses for local real estates. These policies triggered the physical separation between job opportunities and residential location. Poor people tended to live farther and farther from the central part of city because of the increased convenient real estate opportunities in the farthest neighborhoods of the urban sprawl.

In addition, over the past few years, two important transport projects have been approved. One involves the improvement of the quality of the road network, having as the most prominent project the creation of a double-decker system of elevated highways over the ring road. The other project is putting in place the rapid bus transit system (*Metrobus*). These two projects aimed to complement the transport opportunities provided by two new metro lines built in the last two decades (plus a third line opened in 2012) and serving the central part of the city.

Nevertheless, all these transport facilities do not guarantee the same degree of accessibility to all the locations of the town. This situation exacerbates the mobility problems due to the separation of job and residential areas at urban level. Under this perspective, it is understandable to think that, if possible, some individuals are not eager to commute to reach their job place. Instead, they may turn to be more prone to search for job opportunities near their neighborhoods or in them and, so, the importance of social interaction in the job-search action in districts far from the CBD is expected to increase substantially.[9]

IV.3.3 Segregation indices

As we discussed, segregation is a distinguishing feature of the population distribution in Mexico City. At this point it is relevant for our analysis to quantify the extent of this phenomenon in this metropolitan area with respect to the three selected labor market outcomes.

[9]It is also worth to mention that the resurgence of the urban crime rate increased the number of gated communities, not only for wealthy households (that tend to be isolated for their preferences to live in individual dwellings) but also for middle and low income households (García-Peralta and Hofer, 2006) increased as well. This effect contributed to exacerbate the spatial segregation effect and reduce the social interaction opportunities.

There are several methodologies to measure residential segregation. Massey and Denton (1988) identified five dimensions of segregation: evenness, concentration, centralization, exposure and clustering. Each dimension can be measure by one or more indices. The most common indices to measure segregation are the dissimilarity and the isolation/exposure indices. The dissimilarity index measures the degree of spatial uniformity of a population group. The exposure index measures the group's degree of isolation from other groups. In the spirit of Massey and Denton (1988), we retrieve their indices of segregation to measure two of our key variables: the number of non-employed individuals and the number of informal workers.[10] Additionally, we use the Gini index to measure the wage inequality across census tracts.

In Table IV.1, we report the segregation indices. The value of these indices is not very high and their evolution over time is not monotonic. Segregation indices are higher for informal workers than for non-employed persons. According to the dissimilarity index, the degree of segregation of informal versus non informal workers is larger than the degree of segregation of employed versus non-employed persons. In terms of gender, we find larger differences for the non-employed persons than for informal workers. The spatial patterns of non-employed women and female informal workers seem to be more segregated than among men for each type of index. As for the isolation index, the results confirm that informal workers are more likely to be segregated from the rest of population than non-employed persons. It implies that informal workers are less likely to interact with the rest of the population within their neighborhoods than non-employed persons.

Table IV.1: Segregation indices 1990, 2000 and 2010

	1990			2000			2010		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Dissimilarity Index									
Non-employed	0.1057	0.1579	0.1849	0.0966	0.0959	0.1619	0.0959	0.1101	0.1508
Informal workers	0.1918	0.1826	0.2095	0.1924	0.1855	0.2195	0.1755	0.1762	0.1917
η^2 Isolation Index									
Non-employed	0.0178	0.0235	0.0505	0.0125	0.0066	0.0398	0.0131	0.0076	0.0365
Informal workers	0.0493	0.0474	0.0586	0.0566	0.0531	0.0736	0.0501	0.0518	0.0585

Table IV.2: Gini index 1990, 2000 and 2010

	1990		2000		2010	
	Gini	95% Conf. Interval	Gini	95% Conf. Interval	Gini	95% Conf. Interval
Average real wages						
Total	0.2563	0.2470 - 0.2634	0.2673	0.2590 - 0.2739	0.2720	0.2624 - 0.2797
Men	0.2995	0.2906 - 0.3066	0.3129	0.3050 - 0.3197	0.3012	0.2915 - 0.3128
Women	0.2551	0.2478 - 0.2663	0.2472	0.2407 - 0.2573	0.2506	0.2442 - 0.2617

The Gini index indicates that the degree of inequality of average wage among the different tracts has been constant during the last two decades (see Table IV.2). The changes in Gini index outcomes over time are not statistically significant. But, again, there is always a gender-difference pattern: wage inequality for men across census tract is larger than that among women.

[10]The formulas of both segregation indices are presented in Appendix A (A.4)

Nevertheless, these indices are non-informative about the potential variation of the spatial distribution of labor market outcomes. Therefore, in order to address this question, we need to proceed with the exploratory spatial data analysis (ESDA).

IV.3.4 Exploratory spatial data analysis

The ESDA technique allows identifying the residential segregation or spatial patterns in a sample of observations. This technique can be exploited to draw the spatial distribution and the spatial dependence of observations. In our case, first we consider more convenient to present various deciles maps that depict the spatial distribution of non-employment rates, informal employment rates, and real wages by gender and year. Next, we calculate the global and local measures of spatial dependence. A positive spatial dependence involves that the spatial distribution of individuals (taking into account a selected number of socioeconomic characteristics) is not random. In other words, this technique allows for detecting the potential spatial concentration of individuals sharing similar characteristics.

Figures IV.4, IV.5 and IV.6 present the observed no-randomization patterns of non-employment rate, informal employment rate, and wages. The intra-urban distribution of non-employment rate follows a central-peripheral pattern. There is a concentration of low non-employment rates at the center of the city and a concentration of high non- employment rates in the periphery of the city (see Figure IV.4). Meanwhile, the informal employment rate and wages present east-west division pattern. The wealthiest zones are located in the western part of the city, and the poorest zones in the eastern part (see Figure IV.6). The same pattern is observed for the informal employment rate: the highest rates are in the east part, while the low rates in the west of the city (see Figure IV.5). However, the distribution patterns of the job informal employment rate differ slightly from those of wages. The spatial patterns of higher wages reveal a higher degree of centrality than low informal employment rates. These spatial patterns indicate that Mexico City might be residentially segregated.

Residential segregation in terms of the non-employment rate appears not to have significantly changed over time. However, the spatial distribution of wages and informal employment rate have changed slightly, especially the informal employment rate.

There is a remarkable difference in spatial patterns of non-employment rates between women and men. The female non-employment rates have an almost constant spatial pattern over time, while the male non-employment rate seems to be less residentially segregated over time. However, it is not the case of informal employment rate and wages, the spatial patterns by gender of these variables seem to be similar in each year and over time.

In order to test the hypothesis of spatial autocorrelation in the non-employment rate, the informal employment rate, and the logarithm of real wages, we calculate two global indices, Moran's I and G(d) test of Getis Ord. Furthermore, local Moran's I is calculated. The formulas of these indices are found in the Appendix A.

Table IV.3 tracks the Moran's I over the three periods. We calculate the Moran's I for three spatial weight

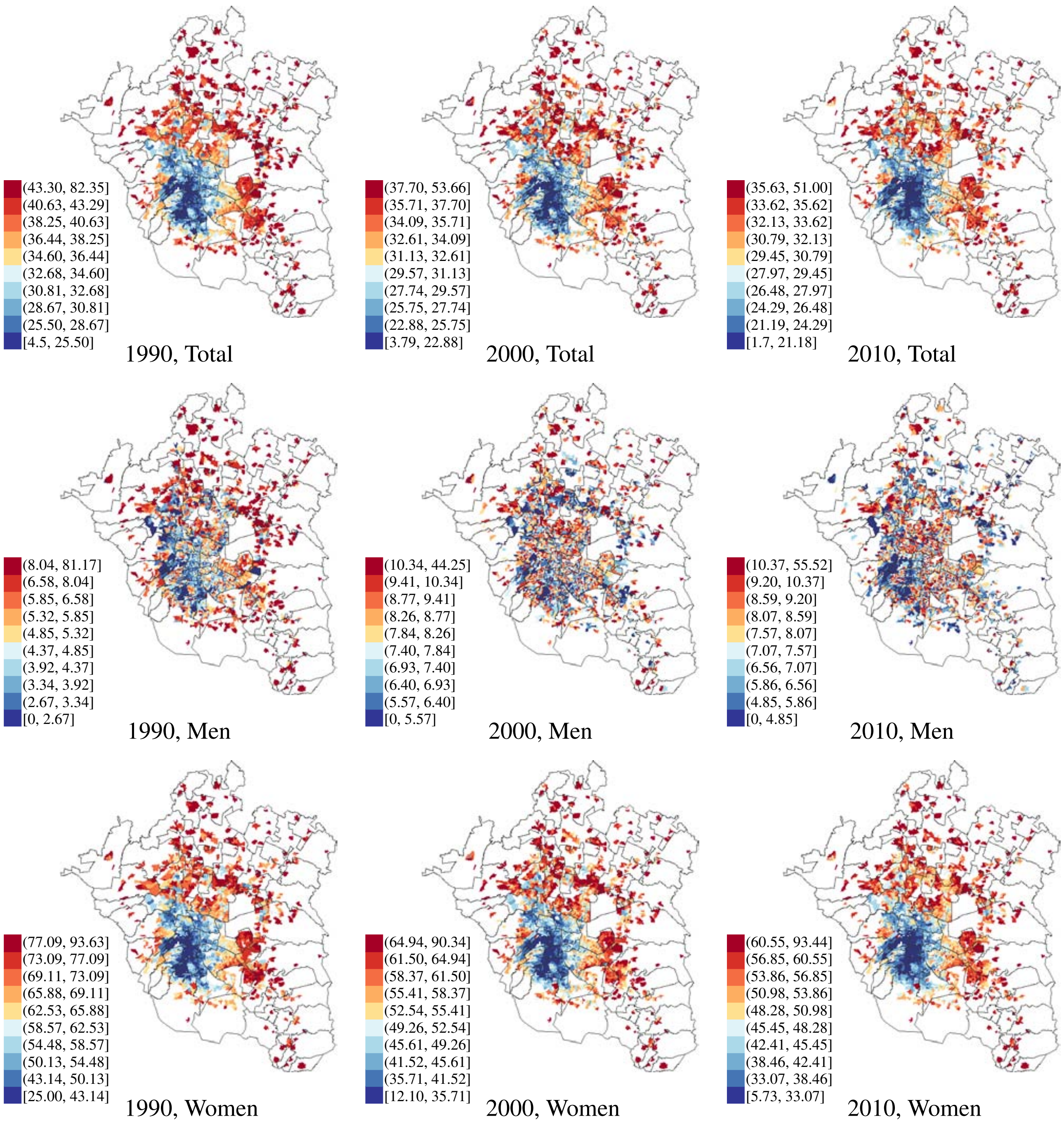

Figure IV.4: Non-employment rate by gender

matrix in order to perform a robustness check of our results. We consider (d(11km)) the inverse of distance d_{ij} between tract i and j with a threshold distance of 11 km in order to avoid 'islands', (knn8) the k nearest neighbors with $k = 8$, and (knn8*) the k nearest neighbors with $k = 8$ weighed by the inverse distance d_{ij} between tract i and j.[11] All spatial weight matrices are row standardized. The Moran's I for three variables are positive. This means that census tracts with high values are spatially close to tracts whose values are above the average, while tracts with values below the average are more likely to be surrounded by other tracts with low values.

To the same extent, this test reveals that the spatial autocorrelation of informal employment rate increased

[11]Each tract has a mean of six neighbors.

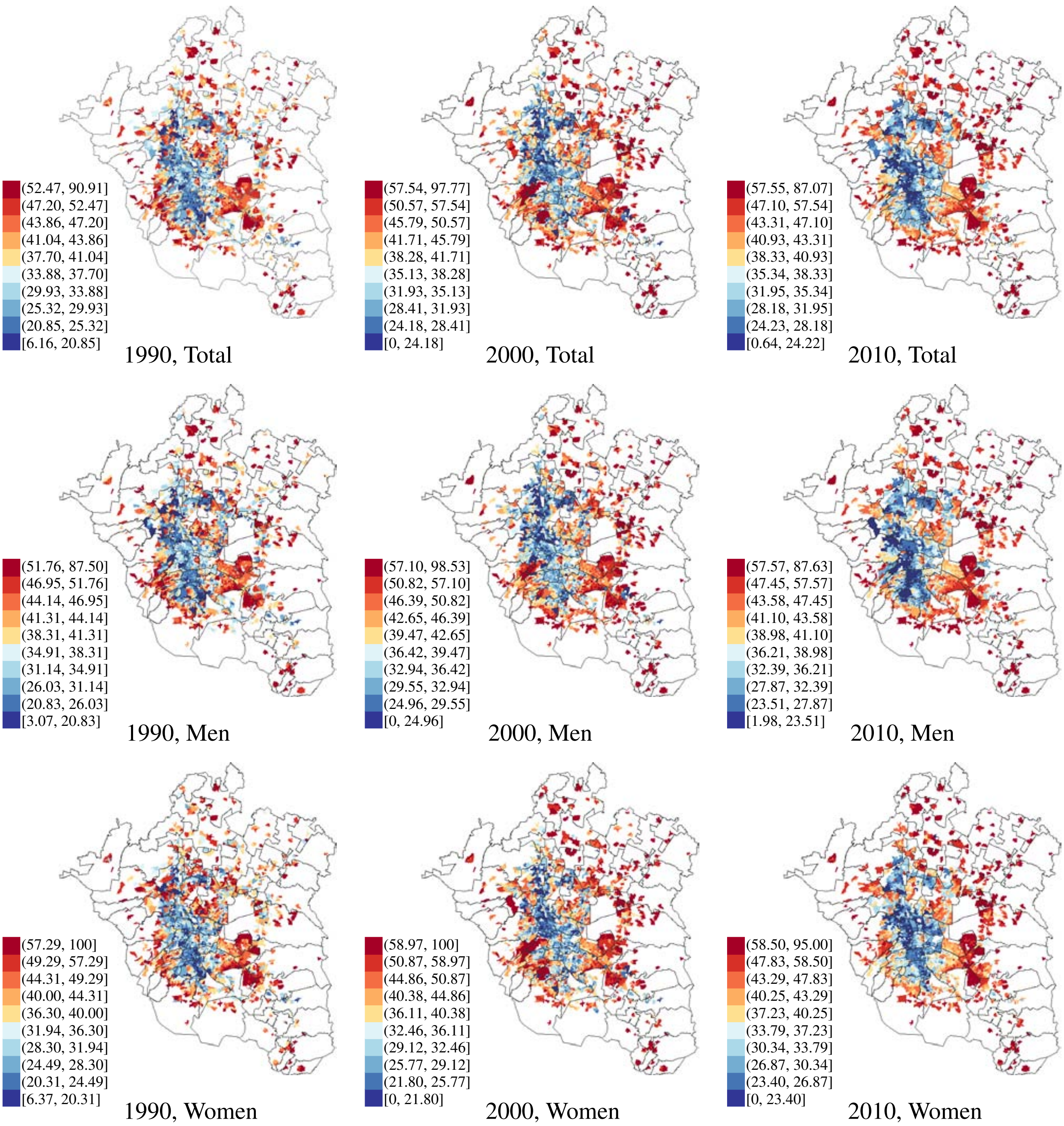

Figure IV.5: Percentage of informal workers by gender

during this period. Likewise, the spatial autocorrelation of wages rose from 1990 to 2000 but remained constant from 2000 to 2010. Finally, the spatial autocorrelation of the non-employment rate has slightly diminished. Overall, these results indicate that the spatial dependence of our selected variables is substantive, especially for the non-employment rate and the informal employment rate.

The spatial dependence of informal employment rates and wages of men and women do not present important gender differences, except for wages in 1990. The Moran's I is greater for men's wages than for the women's. This result is clearly visible in the previous decile maps (Figure IV.6). Comparing the outcome of Figure IV.4 with the outcome of Figure IV.1 one may deduce that this difference may be due to the low labor

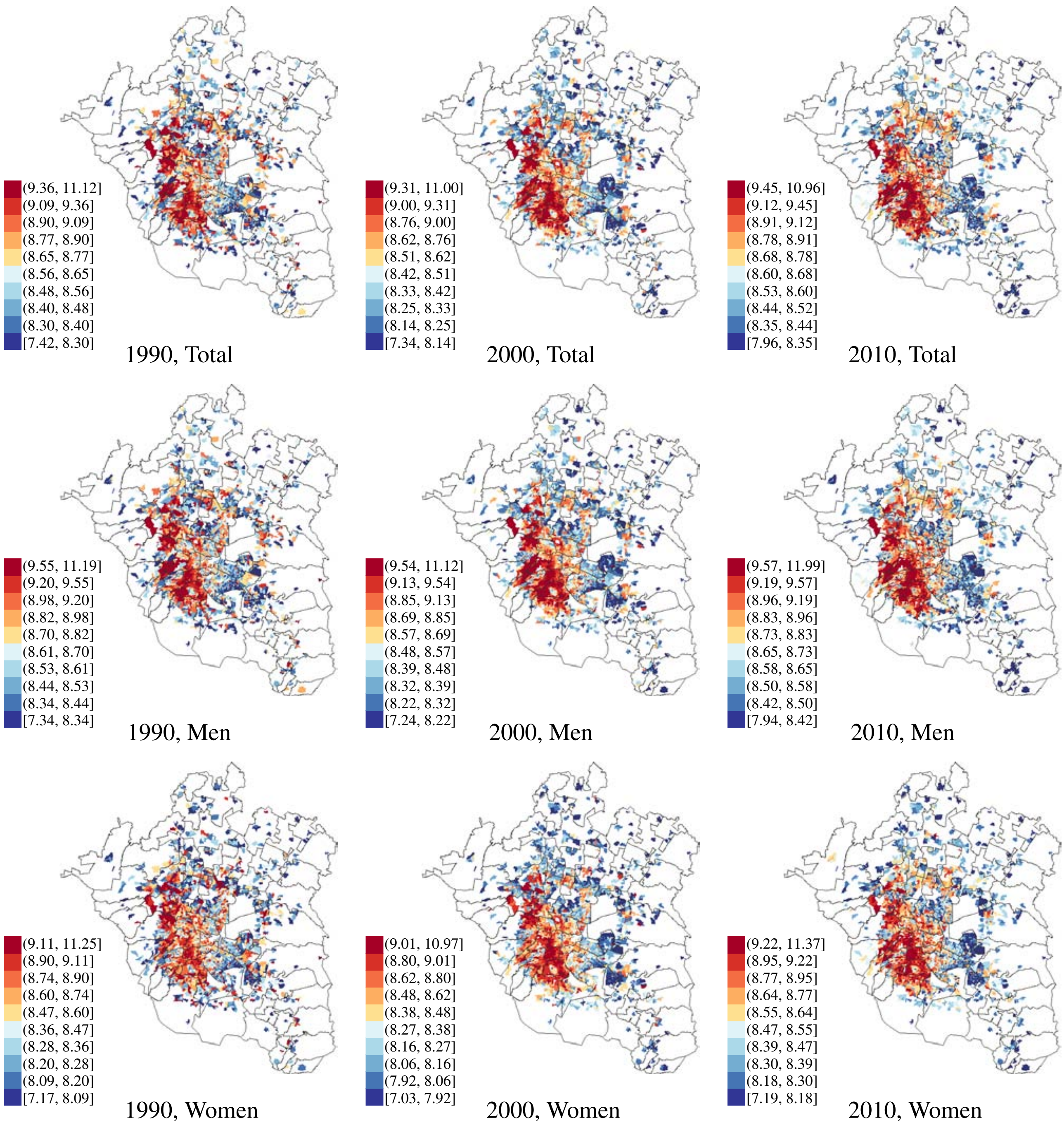

Figure IV.6: ln average real wages by gender

force participation rates among women in 1990. Women seem presenting a spatial dependence in the case of the non-employment rate, and the spatial autocorrelation of the male non-employment rate decreased strongly over time.

The global G or G(d) test is calculated using two binary spatial weight matrix. First, we select a spatial weight matrix with a 11km-radius band (d(11km)), and the second matrix is defined by taking into account the k nearest neighbors with $k = 8$ (knn8). The literature recommends to consider a binary spatial weight matrix to calculate this index because it measures the degree of clustering within a distance band, d (Moreno-Serrano and Vayá Valcarce, 2000). As we mention in the Appendix A (A.3), in the case of finding spatial autocorrelation, positive z-values of this index indicates that high values for a given attribute are clustered in the city, while negative z-values reflects that low values of this attribute are clustered.

Table IV.3: Moran's I 1990, 2000 and 2010

	1990			2000			2010		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate									
d(11km)	0.6425***	0.4633***	0.6106***	0.5363***	0.1386***	0.5596***	0.5741***	0.0844***	0.6092***
	(346.31)	(251.19)	(328.97)	(288.97)	(74.98)	(301.52)	(309.32)	(45.76)	(328.25)
knn8	0.8041***	0.5278***	0.8448***	0.7498***	0.2232***	0.7955***	0.7689***	0.2243***	0.8121***
	(113.97)	(75.26)	(119.69)	(106.25)	(31.73)	(112.71)	(108.96)	(31.94)	(115.06)
knn8*	0.8413***	0.5924***	0.8622***	0.7752***	0.2737***	0.8159***	0.7877***	0.2484***	0.8319***
	(108.86)	(77.12)	(111.52)	(100.28)	(35.52)	(105.54)	(101.90)	(32.28)	(107.61)
Informal employment rate									
d(11km)	0.3588***	0.3412***	0.3515***	0.4270***	0.4501***	0.3982***	0.6016***	0.5791***	0.5994***
	(193.34)	(183.91)	(189.46)	(230.11)	(242.54)	(214.59)	(324.15)	(312.03)	(322.99)
knn8	0.6711***	0.6439***	0.6550***	0.7142***	0.7068***	0.6988***	0.8308***	0.8175***	0.8193***
	(95.09)	(91.24)	(92.81)	(101.20)	(100.16)	(99.02)	(117.72)	(115.84)	(116.09)
knn8*	0.7084***	0.6841***	0.6876***	0.7508***	0.7445***	0.7324***	0.8504***	0.8397***	0.8365***
	(91.64)	(88.50)	(88.95)	(97.13)	(96.32)	(94.75)	(110.02)	(108.63)	(108.22)
ln w									
d(11km)	0.2357***	0.2526***	0.1887***	0.3588***	0.3536***	0.3750***	0.3547***	0.3682***	0.3748***
	(127.06)	(136.16)	(101.75)	(193.38)	(190.60)	(202.14)	(191.17)	(198.48)	(202.01)
knn8	0.5112***	0.5593***	0.3871***	0.6394***	0.6629***	0.6109***	0.6145***	0.6361***	0.5985***
	(72.45)	(79.27)	(54.88)	(90.60)	(93.94)	(86.57)	(87.09)	(90.15)	(84.82)
knn8*	0.5374***	0.5832***	0.4142***	0.6586***	0.6809***	0.6301***	0.6266***	0.6486***	0.6120***
	(69.53)	(75.46)	(53.60)	(85.21)	(88.09)	(81.52)	(81.07)	(83.93)	(79.19)

Table IV.4 presents the results of the G(d) test for the period of time we are considering. We observe a significant clustering process for low values of non-employment and informal employment when considering large distances or several neighbors (see Table IV.4 row – d(11km) –) and significant clustering of high values of these variables at short distances or with a small number of neighbors (see Table I IV.4 row – knn8 –). Instead, there is a clustering effect for high values of wages at short and long distances. In absolute terms, the significance of clustering of informal employment rates increased during the last two decades whereas the other two variables depict a U-shape tendency. As in the case of Moran's I, we find remarkably differences by gender in the clustering of non-employment rates. The significant clustering of male non- employment rates only occurs at short distances or with a small number of neighbors. These patterns will be confirmed by the results of the local Moran's I.

Table IV.4: G(d) test 1990, 2000 and 2010

	1990			2000			2010		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate									
d(11km)	0.1389***	0.1177***	0.1422***	0.1450***	0.1556***	0.1427***	0.1449***	0.1607*	0.1417***
	(-41.93)	(-24.66)	(-39.77)	(-37.10)	(-10.00)	(-36.90)	(-35.76)	(-2.57)	(-37.26)
knn8	0.0018***	0.0022***	0.0018***	0.0018***	0.0018***	0.0018***	0.0018***	0.0018***	0.0018***
	(35.93)	(54.90)	(36.50)	(28.18)	(12.16)	(34.74)	(33.55)	(20.51)	(38.10)
Informal employment rate									
d(11km)	0.1451***	0.1481***	0.1399***	0.1423***	0.1452***	0.1374***	0.1364***	0.1389***	0.1318***
	(-21.64)	(-18.46)	(-23.99)	(-24.19)	(-22.03)	(-26.20)	(-33.36)	(-29.56)	(-35.48)
knn8	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***	0.0019***
	(41.70)	(39.15)	(46.37)	(43.42)	(41.38)	(47.68)	(52.52)	(52.89)	(56.26)
ln w									
d(11km)	0.1649***	0.1653***	0.1652***	0.1665***	0.1668***	0.1670***	0.1663***	0.1665***	0.1666***
	(15.58)	(16.68)	(17.64)	(27.75)	(25.90)	(32.40)	(26.51)	(25.83)	(29.82)
knn8	0.0018***	0.0018***	0.0018***	0.0018***	0.0018***	0.0018***	0.0018***	0.0018***	0.0018***
	(7.99)	(9.12)	(6.82)	(9.71)	(10.23)	(10.97)	(8.32)	(8.65)	(9.67)

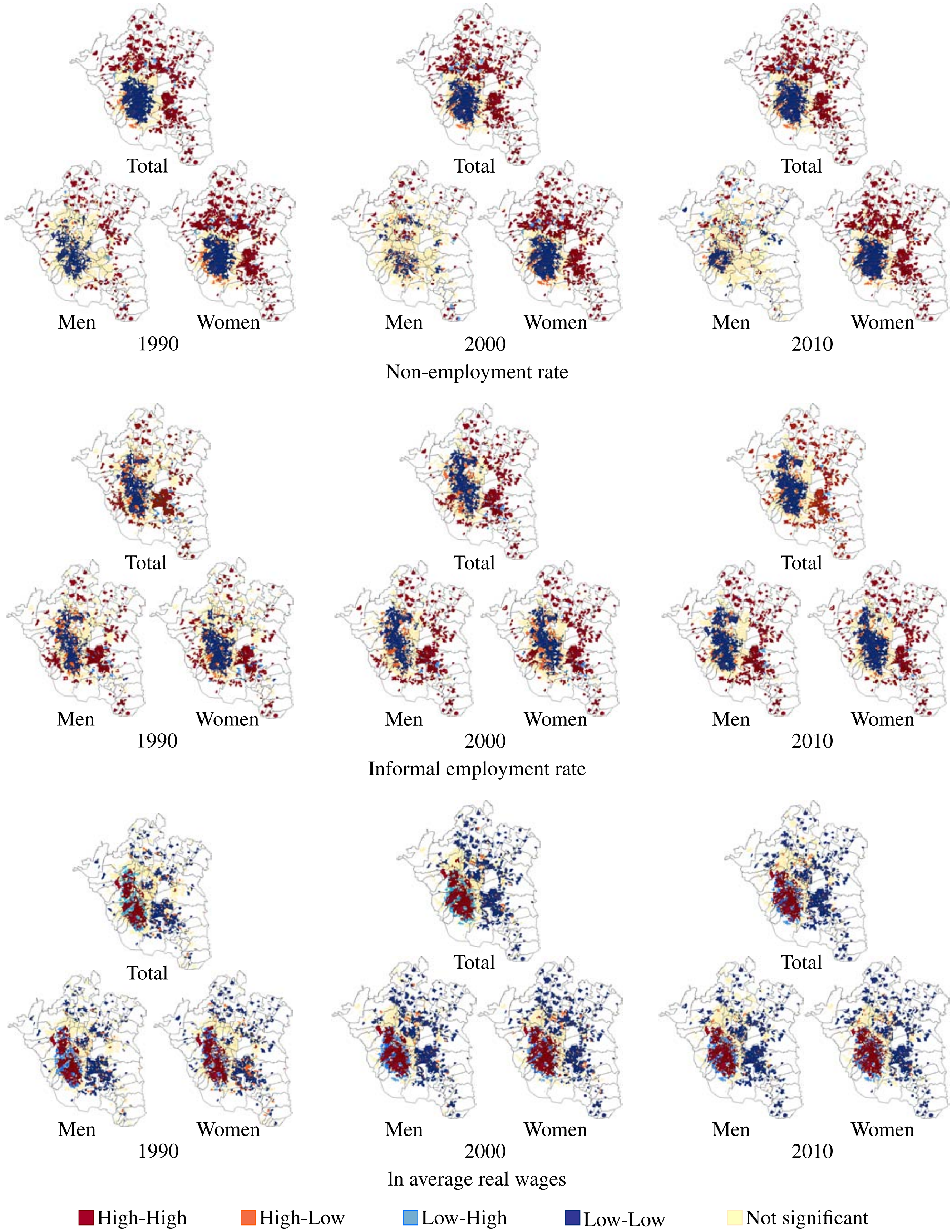

Figure IV.7: Local Moran's I by gender

Figure IV.7 presents the local Moran's I. Local Moran's I depicts the type of cluster formation. The case of "*High-High*" values means that a census tract with an above average value (for a selected variable) is surrounded by census tracts with above average value. Similarly, the case of "*Low-Low*" values corresponds to a situation in which a census tract with a value for the selected variable below the average value is surrounded by census tracts sharing the same feature.

The maps of local Moran's I replicate the spatial patterns depicted in previous exercises. Low non-employment rates are concentrated in the inner city, and high non-employment values are in the periphery of the city. These patterns seem to be constant over time. With respect to informal employment rate, the concentration of low and high values have accrued an east-west division. There were some clusters of high values of informal employment in western part of the city that have disappeared during the last two decades. The concentration of high and low average real wages have a southwest and northeast division. Finally, the local Moran's I by gender only shows larger differences in non-employment rates. The concentration of low male non-employment rates disappeared in the last these two decades.

To sum up, first we isolated an important spatial component for the three labor market outcomes. Nonetheless, there are different spatial distribution patterns. On the one hand, the non-employment rate follows a center-periphery separation mostly driven by the behavior of women. On the other hand, wages and informality are spatially distributed according to an east-west separation following the typical income divide of the city.

IV.4 Empirical strategy

The principal results stemming from the previous section is that the geographic distribution patterns of non-employment rates, informal employment rates and average wages are not random. This feature may find their principal cause in the existence of neighborhood composition and spillover effects. The scope of this chapter is to present a quantitative exercise to determine the extent local or global spillover effects impact on selected labor market outcomes, using aggregated data.

In the spatial econometrics literature, the mixed regressive and spatial autoregressive models are commonly exploited to model global spatial spillover effects.[12] Instead, local spillover effects are estimated using lagged independent variables (Elhorst, 2014).[13] In this study we adopt the IV/GMM estimation strategy because our data present heteroskedastic and non-normal disturbances. In fact, the spatial econometrics literature remarks that the coefficient of the spatial autoregressive error term estimated by using maximum likelihood or Bayesian methods is inconsistent because of the presence of heteroscedasticity and non-normal disturbances (Lin and Lee, 2010). Nevertheless, one of the disadvantages of the IV/GMM estimation is that the parameters of the spatial

[12]For instance, General nesting spatial model (GNS), spatial Durbin model (SDM), Spatial Cliff-Ord-type model (SARAR/SAC), spatial lag model/spatial autoregressive model (SLM/SAR). The endogenous spatial lag or error terms in these models are estimated with maximum likelihood, quasi maximum likelihood, instrumental variables/generalized method of moments (IV/GMM), and Bayesian methods.

[13]For instance, spatial cross-regressive model (SLX), spatial Durbin error model (SDEM). The spillover effects of the spatial error model (SEM) are zero by construction.

autoregressive terms are not restricted to the interval (1,-1) or $(1/r_{min}, 1)$, where r_{min} equals the most negative purely real characteristic root of row-normalized spatial weight matrix. This means that spatial dependence could be greater than one and we could have identification problems for global spillover effects.

There is a discussion about which model is more convenient in order to fit better the data. Spatial econometrics literature emphasizes the importance of the underlying working hypothesis in the definition of the most suitable model (Gibbons and Overman, 2012; Elhorst, 2014). For instance, a model with endogenous interaction effects (such as SLM or SDM)[14] assumes that the outcome in one neighborhood depends on that in other neighborhoods, and on a set of neighborhood characteristics. In contrast, a model with interaction effects in the error term, such as SEM or SDEM, posits that the outcome in one neighborhood depends on a set of neighborhood characteristics and unobserved characteristics omitted from the model that neighborhoods hold in common.

Some authors reveal preferences for SDM, SDEM or GNS to SLM or SARAR/SAC models because the last two models assume that feedback effects and indirect effects are constant for all independent variables. The feedback effects and indirect effects in SDM and GNS models vary across the explanatory variables. Moreover, feedback effects and indirect effects cannot be always significant: it depends on the explanatory variables. Finally, some authors suggest to follow a progressive augmenting strategy. It means to begin with the estimation of the simplest model (i.e. the SLX model) and then tailor the most suitable specification in accordance with the intermediate results. The estimation of the SLX model has a direct interpretation of the coefficients and it does not suffer from the overparameterization problem. However, by assumption this model has no feedback effects and it can take into account only local spillover effects. In the light of this academic discussion, our empirical strategy is driven by the choice to estimate several alternative spatial econometric models to pursue robust estimations that fit our scope.

We estimate two classes of models. First, we estimate a three cross-section-type model in which we consider each year separately. Then, we perform panel data estimations.[15]

The general specification of spatial models is the following:

$$\begin{aligned} \mathbf{Y}_t &= \lambda \mathbf{W}\mathbf{Y}_t + \alpha \boldsymbol{\iota}_N + \mathbf{X}_t\boldsymbol{\beta} + \mathbf{W}\mathbf{X}_t\boldsymbol{\theta} + \mathbf{u}_t \\ \mathbf{u}_t &= \rho \mathbf{W}\mathbf{u}_t + \epsilon_t \end{aligned} \tag{IV.1}$$

where $\mathbf{Y}$ represents the corresponding dependent variable (non-employment rate, informal employment rate and logged wage), $\mathbf{X}$ is a vector of contextual variables and control variables, $\mathbf{W}$ is the weight (or adjacency) matrix, $\mathbf{WY}$ denotes the endogenous interactions effects among the dependent variables, $\mathbf{WX}$ the exogenous interaction effects (or contextual effects as Manski (1993) defines them) among the independent variables, and $\mathbf{Wu}$ the interaction effects among the disturbance term of different neighborhoods (Elhorst, 2014). The spatial weight matrix, $\mathbf{W}$, describes the spatial configuration or spatial interactions of the units in the sample. $\boldsymbol{\iota}_N$ is a

[14]Refer to figure IV.8 for the acronyms.

[15]We also perform a very preliminary analysis of possible dynamic effects of spillover effects, because we have only three periods (see Appendix IV.A, Table IV.A.23).

vector of ones. We estimate all cross-section models using the methodology proposed by Araiz, et al. (2010). The taxonomy of the different spatial dependence models for cross-section data are presented in Figure IV.8. For instance, if $\boldsymbol{\theta} = 0$, the model is SARAR/SAC; if $\rho = 0$, the model is SDM; if $\lambda = 0$, the model is SDEM; if $\boldsymbol{\theta} = 0$ and $\rho = 0$, the model is SLM; if $\boldsymbol{\theta} = 0$ and $\lambda = 0$, the model is SEM; if $\rho = 0$ and $\lambda = 0$, the model is SLX.

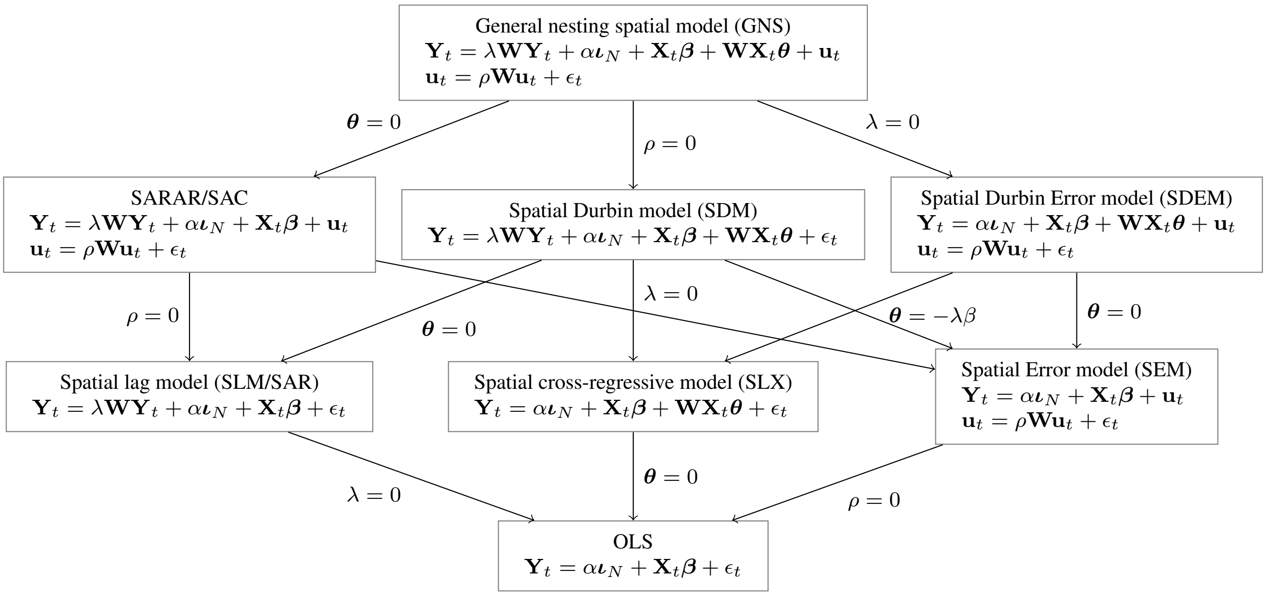

Figure IV.8: Spatial dependence models for cross-section data

Source: Halleck Vega and Elhorst (2015)

However, we cannot forget that there are correlated effects or unobservable variables (such as background variables, that affect the dependent variable). Failing to account for these variables might bias estimation results. In order to control for omitted unobservable variables we introduce both a time and spatial specific effects for each neighborhood. Therefore, we augment the model IV.1 with spatial specific and time-period specific effects as follow:

$$
\begin{aligned}
\mathbf{Y}_t &= \lambda \mathbf{W}\mathbf{Y}_t + \alpha \boldsymbol{\iota}_N + \mathbf{X}_t\boldsymbol{\beta} + \mathbf{W}\mathbf{X}_t\boldsymbol{\theta} + \boldsymbol{\mu} + \xi_t \boldsymbol{\iota}_N + \mathbf{u}_t \\
\mathbf{u}_t &= \rho \mathbf{W}\mathbf{u}_t + \boldsymbol{\epsilon}_t \qquad \text{(IV.2)}
\end{aligned}
$$

where $\boldsymbol{\mu} = (\mu_1, \ldots, \mu_N)^T$ is the spatial specific effect and $\xi_t \boldsymbol{\iota}_N$ is the time-period specific effect. The spatial and time-period specific effects may be treated as fixed effects or as random effects. We estimate all panel data models using the methodology proposed by Badinger and Egger (2014).[16]

In all models, we assume as spatial weight matrix $\mathbf{W}$ the eight nearest neighbors weighted by inverse distance between each centroid.[17] We assume these spatial weight matrix as time invariant.

[16]All models are estimated using R-program. The R code for the general model is in the Appendix B. There are no codes in most common software programs to estimate spatial panel data models with heteroskedastic disturbances.

[17]We also estimated all models with spatial weight matrix of eight nearest neighbors (no weighted by inverse distance), and the results did not change a lot. However, we estimated these models with an inverse of distance spatial weight matrix with a threshold distance of 11 km, and we could not identify the parameters because this matrix generated too much dependence. Restricting the number of interactions is recommended in order to identify the parameter (Gibbons et al., 2014).

As the literature recently discusses, the coefficients of spatial econometric models are not directly interpretable. In order to test the existence of local or global effects, it is better to use a partial derivative interpretation of the impact from changes to the variables (LeSage and Pace, 2009). Direct, indirect and total effects are estimated by simulating 200 parameters from the estimated mean and variance-covariance matrix. Then, these results are used in the nonlinear partial derivative relationship to produce an empirical estimate of the mean and dispersion of the scalar summary effects estimates.

The formulas of direct and indirect impacts corresponding to different kinds of spatial econometric models are presented in Table IV.5.

Table IV.5: Direct and indirect effects of different kinds of spatial econometric models

Model	Direct effects	Indirect effects
OLS/SEM	β_k	0
SAC/SLM	Diagonal elements of $(\mathbf{I}-\lambda\mathbf{W})^{-1}\beta_k$	Off diagonal elements of $(\mathbf{I}-\lambda\mathbf{W})^{-1}\beta_k$
SLX/SDEM	β_k	θ_k
SDM/GNS	Diagonal elements of $(\mathbf{I}-\lambda\mathbf{W})^{-1}(\beta_k+\mathbf{W}\theta_k)$	Off diagonal elements of $(\mathbf{I}-\lambda\mathbf{W})^{-1}(\beta_k+\mathbf{W}\theta_k)$

Source: Halleck Vega and Elhorst (2015)

The direct effects embed the direct impacts of the explanatory variables on dependent variables. Instead, the indirect effects allow identifying the existence of spillover effects. The significance of the indirect effects means that spillover effects exist. The spillover effects can be global or local.[18] The existence of global spillover effects implies that the coefficient of the spatial autoregressive term is different from zero, $\lambda \neq 0$, and the indirect spillover effects are significant. Instead, the existence of local spillover effects only requires that the exogenous interaction effects among the independent variables are significant.

The sample for the estimation includes males and females between 18 and 65 years old belonging to one of the census tracts in Mexico City. Our dependent variables are the non-employment rate, informal employment rate, and logged average real wages. The explanatory variables are a social deprivation index, a job accessibility index, the average years of education, the average age and the population density in each census tract. In the case of non-employment rate, we include an age dependency ratio. Following the definition of Manski (1993) of contextual effects, we call these explanatory variables as "contextual variables" since they are used as proxies for these effects, except for population density which is a control variable.[19]

The social deprivation index is a composite index constructed by principal component analysis that measures the main characteristics of neighborhood-related dwellings. The variables that contain this index are presented in Appendix A Table A.1.2. The job accessibility index measures the potential job opportunities and it is constructed using a job potential index. The formula of this index are presented in Appendix A equation (A.2).[20] The average years of education measures the human capital and/or the socioeconomic composition of the pop-

[18]The spillover effects are global when feedback effects are present.

[19]Exogenous or contextual effects refer to influences exerted by the exogenous characteristics of a reference group on the individual decision-taking process, neighborhood characteristics for instance. We use similar proxies for these effects in Chapter III, such as SDI and AI.

[20]We also estimate the spatial model using the employment density, and the results do not change.

Table IV.6: Descriptive stiatistics 1990, 2000 and 2010

Dependent variables								
Total non-employment rate			Total informal employment rate			ln w		
1990	2000	2010	1990	2000	2010	1990	2000	2010
0.3491 (0.0792)	0.3078 (0.0588)	0.2895 (0.0578)	0.3714 (0.1213)	0.3988 (0.1348)	0.3909 (0.1230)	8.75 (0.4245)	8.62 (0.4430)	8.78 (0.4447)
Male non-employment rate			Male informal employment rate			ln w of men		
1990	2000	2010	1990	2000	2010	1990	2000	2010
0.0552 (0.0401)	0.0800 (0.0234)	0.0765 (0.0265)	0.3734 (0.1190)	0.4047 (0.1290)	0.3914 (0.1260)	8.83 (0.4879)	8.73 (0.5084)	8.87 (0.4814)
Female non-employment rate			Female informal employment rate			ln w of women		
1990	2000	2010	1990	2000	2010	1990	2000	2010
0.6133 (0.1267)	0.5154 (0.1121)	0.4762 (0.1074)	0.3744 (0.1422)	0.3856 (0.1488)	0.3874 (0.1348)	8.55 (0.4246)	8.42 (0.4196)	8.63 (0.4159)

Explanatory variables I								
Average years of education age working persons (Education)			Average years of education of workers (Education)			Average years of education of salaried workers (Education)		
1990	2000	2010	1990	2000	2010	1990	2000	2010
7.89 (1.98)	9.22 (1.88)	10.52 (1.95)	8.27 (1.98)	9.78 (1.84)	11.19 (1.92)	8.25 (1.98)	9.90 (1.76)	10.90 (1.87)
Average age of age working persons (Age)			Average age of workers (Age)			Average age of salaried workers (Age)		
1990	2000	2010	1990	2000	2010	1990	2000	2010
33.77 (1.53)	35.33 (1.72)	38.47 (1.97)	33.02 (1.51)	34.04 (1.75)	36.51 (1.86)	33.03 (1.52)	33.89 (1.82)	37.12 (2.31)
Age dependency ratio (Child)								
1990	2000	2010						
1.00 (0.52)	0.75 (0.26)	0.64 (0.19)						

Explanatory ariables II								
Social deprivation index (SDI)			Job accesibility index (AI)			Population density		
1990	2000	2010	1990	2000	2010	1990	2000	2010
-0.0005 (2.0288)	0.0006 (1.8311)	0.0005 (1.6624)	0.3565 (0.2558)	0.5662 (0.3884)	0.5103 (0.3174)	135.08 (108.65)	149.87 (101.94)	147.99 (93.71)

The explanatory variables I differ for each dependent variable. Age working persons exclude students, disabled and retired persons. The average years of education and average years old of age working persons (columns 1 to 3) are explanatory variables of non-employment rates, as well as, the number of children per women. The average years of education and average age of workers (columns 4 to 6) are explanatory variables of informal employment rates. The average years of education and average age of salaried workers (columns 7 to 9) are explanatory variables of wages. All models for every dependent variable include the explanatory variables II. Standard deviation in parenthesis.

ulation of each neighborhood (or the degree of residential segregation of an area). The average age of a single census tract is a proxy for the age structure of this tract. The age dependency ratio is the ratio between dependent children and total working-age women as a proxy of the time that women have to dedicate to childcare.[21] We expect an opposite effect of this variable on men as it can portray the economic pressure that child support exerts on men. Finally, the population density is included in other to control for the heterogeneity in size of census tracts. The census tracts have different sizes in terms of population and area. The descriptive statistics of these variables are presented in Table IV.6.

[21] We consider as a dependent child a person younger than 12 years old.

In terms of the census tracts' socioeconomic composition, one may remark that the average years of education and the average age has risen during the period (see Figure IV.9). There is a shift of these variables' distribution towards higher values. Meanwhile, the age dependency ratio decreased during the period, because the age dependency ratio drops. Instead, we observe a sharp increase in the social deprivation index between 1990 and 2000.[22] In other words, the dwelling conditions measured by this index are worse in 2000 and 2010 than in 1990.

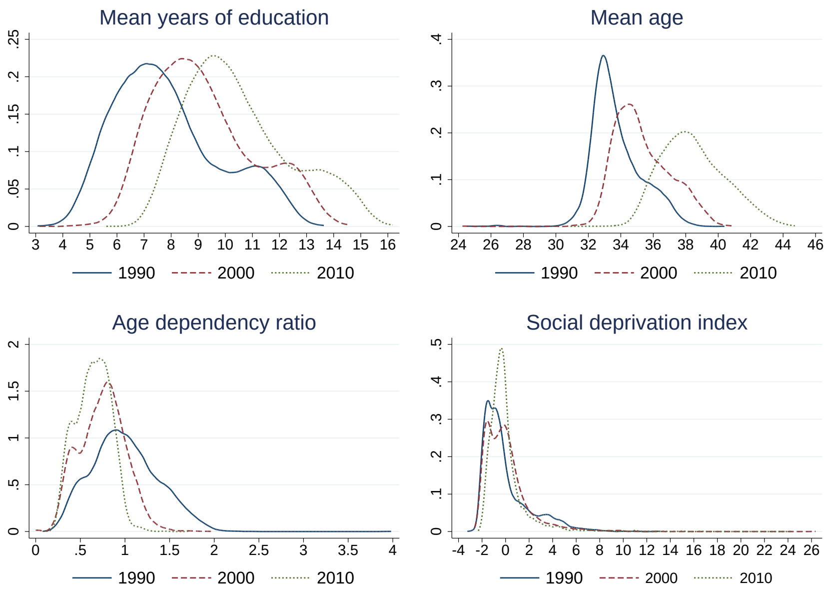

Figure IV.9: Kernel function of census tracts's socieconomic variables

IV.5 Results

First, we present the results of the cross-section estimations and, in the next subsection, we do the same for panel data. We discuss the effects of each explanatory variable on each dependent variable in the following order: (1) non-employment rates, (2) informal employment rates, and (3) wages. The estimation strategy is stepping gradually from the simplest model (least squares model) to the most complex (general nested model).

IV.5.1 Cross-section estimations

In most of the cases, the coefficients of the least squares estimations suffer from a downward bias because the indirect effects of the variables are not taken into account (see cross-section estimations of Appendix IV.A, Table IV.A.1). But we can control for them in models including spatially lagged independent variables (SLX). Nonetheless, we still experience the possibility of an omitted-variable bias because neither endogenous nor correlated effects are included in this class of estimations. However, overall with SLX models, we are able to detect the presence of at least local spillovers for the three labor market outcomes, namely non-employment rate, informal employment rate, and real wages, for each period of time: 1990, 2000 and 2010 (see Appendix IV.A

[22]The formula of social deprivation index is presented in Appendix A and the variables that compose this index are in the same Appendix Table A.1.2

Tables IV.A.6 and IV.A.7).

Instead, the SLM and SARAR/SAC models, Appendix IV.A Tables IV.A.2 to IV.A.5 indicate the possibility of the existence of global spillover effects in non-employment rates for the whole period and, recently, in informal employment. The feedback effects (or global spillover effects) are at least 3% in the case of non-employment and reach up to 3% for informal employment.[23] The feedback effects of wages are very low (less than 1% in 2000 and 2010, and zero in 1990); this means that the spillovers are more local than global. Instead, SLM and SARAR/SAC models assume that feedback effects and indirect effects are constant for all independent variables. However, a common criticism to this class of models is that the autoregressive parameter (λ) could be capturing the effects of lagged independent variables instead of the endogenous effects. Therefore, it is recommended estimating them using other models such as SLX, SDEM, SDM or GNS. The simplest model is the SLX and it is quite manageable because it provides the direct interpretation of the coefficients. We start with this model to check the existence of spillovers and, then we proceed to more complex models to discern whether these spillovers are global or local. The impacts of each explanatory variable on each independent variable are discussed below (and we refer to Tables IV.7, IV.8, and IV.9).

Non-employment rates

The coefficients of contextual variables (no spatially lagged) have the expected signs in all cross-section estimations of non-employment rates (see cross-section estimations of Appendix IV.A, Tables IV.A.1 to IV.A.11). We identify a positive relationship between the social deprivation index (SDI) and the non-employment rates, while job accessibility (AI) and the average years of education exert a negative impact on the non-employment rates. We cannot interpret the sign of the average age in the same manner as in the case of individual data estimation because we cannot distinguish the age effect from a cohort effect. Finally, we obtain a positive sign in the case of women for the age dependency ratio and a negative sign for men as one should expect.

As we pointed out in previous sections, there are important differences between women and men in the output of the estimation for non-employment rates. The coefficients of the explanatory variables record a larger magnitude for women than for men and they help to explain better the spatial patterns of female non-employment rates with respect to the case of male non-employment rates (see the goodness of fit measures of Appendix IV.A Tables from IV.A.1 to IV.A.10). This could be due to the fact that women are more sensitive to spatial frictions than men in deciding the participation in the labor market.

We found minor local spillovers of SDI in the case of male non-employment rate, but they disappeared in the most recent years. There are no spillover effects of SDI in female non-employment rates. SDI only produces indirect effects on male non-employment rate and direct effects on the female one since 2000, as we can see in Table IV.7.[24]

[23] In other words, 3% of the direct effect corresponds to feedback effects. The direct effect minus the coefficient of a selected variable is the feedback effect of this variable, and the percentage is the ratio between this subtraction and direct effect.

[24] The SLX cross-section model indicates that the indirect effect of SDI on female non-employment rate is negative. However, the

Table IV.7: Cross-section models: non-employment rates.

Variable		Year	Impacts	OLS	SLM	SAC	SLX	SDEM	SDM	GNS
Social deprivation index	Men	1990	Direct	0.0025***	0.0010*	0.0009*	0.0012	0.0012	0.0014	0.0013
			Indirect	-	0.0030	0.0031	0.0014	0.0029*	0.0258	0.0183
		2000	Direct	0.0018***	0.0009	0.0010*	-0.00001	0.0001	0.0001	0.0009
			Indirect	-	0.0008	0.0009*	0.0042***	0.0039***	0.0041*	0.0004
		2010	Direct	0.0008*	0.0010*	0.0008**	0.0010*	0.0009*	0.0010	0.0010
			Indirect	-	0.0020	0.0019	-0.0003	0.0002	0.0036	0.0037
	Women	1990	Direct	0.0011	0.0007	0.0015*	0.0013	0.0014	0.0009	0.0009
			Indirect	-	0.0005	0.0009*	-0.0055***	0.0009	-0.0009	-0.0003
		2000	Direct	0.0001	0.0011	0.0019*	0.0022*	0.0020*	0.0019*	0.0019*
			Indirect	-	0.0008	0.0012*	-0.0066***	-0.0018	-0.0021	-0.0018
		2010	Direct	0.0015*	0.0019**	0.0024**	0.0027**	0.0028***	0.0024**	0.0024**
			Indirect	-	0.0016*	0.0019**	-0.0025	0.0006	0.0029	0.0027
Job accessibility index	Men	1990	Direct	-0.0176***	-0.0043***	-0.0050***	-0.0119***	-0.0087***	-0.0058	-0.0063
			Indirect	-	-0.0130**	-0.0163***	-0.0590***	-0.0348***	-0.1305	-0.1291
		2000	Direct	-0.0029**	-0.0019*	-0.0023***	-0.0020**	-0.0020**	-0.0020*	-0.0020*
			Indirect	-	-0.0017*	-0.0043**	-0.0116***	-0.0106***	-0.0122**	-0.0122**
		2010	Direct	-0.0062***	-0.0030*	-0.0043***	-0.0043***	-0.0038**	-0.0026	-0.0029
			Indirect	-	-0.0059	-0.0099	-0.0215***	-0.0174***	-0.0266	-0.0325
	Women	1990	Direct	-0.0597***	-0.0207***	-0.0080***	-0.0283***	-0.0217***	-0.0141***	-0.0137***
			Indirect	-	-0.0165***	-0.0051***	-0.1377***	-0.0882***	-0.0869***	-0.0819***
		2000	Direct	-0.0326***	-0.0130***	-0.0062***	-0.0179***	-0.0150***	-0.0122***	-0.0119***
			Indirect	-	-0.0094***	-0.0039***	-0.0877***	-0.0645***	-0.0651***	-0.0624***
		2010	Direct	-0.0405***	-0.0135***	-0.0078***	-0.0225***	-0.0181***	-0.0138***	-0.0141***
			Indirect	-	-0.0117***	-0.0060***	-0.1054***	-0.0722***	-0.0766***	-0.0799***
Average years of education	Men	1990	Direct	-0.0119***	-0.0061***	-0.0058***	-0.0086***	-0.0082***	-0.0082	-0.0082
			Indirect	-	-0.0184***	-0.0189***	-0.0062***	-0.0047***	-0.0322	-0.0258
		2000	Direct	-0.0093***	-0.0078***	-0.0075***	-0.0085***	-0.0086***	-0.0085***	-0.0085***
			Indirect	-	-0.0067***	-0.0066***	-0.0011	-0.0008	-0.0030	-0.0028
		2010	Direct	-0.0054***	-0.0040***	-0.0034***	-0.0044***	-0.0043***	-0.0041	-0.0113***
			Indirect	-	-0.0079	-0.0079	-0.0010	-0.0017	-0.0071	-0.0041
	Women	1990	Direct	-0.0424***	-0.0277***	-0.0311***	-0.0325***	-0.0324***	-0.0317***	-0.0316***
			Indirect	-	-0.0221***	-0.0199***	-0.0096***	-0.0073***	-0.0148***	-0.0150***
		2000	Direct	-0.0350***	-0.0241***	-0.0262***	-0.0277***	-0.0276***	-0.0267***	-0.0267***
			Indirect	-	-0.0174***	-0.0165***	-0.0096***	-0.0066*	-0.0111**	-0.0112**
		2010	Direct	-0.0256***	-0.0164***	-0.0175***	-0.0177***	-0.0182***	-0.0175***	-0.0175***
			Indirect	-	-0.0142***	-0.0134***	-0.0070***	-0.0036	-0.0058	-0.0056
Average age	Men	1990	Direct	0.0094***	0.0041***	0.0040***	0.0044***	0.0042***	0.0035	0.0036
			Indirect	-	0.0125***	0.0131***	0.0111***	0.0055**	0.0104	0.0124
		2000	Direct	0.0051***	0.0036***	0.0036***	0.0030*	0.0031**	0.0031**	0.0031**
			Indirect	-	0.0031***	0.0031***	0.0045***	0.0046***	0.0050*	0.0049**
		2010	Direct	0.0012**	-0.0004	-0.00001	-0.0005**	-0.0006	-0.0010	-0.0010
			Indirect	-	-0.0009	-0.00001	0.0041*	0.0036*	0.0018	0.0014
	Women	1990	Direct	-0.0110***	-0.0072***	-0.0086***	-0.0076***	-0.0087***	-0.0079***	-0.0079***
			Indirect	-	-0.0057***	-0.0055***	0.0076***	-0.0026	0.0011	-0.0001
		2000	Direct	-0.0019*	-0.0010	-0.0025	-0.0026	-0.0027	-0.0024	-0.0024
			Indirect	-	-0.0007	-0.0016	0.0136***	0.0074	0.0089	0.0084
		2010	Direct	0.0164***	0.0125***	0.0123***	0.0113***	0.0117***	0.0112***	0.0112***
			Indirect	-	0.0109***	0.0094***	0.0088***	0.0074**	0.0112***	0.0113***
Age dependency ratio	Men	1990	Direct	-0.0053***	-0.0067***	-0.0068***	-0.0052	-0.0062***	-0.0112	-0.0102
			Indirect	-	-0.0203*	-0.0224**	-0.0101	-0.0144*	-0.0289	-0.1544
		2000	Direct	-0.0295***	-0.0297***	-0.0286***	-0.0335***	-0.0340***	-0.0339***	-0.0337***
			Indirect	-	-0.0256**	-0.0250**	-0.0006	0.0042	-0.0094	-0.0097
		2010	Direct	-0.0341***	-0.0439*	-0.0354*	-0.0486**	-0.0491**	-0.0536	-0.0536
			Indirect	-	-0.0878	-0.0817	0.0240	0.0165	-0.0680	-0.0644
	Women	1990	Direct	0.0164***	0.0080	0.0053	0.0076	0.0056	0.0073	0.0070
			Indirect	-	0.0064	0.0034	0.0635***	0.0131	0.0451*	0.0397*
		2000	Direct	0.1146***	0.0651***	0.0558***	0.0557***	0.0565***	0.0542***	0.0540***
			Indirect	-	0.0470***	0.0350***	0.1225***	0.0962**	0.1140***	0.1118**
		2010	Direct	0.3609***	0.2350***	0.2398***	0.2385***	0.2437***	0.2340***	0.2339***
			Indirect	-	0.2042***	0.1837***	0.1355***	0.1517***	0.2112***	0.2109***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

There are important spillover effects of job accessibility and different spatial models that support this statement. In the case of female non-employment rates, the feedback effects are very high and statistically significant.

indirect impacts disappear when we introduce correlated effects (SDEM model) or endogenous effects (SDM) or both.

Therefore, spillover effects are of global type. The feedback effects for the case of job accessibility are more than 30% of the total effect in the case of female non-employment rates (see Appendix IV.A Table IV.A.22). There are no feedback effects in the case of men and the job accessibility only have local spillover effects on male non-employment rates.

The variable with the most significant coefficient is the average years of education. The impact of this variable decreases over time in all the estimations. There are local spillover effects stemming from the average years of education on female non-employment rates but not on men. However, this local spillover effect diminished and finally disappeared by 2010. The results of SDM and GNS models confirm that there are no feedback effects in the average years of education in most of the estimations.

The average age structure is positively associated with the male non-employment rate in 1990 and 2000, but this relation is null in 2010. We observe a change in the sign of coefficient of average age in the equations for female non-employments rates. The sign was negative in 1990 and positive in 2010, whereas in 2000 it was no significant. This effect can be associated with the habit of young women to enter the labor force whereas old women exit from it. The average age produces local spillover effects on the male non-employment rate. In 2000 these spillovers effects were global because feedback effects are estimated around 8% (see Appendix IV.A Table IV.A.22). Also the average structure of age generate positive local spillover effects on female non-employment rate in 1990 and 2000. In 2010 we find global and positive spillover effects of the average age on the female non-employment rate. But, overall, the indirect effects of the average age on non-employment rates are lower than direct ones.

The age dependency ratio generates at least local spillover effects on non-employment rates. In 1990, these spillovers were just local and they become global from 2000 onward with the estimated magnitude of feedback effects between 4% and 12% in accordance to the model and the year of reference for women. In the case of men, the spillover effects become global in 2010 with feedback effects from 0.4% to 2.3%, as Appendix IV.A Table IV.A.22 shows.

Informal employment rates

The coefficients of the contextual variables, such as SDI and education, have the expected signs in all cross-section estimations. That is, SDI positively relates with informal employment, whereas the average years of education display a negative estimated coefficient. In the case of job accessibility, the sign can be either positive or negative in the informal employment estimations in accordance with the type of jobs (formal vs. informal).[25] Finally, as we mentioned before, we cannot predict the sing of the average age as a contextual variable because this variable measures the average age structure of each tract.

The spillovers of SDI can be considered local for informal employment in 1990 or global with small feed-

[25]If the informal (formal) jobs have greater effects than the formal (informal) jobs, the sign of job accessibility will be positive (negative).

Table IV.8: Cross-section models: informal employment rates.

Variable		Year	Impacts	OLS	SLM	SAC	SLX	SDEM	SDM	GNS
Social deprivation index	Men	1990	Direct	0.0108***	0.0106***	0.0078***	0.0071***	0.0076***	0.0072***	0.0073***
			Indirect	-	0.0002	-0.0003	0.0057**	0.0020	0.0047*	0.0040*
		2000	Direct	0.0203***	0.0134***	0.0097***	0.0080***	0.0092***	0.0097***	0.0097***
			Indirect	-	0.0091***	0.0033***	0.0257***	0.0077*	0.0206***	0.0194***
		2010	Direct	0.0174***	0.0102***	0.0093***	0.0077***	0.0088***	0.0093***	0.0093***
			Indirect	-	0.0087***	0.0064***	0.0127***	0.0047	0.0108***	0.0100***
	Women	1990	Direct	0.0224***	0.0214***	0.0196***	0.0187***	0.0189***	0.0187***	0.0185***
			Indirect	-	0.0013*	0.0005	0.0057*	0.0026	0.0052**	0.0039*
		2000	Direct	0.0127***	0.0079***	0.0070**	0.0054*	0.0064**	0.0064***	0.0065**
			Indirect	-	0.0058***	0.0037**	0.0098**	0.0007	0.0065	0.0045
		2010	Direct	0.0154***	0.0102***	0.0093***	0.0077***	0.0088***	0.0093***	0.0093***
			Indirect	-	0.0087***	0.0064***	0.0127***	0.0047	0.0108***	0.0100***
Job accessibility index	Men	1990	Direct	0.0161***	0.0003	0.0014	0.0066	0.0034	0.0115***	0.0097**
			Indirect	-	0.0164***	-0.00006	0.0348***	0.0147	0.0594***	0.0394***
		2000	Direct	0.0017	0.0086**	-0.0014	0.0019	-0.0028	0.0058*	0.0057*
			Indirect	-	0.0058**	-0.0005	0.0255***	-0.0015	0.0628**	0.0578***
		2010	Direct	-0.0334***	-0.0086***	-0.0040*	-0.0139***	-0.0098***	-0.0101***	-0.0080**
			Indirect	-	-0.0072***	-0.0027*	-0.0590***	-0.0327**	-0.0391***	-0.0271*
	Women	1990	Direct	-0.0069	-0.0045	-0.0043	-0.0074*	-0.0076	-0.0057	-0.0049
			Indirect	-	-0.0003	-0.0001	-0.0151	-0.0165	-0.0038	-0.0015
		2000	Direct	-0.0050	0.0059	-0.0012	0.0007	-0.0058	0.0041	0.0027
			Indirect	-	0.0044	-0.0006	0.0210*	-0.0161	0.0417**	0.0276
		2010	Direct	-0.0385***	-0.0111***	-0.0068**	-0.0142***	-0.0138***	-0.0089**	-0.0088**
			Indirect	-	-0.0095***	-0.0046**	-0.0536***	-0.0421***	-0.0292*	-0.0277
Average years of education	Men	1990	Direct	-0.0463***	-0.0457***	-0.0466***	-0.0477***	-0.0469***	-0.0463***	-0.0464***
			Indirect	-	-0.0008	0.0021	-0.0016	0.0021	-0.0062*	-0.0034
		2000	Direct	-0.0344***	-0.0246***	-0.0289***	-0.0312***	-0.0299***	-0.0292***	-0.0292***
			Indirect	-	-0.0167***	-0.0100***	-0.0107**	-0.0061	-0.0189**	-0.0224**
		2010	Direct	-0.0313***	-0.0213***	-0.0261***	-0.0268***	-0.0265***	-0.0257***	-0.0257***
			Indirect	-	-0.0178***	-0.0177***	-0.0004	-0.0087**	-0.0057*	-0.0103***
	Women	1990	Direct	-0.0510***	-0.0490***	-0.0488***	-0.0495***	-0.0494***	-0.0486***	-0.0487***
			Indirect	-	-0.0029*	-0.0012	-0.0042	-0.0038	-0.0060**	-0.0053
		2000	Direct	-0.0364***	-0.0251***	-0.0267***	-0.0299***	-0.0290***	-0.0293***	-0.0288***
			Indirect	-	-0.0184***	-0.0140***	-0.0227***	-0.0146*	-0.0243***	-0.0212**
		2010	Direct	-0.0276***	-0.0186***	-0.0242***	-0.0239***	-0.0245***	-0.0232***	-0.0232***
			Indirect	-	-0.0159***	-0.0165***	0.0048*	-0.0019	-0.0016	-0.0035
Average age	Men	1990	Direct	0.0080***	0.0079***	0.0002	-0.0005	0.0001	0.0003	0.0005
			Indirect	-	0.0001	-0.00001	0.0160***	0.0039	0.0120***	0.0080**
		2000	Direct	0.0029	0.0015	-0.0072**	-0.0077**	-0.0081***	-0.0066**	-0.0065**
			Indirect	-	0.0010	-0.0025**	0.0262***	0.0065	0.0166**	0.0152*
		2010	Direct	-0.0113***	-0.0066***	-0.0084***	-0.0084***	-0.0086***	-0.0080***	-0.0082***
			Indirect	-	-0.0055***	-0.0057***	-0.0008	-0.0028	-0.0036	-0.0049
	Women	1990	Direct	0.0129***	0.0123***	0.0064***	0.0058**	0.0056**	0.0058**	0.0054**
			Indirect	-	0.0007*	0.0002	0.0149***	0.0119***	0.0136***	0.0113***
		2000	Direct	0.0006	-0.0004	-0.0091***	-0.0089**	-0.0094***	-0.0076**	-0.0081***
			Indirect	-	-0.0003	-0.0048**	0.0270***	0.0120*	0.0190***	0.0132*
		2010	Direct	-0.0193***	-0.0110***	-0.0100***	-0.0109***	-0.0106***	-0.0107***	-0.0106***
			Indirect	-	-0.0094***	-0.0068***	-0.0170***	-0.0093**	-0.0169***	-0.0158***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

back effects for male informal employment (the feedback effects accounts 2% of direct effects). However, the feedback effects increase around 10% in the following decades. With respect to female informal employment, the local spillovers of SDI become global with a feedback effect of 5% (see Table IV.A.22 in Appendix IV.A). Moreover, the indirect effects of SDI on informal employment are larger than the direct effects in 2000 and 2010.

The spillovers of the accessibility index are global for male informal employment. In 1990 job accessibility does not have effects on the female informal employment. In 2000 job accessibility has only indirect effects on the female informal employment and in particular we are able to identify only local spillovers. In 2010 these local spillovers on female informal employment become global. We remark that the access to jobs has a positive impact on informal employment in 1990 and 2000. However, the access to jobs decreases informal employment in 2010. Overall, this means that in 1990 and 2000, the informal jobs have a larger effect than formal jobs on job informal employment and the contrary happens in 2010.

The coefficient of the average years of education is the most statistically significant variable, but its significance falls in all estimations during the last two decades. Again, we record local spillover effects of the average years of education or global spillover effects with a low feedback effect (whose size can be quantified around 2%) on informal employment. However, this local spillover effect diminished during these decades. Local spillover effects of the average years of education on the female informal employment are not significant in 2010.

The spillover effects of average age on the male informal employment rate are local and positive in 1990 and global and positive in 2000. These spillovers are not significant on male informal employment in 2010. In the case of the female informal employment rate, the spillovers of average age are global; in 1990, these spillovers were positive but they became negative in 2010. When there are indirect impacts of the average age on informal employment rates, these are greater than direct impacts in absolute terms.

Wages

The coefficients of the contextual variables have the expected signs when they are significant in all estimations. That is, there is a negative relationship of SDI with respect to real wages. In the case of job accessibility, the association with real wages is positive. We expect that the higher average years of education in a tract will be associated with a higher average real wage in that tract. In the case of the average age structure, we cannot predict a statistical significant sign for the coefficient.

SDI has local spillover effects on male wages in 2000 and global spillovers in 2010 with an estimated feedback effect of 14%. SDI presents no spillovers on female wages in 1990 and in 2010, but SDI does produce global spillovers in 2000 with estimated feedback effects of 5% (see Appendix IV.A Table IV.A.22). When an indirect impact effect is detected, its magnitude surpass the direct impacts of SDI on wages.

Job accessibility only records local spillovers in the case of male wages. AI has local spillover effects on female wages in 1990, which becomes global in 2000. The size of the indirect effects of AI exceeds the one for direct effects in all dependent variables.

The average years of education is the most significant variable. However, we do not find indirect impacts or local spillover effects of the average years of education on wages. Meanwhile, the average structure of age generates local and negative spillover effects on real wages of men in 1990 but it does not generate spillovers in 2000 and 2010. In the case of real wages of women, the average age does not record spillover effects. There have been positive direct effects of the average age on wages since 2000, but this direct impact diminishes in 2010.

Table IV.9: Cross-section models: ln wages.

Variable		Year	Impacts	OLS	SLM	SAC	SLX	SDEM	SDM	GNS
Social deprivation index	Men	1990	Direct	-0.0028	-0.0019	0.0002	-0.0045	-0.0032	-0.0047	-0.0023
			Indirect	-	-0.0002	0.00002	-0.0035	-0.0010	-0.0017	-0.0022
		2000	Direct	0.0203***	-0.0281***	-0.0100	-0.0105	-0.0098	-0.0111	-0.0107
			Indirect	-	-0.0114***	-0.0034	-0.0709***	-0.0587***	-0.0679***	-0.0657***
		2010	Direct	-0.0161***	-0.0094***	-0.0061*	-0.0042	-0.0057*	-0.0070*	-0.0070*
			Indirect	-	-0.0028***	-0.0017*	-0.0274***	-0.0096	-0.0173**	-0.0178**
	Women	1990	Direct	-0.0138***	-0.0132**	-0.0159**	-0.0207**	-0.0212**	-0.0230***	-0.0225***
			Indirect	-	-0.0007	-0.0009	0.0111	0.0129	0.0144	0.0132
		2000	Direct	-0.0338***	-0.0281***	-0.0256***	-0.0212***	-0.0213***	-0.0209***	-0.0209***
			Indirect	-	-0.0078***	-0.0068***	-0.0276***	-0.0236***	-0.0262***	-0.0261***
		2010	Direct	-0.0157***	-0.0129***	-0.0126***	-0.0111***	-0.0119***	-0.0131***	-0.0129***
			Indirect	-	-0.0034***	-0.0030***	-0.0077	-0.0050	-0.0027	-0.0043
Job accessibility index	Men	1990	Direct	0.0210	0.0085	-0.0075	0.0332	0.0191	0.0338	0.0030
			Indirect	-	0.0009	-0.0007	0.1875***	0.0947	0.1178**	0.0210
		2000	Direct	0.0717***	0.0280*	-0.0062	0.0388**	0.0186	0.0266	0.0196
			Indirect	-	0.0114*	-0.0021	0.2763***	0.1342**	0.1887***	0.1400**
		2010	Direct	0.1083***	0.0477*	0.0059	0.0621**	0.0431*	0.0489*	0.0492*
			Indirect	-	0.0208**	0.0023	0.3842***	0.2443***	0.2815***	0.2865***
	Women	1990	Direct	0.0265	0.0209	-0.0002	0.0214	0.0225	0.0224	0.0193
			Indirect	-	0.0011	-0.00001	0.1474***	0.1435*	0.1044*	0.0903
		2000	Direct	0.0674***	0.0380***	0.0233**	0.0353***	0.0326***	0.0325***	0.0321***
			Indirect	-	0.0106***	0.0062**	0.1951***	0.1599***	0.1377***	0.1349***
		2010	Direct	0.0988***	0.0635***	0.0387**	0.0621***	0.0568***	0.0508**	0.0510**
			Indirect	-	0.0169***	0.0094**	0.2565***	0.1948***	0.1593**	0.1837***
Average years of education	Men	1990	Direct	0.1835***	0.1712***	0.1717***	0.1740***	0.1719***	0.1733***	0.1717***
			Indirect	-	0.0181**	0.0156*	0.0124	0.0209	0.0146	0.0214
		2000	Direct	0.1442***	0.1185***	0.1456***	0.1469***	0.1473***	0.1450***	0.1450***
			Indirect	-	0.0482***	0.0489***	-0.0321	-0.0194	-0.0203	-0.0162
		2010	Direct	0.1587***	0.1335***	0.1438***	0.1457***	0.1443***	0.1431***	0.1432***
			Indirect	-	0.0395***	0.0557***	-0.0005	0.0198	0.0196	0.0192
	Women	1990	Direct	0.1252***	0.1207***	0.1168***	0.1160***	0.1136***	0.1121***	0.1117***
			Indirect	-	0.0064	0.0066	0.0156	0.0219	0.0235	0.0243
		2000	Direct	0.1442***	0.1185***	0.1456***	0.1469***	0.1473***	0.1450***	0.1450***
			Indirect	-	0.0482***	0.0489***	-0.0321	-0.0194	-0.0203	-0.0162
		2010	Direct	0.1444***	0.1293***	0.1353***	0.1388***	0.1376***	0.1362***	0.1370***
			Indirect	-	0.0344***	0.0328***	-0.0097	0.0029	0.0124	0.0086
Average age	Men	1990	Direct	0.0017	0.0016	0.0126	0.0139	0.0138	0.0122	0.0136
			Indirect	-	0.0002	0.0011	-0.0306**	-0.0248	-0.0241*	-0.0158
		2000	Direct	0.0537***	0.0389***	0.0394***	0.0408***	0.0417***	0.0394***	0.0399***
			Indirect	-	0.0158***	0.0132**	0.0012	0.0084	0.0147	0.0180
		2010	Direct	0.0255***	0.0116**	0.0126**	0.0141**	0.0142***	0.0131***	0.0131**
			Indirect	-	0.0051**	0.0049**	0.0019	0.0044	0.0059	0.0057
	Women	1990	Direct	-0.0018	-0.0018	0.0030	0.0055	0.0055	0.0056	0.0054
			Indirect	-	-0.0001	0.0002	-0.0215	-0.0237	-0.0200	-0.0183
		2000	Direct	0.0437***	0.0338***	0.0333***	0.0314***	0.0314***	0.0308***	0.0308***
			Indirect	-	0.0094***	0.0089***	0.0039	0.0072	0.0099	0.0102
		2010	Direct	0.0218***	0.0122***	0.0109**	0.0097*	0.0105**	0.0093**	0.0091*
			Indirect	-	0.0032***	0.0026**	0.0142*	0.0086	0.0119	0.0128

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

To conclude the discussion of the cross-section estimation, we identify that the feedback effects of the male non-employment rate are very high in 1990 and 2010 (more than 11% in SLM and SARAR/SAC models, in contrast to feedback effects of female non-employment rate which are less than 4%). This generates a large dependence on the explanatory variables that causes identification problems in SDM and GSN models (direct, indirect and total effects are not significant – see Appendix IV.A Tables IV.A.9 and IV.A.11 –). Therefore, we turn to the SLX model to analyze the presence of spillovers. Due to these identification problems, it is possible that local spillovers on the male non-employment rate are eventually global. The inclusion of either local or global spillover effects in the estimations substantially increases the goodness-of-fit compared to least squares estimation of male non-employment rates.

With respect to informal employment rate, we find local and global spillover effects in most of the explanatory variables, contrary to wages estimation in which half of the variables has local or global spillover effects.

IV.5.2 Panel data estimations

In this subsection, we present the results of panel data models estimated with fixed effects. On the bases of the results of the preliminary Hausman test, fixed effects have been preferred to random effects. Overall, time-specific effects are significant for half of male non-employment rate estimations (SLM, SLX and SDEM), and in four for the female non-employment rate estimations (SLM, SAC, SLX and SDM). We present estimations with space-specific effects in the case of non-employment rate estimations. Time-specific effects are significant in all informal employment rate and average real wage estimations, except for informal employment rate GNS model.

Unfortunately it is possible that panel data estimations are overparameterized, especially in the case of the most complex models such as SDM, SDEM and GNS. Therefore, the significance levels of all variables tend to shrink and become not significant in these models (see Appendix IV.A Tables IV.A.17, IV.A.18 and IV.A.20). However, we can concentrate our discussion on the estimation results of the simplest models such as SLX in order to at least identify the existence of local spillovers. Despite the fact that most spatially-lagged explanatory variables are not significant in the non-employment estimation, we can identify global spillovers in female non-employment and informal employment rates because the direct, indirect, and total effects are significant in SDM and GNS two-ways models (both space-specific and time-specific models).

Non-employment rates

In panel data models, the coefficients of contextual variables have the expected signs when we include both space- and time-specific effects, except for the case of the job accessibility index that is positive in some estimations (see Appendix IV.A, Tables from IV.A.12 to IV.A.21). In the case of non-employment rates, we observe that fixed effects record a concentration of low values in the inner city and the highest values cluster in the peripheral part of the city. This pattern is highly related to the pattern of job accessibility and the changes in employment. Due to the decentralization of employment, job accessibility slightly increased at the periphery, while it decreased marginally at the center of the city. Therefore, the non-employment rates diminished in zones with low job accessibility and increased in zones with high job accessibility.

SLM and SARAR/SAC fixed-effects-panel-data-models have greater feedback effects than the corresponding cross-section estimations. The feedback effects of the male non-employment rate accounts from 38% to 44% as compared with female non-employment rate, whose effects range from 3% to 10%.

In contrast to cross-section estimations, we find unexpected negative local spillovers effects of social deprivation index on non-employment rates (see Table IV.A.16). However, the impacts of the SLX two-ways model and the SDM and GNS models indicate that there are no local spillover effects of SDI on non-employment rates,

Table IV.10: Panel data models: non-employment rates.

Space specific fixed effects								
Variable		Impacts	SLM	SAC	SLX	SDEM	SDM	GNS
SDI	Men	Direct	-0.0004	-0.0004	-0.0004	-0.0005	-0.0005	-0.0005
		Indirect	-0.0072	-0.0068	-0.0054***	-0.0037*	-0.0133	-0.0144
	Women	Direct	0.0024***	0.0030***	0.0028***	0.0036***	0.0031***	0.0033***
		Indirect	0.0041***	0.0047*	-0.0059***	0.0010	0.0012	0.0034
AI	Men	Direct	0.0110	0.0119	0.0283***	0.0221***	0.0060	0.0063
		Indirect	0.2016	0.1914	0.1258***	0.1130***	0.1871	0.1873
	Women	Direct	-0.0250***	-0.0188***	0.1258***	-0.0241*	-0.0100***	-0.0105*
		Indirect	-0.0438***	-0.0291***	-0.0764***	-0.0937	-0.0727***	-0.0757*
Education	Men	Direct	-0.0077	-0.0071	-0.0064***	-0.0065***	-0.0070	-0.0068
		Indirect	-0.1409	-0.1137	-0.0103***	-0.0086***	-0.0640	-0.0579
	Women	Direct	-0.0199***	-0.0210***	-0.0207***	-0.0206***	-0.0197***	-0.0199***
		Indirect	-0.0348***	-0.0325***	-0.0209***	-0.0118*	-0.0303***	-0.0316*
Age	Men	Direct	0.0029	0.0027	0.0029***	0.0028**	0.0026	0.0026
		Indirect	0.0534	0.0428	0.0066***	0.0055***	0.0225	0.0211
	Women	Direct	0.0025***	0.0021*	0.0017	0.0004	0.0016*	0.0016
		Indirect	0.0044***	0.0033	0.0039***	-0.0028	0.0068***	0.0068
Child	Men	Direct	-0.0110	-0.0102	-0.0038**	-0.0050**	-0.0076	-0.0070
		Indirect	-0.2005	-0.1644	0.0105**	0.0029	-0.0897	-0.0692
	Women	Direct	0.0105	0.0090	0.0124	0.0074	0.0114*	0.0108
		Indirect	0.0185	0.0139	0.0865***	0.0093	0.0734***	0.0607
Both space and time specific fixed effects								
Variable		Impacts	SLM	SAC	SLX	SDEM	SDM	GNS
SDI	Men	Direct	-0.0006	-0.0006	-0.0003	-0.0005	0.0001	-0.0018
		Indirect	-0.0067	-0.0073	-0.0058***	-0.0037*	0.0050	0.0122
	Women	Direct	0.0031***	0.0034***	0.0034***	0.0040***	0.0034***	0.0036
		Indirect	0.0025***	0.0023*	-0.0014	0.0031	0.0026	0.0052
AI	Men	Direct	0.0023	0.0037	0.0935***	0.0158***	-0.0035	0.0362
		Indirect	0.0270	0.0471	0.0852***	0.0830***	-0.1748	-0.2372
	Women	Direct	0.0082**	0.0032	0.0852***	-0.0011	0.0010	0.0002
		Indirect	0.0068**	0.0022	0.0416***	0.0047	0.0227	0.0128
Education	Men	Direct	-0.0074	-0.0070	-0.0056***	-0.0057***	-0.0037	-0.0168
		Indirect	-0.0877	-0.0884	-0.0042***	-0.0038	0.0652	0.0825
	Women	Direct	-0.0182***	-0.0192***	-0.0189***	-0.0187***	-0.0185***	-0.0191***
		Indirect	-0.0152***	-0.0129***	-0.0005	-0.0021	-0.0144	-0.0180
Age	Men	Direct	0.0028	0.0027	0.0034***	0.0035***	0.0014	0.0072
		Indirect	0.0329	0.0345	0.0123***	0.0104***	-0.0260	-0.0363
	Women	Direct	0.0029***	0.0023	0.0021*	0.0015	0.0019	0.0018
		Indirect	0.0024***	0.0015	0.0074***	0.0026	0.0081**	0.0073
Child	Men	Direct	-0.0087	-0.0086	-0.0037**	-0.0053**	-0.0014	-0.0451
		Indirect	-0.1025	-0.1085	0.0133***	0.0038	0.2211	0.2642
	Women	Direct	0.0103	0.0087	0.0099	0.0072	0.0099	0.0093
		Indirect	0.0085	0.0059	0.0493***	-0.0026	0.0497**	0.0347

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

except for male non-employment rates. The local spillovers effect of the social deprivation index on male non-employment rates is not robust to different spatial econometric models. Additionally, the direct effects of SDI on female non-employment rates are slightly greater in panel data than in the cross-section data models.

The SLX panel model shows that there are at least local spillovers of the job accessibility index (AI) on non-employment rates. However, the sign of these spillover effects depends on the type of fixed effects. When the fixed effects are space-type, the spillover effects of AI are positive on the male non-employment rate and negative on the female non-employment rate. If the fixed effects are space- and time-type, the spillovers of job accessibility are positive on the non-employment rates. These changes in signs of spillovers could be due to the employment decentralization process that occurred during the period we are taking into account.

Contrary to the cross-section estimations, panel data estimations detect clearly that the average years of education have negative and local spillover effects on the non-employment rates. In the case of female non-employment rates the spillovers can be global with feedback effects whose size ranges from 3% to 9% (see Appendix IV.A Table IV.A.22). The average years of education is a variable that can hide an important number of unobserved variables that might cause endogenous effects (e.g., school, peer effects related to human capital accumulation, the shaping of social networks either at school or in the neighborhood). In other words, people with similar educational backgrounds and socio-economic status tend to settle in similar areas because they share common unobserved interest or values.

The average age structure generates positive local spillover effects on the non-employment rates. As cross-section estimations depict, the panel data estimations confirm that there are at least positive and local spillover effects of the age-dependency ratio on the female non-employment rate. Additionally, we identify that there are also positive and local spillover effects of the age-dependency ratio on male non-employment rates. This means that the effects of age-dependency ratio are beyond its own census tract.

Informal employment rates

The coefficients of contextual variables have the expected signs when we include both space- and time-specific fixed effects in panel data models for the estimation of the determinants of the informal employment rates. The relationship between SDI and informal employment rate is positive. Meanwhile, job accessibility only relates negatively to male informal employment rate. The average years of education and average age have a negative association with informal employment rate. The feedback effects of SLM and SARAR/SAC panel models present a magnitude from 5.5% to 8% respectively.

Table IV.11: Panel data models: informal employment rates.

Variable		Impacts	SLM	SAC	SLX	SDEM	SDM	GNS
SDI	Men	Direct	0.0045***	0.0076***	0.0074***	0.0072***	0.0065***	0.0075***
		Indirect	0.0067***	0.0105***	-0.0089***	-0.0001	-0.0034	-0.0043
	Women	Direct	0.0052***	0.0089***	0.0081***	0.0076***	0.0070***	0.0086***
		Indirect	0.0079***	0.0096***	-0.0096***	-0.0040	-0.0043	0.0045
AI	Men	Direct	-0.0205***	-0.0117	-0.0203**	-0.0012	-0.0175**	-0.0153
		Indirect	-0.0308***	-0.0163	-0.0604***	0.0317	-0.0683**	-0.0450
	Women	Direct	-0.0027	0.0007	-0.0021	-0.0086	-0.0028	-0.0042
		Indirect	-0.0042	0.0007	-0.0035	-0.0403	-0.0091	-0.0200
Education	Men	Direct	-0.0347***	-0.0344***	-0.0350***	-0.0324***	-0.0345***	-0.0345***
		Indirect	-0.0521***	-0.0476***	-0.0413***	-0.0193***	-0.0579***	-0.0488***
	Women	Direct	-0.0399***	-0.0362***	-0.0399***	-0.0359***	-0.0394***	-0.0363***
		Indirect	-0.0601***	-0.0389***	-0.0519***	-0.0244***	-0.0631***	-0.0290**
Age	Men	Direct	-0.0075***	-0.0058***	-0.0062***	-0.0053**	-0.0063***	-0.0060***
		Indirect	-0.0113***	-0.0080**	-0.0122***	-0.0044	-0.0161***	-0.0114
	Women	Direct	-0.0061***	-0.0066***	-0.0052***	-0.0055**	-0.0059***	-0.0049**
		Indirect	-0.0092***	-0.0070**	-0.0072***	-0.0002	-0.0066**	0.0024

* p <0.05, ** p <0.01, *** p <0.001. The estimations include both space and time specific fixed effects.

SDM and GNS two-ways models do not confirm the existence of spillover effects of SDI on informal employment rates when we analyze these rates by gender. In general, the direct impacts of SDI on informal employment are lower in panel data than the average impacts in the case of cross-section estimations.

The sign of spillovers of AI on informal employment depends on the fixed effects. If the fixed effects are only space-type the AI detects positive spillovers on informal employment. Also, if the fixed effects are space- and time-type the AI identifies negative spillovers on informal employment. Once more, these changes in the signs of the coefficients of the spillovers can be due to the employment decentralization that occurred during this period of time. We can partially control these changes with time-specific fixed effects in the case of informal employment. Therefore, there is evidence that the spillover effects are negative on male informal employment. Moreover, these spillovers can be global in the case of male informal employment because there are feedback effects whose magnitude turns to be from 17.8% to 23.9% as in SDM and GNS models (see Appendix IV.A Table IV.A.22).

Panel data estimations show clear evidence that the average years of education have a negative and local spillover effect on informal employment rates, while this was not the case when performing cross-section estimations. Also, the spillover effects of the average years of education can be global in informal employment rates with feedback effects with a magnitude from 3% to 9%. The previous discussion about the potential endogeneity problem laying behind the education variable applies here as well.

When we control for both space- and time-specific fixed effects, there appears negative local spillover effects of average age structure on informality rates that can be global as detected by the feedback effects of the SDM and GNS models (ranging between 5% to 15%). If we only include space-type fixed effects, the sign of spillovers on informal employment of the average age is positive.

Wages

When we include both space- and time-specific fixed effects, the coefficients of contextual variables have the expected signs in wage estimations. There is a negative relationship of the SDI with respect to the real wages. In the case of the job accessibility, average years of education, and average age display a positive relationship with real wages. Average real wages generate feedback effects whose magnitude ranges from 4% to 12%, as SLM and SAC models indicate.

There is no clear evidence of potential spillover effects of the SDI and the average years of education on wages. The SLM only detect a negative spillover of SDI, whereas the SLX with space- and time-fixed effects depicts a positive spillover effect on female wages. There are negative spillover effects of education on wages when we introduce space-specific effects, but these spillover effects disappear when we introduce both space- and time- fixed effects.

The sign of spillovers of AI on wages depends on the fixed effects, as in the informal employment estimations. If the fixed effects are only space-type, the AI has negative spillovers on wages. If the fixed effects are

Table IV.12: Panel data models: ln wages.

Variable		Impacts	SLM	SAC	SLX	SDEM	SDM	GNS
SDI	Men	Direct	-0.0081***	-0.0065	-0.0120***	-0.0115*	-0.0109	-0.0108
		Indirect	-0.0067**	-0.0072	0.0085	0.0071	-0.0242	-0.0182
	Women	Direct	-0.0065*	-0.0017	-0.0123***	-0.0119	-0.0117	-0.0115
		Indirect	-0.0096*	-0.0036	0.0243***	0.0185	0.0267	0.0297
AI	Men	Direct	0.1300***	0.2311***	0.0939***	0.0982	0.0053	0.0124
		Indirect	0.1077***	0.2576**	0.7304***	0.6933**	0.4031	0.4181
	Women	Direct	0.1220***	0.2307**	0.1314***	0.1033*	0.0141	0.0199
		Indirect	0.1801***	0.5005	0.8253***	0.5254***	0.6443	0.8904
Education	Men	Direct	0.1100***	0.0894***	0.1194***	0.1197***	0.1251***	0.1249
		Indirect	0.0911***	0.0997**	-0.0190*	-0.0194	0.2387	0.1861
	Women	Direct	0.1025***	0.0723***	0.1087***	0.1088***	0.1221	0.1156
		Indirect	0.1513***	0.1569	-0.0023	-0.0009	0.7567	0.5849
Age	Men	Direct	0.0181***	0.0146**	0.0141***	0.0146*	0.0161*	0.0163
		Indirect	0.0150***	0.0162*	0.0005	0.0001	0.0441	0.0374
	Women	Direct	0.0224***	0.0165**	0.0187***	0.0194***	0.0184	0.0172
		Indirect	0.0331***	0.0357	0.0140**	0.0082	0.0903	0.0647

* p <0.05, ** p <0.01, *** p <0.001. The estimations include both space and time specific fixed effects.

both space- and time-specific, the AI has positive spillovers on wages. Again, these changes in the sign of the spillover coefficient can be due to the employment decentralization that occurred during this period. We can partially control for these changes with time-specific fixed effects. Then, in this case, there is evidence that spillover effects of AI on wages are positive. We observe positive and local spillover effects of average-age structure on wages. However, if we introduce both space- and time-specific fixed effects, these spillover effects become no significant in the case of men's wages.

The persistent of these patterns is not very high as time-space simultaneous model shown (see Appendix Table IV.A.23). Neighborhood characteristics explain the spatial patterns of non-employment rates, informal employment rates and real wages. However, the AI are not significant. It is possible that we do not capture the effects of job accessibility, as we do not introduce a spatial lag of AI and this variable has extended effects beyond the census area.[26]

IV.6 Discussion

In a neighborhood context, the existence of local spillover effects implies that the contextual effects have a more extensive area of influence. Global spillover effects capture the possible presence of feedback effects or endogenous effects. Table IV.13 reports the main results about spillover effects on the three labor market outcomes: non-employment rate, informal employment rate, and wages. Additionally, Table IV.14 reports the range of feedback effects of panel data models.

In summary, we find that contextual variables explain the observed spatial patterns of the three labor market outcomes (non-employment rate, informal employment rate and real wages). The job accessibility and average years of education have greatly influenced the spatial patterns of these labor market outcomes. The fact that

[26]We only estimate a time-space simultaneous model because we have only three periods. Therefore, the results have to be interpreted with caution.

indirect effects are larger than direct effects implies that contextual variables produce spillover effects on the neighboring areas. The empirical evidence points out that these spillover effects are global on female non-employment rate and become global on informal employment rate (see Table IV.13). Instead, in the case of male non-employment rate and wages only local spillovers effects have been detected. Both facts imply that spillover effects are larger for non-employment rates and informal employment rates than for wages. In other words, both the exogenous and endogenous effects determine the spatial patterns of female non-employment rates and informal employment rates. Meanwhile, only the neighborhood composition characteristics (contextual variables) affect the spatial distribution of male non-employment rates and wages.

We find clear evidence of the endogenous effects on female non-employment and informal employment rate (refer to Tables IV.13 and IV.14). The existence of the endogenous effects on these labor market outcomes implies that neighborhood effects are generated by social interactions through job accessibility and/or education. The diffusion of job information through social interactions decreases the female non-employment rates and informal employment rates. Furthermore, the endogenous effects of job accessibility are greater than those of average education.

There are two possibilities that could explain the non-identification of endogenous effects on wages (see Table IV.13). One possibility is that social interactions are not relevant or do not affect the average real wages. This means that the social interactions affect the type of job (namely formal or informal) that can be found, but they do not affect wages. Beyond of social interactions, also social networks may affect the level of wages. However, we cannot investigate furtherly this question with data at hand because we deal with aggregated data and this makes extremely difficult to capture the neighborhood social networks. The second possibility is that our empirical model is weakly identified or is overparameterized, particularly in the case of panel data estimations. The inclusion of more than one spatially-lagged variable along with fixed effects generates too much spatial dependence that does not allow the correct identification.

The analysis of the changes over time of the labor market outcomes indicates that neighborhood characteristics and social interactions increasingly explain the spatial patterns of informal employment rates and wages, as confirmed by the measures of goodness-of-fit. In the case of the female non-employment rate, the neighborhood characteristics and the social interactions remain relevant over time. Meanwhile, the neighborhood characteristics and the social interaction effects explain less and less the spatial patterns of male non-employment rates.

The increasing importance of neighborhood characteristics and social interactions in the case of job informality and wages entails two order of explanations. The first reason could be that the increase of spatial mismatch raises the cost of commuting and of job search. Commuting becomes more expensive in terms of time and the availability of less expensive real estate properties in the periphery increases the commuting distance. The average commuting time was 58 minutes in 1994 but it rises to 67 minutes in 2007 (Casado, 2014). [27] The

[27] In 1990, traveling speed was 38.5kpm. This speed reduced to 21kpm in 2004, and in 2007 the estimated speed was 17kpm.

Table IV.13: Summary of spillover effects

	Cross-section						Panel data	
	Men			Women			Men	Women
	1990	2000	2010	1990	2000	2010		
Non-employment rate								
SDI	No	Local	No	No	No	No	Local	No
AI	Local	Local	Local	Global	Global	Global	Local	Global
Education	Local	No	No	Local	Local	No	Local	Global
Age	Local	Local	Global	Local	Local	Local	Local	Local
Child	Local	Local	Global	Local	Local	Global	Local	Local
Informal employment rate								
SDI	Local	Global	Global	Local	No	Global	No	No
AI	Global	Global	Global	No	Local	Global	Global	No
Education	Local	Global	Global	Local	Local	No	Global	Global
Age	Local	Global	No	Global	Global	Global	Global	Global
Wages								
SDI	No	Local	Global	No	Global	No	No	No
AI	Local	Local	Local	Local	Global	Global	Local	Local
Education	No	No	No	No	No	No	No	No
Age	Local	No	No	No	No	No	No	Local

"No" means no spillover effects, "Local" refers to local spillover effects and "Global" denotes global spillover effects. These results come from SLX, SDEM, SDM and GNS models.

Table IV.14: Panel data models: Summary of feedback effects

	Non-employment rate		Informal employment rate	
	Men	Women	Men	Women
AI	–	$(42.1\%, 42.4\%)$	$(17.8\%, 23.9\%)$	–
Education	–	$(6.4\%, 6.9\%)$	$(7.7\%, 9.1\%)$	$(3.3\%, 8.9\%)$
Age	–	–	$(10.8\%, 15.0\%)$	$(-2.6\%, 5.8\%)$

The percentage of feedback effects is the following ratio: (direct effect of X $-$ estimated coefficient of X)/(direct effect of X). A negative percentage means that the feedback effect have a opposite impact that the direct effect does have. These results come from SDM and GNS models.

second reason could be associated with the increase of residential segregation measured by the average years of education that impact of the quality (and strength) of the neighborhood social networks. This is especially relevant in the case of job informality because the individuals who live in deprived neighborhoods (that are places with levels of education well below the average) have greater probability to receive an informal job offer than a formal job offer. In this sense, there are two mechanisms that favor this type of outcome. The first mechanism is the availability of relatively close informal job opportunities in these deprived neighborhoods. The second mechanism is the particular strength of neighborhood social networks that are extremely effective in the case of informal workers. [28]

In the case of the female non-employment rate, the neighborhood characteristics and social interactions remain relevant throughout all the period. The only variable that exerts more influence in recent time than in the past is the age-dependency ratio. This variable highly constrains the labor-market participation of women. This could be because fewer and fewer women only devote their time to childcare, given the increase of female-labor market participation.[29]

[28] See Chapter III of this thesis.

[29] It is important to remark that the variables are aggregated and do not have the same interpretation as individual data. In this sense,

The spatial patterns of male non-employment rate could be specifically different in the case of Mexico City or Mexican cities, as it is discussed in the Introduction of this thesis. The geographic location of male unemployment has become random during these two decades. The depicted maps in subsection IV.3.4 corroborated this fact. Therefore, the neighborhood characteristics and the social interaction effects are able to explain only a small part of these patterns. This can be because the Mexican labor market adjusts to unexpected disequilibria first via prices or wages rather than employment (Negrete-Prieto, 2011).

IV.7 Conclusions

Spillover effects are larger for non-employment rates and informal employment rates than for wages. Moreover, the empirical evidence points out that these spillover effects are global for female non-employment rate and become global for the informal employment rate. In the case of wages, there is no clear evidence of global spillovers. However, in the case of average real wages the contextual variables spillover their effects beyond their own area; that is, there exist at least local spillovers on the determination of average real wages.

The most relevant variables that generate at least local spillovers are job accessibility and average years of education. We find different magnitudes of feedback effects of these variables on informal employment rates. The former generates greater feedback effects than the latter. The presence of feedback effects implies that social interactions, (in addition to neighborhood characteristics), affect the spatial patterns of informal employment rates.

The existence of global spillover effects entails that public policies will have greater effects on labor market outcomes, especially in the case of female non-employment rate and informal employment rate. This means that the endogenous effects through social interactions upgrade the outcomes of macroeconomic policies focused on employment.

It is difficult to change the geographic location households and residential segregation in order to improve neighborhoods' socioeconomic characteristics. The observed spatial patterns of wealthy and poor households are due to real estate market and some public policies that have encouraged these patterns, as it was described in Chapter III. The results of this chapter point out that neighborhood characteristics help to explain those observed spatial patters. That is the reason to recommend that public policies should improve socioeconomic characteristics of the less attractive neighborhoods. Some public policies can be aimed to assist poor neighborhoods, in the sense that jobs can be created in these zones or the access to formal jobs can be improved. Other public policies could target to increase the average education of a neighborhood by improving the public education in these poor neighborhoods. However, the effects of this policy are expected to be perceived in the long rum.

With the possibility to access to better data, future research should address the identification problem that has been detected in the case of male non-employment rates and wages, and it should be able to discern the nature

the availability of fewer women for the childcare in the neighborhood or household limits their participation to labor market.

of spillovers on these variables. In this analysis, we deal with an exogenous weighting matrix in order to lessen the endogeneity problems. In order to address this endogeneity problem, Kelejian and Piras (2014) suggest an instrumental variable strategy to create an endogenous spatial weighting matrix. Finally, we do not estimate more complex space dynamic models since our data availability limits to three periods only. Future studies should be able to extend the time span and estimate space dynamic models with space-lagged independent variables along with space-lagged dependent variable to properly account for this dynamic dimension.

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Appendix IV.A Tables

Table IV.A.1: OLS 1990, 2000 and 2010

	1990			2000			2010		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate									
SDI	0.0026***	0.0025***	0.0011	0.0007	0.0018***	0.0001	0.0009*	0.0008*	0.0015*
	(4.99)	(6.01)	(1.84)	(1.75)	(6.49)	(0.21)	(2.39)	(2.42)	(2.51)
AI	-0.0477***	-0.0176***	-0.0597***	-0.0189***	-0.0029**	-0.0326***	-0.0255***	-0.0062***	-0.0405***
	(-17.46)	(-7.92)	(-18.70)	(-15.57)	(-3.29)	(-16.03)	(-15.51)	(-4.63)	(-15.96)
Education	-0.0307***	-0.0119***	-0.0424***	-0.0232***	-0.0093***	-0.0350***	-0.0168***	-0.0054***	-0.0256***
	(-47.49)	(-22.63)	(-56.10)	(-46.65)	(-26.06)	(-41.94)	(-31.61)	(-12.52)	(-31.17)
Age	0.0089***	0.0094***	-0.0110***	0.0043***	0.0051***	-0.0019*	0.0109***	0.0012**	0.0164***
	(13.51)	(17.57)	(-14.20)	(8.36)	(13.80)	(-2.24)	(19.02)	(2.60)	(18.51)
Child	0.0033*	-0.0053***	0.0164***	0.0407***	-0.0295***	0.1146***	0.1628***	-0.0341***	0.3609***
	(2.16)	(-4.21)	(9.12)	(11.42)	(-11.51)	(19.21)	(25.03)	(-6.41)	(35.91)
Population density	-0.0001***	-0.00003***	-0.0002***	-0.0001***	-0.00001	-0.0001***	-0.00002***	0.00003***	-0.0001***
	(-21.08)	(-5.84)	(-21.23)	(-11.64)	(-1.66)	(-11.90)	(-3.75)	(6.53)	(-8.15)
Constant	0.3227***	-0.1535***	1.3450***	0.3577***	0.0094	0.8528***	-0.0425	0.1075***	-0.0874*
	(16.16)	(-9.47)	(57.65)	(19.14)	(0.70)	(27.23)	(-1.74)	(5.40)	(-2.32)
N	4572	4572	4572	4572	4572	4572	4572	4572	4572
Adjusted R^2	0.7169	0.2720	0.8489	0.7598	0.2128	0.8147	0.7053	0.0636	0.7963
R^2	0.7173	0.2729	0.8491	0.7601	0.2138	0.8149	0.7057	0.0648	0.7965
Jarque Bera test	19807.15	1452774.00	1163.05	2287.28	314629.30	1391.55	4510.50	376224.30	357.66
Breusch-Pagan test	323.66	117.15	818.52	256.38	110.93	334.62	165.94	122.73	145.64
RLM-error	1611.85***	1767.52***	215.79***	547.38***	989.21***	3.12	515.27***	1004.35***	9.11**
RLM-lag	530.78***	617.42***	169.71***	386.83***	416.96***	68.13***	454.75***	508.61***	14.28***
Sarma	5634.50***	4544.68***	3646.89***	2325.80***	2976.34***	522.85***	2872.93***	3488.22***	817.41***
Informal employment rate									
SDI	0.0131***	0.0108***	0.0224***	0.0157***	0.0203***	0.0127***	0.0157***	0.0174***	0.0154***
	(18.56)	(13.70)	(28.37)	(13.06)	(18.03)	(9.16)	(20.10)	(20.56)	(17.06)
AI	0.0060	0.0161***	-0.0069	0.0006	0.0017	-0.0050	-0.0334***	-0.0334***	-0.0385***
	(1.53)	(3.70)	(-1.59)	(0.15)	(0.48)	(-1.11)	(-9.98)	(-9.22)	(-9.95)
Education	-0.0477***	-0.0463***	-0.0510***	-0.0368***	-0.0344***	-0.0364***	-0.0295***	-0.0313***	-0.0276***
	(-52.14)	(-45.58)	(-49.96)	(-20.50)	(-20.55)	(-17.68)	(-29.96)	(-29.43)	(-24.33)
Age	0.0090***	0.0080***	0.0129***	0.0028	0.0029	0.0006	-0.0139***	-0.0113***	-0.0193***
	(9.44)	(7.55)	(12.03)	(1.68)	(1.88)	(0.32)	(-14.42)	(-10.82)	(-17.24)
Population density	0.000001	0.00002	-0.00001	-0.0003***	-0.0002***	-0.0004***	-0.0001***	-0.0001***	-0.0002***
	(0.14)	(1.49)	(-0.87)	(-18.82)	(-11.06)	(-24.40)	(-11.59)	(-5.73)	(-15.26)
Constant	0.4646***	0.4827***	0.3746***	0.7057***	0.6646***	0.7867***	1.2660***	1.1820***	1.4490***
	(17.14)	(16.04)	(12.38)	(16.03)	(16.13)	(15.52)	(44.97)	(38.84)	(44.57)
N	4572	4572	4572	4572	4572	4572	4572	4572	4572
Adjusted R^2	0.7458	0.6749	0.7696	0.5094	0.5314	0.4671	0.7183	0.6859	0.6871
R^2	0.7461	0.6753	0.7699	0.5099	0.5319	0.4677	0.7186	0.6862	0.6874
Jarque Bera test	1944.71	1869.51	2996.34	719.37	510.96	815.01	650.60	690.41	845.81
Breusch-Pagan test	192.26	202.95	303.95	369.87	342.59	406.59	697.84	665.10	502.31
RLM-error	3301.08***	3079.84***	1354.34***	2046.36***	2157.09***	1448.19***	3168.50***	3070.23***	2386.24***
RLM-lag	1.25	5.88*	4.22*	90.30***	80.48***	122.48***	362.10***	291.16***	369.01***
Sarma	5102.68***	5273.02***	2196.41***	7155.89***	7020.05***	6219.69***	8070. 0***	8130.24***	6990.35***
ln w									
SDI	-0.0030	-0.0028	-0.0138***	-0.0305***	-0.0387***	-0.0338***	-0.0126***	-0.0161***	-0.0157***
	(-0.90)	(-0.73)	(-3.59)	(-9.82)	(-10.19)	(-11.99)	(-4.16)	(-4.61)	(-5.61)
AI	-0.0087	0.0210	0.0265	0.0576***	0.0717***	0.0674***	0.0912***	0.1083***	0.0988***
	(-0.47)	(1.00)	(1.24)	(5.49)	(5.57)	(7.04)	(6.90)	(7.16)	(8.14)
Education	0.1569***	0.1835***	0.1252***	0.1383***	0.1442***	0.1280***	0.1598***	0.1587***	0.1444***
	(36.71)	(38.08)	(25.56)	(29.59)	(25.17)	(30.02)	(39.07)	(33.89)	(38.43)
Age	0.0026	0.0017	-0.0018	0.0452***	0.0537***	0.0437***	0.0188***	0.0255***	0.0218***
	(0.59)	(0.34)	(-0.35)	(10.64)	(10.29)	(11.26)	(5.73)	(6.80)	(7.24)
Population density	-0.0006***	-0.0008***	-0.0003***	-0.0007***	-0.0010***	-0.0003***	-0.0005***	-0.0006***	-0.0003***
	(-13.62)	(-15.34)	(-6.05)	(-16.99)	(-20.23)	(-8.44)	(-12.25)	(-12.50)	(-6.97)
Constant	7.4580***	7.3630***	7.6100***	5.7870***	5.5880***	5.6820***	6.3750***	6.2350***	6.2420***
	(58.90)	(51.56)	(52.41)	(51.39)	(40.40)	(55.20)	(69.93)	(59.74)	(74.51)
N	4572	4572	4572	4572	4572	4572	4572	4572	4572
Adjusted R^2	0.5295	0.5470	0.3818	0.6756	0.6289	0.6983	0.6663	0.6268	0.6779
R^2	0.5300	0.5475	0.3824	0.6760	0.6293	0.6987	0.6667	0.6272	0.6783
Jarque Bera test	9328.65	7578.24	11445.02	48419.78	21938.44	145817.70	9157.09	15294.15	17582.20
Breusch-Pagan test	61.76	140.63	60.99	83.96	216.04	45.25	109.94	141.76	58.78
RLM-error	595.65***	910.33***	167.45***	829.62***	1251.60***	219.80***	561.74***	723.00***	243.63***
RLM-lag	0.63	3.78	0.21	58.05***	79.85***	61.27***	43.32***	75.97***	43.29***
Sarma	1480.20***	2267.73***	642.56***	2019.35***	3299.83***	716.85***	1423.11***	2133.47***	731.11***

t statistic in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table IV.A.2: Spatial lag model 1990, 2000 and 2010

	1990			2000			2010		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate (U)									
SDI	0.0012**	0.0008*	0.0006	0.0007	0.0008	0.0010	0.0012**	0.0009*	0.0018*
	(2.64)	(1.99)	(1.01)	(1.60)	(1.78)	(1.28)	(2.91)	(2.36)	(2.51)
AI	-0.0114***	-0.0036***	-0.0200***	-0.0073***	-0.0019**	-0.0125***	-0.0068***	-0.0026*	-0.0129***
	(-7.42)	(-3.80)	(-8.40)	(-7.00)	(-2.67)	(-7.54)	(-5.07)	(-2.32)	(-6.23)
Education	-0.0162***	-0.0051***	-0.0267***	-0.0158***	-0.0074***	-0.0233***	-0.0099***	-0.0035***	-0.0157***
	(-23.13)	(-9.45)	(-29.40)	(-17.27)	(-12.51)	(-14.99)	(-17.16)	(-5.75)	(-16.62)
Age	0.0051***	0.0035***	-0.0069***	0.0035**	0.0034***	-0.0010	0.0071***	-0.0004	0.0120***
	(5.70)	(4.28)	(-6.30)	(3.07)	(3.69)	(-0.50)	(5.89)	(-0.26)	(9.89)
Child	-0.0022	-0.0056***	0.0077	0.0141*	-0.0285***	0.0630***	0.0801***	-0.0390**	0.2250***
	(-1.61)	(-3.45)	(1.24)	(2.11)	(-5.51)	(5.01)	(5.36)	(-2.88)	(10.77)
Population density	-0.0001***	-0.000004	-0.0001***	-0.00003***	-0.000004	-0.0001***	-0.000004	0.00001*	-0.00003***
	(-12.23)	(-1.42)	(-14.80)	(-6.26)	(-1.21)	(-6.94)	(-0.78)	(2.11)	(-4.29)
Constant	0.1029***	-0.0569*	0.7851***	0.1784***	0.0124	0.5079***	-0.0940	0.0989	-0.1854***
	(3.56)	(-2.33)	(20.43)	(4.40)	(0.39)	(7.31)	(-1.88)	(1.66)	(-3.39)
W*U (λ)	0.6229***	0.7921***	0.4639***	0.4835***	0.4852***	0.4385***	0.5769***	0.7041***	0.4876***
	(36.88)	(22.30)	(33.92)	(23.57)	(8.65)	(25.33)	(25.32)	(7.86)	(25.85)
Adjusted R^2	0.8828	0.6111	0.9195	0.8365	0.3013	0.8793	0.8190	0.2173	0.8785
R^2	0.8830	0.6117	0.9196	0.8367	0.3023	0.8795	0.8192	0.2185	0.8787
R^2 (ratio)	0.8216	0.5177	0.8935	0.8095	0.2746	0.8537	0.7847	0.2093	0.8474
Informal employment rate (I)									
SDI	0.0169***	0.0166***	0.0201***	0.0068***	0.0069***	0.0085***	0.0035***	0.0041***	0.0048***
	(18.75)	(18.26)	(17.79)	(10.39)	(11.98)	(11.21)	(7.36)	(8.01)	(6.62)
AI	0.0176***	0.0186***	0.0074**	0.0491***	0.0394***	0.0664***	-0.0126**	-0.0188***	-0.0020
	(7.14)	(8.36)	(2.68)	(8.57)	(8.24)	(12.91)	(-2.58)	(-3.91)	(-0.31)
Education	-0.0143***	-0.0129***	-0.0187***	-0.0105***	-0.0095***	-0.0140***	-0.0343***	-0.0318***	-0.0366***
	(-20.58)	(-19.42)	(-21.27)	(-14.06)	(-15.97)	(-16.20)	(-36.75)	(-33.14)	(-32.09)
Age	0.0057***	0.0045***	0.0081***	0.0043***	0.0038***	0.0069***	-0.0067***	-0.0069***	-0.0056***
	(10.36)	(8.42)	(11.65)	(8.17)	(9.19)	(10.82)	(-11.46)	(-11.36)	(-7.70)
Population density	-0.00002*	0.00002**	-0.0001***	0.00004**	0.00005***	-0.00001	-0.00003*	0.00001	-0.0001***
	(-2.38)	(2.86)	(-8.59)	(2.83)	(3.85)	(-0.49)	(-2.31)	(0.48)	(-5.13)
Constant	0.1382***	0.1501***	0.1295***						
	(22.57)	(23.13)	(19.74)						
W*I (λ)	0.4859***	0.5128***	0.4338***	0.9200***	0.9734***	0.6352***	0.6395***	0.6332***	0.6290***
	(9.50)	(9.90)	(7.72)	(19.74)	(25.44)	(13.70)	(31.59)	(29.44)	(27.01)
R^2	0.8540	0.8540	0.8086	0.9239	0.9192	0.8906	0.9275	0.9231	0.9020
$Corr^2$	0.5108	0.5108	0.5373	0.0023	0.0012	0.0481	0.2875	0.2816	0.2068
ln w									
SDI	-0.0027	-0.0019	-0.0132***	-0.0236***	-0.0277***	-0.0279***	-0.0094***	-0.0105***	-0.0128***
	(-0.79)	(-0.50)	(-3.31)	(-4.98)	(-4.65)	(-9.11)	(-3.87)	(-3.90)	(-6.20)
AI	-0.0129	0.0084	0.0209	0.0277**	0.0276*	0.0377***	0.0512**	0.0470**	0.0630***
	(-0.79)	(0.43)	(1.15)	(2.75)	(2.26)	(4.30)	(3.27)	(2.69)	(4.21)
Education	0.1518***	0.1710***	0.1206***	0.1178***	0.1169***	0.1096***	0.1406***	0.1314***	0.1284***
	(23.93)	(23.98)	(16.25)	(12.17)	(10.77)	(13.26)	(28.90)	(24.63)	(27.42)
Age	0.0026	0.0016	-0.0018	0.0345***	0.0383***	0.0335***	0.0089*	0.0115**	0.0121***
	(0.49)	(0.27)	(-0.28)	(4.09)	(4.20)	(4.85)	(2.45)	(2.92)	(3.41)
Population density	-0.0006***	-0.0007***	-0.0003***	-0.0006***	-0.0008***	-0.0003***	-0.0004***	-0.0005***	-0.0002***
	(-13.17)	(-13.91)	(-5.91)	(-12.87)	(-14.34)	(-7.29)	(-10.23)	(-10.00)	(-6.17)
Constant	7.0988***	6.6114***	7.2144***	4.3190***	3.7639***	4.3350***	4.9122***	4.2706***	4.9245***
	(22.23)	(21.05)	(16.99)	(14.94)	(12.37)	(17.32)	(25.18)	(20.04)	(27.01)
W*ln w (λ)	0.0459	0.0967**	0.0506	0.2359***	0.2990***	0.2237***	0.2330***	0.3144***	0.2157***
	(1.26)	(2.83)	(1.00)	(9.14)	(11.11)	(9.49)	(8.72)	(10.96)	(7.90)
Adjusted R^2	0.5419	0.5778	0.3935	0.7248	0.7172	0.7244	0.7073	0.7000	0.7043
R^2	0.5425	0.5784	0.3943	0.7251	0.7176	0.7248	0.7076	0.7004	0.7047
R^2 (ratio)	0.5305	0.5501	0.3830	0.6897	0.6547	0.7092	0.6794	0.6529	0.6882

t statistic in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table IV.A.3: Impacts of spatial lag model 1990, 2000 and 2010

			1990			2000			2010		
			Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Non-employment rate	Total	SDI	0.0013**	0.0019**	0.0031**	0.0007	0.0006	0.0014	0.0013**	0.0016**	0.0029**
			(2.89)	(2.83)	(2.87)	(1.71)	(1.66)	(1.69)	(3.07)	(2.80)	(2.94)
		AI	-0.0123***	-0.0178***	-0.0302***	-0.0077***	-0.0066***	-0.0142***	-0.0073***	-0.0088***	-0.0161***
			(-7.32)	(-7.36)	(-7.56)	(-7.14)	(-7.66)	(-7.66)	(-5.08)	(-5.22)	(-5.28)
		Education	-0.0175***	-0.0253***	-0.0428***	-0.0165***	-0.0141***	-0.0306***	-0.0106***	-0.0128***	-0.0234***
			(-24.91)	(-14.04)	(-19.64)	(-17.90)	(-14.51)	(-19.98)	(-18.61)	(-11.35)	(-16.29)
		Age	0.0055***	0.0079***	0.0135***	0.0037**	0.0032**	0.0068**	0.0076***	0.0092***	0.0168***
			(5.55)	(4.77)	(5.12)	(3.07)	(2.99)	(3.05)	(5.85)	(7.41)	(6.82)
		Child	-0.0024	-0.0034	-0.0058	0.0148*	0.0126*	0.0274*	0.0856***	0.1038***	0.1894***
			(-1.80)	(-1.78)	(-1.79)	(2.12)	(2.08)	(2.11)	(5.28)	(6.90)	(6.19)
		Population density	-0.0001***	-0.0001***	-0.0001***	-0.00003***	-0.00003***	-0.0001***	-0.000004	-0.00001	-0.00001
			(-12.24)	(-10.68)	(-12.11)	(-6.27)	(-6.17)	(-6.40)	(-0.59)	(-0.60)	(-0.59)
	Men	SDI	0.0010*	0.0030	0.0040*	0.0009	0.0008	0.0016	0.0010*	0.0020	0.0029
			(2.17)	(1.88)	(1.98)	(1.93)	(1.86)	(1.95)	(2.51)	(1.12)	(1.39)
		AI	-0.0043***	-0.0130**	-0.0173**	-0.0019*	-0.0017*	-0.0036*	-0.0030*	-0.0059	-0.0089
			(-3.54)	(-2.97)	(-3.23)	(-2.56)	(-2.23)	(-2.50)	(-2.36)	(-1.19)	(-1.48)
		Education	-0.0061***	-0.0184***	-0.0245***	-0.0078***	-0.0067***	-0.0145***	-0.0040***	-0.0079	-0.0119
			(-10.97)	(-4.57)	(-5.83)	(-14.69)	(-4.98)	(-10.79)	(-6.18)	(-1.34)	(-1.83)
		Age	0.0041***	0.0125***	0.0166***	0.0036***	0.0031***	0.0066***	-0.0004	-0.0009	-0.0013
			(4.58)	(3.43)	(3.88)	(3.83)	(3.85)	(4.31)	(-0.38)	(-0.46)	(-0.46)
		Child	-0.0067***	-0.0203*	-0.0270**	-0.0297***	-0.0256**	-0.0553***	-0.0439*	-0.0878	-0.1317
			(-3.57)	(-2.46)	(-2.72)	(-5.53)	(-3.15)	(-4.37)	(-2.51)	(-0.89)	(-1.09)
		Population density	-0.000005	-0.00001	-0.00002	-0.000004	-0.000004	-0.00001	0.00002*	0.00003	0.00005
			(-1.27)	(-1.17)	(-1.21)	(-1.05)	(-0.96)	(-1.02)	(2.13)	(1.56)	(1.88)
	Women	SDI	0.0007	0.0005	0.0012	0.0011	0.0008	0.0018	0.0019**	0.0016*	0.0035**
			(1.07)	(1.06)	(1.07)	(1.38)	(1.35)	(1.37)	(2.66)	(2.51)	(2.60)
		AI	-0.0207***	-0.0165***	-0.0372***	-0.0130***	-0.0094***	-0.0223***	-0.0135***	-0.0117***	-0.0253***
			(-8.56)	(-9.20)	(-9.05)	(-7.75)	(-8.16)	(-8.18)	(-6.29)	(-6.47)	(-6.54)
		Education	-0.0277***	-0.0221***	-0.0498***	-0.0241***	-0.0174***	-0.0415***	-0.0164***	-0.0142***	-0.0306***
			(-30.19)	(-20.30)	(-30.64)	(-15.64)	(-13.36)	(-16.42)	(-17.08)	(-11.14)	(-15.07)
		Age	-0.0072***	-0.0057***	-0.0129***	-0.0010	-0.0007	-0.0018	0.0125***	0.0109***	0.0234***
			(-5.98)	(-5.71)	(-5.92)	(-0.37)	(-0.37)	(-0.37)	(9.78)	(11.08)	(11.03)
		Child	0.0080	0.0064	0.0144	0.0651***	0.0470***	0.1121***	0.2350***	0.2042***	0.4392***
			(1.28)	(1.29)	(1.29)	(4.99)	(4.91)	(5.02)	(10.69)	(13.83)	(12.95)
		Population density	-0.0001***	-0.00007***	-0.0002***	-0.0001***	-0.00004***	-0.0001***	-0.00003***	-0.00003***	-0.0001***
			(-15.62)	(-14.15)	(-16.07)	(-6.94)	(-6.84)	(-7.07)	(-4.10)	(-3.83)	(-4.01)
Informal employment rate	Total	SDI	0.0128***	0.0003	0.0131***	0.0102***	0.0069***	0.0171***	0.0098***	0.0079***	0.0177***
			(12.41)	(1.17)	(13.47)	(6.19)	(6.16)	(6.42)	(9.06)	(8.95)	(9.45)
		AI	0.0067*	0.0002	0.0068*	0.0083**	0.0056**	0.0139**	-0.0091***	-0.0073***	-0.0165***
			(2.05)	(0.95)	(2.04)	(2.74)	(2.63)	(2.71)	(-4.53)	(-4.71)	(-4.66)
		Education	-0.0469***	-0.0012	-0.0480***	-0.0263***	-0.0177***	-0.0440***	-0.0203***	-0.0163***	-0.0366***
			(-34.38)	(-1.16)	(-39.10)	(-12.32)	(-9.80)	(-12.67)	(-24.43)	(-15.39)	(-24.36)
		Age	0.0089***	0.0002	0.0091***	0.0014	0.0009	0.0023	-0.0082***	-0.0066***	-0.0148***
			(6.23)	(1.11)	(6.22)	(0.77)	(0.75)	(0.76)	(-9.82)	(-9.68)	(-10.32)
		Population density	0.000001	0.00000003	0.000001	-0.0002***	-0.0001***	-0.0003***	-0.0001***	-0.00005***	-0.0001***
			(0.03)	(0.09)	(0.03)	(-12.23)	(-10.60)	(-13.24)	(-7.96)	(-8.18)	(-8.37)
	Men	SDI	0.0106***	0.0002	0.0107***	0.0134***	0.0091***	0.0225***	0.0105***	0.0088***	0.0193***
			(9.72)	(0.81)	(10.50)	(7.99)	(7.88)	(8.52)	(8.28)	(8.12)	(8.64)
		AI	0.0164***	0.0003	0.0167***	0.0086**	0.0058**	0.0144**	-0.0086***	-0.0072***	-0.0158***
			(4.76)	(0.81)	(4.71)	(3.22)	(3.05)	(3.18)	(-3.78)	(-3.93)	(-3.89)
		Education	-0.0457***	-0.0008	-0.0465***	-0.0246***	-0.0167***	-0.0413***	-0.0213***	-0.0178***	-0.0392***
			(-31.17)	(-0.83)	(-35.02)	(-12.42)	(-9.58)	(-12.67)	(-22.57)	(-14.39)	(-23.50)
		Age	0.0079***	0.0001	0.0080***	0.0015	0.0010	0.0024	-0.0066***	-0.0055***	-0.0120***
			(5.01)	(0.78)	(5.01)	(0.84)	(0.82)	(0.83)	(-7.51)	(-7.30)	(-7.73)
		Population density	0.00002	0.0000003	0.00002	-0.0001***	-0.0001***	-0.0002***	-0.00003**	-0.00002**	-0.00005**
			(1.25)	(0.58)	(1.25)	(-7.64)	(-7.22)	(-7.92)	(-3.15)	(-3.24)	(-3.22)
	Women	SDI	0.0214***	0.0013*	0.0226***	0.0079***	0.0058***	0.0137***	0.0102***	0.0087***	0.0189***
			(18.00)	(2.55)	(20.09)	(4.10)	(4.15)	(4.20)	(10.13)	(9.71)	(10.66)
		AI	-0.0045	-0.0003	-0.0048	0.0059	0.0044	0.0103	-0.0111***	-0.0095***	-0.0206***
			(-1.21)	(-1.04)	(-1.21)	(1.65)	(1.61)	(1.64)	(-4.47)	(-4.62)	(-4.61)
		Education	-0.0490***	-0.0029*	-0.0518***	-0.0251***	-0.0184***	-0.0435***	-0.0186***	-0.0159***	-0.0344***
			(-30.36)	(-2.52)	(-35.61)	(-10.54)	(-8.49)	(-10.66)	(-18.59)	(-13.12)	(-18.64)
		Age	0.0123***	0.0007*	0.0131***	-0.0004	-0.0003	-0.0008	-0.0110***	-0.0094***	-0.0204***
			(8.39)	(2.38)	(8.47)	(-0.07)	(-0.07)	(-0.07)	(-10.23)	(-10.14)	(-10.98)
		Population density	-0.00001	-0.0000004	-0.00001	-0.0003***	-0.0002***	-0.0005***	-0.0001***	-0.0001***	-0.0002***
			(-0.80)	(-0.67)	(-0.79)	(-14.70)	(-11.63)	(-16.69)	(-9.35)	(-10.27)	(-10.45)
ln w	Total	SDI	-0.0027	-0.0001	-0.0028	-0.0238***	-0.0071***	-0.0308***	-0.0094***	-0.0028***	-0.0122***
			(-0.94)	(-0.65)	(-0.95)	(-4.82)	(-4.12)	(-4.81)	(-4.40)	(-3.98)	(-4.48)
		AI	-0.0129	-0.0006	-0.0135	0.0279**	0.0083**	0.0362**	0.0516**	0.0151***	0.0667**
			(-0.82)	(-0.69)	(-0.83)	(2.61)	(2.78)	(2.68)	(3.09)	(3.29)	(3.20)
		Education	0.1519***	0.0073	0.1591***	0.1187***	0.0354***	0.1541***	0.1417***	0.0416***	0.1833***
			(22.63)	(1.34)	(30.41)	(11.98)	(8.48)	(14.14)	(27.70)	(7.14)	(26.12)
		Age	0.0026	0.0001	0.0027	0.0348***	0.0104***	0.0452***	0.0089*	0.0026*	0.0116*
			(0.51)	(0.45)	(0.51)	(4.13)	(3.30)	(4.00)	(2.50)	(2.50)	(2.54)
		Population density	-0.0006***	-0.00003	-0.0006***	-0.0006***	-0.0002***	-0.0008***	-0.0004***	-0.0001***	-0.0006***
			(-12.61)	(-1.33)	(-13.89)	(-12.67)	(-6.68)	(-12.51)	(-10.05)	(-7.01)	(-11.05)
	Men	SDI	-0.0019	-0.0002	-0.0021	-0.0281***	-0.0114***	-0.0395***	-0.0106***	-0.0046***	-0.0153***
			(-0.66)	(-0.61)	(-0.66)	(-4.74)	(-4.12)	(-4.70)	(-3.92)	(-3.67)	(-3.97)
		AI	0.0085	0.0009	0.0094	0.0280*	0.0114*	0.0394*	0.0477*	0.0208**	0.0685**
			(0.42)	(0.33)	(0.42)	(2.17)	(2.25)	(2.21)	(2.51)	(2.68)	(2.59)
		Education	0.1712***	0.0181**	0.1893***	0.1185***	0.0482***	0.1668***	0.1335***	0.0582***	0.1917***
			(22.81)	(2.79)	(30.34)	(10.14)	(9.01)	(11.69)	(23.86)	(8.19)	(22.43)
		Age	0.0016	0.0002	0.0018	0.0389***	0.0158***	0.0547***	0.0116**	0.0051**	0.0167**
			(0.29)	(0.30)	(0.30)	(4.22)	(3.48)	(4.07)	(2.97)	(2.94)	(3.02)
		Population density	-0.0007***	-0.0001**	-0.0008***	-0.0008***	-0.0003***	-0.0011***	-0.0005***	-0.0002***	-0.0007***
			(-13.39)	(-2.72)	(-14.54)	(-14.03)	(-7.51)	(-13.47)	(-9.78)	(-7.32)	(-10.50)
	Women	SDI	-0.0132**	-0.0007	-0.0139**	-0.0281***	-0.0078***	-0.0359***	-0.0129***	-0.0034***	-0.0164***
			(-3.23)	(-0.99)	(-3.20)	(-8.89)	(-5.94)	(-8.76)	(-6.91)	(-5.19)	(-7.10)
		AI	0.0209	0.0011	0.0220	0.0380***	0.0106***	0.0486***	0.0635***	0.0169***	0.0804***
			(1.08)	(0.56)	(1.09)	(4.31)	(4.42)	(4.47)	(3.97)	(4.02)	(4.13)
		Education	0.1207***	0.0064	0.1271***	0.1104***	0.0308***	0.1412***	0.1293***	0.0344***	0.1637***
			(15.87)	(1.09)	(21.40)	(12.87)	(9.16)	(15.44)	(26.16)	(6.68)	(25.45)
		Age	-0.0018	-0.0001	-0.0019	0.0338***	0.0094***	0.0432***	0.0122***	0.0032***	0.0154***
			(-0.32)	(-0.23)	(-0.32)	(4.88)	(3.70)	(4.68)	(3.56)	(3.58)	(3.68)
		Population density	-0.0003***	-0.00002	-0.0003***	-0.0003***	-0.0001***	-0.0004***	-0.0002***	-0.0001***	-0.0003***
			(-6.36)	(-1.09)	(-6.27)	(-7.43)	(-5.43)	(-7.36)	(-6.06)	(-5.28)	(-6.38)

t statistic in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table IV.A.4: SARAR/SAC model 1990, 2000 and 2010

	1990			2000			2010		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate (U)									
SDI	0.0019***	0.0008*	0.0014*	0.0009	0.0010*	0.0018*	0.0013**	0.0007*	0.0024**
	(3.62)	(2.05)	(2.08)	(1.87)	(2.12)	(2.14)	(3.04)	(2.46)	(3.01)
AI	-0.0048***	-0.0041***	-0.0078***	-0.0046***	-0.0022**	-0.0061***	-0.0054***	-0.0037***	-0.0075***
	(-3.52)	(-4.18)	(-3.72)	(-4.70)	(-3.20)	(-4.07)	(-4.17)	(-3.30)	(-4.04)
Education	-0.0189***	-0.0048***	-0.0302***	-0.0169***	-0.0072***	-0.0255***	-0.0104***	-0.0030***	-0.0169***
	(-23.77)	(-9.40)	(-29.25)	(-17.86)	(-12.32)	(-15.38)	(-17.83)	(-5.44)	(-17.13)
Age	0.0046***	0.0033***	-0.0084***	0.0033**	0.0035***	-0.0025	0.0071***	-0.00001	0.0118***
	(4.05)	(4.37)	(-6.52)	(2.63)	(3.97)	(-1.13)	(5.57)	(-0.004)	(8.89)
Child	-0.0026*	-0.0056***	0.0051	0.0110	-0.0274***	0.0543***	0.0814***	-0.0309**	0.2313***
	(-1.97)	(-3.50)	(1.15)	(1.58)	(-5.63)	(4.40)	(5.17)	(-2.87)	(10.39)
Population density	-0.00005***	-0.000004	-0.0001***	-0.00003***	-0.000004	-0.00004***	-0.000003	0.00001*	-0.00003***
	(-8.78)	(-1.64)	(-10.81)	(-5.17)	(-1.20)	(-5.33)	(-0.58)	(2.17)	(-3.48)
Constant	0.1608***	-0.0546*	0.8943***	0.2049***	0.0075	0.6012***	-0.0868	0.0716	-0.1577**
	(4.46)	(-2.41)	(20.78)	(4.58)	(0.25)	(7.95)	(-1.61)	(1.53)	(-2.62)
W*U (λ)	0.5565***	0.8072***	0.4070***	0.4599***	0.4884***	0.4022***	0.5595***	0.7361***	0.4540***
	(29.17)	(24.48)	(29.82)	(21.03)	(9.06)	(21.81)	(24.30)	(9.28)	(23.11)
ρ	0.5942***	-0.1743	0.6228***	0.3368***	-0.1292	0.4825***	0.1952***	-0.4131***	0.4176***
	(18.52)	(-1.51)	(27.72)	(9.21)	(-1.51)	(15.41)	(4.72)	(-4.65)	(14.42)
Adjusted R^2	0.8721	0.6128	0.9133	0.8343	0.3015	0.8756	0.8177	0.2166	0.8755
R^2	0.8723	0.6134	0.9135	0.8345	0.3024	0.8757	0.8180	0.2176	0.8757
R^2 (ratio)	0.8301	0.5222	0.8976	0.8156	0.2732	0.8626	0.7857	0.2160	0.8499
Wald test	1588.69***	42.02***	2281.34***	767.63***	42.89***	998.66***	726.57***	12.96***	1648.63***
Informal employment rate (I)									
SDI	0.0103***	0.0078***	0.0196***	0.0076***	0.0096***	0.0068***	0.0064***	0.0062***	0.0091***
	(9.74)	(7.04)	(14.05)	(4.88)	(6.05)	(3.32)	(7.35)	(6.57)	(8.49)
AI	-0.0010	0.0014	-0.0043	-0.0017	-0.0014	-0.0012	-0.0042*	-0.0039*	-0.0066**
	(-0.43)	(0.59)	(-1.38)	(-0.72)	(-0.60)	(-0.41)	(-2.43)	(-1.99)	(-3.02)
Education	-0.0471***	-0.0466***	-0.0488***	-0.0288***	-0.0286***	-0.0261***	-0.0247***	-0.0253***	-0.0234***
	(-39.12)	(-36.15)	(-30.72)	(-15.18)	(-14.74)	(-12.11)	(-35.01)	(-30.04)	(-24.84)
Age	0.0014	0.0002	0.0064***	-0.0081***	-0.0071**	-0.0089***	-0.0087***	-0.0082***	-0.0097***
	(0.92)	(0.14)	(3.77)	(-3.73)	(-3.25)	(-3.87)	(-12.42)	(-10.47)	(-10.27)
Population density	-0.00001	-0.00001	-0.00001	-0.0001***	-0.0001***	-0.0002***	-0.00001	0.00001	-0.00003**
	(-1.38)	(-0.60)	(-1.01)	(-9.07)	(-5.43)	(-11.31)	(-1.36)	(0.96)	(-2.61)
Constant	0.7307***	0.7714***	0.5617***	0.8643***	0.8334***	0.8383***	0.8306***	0.8105***	0.8477***
	(16.20)	(15.33)	(11.57)	(13.47)	(13.04)	(12.04)	(30.02)	(26.64)	(23.83)
W*I (λ)	-0.0296	-0.0463	0.0246	0.2857***	0.2653***	0.3579***	0.4084***	0.4219***	0.4239***
	(-1.20)	(-1.63)	(1.01)	(9.28)	(8.75)	(10.84)	(19.80)	(18.87)	(18.75)
ρ	0.7786***	0.7872***	0.6400***	0.7879***	0.7730***	0.7282***	0.7558***	0.7403***	0.7113***
	(50.96)	(53.51)	(27.34)	(46.72)	(47.41)	(33.27)	(46.38)	(42.26)	(35.06)
Adjusted R^2	0.7309	0.6491	0.7713	0.6593	0.6644	0.6574	0.8562	0.8417	0.8351
R^2	0.7312	0.6494	0.7716	0.6598	0.6648	0.6577	0.8564	0.8419	0.8353
R^2 (ratio)	0.7628	0.7179	0.7674	0.5953	0.6111	0.5596	0.7769	0.7630	0.7472
Wald test	1051.56***	829.42***	715.65***	1809.76***	1717.88***	1956.56***	3973.86***	3537.23***	3117.06***
ln w									
SDI	-0.0025	0.0002	-0.0159**	-0.0118*	-0.0099	-0.0254***	-0.0063*	-0.0060*	-0.0125***
	(-0.58)	(0.05)	(-3.26)	(-2.42)	(-1.65)	(-7.82)	(-2.51)	(-2.25)	(-5.45)
AI	-0.0146	-0.0075	-0.0002	0.0020	-0.0061	0.0231**	0.0153	0.0059	0.0385**
	(-1.01)	(-0.47)	(-0.01)	(0.23)	(-0.62)	(2.75)	(1.04)	(0.35)	(2.67)
Education	0.1485***	0.1715***	0.1167***	0.1340***	0.1441***	0.1153***	0.1496***	0.1420***	0.1345***
	(22.94)	(24.16)	(15.23)	(12.10)	(11.72)	(12.67)	(31.49)	(27.32)	(28.54)
Age	0.0112	0.0126	0.0030	0.0349***	0.0390***	0.0331***	0.0086*	0.0125**	0.0108**
	(1.74)	(1.72)	(0.42)	(3.59)	(3.73)	(4.33)	(2.29)	(3.06)	(2.98)
Population density	-0.0004***	-0.0005***	-0.0002***	-0.0005***	-0.0006***	-0.0003***	-0.0004***	-0.0004***	-0.0002***
	(-7.82)	(-8.03)	(-4.19)	(-10.76)	(-11.58)	(-6.57)	(-7.94)	(-7.95)	(-5.26)
Constant	6.8069***	6.3293***	7.0589***	4.3358***	3.8221***	4.3666***	5.0125***	4.3665***	5.0548***
	(17.88)	(16.51)	(14.85)	(12.96)	(10.60)	(15.97)	(22.03)	(17.28)	(25.56)
W*ln w (λ)	0.0472	0.0841*	0.0540	0.2146***	0.2590***	0.2160***	0.2130***	0.2883***	0.1997***
	(1.16)	(2.13)	(0.98)	(8.00)	(8.93)	(8.91)	(7.36)	(8.95)	(7.15)
ρ	0.5815***	0.6480***	0.4361***	0.5159***	0.6243***	0.2532***	0.4968***	0.5112***	0.3681***
	(20.62)	(25.88)	(9.61)	(12.89)	(18.51)	(4.84)	(17.14)	(16.52)	(11.57)
Adjusted R^2	0.5391	0.5696	0.3938	0.7196	0.7046	0.7236	0.7038	0.6948	0.7026
R^2	0.5397	0.5700	0.3944	0.7200	0.7049	0.7239	0.7042	0.6951	0.7030
R^2 (ratio)	0.5460	0.5720	0.3883	0.6994	0.6674	0.7135	0.6880	0.6616	0.6908
Wald test	442.39***	623.51***	195.82***	406.73***	802.24***	100.52***	772.26***	1014.16***	529.99***

t statistic in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table IV.A.5: Impacts of SARAR/SAC model 1990, 2000 and 2010

			1990			2000			2010		
			Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Non-employment rate	Total	SDI	0.0020***	0.0023***	0.0043***	0.0009*	0.0007	0.0016*	0.0014**	0.0016**	0.0030**
			(3.85)	(3.76)	(3.84)	(2.00)	(1.93)	(1.98)	(3.20)	(2.91)	(3.07)
		AI	-0.0051**	-0.0057***	-0.0108***	-0.0048***	-0.0038***	-0.0086***	-0.0057***	-0.0065***	-0.0123***
			(-3.26)	(-3.41)	(-3.36)	(-4.66)	(-4.89)	(-4.85)	(-4.12)	(-4.22)	(-4.24)
		Education	-0.0200***	-0.0225***	-0.0425***	-0.0176***	-0.0138***	-0.0314***	-0.0110***	-0.0125***	-0.0236***
			(-25.25)	(-12.63)	(-18.92)	(-19.06)	(-12.91)	(-19.64)	(-19.44)	(-11.10)	(-16.30)
		Age	0.0049***	0.0055***	0.0103***	0.0034**	0.0027*	0.0061**	0.0076***	0.0086***	0.0162***
			(4.00)	(3.61)	(3.82)	(2.63)	(2.52)	(2.60)	(5.51)	(6.71)	(6.26)
		Child	-0.0028*	-0.0031	-0.0059*	0.0114	0.0089	0.0204	0.0865***	0.0982***	0.1847***
			(-1.98)	(-1.96)	(-1.97)	(1.61)	(1.57)	(1.60)	(5.09)	(6.47)	(5.86)
		Population density	-0.00005***	-0.00005***	-0.0001***	-0.00003***	-0.00002***	-0.00005***	-0.000003	-0.000004	-0.00001
			(-9.37)	(-9.17)	(-9.79)	(-5.07)	(-4.94)	(-5.12)	(-0.39)	(-0.41)	(-0.40)
	Men	SDI	0.0009*	0.0031	0.0041	0.0010*	0.0009*	0.0019*	0.0008**	0.0019	0.0028
			(2.22)	(1.85)	(1.96)	(2.29)	(2.03)	(2.23)	(2.91)	(1.35)	(1.64)
		AI	-0.0050***	-0.0163***	-0.0213***	-0.0023***	-0.0020**	-0.0043**	-0.0043***	-0.0099	-0.0142
			(-3.97)	(-3.42)	(-3.70)	(-3.30)	(-2.76)	(-3.20)	(-3.37)	(-1.47)	(-1.84)
		Education	-0.0058***	-0.0189***	-0.0247***	-0.0075***	-0.0066***	-0.0141***	-0.0034***	-0.0079	-0.0114*
			(-10.64)	(-5.49)	(-7.04)	(-13.47)	(-5.13)	(-10.69)	(-6.24)	(-1.69)	(-2.28)
		Age	0.0040***	0.0131***	0.0171***	0.0036***	0.0031***	0.0068***	-0.00001	-0.00001	-0.00002
			(4.67)	(3.99)	(4.42)	(4.20)	(4.43)	(4.90)	(-0.15)	(-0.35)	(-0.32)
		Child	-0.0068***	-0.0224**	-0.0292**	-0.0286***	-0.0250**	-0.0536***	-0.0354*	-0.0817	-0.1172
			(-3.63)	(-2.59)	(-2.83)	(-5.40)	(-3.13)	(-4.30)	(-2.51)	(-0.96)	(-1.14)
		Population density	-0.00001	-0.00002	-0.00002	-0.000004	-0.000004	-0.00001	0.00001*	0.00003	0.00005*
			(-1.55)	(-1.48)	(-1.52)	(-1.04)	(-0.96)	(-1.01)	(2.19)	(1.89)	(2.16)
	Women	SDI	0.0015*	0.0009*	0.0024*	0.0019*	0.0012*	0.0030*	0.0024**	0.0019**	0.0043**
			(2.18)	(2.17)	(2.18)	(2.29)	(2.21)	(2.27)	(3.20)	(2.97)	(3.12)
		AI	-0.0080***	-0.0051***	-0.0131***	-0.0062***	-0.0039***	-0.0101***	-0.0078***	-0.0060***	-0.0138***
			(-3.54)	(-3.63)	(-3.59)	(-4.01)	(-4.11)	(-4.09)	(-3.98)	(-4.07)	(-4.06)
		Education	-0.0311***	-0.0199***	-0.0510***	-0.0262***	-0.0165***	-0.0427***	-0.0175***	-0.0134***	-0.0310***
			(-30.56)	(-17.19)	(-27.67)	(-16.21)	(-12.15)	(-16.32)	(-18.13)	(-10.52)	(-15.14)
		Age	-0.0086***	-0.0055***	-0.0142***	-0.0025	-0.0016	-0.0041	0.0123***	0.0094***	0.0217***
			(-6.22)	(-6.28)	(-6.33)	(-0.98)	(-0.97)	(-0.98)	(8.74)	(9.26)	(9.45)
		Child	0.0053	0.0034	0.0086	0.0558***	0.0350***	0.0908***	0.2398***	0.1837***	0.4236***
			(1.20)	(1.19)	(1.20)	(4.39)	(4.22)	(4.38)	(10.31)	(12.67)	(12.16)
		Population density	-0.0001***	-0.00005***	-0.0001***	-0.00005***	-0.00003***	-0.0001***	-0.00003**	-0.00002**	-0.0001**
			(-10.58)	(-9.43)	(-10.45)	(-5.21)	(-5.01)	(-5.22)	(-3.25)	(-3.07)	(-3.19)
Informal employment rate	Total	SDI	0.0102***	-0.0003	0.0099***	0.0078***	0.0030***	0.0108***	0.0066***	0.0043***	0.0109***
			(9.98)	(-1.07)	(10.19)	(4.82)	(4.21)	(4.85)	(7.25)	(6.47)	(7.21)
		AI	-0.0010	0.00003	-0.0010	-0.0017	-0.0006	-0.0023	-0.0043*	-0.0028*	-0.0071*
			(-0.41)	(0.38)	(-0.41)	(-0.70)	(-0.69)	(-0.70)	(-2.45)	(-2.45)	(-2.46)
		Education	-0.0471***	0.0013	-0.0458***	-0.0291***	-0.0111***	-0.0403***	-0.0254***	-0.0163***	-0.0418***
			(-38.45)	(1.09)	(-31.50)	(-15.35)	(-6.76)	(-13.89)	(-37.53)	(-11.72)	(-24.91)
		Age	0.0014	-0.00004	0.0013	-0.0081***	-0.0031**	-0.0112***	-0.0090***	-0.0058***	-0.0147***
			(0.98)	(-0.54)	(0.98)	(-3.44)	(-3.07)	(-3.40)	(-12.25)	(-10.10)	(-12.68)
		Population density	-0.00001	0.0000004	-0.00001	-0.0001***	-0.00005***	-0.0002***	-0.00001	-0.00001	-0.00002
			(-1.46)	(0.83)	(-1.46)	(-9.19)	(-6.49)	(-9.43)	(-1.39)	(-1.39)	(-1.39)
	Men	SDI	0.0078***	-0.0003	0.0074***	0.0097***	0.0033***	0.0130***	0.0064***	0.0044***	0.0108***
			(7.29)	(0.14)	(7.47)	(5.88)	(4.74)	(5.90)	(6.77)	(5.97)	(6.69)
		AI	0.0014	-0.00006	0.0013	-0.0014	-0.0005	-0.0019	-0.0040*	-0.0027*	-0.0068*
			(0.61)	(0.64)	(0.61)	(-0.58)	(-0.56)	(-0.57)	(-2.02)	(-2.03)	(-2.03)
		Education	-0.0466***	0.0021	-0.0446***	-0.0289***	-0.0100***	-0.0389***	-0.0261***	-0.0177***	-0.0438***
			(-35.56)	(0.12)	(-28.45)	(-14.56)	(-6.62)	(-13.67)	(-30.29)	(-11.09)	(-22.30)
		Age	0.0002	-0.00001	0.0002	-0.0072**	-0.0025**	-0.0097**	-0.0084***	-0.0057***	-0.0142***
			(0.23)	(0.87)	(0.23)	(-2.98)	(-2.70)	(-2.95)	(-10.50)	(-8.80)	(-10.74)
		Population density	-0.00001	0.0000003	-0.00001	-0.0001***	-0.00002***	-0.0001***	0.00001	0.00001	0.00002
			(-0.68)	(0.54)	(-0.67)	(-5.54)	(-4.81)	(-5.65)	(0.89)	(0.87)	(0.88)
	Women	SDI	0.0196***	0.0005	0.0201***	0.0070**	0.0037**	0.0107**	0.0093***	0.0064***	0.0157***
			(13.80)	(1.14)	(14.35)	(3.21)	(3.05)	(3.23)	(8.75)	(7.50)	(8.78)
		AI	-0.0043	-0.0001	-0.0044	-0.0012	-0.0006	-0.0018	-0.0068**	-0.0046**	-0.0114**
			(-1.37)	(-0.76)	(-1.37)	(-0.44)	(-0.43)	(-0.44)	(-3.08)	(-3.05)	(-3.10)
		Education	-0.0488***	-0.0012	-0.0500***	-0.0267***	-0.0140***	-0.0407***	-0.0242***	-0.0165***	-0.0407***
			(-31.03)	(-1.14)	(-29.20)	(-11.99)	(-6.73)	(-11.10)	(-25.11)	(-10.98)	(-20.48)
		Age	0.0064***	0.0002	0.0066***	-0.0091***	-0.0048**	-0.0139***	-0.0100***	-0.0068***	-0.0168***
			(3.75)	(1.02)	(3.74)	(-3.58)	(-3.25)	(-3.54)	(-10.15)	(-8.78)	(-10.49)
		Population density	-0.00001	-0.0000003	-0.00001	-0.0002***	-0.0001***	-0.0003***	-0.00003**	-0.00002**	-0.00005**
			(-1.14)	(-0.59)	(-1.14)	(-11.06)	(-7.41)	(-11.41)	(-2.62)	(-2.68)	(-2.66)
ln w	Total	SDI	-0.0025	-0.0001	-0.0026	-0.0118**	-0.0031*	-0.0150**	-0.0064*	-0.0017*	-0.0080*
			(-0.73)	(-0.49)	(-0.74)	(-2.82)	(-2.52)	(-2.80)	(-2.55)	(-2.38)	(-2.56)
		AI	-0.0146	-0.0007	-0.0153	0.0020	0.0005	0.0026	0.0154	0.0040	0.0194
			(-1.05)	(-0.75)	(-1.05)	(0.20)	(0.15)	(0.19)	(0.95)	(0.90)	(0.94)
		Education	0.1486***	0.0073	0.1559***	0.1349***	0.0358***	0.1707***	0.1506***	0.0395***	0.1901***
			(22.02)	(1.24)	(21.07)	(11.66)	(7.45)	(13.43)	(33.63)	(5.86)	(25.26)
		Age	0.0112	0.0005	0.0117	0.0351***	0.0093**	0.0445***	0.0087*	0.0023*	0.0109*
			(1.80)	(0.96)	(1.80)	(3.63)	(2.83)	(3.49)	(2.41)	(2.38)	(2.45)
		Population density	-0.0004***	-0.00002	-0.0004***	-0.0005***	-0.0001***	-0.0006***	-0.0004***	-0.0001***	-0.0005***
			(-7.97)	(-1.21)	(-8.01)	(-11.62)	(-5.49)	(-10.73)	(-8.12)	(-5.26)	(-8.36)
	Men	SDI	0.0002	0.00002	0.0003	-0.0100	-0.0034	-0.0133	-0.0061*	-0.0024*	-0.0085*
			(-0.09)	(-0.07)	(-0.09)	(-1.44)	(-1.41)	(-1.44)	(-2.31)	(-2.20)	(-2.32)
		AI	-0.0075	-0.0007	-0.0081	-0.0062	-0.0021	-0.0083	0.0059	0.0023	0.0082
			(-0.51)	(-0.53)	(-0.51)	(-0.77)	(-0.77)	(-0.77)	(0.23)	(0.17)	(0.21)
		Education	0.1717***	0.0156*	0.1873***	0.1456***	0.0489***	0.1945***	0.1438***	0.0557***	0.1995***
			(23.32)	(2.10)	(20.89)	(11.00)	(7.61)	(12.57)	(29.50)	(6.52)	(21.18)
		Age	0.0126	0.0011	0.0137	0.0394***	0.0132**	0.0526***	0.0126**	0.0049**	0.0175***
			(1.79)	(1.29)	(1.79)	(3.73)	(2.96)	(3.58)	(3.22)	(3.15)	(3.30)
		Population density	-0.0005***	-0.00004*	-0.0005***	-0.0006***	-0.0002***	-0.0009***	-0.0004***	-0.0002***	-0.0006***
			(-8.24)	(-2.03)	(-8.15)	(-12.18)	(-5.70)	(-10.74)	(-8.23)	(-5.51)	(-8.26)
	Women	SDI	-0.0159**	-0.0009	-0.0168**	-0.0256***	-0.0068***	-0.0324***	-0.0126***	-0.0030***	-0.0156***
			(-3.16)	(-0.97)	(-3.14)	(-7.57)	(-5.19)	(-7.43)	(-6.13)	(-4.54)	(-6.24)
		AI	-0.0002	-0.00001	-0.0002	0.0233**	0.0062**	0.0295**	0.0387**	0.0094**	0.0481**
			(-0.05)	(-0.26)	(-0.07)	(2.74)	(2.83)	(2.80)	(2.79)	(2.81)	(2.86)
		Education	0.1168***	0.0066	0.1234***	0.1161***	0.0310***	0.1470***	0.1353***	0.0328***	0.1680***
			(14.95)	(1.06)	(15.87)	(12.07)	(8.51)	(14.16)	(27.26)	(5.80)	(23.11)
		Age	0.0030	0.0002	0.0032	0.0333***	0.0089***	0.0422***	0.0109**	0.0026**	0.0135**
			(0.40)	(0.33)	(0.40)	(4.34)	(3.30)	(4.16)	(2.87)	(3.00)	(2.97)
		Population density	-0.0002***	-0.00001	-0.0003***	-0.0003***	-0.0001***	-0.0003***	-0.0002***	-0.0001***	-0.0003***
			(-4.35)	(-1.06)	(-4.27)	(-6.29)	(-4.45)	(-6.06)	(-5.42)	(-4.43)	(-5.58)

t statistic in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table IV.A.6: SLX model 1990, 2000 and 2010

	1990			2000			2010		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate									
SDI	0.0022*	0.0012	0.0013	0.0010	-0.00001	0.0022*	0.0017**	0.0010*	0.0027**
	(2.27)	(1.31)	(1.34)	(1.68)	(-0.02)	(2.15)	(2.85)	(2.04)	(2.61)
AI	-0.0253***	-0.0119***	-0.0283***	-0.0106***	-0.0020**	-0.0179***	-0.0146***	-0.0043***	-0.0225***
	(-12.14)	(-9.33)	(-10.07)	(-9.52)	(-2.72)	(-10.00)	(-9.66)	(-3.71)	(-9.52)
Education	-0.0221***	-0.0086***	-0.0325***	-0.0189***	-0.0085***	-0.0277***	-0.0118***	-0.0044***	-0.0177***
	(-20.88)	(-10.82)	(-24.29)	(-17.22)	(-13.02)	(-14.53)	(-18.40)	(-7.06)	(-15.80)
Age	0.0053***	0.0044***	-0.0076***	0.0033*	0.0030*	-0.0026	0.0072***	-0.0005**	0.0113***
	(3.57)	(3.57)	(-4.59)	(2.40)	(2.51)	(-1.11)	(5.26)	(-0.26)	(7.62)
Child	-0.0009	-0.0052	0.0076	0.0105	-0.0335***	0.0557***	0.0895***	-0.0486**	0.2385***
	(-0.58)	(-1.90)	(1.20)	(1.36)	(-5.31)	(4.19)	(5.48)	(-2.96)	(10.67)
Population density	-0.00003**	0.00001	-0.00005***	-0.00001	0.000004	-0.00002*	0.00001	0.00003***	-0.000005
	(-2.82)	(1.48)	(-5.26)	(-1.23)	(0.85)	(-2.05)	(1.96)	(3.88)	(-0.45)
W*SDI	-0.0030*	0.0014	-0.0055***	-0.0016	0.0042***	-0.0066***	-0.0014	-0.0003	-0.0025
	(-2.16)	(1.04)	(-3.44)	(-1.64)	(4.98)	(-4.29)	(-1.60)	(-0.39)	(-1.56)
W*AI	-0.1301***	-0.0590***	-0.1377***	-0.0531***	-0.0116***	-0.0877***	-0.0705***	-0.0215***	-0.1054***
	(-23.44)	(-12.38)	(-23.00)	(-20.47)	(-6.82)	(-21.39)	(-19.56)	(-6.83)	(-18.87)
W*Education	-0.0122***	-0.0062***	-0.0096***	-0.0060***	-0.0011	-0.0096***	-0.0048***	-0.0010	-0.0070***
	(-8.54)	(-5.48)	(-6.20)	(-5.25)	(-1.33)	(-4.88)	(-4.43)	(-1.23)	(-3.73)
W*Age	0.0153***	0.0111***	0.0076***	0.0082***	0.0045***	0.0136***	0.0069***	0.0041*	0.0088***
	(7.75)	(6.41)	(3.35)	(5.91)	(3.98)	(5.71)	(4.91)	(2.54)	(5.06)
W*Child	0.0194**	-0.0101	0.0635***	0.0524***	-0.0006	0.1225***	0.0797***	0.0240	0.1355***
	(3.22)	(-1.28)	(4.65)	(4.55)	(-0.09)	(6.86)	(4.04)	(1.59)	(4.88)
W*Population density	-0.0001***	-0.00002**	-0.0001***	-0.00002*	0.00001	-0.00003*	0.00001	0.00003**	-0.00001
	(-7.56)	(-2.62)	(-6.06)	(-2.57)	(0.53)	(-2.09)	(0.53)	(2.84)	(-0.58)
Constant	-0.0248	-0.3067***	0.9503***	0.1241*	-0.0655*	0.4033***	-0.1469**	0.0143	-0.2109**
	(-0.48)	(-5.56)	(12.34)	(2.41)	(-2.53)	(4.25)	(-3.15)	(0.35)	(-2.84)
Adjusted R^2	0.7789	0.3217	0.8860	0.8006	0.2397	0.8485	0.7536	0.0809	0.8315
R^2	0.7795	0.3234	0.8863	0.8011	0.2417	0.8489	0.7542	0.0833	0.8319
Informal employment rate									
SDI	0.0097***	0.0071***	0.0187***	0.0060**	0.0080***	0.0054*	0.0057***	0.0057***	0.0077***
	(6.23)	(4.27)	(10.28)	(3.19)	(4.20)	(2.39)	(4.04)	(3.35)	(5.63)
AI	0.0004	0.0066	-0.0074*	0.0023	0.0019	0.0007	-0.0127***	-0.0139***	-0.0142***
	(0.13)	(1.94)	(-1.97)	(0.60)	(0.59)	(0.14)	(-5.17)	(-4.91)	(-4.81)
Education	-0.0480***	-0.0477***	-0.0495***	-0.0319***	-0.0312***	-0.0299***	-0.0255***	-0.0268***	-0.0239***
	(-29.68)	(-27.45)	(-25.25)	(-11.94)	(-12.39)	(-9.78)	(-22.18)	(-21.02)	(-17.32)
Age	0.0011	-0.0005	0.0058**	-0.0079**	-0.0077**	-0.0089**	-0.0091***	-0.0084***	-0.0109***
	(0.57)	(-0.24)	(2.69)	(-2.76)	(-2.76)	(-2.94)	(-8.26)	(-7.14)	(-7.90)
Population density	-0.000002	0.00001	-0.00001	-0.0001***	-0.0001**	-0.0002***	0.00001	0.00004*	0.000002
	(-0.14)	(0.40)	(-0.62)	(-5.42)	(-2.66)	(-7.60)	(0.92)	(2.45)	(0.11)
W*SDI	0.0054**	0.0057**	0.0057*	0.0175***	0.0257***	0.0098**	0.0197***	0.0246***	0.0127***
	(2.70)	(2.62)	(2.50)	(5.90)	(9.05)	(2.86)	(8.25)	(8.51)	(6.00)
W*AI	0.0110	0.0348***	-0.0151	0.0290***	0.0255***	0.0210*	-0.0532***	-0.0590***	-0.0536***
	(1.45)	(4.25)	(-1.92)	(3.49)	(3.63)	(2.10)	(-9.37)	(-9.21)	(-8.11)
W*Education	-0.0027	-0.0016	-0.0042	-0.0177***	-0.0107**	-0.0227***	0.0014	-0.0004	0.0048*
	(-1.14)	(-0.63)	(-1.64)	(-4.16)	(-2.90)	(-4.49)	(0.71)	(-0.18)	(2.11)
W*Age	0.0157***	0.0160***	0.0149***	0.0278***	0.0262***	0.0270***	-0.0066***	-0.0008	-0.0170***
	(5.88)	(5.46)	(5.39)	(6.86)	(6.86)	(5.96)	(-3.55)	(-0.40)	(-7.40)
W*Population density	0.000002	-0.00001	0.00002	-0.0003***	-0.0002***	-0.0004***	-0.0001***	-0.0001**	-0.0002***
	(0.08)	(-0.34)	(0.91)	(-8.77)	(-5.27)	(-11.57)	(-6.89)	(-2.94)	(-10.55)
Constant	0.2300***	0.2549***	0.1413**	0.2517**	0.2027*	0.3672***	1.2911***	1.0772***	1.6935***
	(4.42)	(4.37)	(2.89)	(2.68)	(2.26)	(3.55)	(25.34)	(19.74)	(27.33)
Adjusted R^2	0.7516	0.6833	0.7730	0.5413	0.5630	0.5001	0.7527	0.7194	0.7236
R^2	0.7521	0.6840	0.7735	0.5423	0.5640	0.5012	0.7533	0.7200	0.7242
ln w									
SDI	-0.0070	-0.0045	-0.0207**	-0.0087	-0.0105	-0.0212***	-0.0048	-0.0042	-0.0111***
	(-1.19)	(-0.72)	(-2.84)	(-1.55)	(-1.45)	(-5.52)	(-1.58)	(-1.20)	(-3.87)
AI	0.0090	0.0332	0.0214	0.0300**	0.0388**	0.0353***	0.0563***	0.0621**	0.0621***
	(0.53)	(1.58)	(1.16)	(2.62)	(2.60)	(3.81)	(3.41)	(3.28)	(4.02)
Education	0.1499***	0.1740***	0.1160***	0.1394***	0.1469***	0.1254***	0.1524***	0.1457***	0.1388***
	(19.83)	(20.58)	(13.22)	(10.71)	(9.76)	(11.53)	(27.93)	(23.67)	(26.73)
Age	0.0138	0.0139	0.0055	0.0358***	0.0408***	0.0314***	0.0094*	0.0141**	0.0097*
	(1.83)	(1.64)	(0.64)	(3.34)	(3.40)	(3.59)	(2.18)	(2.91)	(2.37)
Population density	-0.0004***	-0.0005***	-0.0002***	-0.0006***	-0.0007***	-0.0003***	-0.0005***	-0.0005***	-0.0003***
	(-6.14)	(-6.78)	(-3.34)	(-9.65)	(-10.30)	(-6.60)	(-7.45)	(-7.53)	(-5.67)
W*SDI	0.0025	-0.0035	0.0111	-0.0519***	-0.0709***	-0.0276***	-0.0183***	-0.0274***	-0.0077
	(0.29)	(-0.39)	(1.07)	(-7.53)	(-7.60)	(-5.02)	(-4.05)	(-5.01)	(-1.87)
W*AI	0.0816*	0.1875***	0.1474***	0.2034***	0.2763***	0.1951***	0.3044***	0.3842***	0.2565***
	(1.96)	(3.70)	(3.34)	(8.35)	(8.76)	(10.00)	(9.77)	(10.35)	(9.23)
W*Education	0.0126	0.0124	0.0156	-0.0187	-0.0321	-0.0070	-0.0090	-0.0005	-0.0097
	(1.22)	(1.08)	(1.31)	(-1.37)	(-1.92)	(-0.59)	(-1.01)	(-0.05)	(-1.20)
W*Age	-0.0259*	-0.0306**	-0.0215	-0.0021	0.0012	0.0039	0.0063	0.0019	0.0142*
	(-2.48)	(-2.64)	(-1.81)	(-0.19)	(0.09)	(0.41)	(0.91)	(0.24)	(2.28)
W*Population density	-0.0005***	-0.0008***	-0.0002*	-0.0005***	-0.0009***	-0.0002**	-0.0005***	-0.0006***	-0.0002*
	(-5.57)	(-6.81)	(-2.36)	(-6.20)	(-8.39)	(-2.76)	(-5.20)	(-5.88)	(-2.48)
Constant	7.9036***	7.9405***	8.0003***	6.3102***	6.2379***	6.0031***	6.5953***	6.6403***	6.2577***
	(38.85)	(32.69)	(33.32)	(27.68)	(22.19)	(32.72)	(42.42)	(35.96)	(43.49)
Adjusted R^2	0.5337	0.5537	0.3837	0.6894	0.6496	0.7092	0.6646	0.6444	0.6881
R^2	0.5347	0.5547	0.3851	0.6901	0.6504	0.7098	0.6652	0.6451	0.6888

t statistic in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table IV.A.7: Spatial durbin error model 1990, 2000 and 2010

	1990			2000			2010		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate									
SDI	0.0023***	0.0012	0.0014	0.0009	0.0001	0.0020*	0.0017***	0.0009*	0.0028***
	(3.58)	(1.69)	(1.83)	(1.80)	(0.14)	(2.20)	(3.37)	(2.22)	(3.35)
AI	-0.0155***	-0.0087***	-0.0217***	-0.0095***	-0.0020**	-0.0150***	-0.0120***	-0.0038**	-0.0181***
	(-8.39)	(-6.31)	(-8.55)	(-8.67)	(-2.66)	(-8.54)	(-8.11)	(-3.17)	(-8.01)
Education	-0.0216***	-0.0082***	-0.0324***	-0.0189***	-0.0086***	-0.0276***	-0.0121***	-0.0043***	-0.0182***
	(-25.34)	(-12.34)	(-29.79)	(-18.87)	(-14.04)	(-15.90)	(-21.08)	(-7.34)	(-18.11)
Age	0.0042**	0.0042***	-0.0087***	0.0033*	0.0031**	-0.0027	0.0072***	-0.0006	0.0117***
	(3.09)	(3.83)	(-6.02)	(2.46)	(2.65)	(-1.21)	(5.32)	(-0.33)	(8.45)
Child	-0.0035*	-0.0062***	0.0056	0.0108	-0.0340***	0.0565***	0.0909***	-0.0491**	0.2437***
	(-2.57)	(-3.38)	(1.22)	(1.49)	(-5.61)	(4.53)	(5.64)	(-3.13)	(11.12)
Population density	-0.00003***	0.000004	-0.0001***	-0.00001*	0.000003	-0.00003**	0.00001	0.00003***	-0.00001
	(-5.90)	(0.78)	(-8.36)	(-1.99)	(0.73)	(-3.16)	(1.60)	(4.16)	(-1.41)
W*SDI	0.0024	0.0029*	0.0009	0.0004	0.0039***	-0.0018	0.0004	0.0002	0.0006
	(1.56)	(1.99)	(0.56)	(0.29)	(4.23)	(-0.84)	(0.34)	(0.18)	(0.31)
W*AI	-0.0661***	-0.0348***	-0.0882***	-0.0430***	-0.0106***	-0.0645***	-0.0510***	-0.0174***	-0.0722***
	(-8.87)	(-5.27)	(-9.79)	(-11.67)	(-4.84)	(-10.64)	(-10.15)	(-3.99)	(-9.29)
W*Education	-0.0090***	-0.0047***	-0.0073***	-0.0047**	-0.0008	-0.0066*	-0.0039*	-0.0017	-0.0036
	(-4.49)	(-3.48)	(-3.43)	(-2.74)	(-0.89)	(-2.05)	(-2.53)	(-1.61)	(-1.29)
W*Age	0.0045	0.0055**	-0.0026	0.00619**	0.0046***	0.0074	0.0060***	0.0036*	0.0074**
	(1.70)	(2.91)	(-1.15)	(2.64)	(4.15)	(1.57)	(3.92)	(2.53)	(2.93)
W*Child	-0.0117	-0.0144*	0.0131	0.04446**	0.0042	0.0962**	0.0786***	0.0165	0.1517***
	(-1.69)	(-2.08)	(1.76)	(2.75)	(0.62)	(3.20)	(3.45)	(1.08)	(3.78)
W*Population density	-0.0001***	-0.00002*	-0.0001***	-0.00002*	0.00001	-0.00004	0.000001	0.00002*	-0.000005
	(-4.67)	(-2.06)	(-4.60)	(-2.09)	(0.77)	(-1.78)	(0.05)	(2.05)	(-0.21)
Constant	0.3574***	-0.1321	1.3501***	0.1859	-0.0767*	0.6055**	-0.1307	0.0455	-0.2327
	(3.76)	(-1.87)	(14.67)	(1.83)	(-2.07)	(2.91)	(-1.33)	(0.62)	(-1.54)
ρ	0.8333***	0.7281***	0.7682***	0.6098***	0.3883***	0.6630***	0.6573***	0.4822***	0.6909***
	(49.95)	(24.83)	(49.15)	(30.05)	(12.94)	(31.52)	(42.98)	(21.12)	(48.83)
Adjusted R^2	0.7575	0.3094	0.8786	0.7990	0.2394	0.8460	0.7499	0.0798	0.8281
R^2	0.7581	0.3112	0.8790	0.7996	0.2414	0.8464	0.7506	0.0822	0.8286
R^2 (ratio)	0.6531	0.2770	0.8228	0.7815	0.2383	0.8312	0.7112	0.0805	0.7904
Informal employment rate									
SDI	0.0100***	0.0076***	0.0189***	0.0071***	0.0092***	0.0064**	0.0063***	0.0060***	0.0088***
	(9.15)	(6.64)	(12.26)	(4.76)	(6.26)	(3.20)	(7.54)	(6.68)	(8.41)
AI	-0.0012	0.0034	-0.0076	-0.0045	-0.0028	-0.0058	-0.0106***	-0.0098***	-0.0138***
	(-0.37)	(1.06)	(-1.96)	(-1.31)	(-0.89)	(-1.41)	(-4.57)	(-3.62)	(-5.04)
Education	-0.0474***	-0.0469***	-0.0494***	-0.0306***	-0.0299***	-0.0290***	-0.0255***	-0.0265***	-0.0245***
	(-39.33)	(-36.22)	(-30.81)	(-14.92)	(-14.53)	(-12.66)	(-33.75)	(-29.09)	(-24.69)
Age	0.0013	0.0001	0.0056**	-0.0085***	-0.0081***	-0.0094***	-0.0091***	-0.0086***	-0.0106***
	(0.87)	(0.05)	(3.24)	(-3.56)	(-3.40)	(-3.73)	(-11.94)	(-10.36)	(-10.48)
Population density	-0.00001	-0.00001	-0.00001	-0.0001***	-0.0001***	-0.0002***	-0.000004	0.00002	-0.00001
	(-1.43)	(-0.75)	(-0.71)	(-9.08)	(-5.24)	(-11.25)	(-0.43)	(1.74)	(-1.39)
W*SDI	0.0019	0.0020	0.0026	0.0023	0.0077*	0.0007	0.0073**	0.0072**	0.0047
	(0.84)	(0.83)	(1.04)	(0.71)	(2.49)	(0.18)	(2.86)	(2.87)	(1.89)
W*AI	0.0009	0.0147	-0.0165	-0.0092	-0.0015	-0.0161	-0.0358***	-0.0327**	-0.0421***
	(0.08)	(1.26)	(-1.34)	(-0.75)	(-0.14)	(-1.08)	(-3.81)	(-3.09)	(-3.77)
W*Education	0.0012	0.0021	-0.0038	-0.0109*	-0.0061	-0.0146*	-0.0054*	-0.0087**	-0.0019
	(0.40)	(0.67)	(-1.23)	(-1.98)	(-1.23)	(-2.23)	(-2.30)	(-3.28)	(-0.66)
W*Age	0.0050	0.0039	0.0119***	0.0084	0.0065	0.0120*	-0.0041	-0.0028	-0.0093**
	(1.39)	(1.03)	(3.46)	(1.64)	(1.41)	(2.01)	(-1.74)	(-1.01)	(-3.14)
W*Population density	-0.00001	0.000001	-0.00001	-0.0003***	-0.0001***	-0.0004***	-0.0001***	-0.0001	-0.0002***
	(-0.29)	(0.03)	(-0.52)	(-6.27)	(-3.75)	(-7.74)	(-3.67)	(-1.91)	(-5.37)
Constant	0.5516***	0.6086***	0.2473**	0.8793***	0.8474***	0.8263***	1.2576***	1.2288***	1.4650***
	(5.09)	(5.13)	(2.65)	(5.08)	(5.39)	(4.26)	(15.08)	(13.27)	(14.24)
ρ	0.7708***	0.7761***	0.6409***	0.8589***	0.8340***	0.8403***	0.8632***	0.8576***	0.8401***
	(51.77)	(53.94)	(30.78)	(79.82)	(81.69)	(72.54)	(96.96)	(95.82)	(80.81)
Adjusted R^2	0.7459	0.6755	0.7721	0.5194	0.5397	0.4897	0.7378	0.7010	0.7116
R^2	0.7464	0.6762	0.7726	0.5204	0.5407	0.4909	0.7384	0.7017	0.7122
R^2 (ratio)	0.7479	0.6923	0.7612	0.5595	0.5548	0.5157	0.6354	0.6351	0.5990
ln w									
SDI	-0.0064	-0.0032	-0.0212**	-0.0088	-0.0098	-0.0213***	-0.0063*	-0.0057*	-0.0119***
	(-1.27)	(-0.62)	(-3.23)	(-1.88)	(-1.70)	(-6.06)	(-2.47)	(-2.08)	(-4.67)
AI	0.0050	0.0191	0.0225	0.0216*	0.0186	0.0326***	0.0445**	0.0431*	0.0568***
	(0.31)	(1.02)	(1.22)	(2.22)	(1.55)	(3.79)	(2.81)	(2.41)	(3.77)
Education	0.1478***	0.1719***	0.1136***	0.1390***	0.1473***	0.1249***	0.1509***	0.1443***	0.1376***
	(22.43)	(24.23)	(14.01)	(12.05)	(11.49)	(12.21)	(31.57)	(27.44)	(28.93)
Age	0.0132*	0.0138	0.0055	0.0360***	0.0417***	0.0314***	0.0097*	0.0142***	0.0105**
	(1.99)	(1.88)	(0.70)	(3.64)	(3.85)	(3.80)	(2.55)	(3.40)	(2.82)
Population density	-0.0003***	-0.0004***	-0.0002**	-0.0005***	-0.0007***	-0.0003***	-0.0004***	-0.0005***	-0.0003***
	(-6.29)	(-7.11)	(-3.18)	(-10.28)	(-11.28)	(-6.64)	(-7.49)	(-7.73)	(-5.44)
W*SDI	0.0045	-0.0010	0.0129	-0.0424***	-0.0587***	-0.0236***	-0.0061	-0.0096	-0.0050
	(0.47)	(-0.09)	(1.12)	(-4.90)	(-4.93)	(-3.62)	(-1.10)	(-1.43)	(-1.08)
W*AI	0.0546	0.0947	0.1435*	0.1311***	0.1342**	0.1599***	0.2022***	0.2443***	0.1948***
	(0.83)	(1.25)	(2.22)	(4.09)	(3.28)	(6.66)	(4.33)	(4.27)	(5.03)
W*Education	0.0184	0.0209	0.0219	-0.0097	-0.0194	-0.0027	0.0105	0.0198	0.0029
	(1.53)	(1.51)	(1.62)	(-0.70)	(-1.05)	(-0.23)	(0.92)	(1.40)	(0.29)
W*Age	-0.0227	-0.0248	-0.0237	0.0038	0.0084	0.0072	0.0038	0.0044	0.0086
	(-1.79)	(-1.69)	(-1.72)	(0.31)	(0.51)	(0.74)	(0.42)	(0.40)	(1.10)
W*Population density	-0.0005***	-0.0007***	-0.0003*	-0.0006***	-0.0010***	-0.0002*	-0.0004***	-0.0005***	-0.0002
	(-4.18)	(-4.77)	(-2.30)	(-4.98)	(-6.27)	(-2.25)	(-3.43)	(-3.76)	(-1.58)
Constant	7.7907***	7.7202***	8.0413***	6.0692***	5.9336***	5.8711***	6.5203***	6.4006***	6.3307***
	(22.34)	(17.73)	(22.57)	(13.99)	(10.20)	(22.14)	(24.78)	(19.54)	(29.14)
ρ	0.5892***	0.6649***	0.4606***	0.6214***	0.7283***	0.4117***	0.5852***	0.6453***	0.4672***
	(30.86)	(40.10)	(17.79)	(20.13)	(31.04)	(9.60)	(31.06)	(37.67)	(22.94)
Adjusted R^2	0.5335	0.5529	0.3836	0.6876	0.6446	0.7088	0.6763	0.6412	0.6874
R^2	0.5345	0.5539	0.3849	0.6883	0.6454	0.7095	0.6770	0.6420	0.6881
R^2 (ratio)	0.5402	0.5599	0.3884	0.6833	0.6282	0.7089	0.6730	0.6356	0.6792

t statistic in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table IV.A.8: Spatial durbin model 1990, 2000 and 2010

	1990			2000			2010		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate (U)									
SDI	0.0017**	0.0006	0.0010	0.0009	-0.0002	0.0021*	0.0014**	0.0008	0.0023**
	(2.58)	(0.91)	(1.17)	(1.76)	(-0.36)	(2.31)	(2.90)	(1.92)	(2.75)
AI	-0.0047**	-0.0020	-0.0087***	-0.0048***	-0.0012	-0.0081***	-0.0051***	-0.0012	-0.0090***
	(-2.82)	(-1.95)	(-3.56)	(-4.32)	(-1.67)	(-4.59)	(-3.39)	(-0.94)	(-4.25)
Education	-0.0204***	-0.0076***	-0.0314***	-0.0180***	-0.0084***	-0.0264***	-0.0114***	-0.0038***	-0.0175***
	(-24.12)	(-12.44)	(-27.98)	(-17.43)	(-13.16)	(-15.12)	(-20.12)	(-6.38)	(-18.07)
Age	0.0037**	0.0034***	-0.0081***	0.0028*	0.0028*	-0.0030	0.0064***	-0.0012	0.0107***
	(2.71)	(3.30)	(-5.47)	(2.06)	(2.37)	(-1.39)	(4.67)	(-0.64)	(7.59)
Child	-0.0029*	-0.0054***	0.0045	0.0060	-0.0337***	0.0476***	0.0801***	-0.0517**	0.2245***
	(-1.96)	(-4.93)	(1.02)	(0.84)	(-5.50)	(3.98)	(4.86)	(-3.26)	(10.16)
Population density	-0.00002***	0.00001	-0.0001***	-0.00001	0.000002	-0.00003**	0.00001	0.00002***	-0.00001
	(-4.13)	(1.79)	(-7.05)	(-1.53)	(0.57)	(-2.64)	(1.37)	(3.44)	(-1.33)
W*SDI	-0.0007	0.0003	-0.0010	-0.0004	0.0019**	-0.0021	-0.0002	-0.0002	-0.0006
	(-0.91)	(0.35)	(-0.95)	(-0.53)	(2.64)	(-1.81)	(-0.39)	(-0.30)	(-0.52)
W*AI	-0.0122**	-0.0026	-0.0200***	-0.0141***	-0.0047**	-0.0221***	-0.0123***	-0.0030	-0.0204***
	(-3.22)	(-0.85)	(-3.86)	(-5.94)	(-3.28)	(-5.78)	(-3.85)	(-1.03)	(-4.66)
W*Education	0.0133***	0.0062***	0.0182***	0.0079***	0.0036**	0.0116***	0.0064***	0.0022*	0.0099***
	(10.40)	(6.82)	(10.05)	(5.58)	(3.27)	(5.18)	(6.08)	(2.49)	(6.22)
W*Age	-0.0010	-0.0029**	0.0062***	0.0013	0.0006	0.0056*	-0.0021*	0.0013	-0.0034*
	(-0.67)	(-2.74)	(4.15)	(0.94)	(0.51)	(2.34)	(-1.97)	(1.00)	(-2.38)
W*Child	-0.0022	-0.0021	0.0104	0.0135	0.0156*	0.0183	-0.0298	0.0342**	-0.0797**
	(-0.92)	(-0.97)	(1.65)	(1.47)	(2.39)	(1.16)	(-1.90)	(2.82)	(-3.02)
W*Population density	-0.000002	-0.00001	0.00001	-0.000004	0.000001	0.000001	-0.0000002	-0.00001	0.00001
	(-0.24)	(-1.58)	(0.84)	(-0.57)	(0.16)	(0.09)	(-0.02)	(-1.38)	(1.20)
Constant	0.0345	0.0066	0.3449***	0.0592	-0.0249	0.2205*	-0.0586	0.0352	-0.1237*
	(1.12)	(0.23)	(7.78)	(1.29)	(-1.05)	(2.58)	(-1.50)	(0.91)	(-2.07)
W*U (λ)	0.8419***	0.9660***	0.7163***	0.6471***	0.5805***	0.6084***	0.7261***	0.8560***	0.6748***
	(24.56)	(17.31)	(20.50)	(15.52)	(4.94)	(14.46)	(15.00)	(5.09)	(16.87)
Adjusted R^2	0.9089	0.6296	0.9370	0.8516	0.3141	0.8943	0.8256	0.2177	0.8923
R^2	0.9091	0.6306	0.9372	0.8520	0.3159	0.8946	0.8260	0.2197	0.8926
R^2 (ratio)	0.8728	0.6170	0.9216	0.8330	0.3048	0.8744	0.8097	0.2781	0.8714
Informal employment rate (I)									
SDI	0.0095***	0.0070***	0.0186***	0.0069***	0.0085***	0.0061**	0.0066***	0.0066***	0.0087***
	(7.34)	(5.33)	(10.41)	(4.47)	(5.54)	(2.98)	(6.47)	(5.56)	(7.97)
AI	0.0033	0.0081**	-0.0056	0.0021	0.0018	0.0015	-0.0068***	-0.0077**	-0.0071**
	(1.23)	(2.94)	(-1.52)	(0.80)	(0.75)	(0.45)	(-3.50)	(-3.27)	(-3.12)
Education	-0.0468***	-0.0464***	-0.0485***	-0.0293***	-0.0287***	-0.0281***	-0.0246***	-0.0256***	-0.0235***
	(-33.17)	(-31.97)	(-25.43)	(-15.03)	(-14.72)	(-12.24)	(-31.22)	(-27.07)	(-24.39)
Age	0.0010	-0.0004	0.0054**	-0.0081***	-0.0079***	-0.0090***	-0.0086***	-0.0079***	-0.0098***
	(0.57)	(-0.20)	(2.65)	(-3.63)	(-3.50)	(-3.77)	(-11.44)	(-9.46)	(-10.32)
Population density	-0.000001	0.000003	-0.000004	-0.0001***	-0.0001***	-0.0002***	0.00001	0.00003*	0.000001
	(-0.09)	(0.24)	(-0.33)	(-6.91)	(-3.71)	(-8.83)	(0.84)	(2.57)	(0.10)
W*SDI	-0.0008	-0.0011	0.0013	-0.0009	-0.0005	-0.0008	0.0027	0.0047**	-0.0018
	(-0.45)	(-0.62)	(0.47)	(-0.43)	(-0.22)	(-0.31)	(1.83)	(2.61)	(-1.23)
W*AI	0.0180***	0.0274***	-0.0023	0.0190***	0.0165***	0.0173**	-0.0115**	-0.0138**	-0.0060
	(3.68)	(5.57)	(-0.36)	(4.63)	(4.55)	(3.22)	(-2.68)	(-2.67)	(-1.27)
W*Education	0.0143***	0.0201***	0.0030	0.0123***	0.0158***	0.0061	0.0127***	0.0119***	0.0150***
	(4.14)	(5.91)	(0.64)	(4.17)	(6.00)	(1.63)	(8.62)	(6.38)	(9.48)
W*Age	0.0079***	0.0065**	0.0107***	0.0120***	0.0105***	0.0136***	0.0018	0.0028*	0.0003
	(3.41)	(2.73)	(3.86)	(5.08)	(4.61)	(4.98)	(1.48)	(2.25)	(0.16)
W*Population density	-0.00001	-0.00002	0.000001	-0.0001*	-0.00003	-0.0001**	-0.0001***	-0.0001***	-0.0001***
	(-0.75)	(-0.91)	(0.05)	(-2.20)	(-1.27)	(-3.25)	(-5.43)	(-3.77)	(-5.57)
Constant	0.1980***	0.1903***	0.1581***	0.1711**	0.1462**	0.2481***	0.5657***	0.5265***	0.5979***
	(4.79)	(4.37)	(3.57)	(3.22)	(2.94)	(3.61)	(8.75)	(7.39)	(7.46)
W*I (λ)	0.3859***	0.5000***	0.1674*	0.6889***	0.7335***	0.5901***	0.5855***	0.5625***	0.6551***
	(6.00)	(7.70)	(1.98)	(14.22)	(15.33)	(9.70)	(12.88)	(9.79)	(14.40)
Adjusted R^2	0.8330	0.8108	0.7970	0.8153	0.8227	0.7580	0.7378	0.8826	0.8866
R^2	0.8333	0.8112	0.7975	0.8157	0.8231	0.7586	0.7384	0.8829	0.8868
R^2 (ratio)	0.7738	0.7306	0.7761	0.6862	0.7212	0.6073	0.6354	0.7838	0.8084
ln w									
SDI	-0.0087	-0.0047	-0.0234**	-0.0074	-0.0071	-0.0198***	-0.0069*	-0.0060*	-0.0130***
	(-1.42)	(-0.75)	(-3.25)	(-1.45)	(-1.14)	(-5.47)	(-2.44)	(-2.00)	(-4.80)
AI	0.0101	0.0326	0.0197	0.0180	0.0155	0.0264**	0.0337	0.0326	0.0421*
	(0.56)	(1.48)	(0.98)	(1.66)	(1.20)	(2.73)	(1.95)	(1.67)	(2.51)
Education	0.1494***	0.1732***	0.1116***	0.1392***	0.1476***	0.1242***	0.1503***	0.1433***	0.1366***
	(17.91)	(19.32)	(12.10)	(11.59)	(11.19)	(11.85)	(30.32)	(26.08)	(28.21)
Age	0.0120	0.0125	0.0061	0.0342***	0.0389***	0.0304***	0.0080*	0.0129**	0.0087*
	(1.53)	(1.47)	(0.70)	(3.38)	(3.61)	(3.60)	(2.05)	(3.06)	(2.32)
Population density	-0.0004***	-0.0005***	-0.0002**	-0.0005***	-0.0006***	-0.0003***	-0.0004***	-0.0004***	-0.0003***
	(-5.86)	(-6.34)	(-2.91)	(-9.48)	(-10.14)	(-6.49)	(-6.76)	(-6.65)	(-5.23)
W*SDI	0.0047	-0.0013	0.0163	-0.0265***	-0.0320***	-0.0115*	-0.0021	-0.0063	0.0045
	(0.61)	(-0.17)	(1.75)	(-4.42)	(-4.50)	(-2.25)	(-0.55)	(-1.46)	(1.28)
W*AI	0.0495	0.1092*	0.0848*	0.0813***	0.0911***	0.0868***	0.0988**	0.1350**	0.0718*
	(1.34)	(2.39)	(1.97)	(3.72)	(3.44)	(4.31)	(2.73)	(3.11)	(2.16)
W*Education	0.0258	0.0026	0.0001	-0.0614***	-0.0859***	-0.0414**	-0.0633***	-0.0607***	-0.0560***
	(0.88)	(0.09)	(0.004)	(-3.95)	(-5.15)	(-2.96)	(-4.55)	(-3.99)	(-4.78)
W*Age	-0.0207*	-0.0236*	-0.0180	-0.0084	-0.0121	-0.0034	0.0013	-0.0032	0.0028
	(-2.17)	(-2.33)	(-1.68)	(-0.98)	(-1.28)	(-0.42)	(0.24)	(-0.53)	(0.53)
W*Population density	-0.0005**	-0.0006***	-0.0002	-0.0001	-0.0002	-0.00002	-0.0001	-0.0001	0.0001
	(-3.22)	(-3.46)	(-1.44)	(-1.26)	(-1.52)	(-0.36)	(-0.58)	(-1.04)	(0.68)
Constant	8.4543***	7.2743***	6.5306***	3.6338***	2.8679***	3.8467***	3.4399***	3.2419***	3.3557***
	(5.39)	(5.54)	(3.69)	(6.38)	(5.22)	(7.59)	(5.27)	(4.73)	(5.77)
W*ln w (λ)	-0.0866	0.0647	0.1762	0.3921***	0.5049***	0.3352***	0.4616***	0.4928***	0.4575***
	(-0.43)	(0.39)	(0.78)	(4.41)	(5.87)	(4.17)	(4.78)	(4.88)	(5.03)
Adjusted R^2	0.5076	0.5729	0.4207	0.7523	0.7635	0.7353	0.7355	0.7300	0.7225
R^2	0.5087	0.5738	0.4220	0.7528	0.7640	0.7359	0.7360	0.7306	0.7231
R^2 (ratio)	0.5353	0.5540	0.3906	0.7082	0.6910	0.7194	0.7035	0.6796	0.7088

t statistic in parenthesis. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table IV.A.9: Impacts of spatial durbin model 1990, 2000 and 2010

			1990			2000			2010		
			Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Non-employment rate	Total	SDI	0.0019**	0.0043	0.0062	0.0009*	0.0005	0.0014	0.0016***	0.0027	0.0043
			(2.85)	(1.21)	(1.62)	(1.99)	(0.35)	(0.80)	(3.29)	(1.25)	(1.81)
		AI	-0.0101***	-0.0969***	-0.1070***	-0.0076***	-0.0439***	-0.0514***	-0.0085***	-0.0550***	-0.0636***
			(-4.49)	(-5.49)	(-5.63)	(-5.72)	(-8.88)	(-9.06)	(-4.71)	(-6.54)	(-6.68)
		Education	-0.0210***	-0.0235***	-0.0445***	-0.0183***	-0.0092***	-0.0276***	-0.0116***	-0.0067*	-0.0183***
			(-23.39)	(-3.68)	(-6.54)	(-18.11)	(-4.39)	(-10.43)	(-19.48)	(-2.49)	(-6.15)
		Age	0.0044**	0.0129*	0.0172*	0.0033*	0.0080**	0.0112**	0.0068***	0.0089***	0.0157***
			(3.23)	(2.01)	(2.47)	(2.37)	(2.68)	(3.13)	(5.02)	(3.74)	(5.44)
		Child	-0.0044*	-0.0279	-0.0323	0.0088	0.0443*	0.0531*	0.0846***	0.0991**	0.1837***
			(-2.30)	(-1.56)	(-1.68)	(1.14)	(2.24)	(2.31)	(5.27)	(2.89)	(4.50)
		Population density	-0.00003***	-0.0001***	-0.0002***	-0.00001*	-0.00003	-0.00004*	0.00001	0.00002	0.00003
			(-5.43)	(-3.64)	(-4.25)	(-2.02)	(-1.90)	(-2.52)	(1.61)	(0.97)	(1.31)
	Men	SDI	0.0014	0.0258	0.0272	0.0001	0.0041*	0.0042*	0.0010	0.0036	0.0046
			(0.11)	(-0.10)	(-0.10)	(0.30)	(2.30)	(2.22)	(0.97)	(0.11)	(0.12)
		AI	-0.0058	-0.1305	-0.1363	-0.0020*	-0.0122**	-0.0142**	-0.0026	-0.0266	-0.0292
			(-0.11)	(0.02)	(0.01)	(-2.43)	(-2.80)	(-2.96)	(-0.42)	(-0.09)	(-0.09)
		Education	-0.0082	-0.0322	-0.0403	-0.0085***	-0.0030	-0.0115***	-0.0041	-0.0071	-0.0112
			(-0.35)	(0.05)	(0.01)	(-13.03)	(-1.69)	(-5.23)	(-1.86)	(-0.11)	(-0.12)
		Age	0.0035	0.0104	0.0139	0.0031**	0.0050*	0.0081***	-0.0010	0.0018	0.0008
			(0.25)	(0.03)	(0.06)	(2.99)	(2.51)	(3.55)	(-0.55)	(-0.06)	(-0.06)
		Child	-0.0112	-0.2065	-0.2177	-0.0339***	-0.0094	-0.0433**	-0.0536	-0.0680	-0.1217
			(-0.12)	(0.10)	(0.09)	(-5.93)	(-0.91)	(-3.05)	(-1.50)	(-0.09)	(-0.10)
		Population density	0.000006	-0.00002	-0.00002	0.000003	0.000005	0.00001	0.00003*	0.00005	0.0001
			(0.44)	(-0.06)	(-0.05)	(0.61)	(0.40)	(0.52)	(2.26)	(0.04)	(0.08)
	Women	SDI	0.0009	-0.0009	-0.0001	0.0019*	-0.0021	-0.0002	0.0024**	0.0029	0.0053
			(1.20)	(-0.32)	(0.04)	(2.06)	(-0.72)	(-0.03)	(2.86)	(1.05)	(1.81)
		AI	-0.0141***	-0.0869***	-0.1011***	-0.0122***	-0.0651***	-0.0773***	-0.0138***	-0.0766***	-0.0905***
			(-4.41)	(-5.83)	(-5.86)	(-6.74)	(-9.10)	(-9.30)	(-5.57)	(-7.41)	(-7.53)
		Education	-0.0317***	-0.0148***	-0.0465***	-0.0267***	-0.0111**	-0.0378***	-0.0175***	-0.0058	-0.0233***
			(-29.24)	(-5.26)	(-15.06)	(-15.17)	(-3.28)	(-8.64)	(-17.27)	(-1.33)	(-5.07)
		Age	-0.0079***	0.0011	-0.0068	-0.0024	0.0089	0.0065	0.0112***	0.0112***	0.0224***
			(-5.84)	(0.19)	(-1.82)	(-1.08)	(1.72)	(1.08)	(7.98)	(3.73)	(6.35)
		Child	0.0073	0.0451*	0.0524**	0.0542***	0.1140***	0.1682***	0.2340***	0.2112***	0.4452***
			(1.62)	(2.49)	(2.59)	(4.11)	(3.40)	(4.07)	(10.39)	(3.91)	(6.94)
		Population density	-0.00006***	-0.0001***	-0.0001***	-0.00003**	-0.00003	-0.00006**	-0.00001	0.00002	0.000005
			(-8.77)	(-4.21)	(-6.39)	(-3.15)	(-1.77)	(-2.96)	(-1.40)	(0.61)	(0.15)
Informal employment rate	Total	SDI	0.0097***	0.0045*	0.0143***	0.0075***	0.0118**	0.0193***	0.0074***	0.0150***	0.0225***
			(7.83)	(2.52)	(9.39)	(5.17)	(2.92)	(4.19)	(7.23)	(6.41)	(8.63)
		AI	0.0048	0.0298***	0.0347***	0.0061*	0.0618***	0.0679***	-0.0089***	-0.0352***	-0.0441***
			(1.69)	(3.39)	(3.38)	(2.17)	(3.75)	(3.71)	(-3.94)	(-3.97)	(-4.36)
		Education	-0.0468***	-0.0060**	-0.0528***	-0.0303***	-0.0245***	-0.0549***	-0.0246***	-0.0041	-0.0287***
			(-32.12)	(-2.60)	(-24.49)	(-15.72)	(-3.67)	(-7.62)	(-29.41)	(-1.76)	(-10.76)
		Age	0.0016	0.0128***	0.0144***	-0.0067**	0.0193***	0.0127*	-0.0090***	-0.0075***	-0.0165***
			(0.90)	(5.00)	(6.25)	(-3.04)	(3.40)	(1.99)	(-12.63)	(-3.44)	(-6.81)
		Population density	-0.000002	-0.00002	-0.00002	-0.0001***	-0.0004***	-0.0005***	-0.000002	-0.0002***	-0.0002***
			(-0.19)	(-0.98)	(-1.13)	(-8.37)	(-6.92)	(-8.74)	(-0.23)	(-6.76)	(-6.26)
	Men	SDI	0.0072***	0.0047*	0.0119***	0.0097***	0.0206***	0.0302***	0.0076***	0.0182***	0.0259***
			(5.62)	(2.35)	(6.61)	(6.19)	(4.35)	(5.73)	(6.72)	(6.33)	(8.08)
		AI	0.0115***	0.0594***	0.0709***	0.0058*	0.0628**	0.0686**	-0.0101***	-0.0391***	-0.0491***
			(4.17)	(4.70)	(4.96)	(1.98)	(3.17)	(3.13)	(-3.64)	(-3.97)	(-4.29)
		Education	-0.0463***	-0.0062*	-0.0526***	-0.0292***	-0.0189**	-0.0482***	-0.0257***	-0.0057*	-0.0314***
			(-34.96)	(-2.48)	(-21.25)	(-14.30)	(-2.78)	(-6.14)	(-28.59)	(-2.17)	(-11.59)
		Age	0.0003	0.0120***	0.0123***	-0.0066**	0.0166**	0.0100	-0.0080***	-0.0036	-0.0116***
			(0.29)	(3.88)	(4.33)	(-3.04)	(2.62)	(1.40)	(-10.04)	(-1.67)	(-4.80)
		Population density	0.000002	-0.00003	-0.00002	-0.0001***	-0.0002***	-0.0003***	0.00002*	-0.0001***	-0.0001*
			(0.16)	(-1.08)	(-1.00)	(-4.84)	(-4.51)	(-5.49)	(2.26)	(-3.36)	(-2.20)
	Women	SDI	0.0187***	0.0052**	0.0239***	0.0064***	0.0065	0.0129**	0.0093***	0.0108***	0.0201***
			(11.01)	(2.65)	(17.75)	(3.40)	(1.68)	(3.00)	(9.04)	(4.11)	(6.85)
		AI	-0.0057	-0.0038	-0.0095	0.0041	0.0417**	0.0458**	-0.0089**	-0.0292*	-0.0381*
			(-1.43)	(-0.41)	(-0.88)	(1.17)	(3.09)	(2.99)	(-3.10)	(-2.17)	(-2.51)
		Education	-0.0486***	-0.0060**	-0.0547***	-0.0293***	-0.0243***	-0.0536***	-0.0232***	-0.0016	-0.0247***
			(-26.82)	(-2.61)	(-31.82)	(-12.94)	(-3.59)	(-7.29)	(-23.86)	(-0.50)	(-6.46)
		Age	0.0058**	0.0136***	0.0194***	-0.0076**	0.0190***	0.0114	-0.0107***	-0.0169***	-0.0276***
			(2.81)	(5.39)	(10.89)	(-3.26)	(3.52)	(1.87)	(-10.46)	(-5.15)	(-7.34)
		Population density	-0.000004	0.0000001	-0.000004	-0.0002***	-0.0005***	-0.0007***	-0.00002	-0.0002***	-0.0003***
			(-0.32)	(0.01)	(-0.21)	(-11.57)	(-9.76)	(-13.18)	(-1.49)	(-8.25)	(-8.11)
ln w	Total	SDI	-0.0087	0.0051	-0.0037	-0.0097	-0.0461***	-0.0558***	-0.0073*	-0.0093	-0.0166**
			(-1.40)	(0.61)	(-0.91)	(-1.88)	(-5.80)	(-6.57)	(-2.46)	(-1.82)	(-3.04)
		AI	0.0095	0.0454	0.0549	0.0249*	0.1384***	0.1634***	0.0448*	0.2012***	0.2460***
			(0.53)	(1.37)	(1.45)	(2.22)	(5.29)	(5.05)	(2.55)	(4.22)	(4.21)
		Education	0.1492***	0.0121	0.1613***	0.1379***	-0.0099	0.1280***	0.1497***	0.0117	0.1615***
			(18.24)	(1.01)	(22.13)	(12.40)	(-0.68)	(10.58)	(30.78)	(1.11)	(12.18)
		Age	0.0123	-0.0203*	-0.0080	0.0344***	0.0080	0.0425***	0.0084*	0.0088	0.0172
			(1.57)	(-2.11)	(-1.20)	(3.50)	(0.81)	(3.53)	(2.28)	(1.03)	(1.83)
		Population density	-0.0004***	-0.0004***	-0.0008***	-0.0005***	-0.0005***	-0.0010***	-0.0004***	-0.0004***	-0.0009***
			(-6.00)	(-4.56)	(-12.68)	(-10.07)	(-4.65)	(-9.63)	(-7.42)	(-3.59)	(-7.58)
	Men	SDI	-0.0047	-0.0017	-0.0064	-0.0111	-0.0679***	-0.0790***	-0.0070*	-0.0173**	-0.0243***
			(-0.71)	(-0.34)	(-1.30)	(-1.83)	(-5.78)	(-5.88)	(-2.27)	(-2.74)	(-3.62)
		AI	0.0338	0.1178**	0.1516**	0.0266	0.1887***	0.2153***	0.0489*	0.2815***	0.3304***
			(1.62)	(2.77)	(3.09)	(1.80)	(4.82)	(4.46)	(2.47)	(4.98)	(4.88)
		Education	0.1733***	0.0146	0.1879***	0.1450***	-0.0203	0.1247***	0.1431***	0.0196	0.1627***
			(19.90)	(1.14)	(22.62)	(10.76)	(-1.17)	(6.66)	(26.79)	(1.40)	(9.94)
		Age	0.0122	-0.0241*	-0.0119	0.0394***	0.0147	0.0540**	0.0131***	0.0059	0.0190
			(1.48)	(-2.26)	(-1.35)	(3.63)	(1.14)	(3.22)	(3.33)	(0.56)	(1.61)
		Population density	-0.0005***	-0.0006***	-0.0011***	-0.0007***	-0.0010***	-0.0016***	-0.0005***	-0.0006***	-0.0011***
			(-6.75)	(-5.86)	(-12.98)	(-11.48)	(-5.89)	(-9.60)	(-7.50)	(-4.13)	(-7.62)
	Women	SDI	-0.0230***	0.0144	-0.0086	-0.0209***	-0.0262***	-0.0471***	-0.0131***	-0.0027	-0.0158***
			(-3.50)	(1.36)	(-1.13)	(-6.02)	(-4.43)	(-7.91)	(-5.05)	(-0.50)	(-3.39)
		AI	0.0224	0.1044*	0.1268*	0.0325***	0.1377***	0.1702***	0.0508**	0.1593**	0.2101**
			(1.08)	(2.08)	(2.17)	(3.43)	(5.84)	(6.09)	(2.86)	(2.93)	(3.17)
		Education	0.1121***	0.0235	0.1356***	0.1237***	0.0009	0.1246***	0.1362***	0.0124	0.1486***
			(12.92)	(1.42)	(9.50)	(12.04)	(0.16)	(12.41)	(30.17)	(1.12)	(10.89)
		Age	0.0056	-0.0200	-0.0145	0.0308***	0.0099	0.0407***	0.0093**	0.0119	0.0212*
			(0.63)	(-1.46)	(-1.21)	(4.17)	(1.19)	(4.35)	(2.61)	(1.42)	(2.39)
		Population density	-0.0002**	-0.0002*	-0.0004***	-0.0003***	-0.0002*	-0.0005***	-0.0003***	-0.0001	-0.0004***
			(-2.99)	(-2.05)	(-4.34)	(-7.00)	(-2.20)	(-6.41)	(-5.58)	(-1.19)	(-3.89)

t statistic in parenthesis. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table IV.A.10: General nesting spatial model 1990, 2000 and 2010

	1990			2000			2010		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate (U)									
SDI	0.0017*	0.0007	0.0009	0.0009	-0.0002	0.0021*	0.0015**	0.0009*	0.0023**
	(2.56)	(1.00)	(1.12)	(1.76)	(-0.39)	(2.31)	(2.91)	(2.02)	(2.73)
AI	-0.0046**	-0.0022*	-0.0085***	-0.0048***	-0.0013	-0.0080***	-0.0052***	-0.0012	-0.0091***
	(-2.76)	(-2.18)	(-3.51)	(-4.34)	(-1.73)	(-4.53)	(-3.55)	(-1.00)	(-4.30)
Education	-0.0203***	-0.0077***	-0.0313***	-0.0180***	-0.0084***	-0.0263***	-0.0115***	-0.0039***	-0.0175***
	(-24.23)	(-12.82)	(-28.24)	(-17.41)	(-12.98)	(-15.17)	(-20.32)	(-6.65)	(-18.07)
Age	0.0037**	0.0034***	-0.0081***	0.0028*	0.0028*	-0.0030	0.0064***	-0.0011	0.0106***
	(2.73)	(3.36)	(-5.55)	(2.06)	(2.36)	(-1.38)	(4.64)	(-0.60)	(7.53)
Child	-0.0029*	-0.0054***	0.0045	0.0060	-0.0335***	0.0475***	0.0806***	-0.0524**	0.2246***
	(-2.00)	(-5.06)	(1.04)	(0.84)	(-5.42)	(4.00)	(4.87)	(-3.26)	(10.20)
Population density	-0.00002***	0.00001*	-0.0001***	-0.00001	0.000003	-0.00003**	0.00001	0.00002***	-0.00001
	(-4.29)	(1.98)	(-7.21)	(-1.50)	(0.66)	(-2.73)	(1.58)	(3.48)	(-1.21)
W*SDI	-0.0006	0.0001	-0.0007	-0.0004	0.0020**	-0.0020	-0.0005	-0.0003	-0.0007
	(-0.75)	(0.18)	(-0.72)	(-0.56)	(2.76)	(-1.67)	(-0.76)	(-0.66)	(-0.65)
W*AI	-0.0118**	-0.0036	-0.0192***	-0.0142***	-0.0049***	-0.0215***	-0.0128***	-0.0029	-0.0207***
	(-3.09)	(-1.21)	(-3.72)	(-6.00)	(-3.55)	(-5.61)	(-4.13)	(-1.06)	(-4.79)
W*Education	0.0129***	0.0063***	0.0178***	0.0080***	0.0036***	0.0113***	0.0070***	0.0027***	0.0102***
	(9.94)	(7.61)	(9.88)	(5.66)	(3.43)	(4.98)	(7.36)	(3.50)	(6.58)
W*Age	-0.0010	-0.0027**	0.0058***	0.0013	0.0006	0.0054*	-0.0024*	0.0011	-0.0035*
	(-0.65)	(-2.73)	(3.94)	(0.95)	(0.48)	(2.14)	(-2.09)	(0.81)	(-2.51)
W*Child	-0.0026	-0.0016	0.0090	0.0135	0.0152*	0.0183	-0.0329*	0.0386**	-0.0837**
	(-1.06)	(-0.79)	(1.60)	(1.49)	(2.33)	(1.12)	(-2.04)	(2.94)	(-3.25)
W*Population density	-0.000003	-0.00001	0.00001	-0.000004	0.000001	0.000001	-0.000002	-0.00001	0.00001
	(-0.36)	(-1.89)	(0.75)	(-0.57)	(0.14)	(0.07)	(-0.19)	(-1.71)	(1.15)
Constant	0.0389	0.0005	0.3662***	0.0583	-0.0243	0.2321*	-0.0548	0.0284	-0.1207*
	(1.15)	(0.02)	(7.67)	(1.30)	(-1.17)	(2.51)	(-1.82)	(1.06)	(-2.19)
W*U (λ)	0.8359***	0.9578***	0.7099***	0.6341***	0.5768***	0.6028***	0.7437***	0.8828***	0.6832***
	(23.32)	(20.44)	(20.59)	(14.10)	(5.25)	(14.04)	(17.17)	(6.26)	(17.72)
ρ	0.1254	-0.3371*	0.1199	-0.0371	-0.1740	0.0986	-0.3330***	-0.2930**	-0.1427
	(1.24)	(-2.44)	(1.68)	(-0.45)	(-1.46)	(1.26)	(-4.12)	(-2.89)	(-1.94)
Adjusted R^2	0.9086	0.6294	0.9369	0.8517	0.3140	0.8941	0.8318	0.2155	0.8926
R^2	0.9088	0.6304	0.9371	0.8521	0.3158	0.8944	0.8322	0.2176	0.8928
R^2 (ratio)	0.8734	0.6100	0.9224	0.8327	0.3033	0.8752	0.8138	0.2896	0.8717
Informal employment rate (I)									
SDI	0.0096***	0.0071***	0.0185***	0.0070***	0.0086***	0.0063**	0.0065***	0.0064***	0.0088***
	(8.70)	(6.06)	(11.66)	(4.65)	(5.64)	(3.10)	(7.29)	(6.56)	(8.19)
AI	0.0027	0.0080**	-0.0049	0.0022	0.0019	0.0011	-0.0065***	-0.0064**	-0.0071**
	(0.97)	(2.87)	(-1.27)	(0.85)	(0.81)	(0.33)	(-3.30)	(-2.74)	(-3.08)
Education	-0.0469***	-0.0464***	-0.0487***	-0.0292***	-0.0286***	-0.0278***	-0.0245***	-0.0254***	-0.0234***
	(-38.18)	(-35.12)	(-29.55)	(-15.35)	(-14.78)	(-12.77)	(-33.40)	(-28.58)	(-24.64)
Age	0.0013	0.0001	0.0052**	-0.0078***	-0.0077***	-0.0090***	-0.0086***	-0.0080***	-0.0097***
	(0.87)	(0.07)	(2.94)	(-3.60)	(-3.46)	(-3.88)	(-11.99)	(-10.09)	(-10.37)
Population density	-0.00001	-0.000002	-0.00001	-0.0001***	-0.0001***	-0.0002***	0.0000003	0.00002	-0.000002
	(-0.82)	(-0.14)	(-0.62)	(-7.59)	(-3.88)	(-9.55)	(0.04)	(1.93)	(-0.18)
W*SDI	0.0011	0.0006	0.0015	-0.0007	-0.0002	-0.0010	0.0016	0.0029	-0.0021
	(0.64)	(0.34)	(0.57)	(-0.37)	(-0.08)	(-0.40)	(1.04)	(1.92)	(-1.38)
W*AI	0.0150*	0.0256***	-0.0008	0.0176***	0.0164***	0.0134*	-0.0105*	-0.0103	-0.0057
	(2.53)	(4.52)	(-0.10)	(3.68)	(4.24)	(2.09)	(-2.12)	(-1.76)	(-1.15)
W*Education	0.0067	0.0123**	0.0006	0.0095**	0.0148***	0.0039	0.0095***	0.0082***	0.0140***
	(1.87)	(3.23)	(0.13)	(2.92)	(5.39)	(0.93)	(5.82)	(4.12)	(8.34)
W*Age	0.0062**	0.0057*	0.0096***	0.0108***	0.0102***	0.0114***	0.0016	0.0018	0.0004
	(2.74)	(2.42)	(3.45)	(4.63)	(4.53)	(4.01)	(1.20)	(1.23)	(0.27)
W*Population density	-0.000005	-0.000003	-0.00001	-0.0001**	-0.00003	-0.0001***	-0.0001***	-0.00004**	-0.0001***
	(-0.31)	(-0.16)	(-0.65)	(-2.79)	(-1.41)	(-3.58)	(-4.18)	(-2.69)	(-5.21)
Constant	0.3799***	0.3362***	0.2476***	0.2579***	0.1704**	0.3762***	0.6181***	0.6184***	0.6010***
	(5.68)	(5.09)	(3.39)	(3.63)	(3.04)	(3.85)	(8.72)	(7.77)	(7.14)
W*I (λ)	0.1936*	0.3136***	0.1101	0.6248***	0.7104***	0.5225***	0.5528***	0.5239***	0.6490***
	(2.45)	(3.73)	(1.20)	(10.96)	(13.80)	(7.19)	(11.60)	(9.05)	(13.58)
ρ	0.6825***	0.6430***	0.5885***	0.4386***	0.1643*	0.5302***	0.5776***	0.5875***	0.0956
	(18.65)	(13.10)	(11.45)	(5.80)	(2.01)	(7.22)	(11.88)	(10.98)	(1.17)
R^2	0.7965	0.7731	0.7890	0.8016	0.8193	0.7387	0.8962	0.8745	0.8858
Adjusted R^2	0.7969	0.7736	0.7895	0.8020	0.8197	0.7393	0.8965	0.8747	0.8861
R^2 (ratio)	0.7687	0.7157	0.7750	0.6683	0.7137	0.5924	0.8117	0.7781	0.8075
ln w									
SDI	-0.0064	-0.0023	-0.0228***	-0.0073	-0.0070	-0.0198***	-0.0067*	-0.0060	-0.0128***
	(-1.29)	(-0.45)	(-3.44)	(-1.51)	(-1.18)	(-5.48)	(-2.32)	(-1.91)	(-4.52)
AI	-0.0031	0.0027	0.0175	0.0147	0.0117	0.0261**	0.0331	0.0325	0.0402*
	(-0.18)	(0.14)	(0.85)	(1.42)	(0.95)	(2.71)	(1.89)	(1.64)	(2.42)
Education	0.1476***	0.1714***	0.1113***	0.1387***	0.1471***	0.1241***	0.1506***	0.1434***	0.1379***
	(20.47)	(22.13)	(12.46)	(12.02)	(11.67)	(11.89)	(29.60)	(25.57)	(27.74)
Age	0.0126	0.0138	0.0058	0.0344***	0.0392***	0.0304***	0.0080*	0.0129**	0.0084*
	(1.83)	(1.77)	(0.69)	(3.47)	(3.72)	(3.61)	(2.00)	(3.00)	(2.17)
Population density	-0.0003***	-0.0004***	-0.0002**	-0.0005***	-0.0006***	-0.0003***	-0.0004***	-0.0004***	-0.0003***
	(-5.98)	(-6.44)	(-2.87)	(-9.67)	(-10.39)	(-6.47)	(-6.70)	(-6.57)	(-5.43)
W*SDI	0.0035	-0.0019	0.0148	-0.0271***	-0.0337***	-0.0116*	-0.0023	-0.0064	0.0046
	(0.45)	(-0.22)	(1.54)	(-4.57)	(-4.82)	(-2.26)	(-0.60)	(-1.45)	(1.33)
W*AI	0.0108	0.0166	0.0771	0.0665**	0.0732**	0.0854***	0.0994**	0.1352**	0.0719*
	(0.25)	(0.34)	(1.63)	(3.06)	(2.81)	(4.23)	(2.74)	(3.08)	(2.30)
W*Education	0.0173	0.0069	0.0060	-0.0549***	-0.0786***	-0.0408**	-0.0680***	-0.0622***	-0.0684***
	(0.68)	(0.26)	(0.22)	(-3.69)	(-4.93)	(-2.92)	(-4.85)	(-4.02)	(-6.16)
W*Age	-0.0142	-0.0158	-0.0169	-0.0052	-0.0084	-0.0031	0.0007	-0.0035	0.0020
	(-1.32)	(-1.26)	(-1.46)	(-0.64)	(-0.92)	(-0.38)	(0.14)	(-0.57)	(0.40)
W*Population density	-0.0004**	-0.0005**	-0.0002	-0.0002	-0.0003*	-0.00003	-0.00004	-0.0001	0.0001
	(-3.11)	(-3.23)	(-1.80)	(-1.72)	(-2.09)	(-0.39)	(-0.37)	(-0.96)	(1.13)
Constant	7.6690***	6.8735***	6.7908***	3.7690***	3.0094***	3.8581***	3.2981***	3.1989***	2.9564***
	(5.13)	(5.05)	(3.67)	(6.44)	(5.34)	(7.56)	(5.05)	(4.61)	(5.46)
W*ln w (λ)	-0.0137	0.0765	0.1382	0.3579***	0.4678***	0.3321***	0.4852***	0.5003***	0.5221***
	(-0.07)	(0.45)	(0.59)	(3.96)	(5.38)	(4.11)	(5.01)	(4.89)	(6.10)
ρ	0.6291***	0.6869***	0.4578***	0.3201**	0.3347**	0.0028	-0.3461**	-0.2514*	-0.5211***
	(11.87)	(14.04)	(3.59)	(3.17)	(3.21)	(0.03)	(-3.07)	(-2.08)	(-5.41)
Adjusted R^2	0.5286	0.5751	0.4136	0.7480	0.7576	0.7352	0.7370	0.7308	0.7239
R^2	0.5297	0.5760	0.4149	0.7486	0.7581	0.7358	0.7376	0.7314	0.7245
R^2 (ratio)	0.5404	0.5667	0.3922	0.7073	0.6880	0.7194	0.7059	0.6806	0.7156

t statistic in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table IV.A.11: Impacts of general nesting spatial model 1990, 2000 and 2010

			1990			2000			2010		
			Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Non-employment rate	Total	SDI	0.0019**	0.0046	0.0065	0.0009	0.0004	0.0013	0.0016**	0.0024	0.0039*
			(3.07)	(1.24)	(1.69)	(1.86)	(0.29)	(0.74)	(3.21)	(1.36)	(1.98)
		AI	-0.0097***	-0.0905***	-0.1002***	-0.0076***	-0.0444***	-0.0520***	-0.0090***	-0.0612***	-0.0701***
			(-4.09)	(-4.94)	(-5.03)	(-6.48)	(-9.13)	(-9.42)	(-5.27)	(-8.12)	(-8.20)
		Education	-0.0210***	-0.0237***	-0.0447***	-0.0183***	-0.0092***	-0.0275***	-0.0116***	-0.0058**	-0.0174***
			(-25.48)	(-3.32)	(-5.84)	(-17.89)	(-4.61)	(-10.90)	(-20.69)	(-2.63)	(-6.96)
		Age	0.0043**	0.0124	0.0167*	0.0033*	0.0080**	0.0113**	0.0068***	0.0087***	0.0155***
			(3.05)	(1.89)	(2.30)	(2.33)	(2.83)	(3.22)	(4.94)	(4.38)	(6.57)
		Child	-0.0045*	-0.0289	-0.0334	0.0088	0.0446*	0.0534*	0.0851***	0.1009**	0.1860***
			(-2.20)	(-1.49)	(-1.59)	(1.16)	(2.42)	(2.42)	(5.14)	(3.13)	(5.02)
		Population density	-0.00003***	-0.0001**	-0.0002***	-0.00001*	-0.00003*	-0.00004**	0.00001	0.00002	0.00004
			(-6.06)	(-3.16)	(-3.73)	(-2.00)	(-1.98)	(-2.64)	(1.87)	(1.24)	(1.79)
	Men	SDI	0.0013	0.0183	0.0196	0.0001	0.0042**	0.0043**	0.0010	0.0037	0.0047
			(0.27)	(0.06)	(0.06)	(0.02)	(3.16)	(3.06)	(0.55)	(-0.06)	(-0.06)
		AI	-0.0063	-0.1291	-0.1354	-0.0020**	-0.0125***	-0.0145***	-0.0029	-0.0325	-0.0354
			(-0.31)	(-0.02)	(-0.02)	(-2.60)	(-3.30)	(-3.50)	(-0.24)	(-0.16)	(-0.17)
		Education	-0.0082	-0.0258	-0.0339	-0.0085***	-0.0028	-0.0113***	-0.0041	-0.0059	-0.0100
			(-1.42)	(-0.07)	(-0.07)	(-14.30)	(-1.63)	(-5.88)	(-1.79)	(0.10)	(0.09)
		Age	0.0036	0.0124	0.0160	0.0031**	0.0049**	0.0079***	-0.0010	0.0014	0.0005
			(1.13)	(0.06)	(0.06)	(2.64)	(3.24)	(4.70)	(-0.23)	(-0.02)	(-0.03)
		Child	-0.0102	-0.1544	-0.1645	-0.0337***	-0.0097	-0.0434***	-0.0536	-0.0644	-0.1180
			(-0.27)	(-0.07)	(-0.07)	(-5.61)	(-1.10)	(-3.43)	(-0.71)	(0.05)	(0.04)
		Population density	0.00001	-0.00002	-0.00002	0.000003	0.00001	0.00001	0.00003	0.00006	0.0001
			(0.40)	(-0.10)	(-0.10)	(0.67)	(0.67)	(0.86)	(1.46)	(-0.03)	(-0.02)
	Women	SDI	0.0009	-0.0003	0.0006	0.0019*	-0.0018	0.0001	0.0024**	0.0027	0.0051
			(1.11)	(-0.06)	(0.33)	(2.06)	(-0.59)	(0.05)	(2.90)	(0.99)	(1.73)
		AI	-0.0137***	-0.0819***	-0.0956***	-0.0119***	-0.0624***	-0.0743***	-0.0141***	-0.0799***	-0.0940***
			(-4.56)	(-5.36)	(-5.43)	(-6.46)	(-8.44)	(-8.61)	(-5.77)	(-7.98)	(-8.09)
		Education	-0.0316***	-0.0150***	-0.0466***	-0.0267***	-0.0112**	-0.0378***	-0.0175***	-0.0056	-0.0231***
			(-28.61)	(-5.41)	(-15.57)	(-15.16)	(-3.20)	(-8.41)	(-17.06)	(-1.35)	(-5.20)
		Age	-0.0079***	-0.0001	-0.0080*	-0.0024	0.0084	0.0059	0.0112***	0.0113***	0.0224***
			(-5.96)	(-0.05)	(-2.12)	(-1.08)	(1.52)	(0.94)	(7.70)	(4.27)	(6.78)
		Child	0.0070	0.0397*	0.0467*	0.0540***	0.1118**	0.1658***	0.2339***	0.2109***	0.4447***
			(1.46)	(2.28)	(2.32)	(4.07)	(3.17)	(3.82)	(10.48)	(4.06)	(7.28)
		Population density	-0.0001***	-0.0001***	-0.0002***	-0.00003**	-0.00004	-0.00006**	-0.00001	0.00002	0.00001
			(-8.31)	(-4.08)	(-5.97)	(-3.26)	(-1.72)	(-2.86)	(-1.30)	(0.58)	(0.16)
Informal employment rate	Total	SDI	0.0097***	0.0036*	0.0133***	0.0076***	0.0092*	0.0169***	0.0071***	0.0109***	0.0181***
			(8.35)	(2.09)	(8.16)	(5.06)	(2.17)	(3.38)	(7.80)	(3.75)	(5.41)
		AI	0.0033	0.0189*	0.0222*	0.0053	0.0478**	0.0531**	-0.0083***	-0.0298**	-0.0381**
			(1.07)	(2.32)	(2.12)	(1.79)	(3.18)	(3.10)	(-3.52)	(-2.68)	(-2.97)
		Education	-0.0469***	-0.0030	-0.0499***	-0.0301***	-0.0224**	-0.0525***	-0.0248***	-0.0088**	-0.0335***
			(-39.13)	(-1.29)	(-21.48)	(-15.42)	(-3.16)	(-6.62)	(-31.54)	(-2.93)	(-9.86)
		Age	0.0015	0.0078**	0.0094***	-0.0067**	0.0148*	0.0081	-0.0089***	-0.0068**	-0.0157***
			(1.22)	(3.14)	(3.66)	(-3.00)	(2.51)	(1.15)	(-12.13)	(-2.62)	(-5.22)
		Population density	-0.00001	-0.00001	-0.00002	-0.0001***	-0.0003***	-0.0005***	-0.00001	-0.0001***	-0.0001***
			(-0.85)	(-0.50)	(-0.88)	(-9.32)	(-6.53)	(-8.24)	(-0.76)	(-4.45)	(-4.10)
	Men	SDI	0.0073***	0.0040*	0.0112***	0.0097***	0.0194***	0.0291***	0.0071***	0.0126***	0.0197***
			(6.35)	(1.99)	(5.55)	(6.50)	(4.00)	(5.34)	(7.22)	(4.66)	(6.52)
		AI	0.0097**	0.0394***	0.0491***	0.0057*	0.0578***	0.0634***	-0.0080**	-0.0271*	-0.0351*
			(3.22)	(3.73)	(3.82)	(2.07)	(3.43)	(3.40)	(-2.78)	(-2.12)	(-2.36)
		Education	-0.0464***	-0.0034	-0.0498***	-0.0292***	-0.0184*	-0.0476***	-0.0257***	-0.0103***	-0.0361***
			(-35.87)	(-1.36)	(-18.30)	(-14.86)	(-2.48)	(-5.84)	(-27.10)	(-3.35)	(-10.36)
		Age	0.0005	0.0080**	0.0085**	-0.0065**	0.0152*	0.0087	-0.0082***	-0.0049	-0.0130***
			(0.36)	(2.81)	(2.87)	(-2.86)	(2.41)	(1.18)	(-9.12)	(-1.88)	(-4.06)
		Population density	-0.000002	-0.000005	-0.000006	-0.0001***	-0.0002***	-0.0003***	0.00001	-0.0001*	-0.00005
			(-0.18)	(-0.30)	(-0.36)	(-4.83)	(-4.12)	(-5.02)	(1.58)	(-2.04)	(-1.29)
	Women	SDI	0.0185***	0.0039*	0.0225***	0.0065**	0.0045	0.0110*	0.0093***	0.0100***	0.0193***
			(12.28)	(1.97)	(12.19)	(3.23)	(1.15)	(2.11)	(8.80)	(3.39)	(5.75)
		AI	-0.0049	-0.0015	-0.0064	0.0027	0.0276	0.0303	-0.0088**	-0.0277	-0.0365*
			(-1.34)	(-0.10)	(-0.50)	(0.72)	(1.85)	(1.69)	(-2.95)	(-1.83)	(-2.09)
		Education	-0.0487***	-0.0053	-0.0540***	-0.0288***	-0.0212**	-0.0500***	-0.0232***	-0.0035	-0.0267***
			(-29.39)	(-1.86)	(-18.61)	(-13.02)	(-2.97)	(-6.15)	(-21.53)	(-0.99)	(-6.24)
		Age	0.0054**	0.0113***	0.0166***	-0.0081***	0.0132*	0.0050	-0.0106***	-0.0158***	-0.0264***
			(3.07)	(3.98)	(5.78)	(-3.43)	(2.20)	(0.68)	(-10.47)	(-4.26)	(-6.24)
		Population density	-0.000007	-0.00001	-0.00002	-0.0002***	-0.0004***	-0.0006***	-0.00002	-0.0002***	-0.0003***
			(-0.55)	(-0.67)	(-0.85)	(-11.22)	(-7.59)	(-10.24)	(-1.68)	(-6.70)	(-6.50)
ln w	Total	SDI	-0.0064	0.0036	-0.0028	-0.0094*	-0.0442***	-0.0536***	-0.0073*	-0.0103	-0.0175**
			(-1.11)	(0.39)	(-0.30)	(-1.98)	(-5.07)	(-5.35)	(-2.46)	(-1.94)	(-3.18)
		AI	-0.0031	0.0107	0.0076	0.0197	0.1067***	0.1264***	0.0452*	0.2122***	0.2575***
			(-0.40)	(0.06)	(-0.08)	(1.85)	(3.43)	(3.34)	(2.53)	(4.41)	(4.40)
		Education	0.1475***	0.0151	0.1626***	0.1377***	-0.0072	0.1305***	0.1499***	0.0106	0.1605***
			(20.92)	(1.21)	(12.80)	(13.75)	(-0.37)	(9.26)	(30.83)	(0.96)	(11.41)
		Age	0.0127	-0.0142	-0.0016	0.0348***	0.0108	0.0456**	0.0084*	0.0085	0.0169
			(1.79)	(-1.26)	(-0.19)	(3.60)	(0.99)	(3.18)	(2.28)	(0.96)	(1.75)
		Population density	-0.0003***	-0.0004***	-0.0007***	-0.0005***	-0.0005***	-0.0010***	-0.0004***	-0.0004***	-0.0009***
			(-6.56)	(-3.98)	(-7.17)	(-10.40)	(-4.14)	(-7.77)	(-7.26)	(-3.70)	(-7.92)
	Men	SDI	-0.0023	-0.0022	-0.0045	-0.0107	-0.0657***	-0.0764***	-0.0070*	-0.0178**	-0.0248***
			(-0.38)	(-0.17)	(-0.34)	(-1.81)	(-5.07)	(-5.00)	(-2.20)	(-2.63)	(-3.49)
		AI	0.0030	0.0180	0.0210	0.0196	0.1400**	0.1596**	0.0492*	0.2865***	0.3357***
			(-0.01)	(0.14)	(0.11)	(1.28)	(3.04)	(2.80)	(2.44)	(5.02)	(4.92)
		Education	0.1717***	0.0214	0.1931***	0.1450***	-0.0162	0.1288***	0.1432***	0.0192	0.1624***
			(23.36)	(1.53)	(11.87)	(12.49)	(-0.71)	(6.15)	(25.90)	(1.42)	(10.39)
		Age	0.0136	-0.0158	-0.0022	0.0399***	0.0180	0.0578**	0.0131**	0.0057	0.0188
			(1.74)	(-1.27)	(-0.19)	(3.95)	(1.17)	(2.95)	(3.21)	(0.55)	(1.60)
		Population density	-0.0004***	-0.0005***	-0.0009***	-0.0007***	-0.0010***	-0.0016***	-0.0005***	-0.0006***	-0.0011***
			(-6.84)	(-3.70)	(-5.86)	(-11.48)	(-5.03)	(-7.94)	(-7.20)	(-4.13)	(-7.45)
	Women	SDI	-0.0225***	0.0132	-0.0092	-0.0209***	-0.0261***	-0.0470***	-0.0129***	-0.0043	-0.0172***
			(-3.45)	(1.24)	(-0.95)	(-5.98)	(-4.22)	(-7.57)	(-4.70)	(-1.02)	(-4.02)
		AI	0.0193	0.0903	0.1097	0.0321***	0.1349***	0.1670***	0.0510**	0.1837***	0.2346***
			(0.93)	(1.22)	(1.27)	(3.46)	(5.60)	(5.83)	(2.92)	(4.09)	(4.26)
		Education	0.1117***	0.0243	0.1361***	0.1237***	0.0011	0.1247***	0.1370***	0.0086	0.1455***
			(13.20)	(1.40)	(7.55)	(13.47)	(0.20)	(11.99)	(29.12)	(0.84)	(10.87)
		Age	0.0054	-0.0183	-0.0129	0.0308***	0.0102	0.0410***	0.0091*	0.0128	0.0218*
			(0.74)	(-1.28)	(-0.87)	(4.07)	(1.14)	(4.18)	(2.52)	(1.51)	(2.45)
		Population density	-0.0002**	-0.0003*	-0.0005***	-0.0003***	-0.0002*	-0.0005***	-0.0003***	-0.0002	-0.0005***
			(-2.90)	(-2.10)	(-3.49)	(-6.70)	(-2.19)	(-6.16)	(-5.89)	(-1.73)	(-5.47)

t statistic in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table IV.A.12: Spatial panel lag model

	Random Effects			Fixed Effects			Fixed Effects(twoways)		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate (U)									
SDI	0.0009** (3.28)	0.0010*** (3.41)	0.0024*** (4.38)	-0.0002 (-0.82)	-0.0002 (-0.77)	0.0021*** (4.77)	0.00004 (0.15)	-0.0003 (-1.27)	0.0029*** (6.88)
AI	-0.0072*** (-8.47)	0.0018** (2.98)	-0.0164*** (-10.77)	0.0038* (2.41)	0.0059** (2.71)	-0.0226*** (-8.49)	0.0070** (3.10)	0.0014 (0.68)	0.0079* (2.49)
Education	-0.0154*** (-32.43)	-0.0047*** (-10.92)	-0.0222*** (-31.16)	-0.0125*** (-22.55)	-0.0041*** (-11.79)	-0.0180*** (-21.34)	-0.0111*** (-20.90)	-0.0046*** (-11.22)	-0.0175*** (-21.23)
Age	0.0039*** (12.77)	0.0029*** (8.57)	0.0020*** (4.54)	0.0036*** (14.75)	0.0016*** (7.64)	0.0023*** (6.53)	0.0047*** (8.95)	0.0017*** (3.80)	0.0028*** (3.81)
Child	0.0028 (0.71)	-0.0085* (-2.53)	0.0168 (1.45)	-0.0008 (-0.44)	-0.0059*** (-5.01)	0.0095 (1.68)	-0.0017 (-1.16)	-0.0053*** (-4.92)	0.0099 (1.69)
Population density	-0.00005*** (-12.85)	-0.0000003 (-0.15)	-0.0001*** (-12.85)	-0.0001*** (-8.78)	-0.00002* (-2.46)	-0.0001*** (-12.82)	-0.0001*** (-8.11)	-0.00002** (-2.70)	-0.0001*** (-14.07)
Constant	0.1474*** (35.92)	-0.0328** (18.84)	0.3604*** (24.42)						
W*U (λ)	0.5715*** (14.63)	0.6822*** (-2.95)	0.5799*** (23.91)	0.7380*** (39.73)	0.9721*** (40.36)	0.6717*** (29.51)	0.7414*** (27.59)	0.9520*** (26.68)	0.4756*** (12.09)
R^2	0.9054	0.5514	0.9493	0.9406	0.7133	0.9667	0.9408	0.7139	0.9666
$Corr^2$	0.7622	0.1779	0.8524	0.5836	0.0123	0.8260	0.5965	0.0859	0.8428
Informal employment rate (I)									
SDI	0.0169*** (18.75)	0.0166*** (18.26)	0.0201*** (17.79)	0.0067*** (12.55)	0.0069*** (11.98)	0.0085*** (11.21)	0.0034*** (7.15)	0.0041*** (8.01)	0.0048*** (6.62)
AI	0.0176*** (7.14)	0.0186*** (8.36)	0.0074** (2.68)	0.0490*** (10.48)	0.0394*** (8.24)	0.0664*** (12.91)	-0.0126** (-2.59)	-0.0188*** (-3.91)	-0.0020 (-0.31)
Education	-0.0143*** (-20.58)	-0.0129*** (-19.42)	-0.0187*** (-21.27)	-0.0105*** (-17.23)	-0.0095*** (-15.97)	-0.0140*** (-16.20)	-0.0343*** (-36.73)	-0.0318*** (-33.14)	-0.0366*** (-32.09)
Age	0.0057*** (10.36)	0.0045*** (8.42)	0.0081*** (11.65)	0.0043*** (10.00)	0.0038*** (9.19)	0.0069*** (10.82)	-0.0067*** (-11.47)	-0.0069*** (-11.36)	-0.0056*** (-7.70)
Population density	-0.00002* (-2.38)	0.00002** (2.86)	-0.0001*** (-8.59)	0.00004*** (3.40)	0.00005*** (3.85)	-0.00001 (-0.49)	-0.00003* (-2.37)	0.00001 (0.48)	-0.0001*** (-5.13)
Constant	0.1382*** (22.57)	0.1501*** (23.13)	0.1295*** (19.74)						
W*I (λ)	0.4859*** (9.50)	0.5128*** (9.90)	0.4338*** (7.72)	0.9215*** (24.21)	0.9734*** (25.44)	0.6352*** (13.70)	0.6396*** (31.60)	0.6332*** (29.44)	0.6290*** (27.01)
R^2	0.8540	0.8539833	0.8086338	0.9239	0.9192	0.8906	0.9275	0.9231	0.9020
$Corr^2$	0.5108	0.5108158	0.5372837	0.0023	0.0012	0.0481	0.2877	0.2816	0.2068
ln w									
SDI	-0.0492*** (-17.36)	-0.0516*** (-16.35)	-0.0513*** (-20.59)	-0.0143*** (-5.13)	-0.0171*** (-7.11)	-0.0154*** (-5.64)	-0.0044* (-2.03)	-0.0077*** (-3.36)	-0.0060* (-2.21)
AI	-0.0443*** (-5.25)	-0.0487*** (-4.85)	-0.0109 (-1.40)	-0.2487*** (-9.65)	-0.2731*** (-12.24)	-0.2305*** (-10.44)	0.1325*** (5.16)	0.1248*** (4.51)	0.1122*** (3.90)
Education	0.0614*** (23.71)	0.0635*** (22.82)	0.0581*** (21.13)	0.0430*** (11.01)	0.0411*** (12.23)	0.0362*** (10.91)	0.1100*** (25.07)	0.1057*** (21.68)	0.0942*** (21.82)
Age	0.0018 (0.99)	-0.0022 (-1.20)	0.0140*** (6.73)	-0.0088** (-3.18)	-0.0052* (-2.24)	-0.0041 (-1.54)	0.0220*** (10.00)	0.0173*** (7.43)	0.0206*** (8.16)
Population density	-0.0006*** (-19.08)	-0.0007*** (-18.34)	-0.0004*** (-14.65)	-0.0003*** (-4.50)	-0.0003*** (-5.40)	-0.0003*** (-4.58)	-0.0002*** (-3.85)	-0.0002** (-2.95)	-0.0002* (-2.57)
Constant	4.6304*** (19.00)	4.3715*** (20.49)	4.9420*** (13.59)						
W*ln w (λ)	0.4063*** (27.45)	0.4571*** (24.05)	0.3061*** (30.59)	0.8456*** (15.05)	0.6946*** (12.70)	0.8316*** (18.92)	0.5193*** (13.23)	0.4747*** (9.96)	0.6288*** (14.36)
R^2	0.7138	0.7640	0.6078	0.8277	0.8518	0.7701	0.8400	0.8590	0.7813
$Corr^2$	0.4825	0.4776	0.4734	0.0122	0.0322	0.0398	0.2020	0.1510	0.1838

t statistic in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table IV.A.13: Impacts of spatial panel lag model

			Random Effects			Fixed Effects			Fixed Effects(twoways)		
			Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Non-employment rate	Total	SDI	0.0009***	0.0011**	0.0020***	-0.0003	-0.0006	-0.0009	0.00004	0.0001	0.0001
			(3.51)	(3.21)	(3.36)	(-0.70)	(-0.70)	(-0.70)	(0.14)	(0.15)	(0.15)
		AI	-0.0076***	-0.0091***	-0.0167***	0.0044*	0.0102*	0.0146*	0.0081**	0.0191***	0.0272***
			(-8.17)	(-8.39)	(-8.58)	(2.37)	(2.27)	(2.31)	(3.23)	(3.40)	(3.43)
		Education	-0.0164***	-0.0195***	-0.0360***	-0.0144***	-0.0335***	-0.0479***	-0.0128***	-0.0302***	-0.0430***
			(-35.77)	(-16.38)	(-26.93)	(-23.62)	(-11.46)	(-15.57)	(-21.14)	(-6.55)	(-8.67)
		Age	0.0041***	0.0049***	0.0090***	0.0041***	0.0096***	0.0138***	0.0054***	0.0128***	0.0182***
			(13.20)	(12.20)	(13.80)	(14.50)	(8.67)	(10.55)	(9.42)	(8.10)	(9.89)
		Child	0.0029	0.0035	0.0064	-0.0009	-0.0021	-0.0031	-0.0019	-0.0046	-0.0065
			(0.67)	(0.64)	(0.65)	(-0.59)	(-0.61)	(-0.60)	(-1.29)	(-1.22)	(-1.24)
		Population density	-0.00005***	-0.0001***	-0.0001***	-0.0001***	-0.0002***	-0.0003***	-0.0001***	-0.0002***	-0.0002***
			(-12.62)	(-11.11)	(-12.66)	(-9.76)	(-7.83)	(-8.83)	(-7.62)	(-5.68)	(-6.56)
	Men	SDI	0.0012**	0.0021***	0.0033***	-0.0004	-0.0072	-0.0076	-0.0006	-0.0067	-0.0072
			(3.24)	(3.97)	(3.82)	(-0.35)	(-0.14)	(-0.14)	(-0.17)	(-0.09)	(-0.09)
		AI	0.0020**	0.0037*	0.0058**	0.0110	0.2016	0.2127	0.0023	0.0270	0.0292
			(2.78)	(2.57)	(2.70)	(1.12)	(0.16)	(0.16)	(0.28)	(-0.06)	(-0.06)
		Education	-0.0052***	-0.0095***	-0.0147***	-0.0077	-0.1409	-0.1486	-0.0074	-0.0877	-0.0951
			(-11.50)	(-8.19)	(-12.52)	(-0.59)	(-0.11)	(-0.11)	(-0.25)	(-0.08)	(-0.08)
		Age	0.0032***	0.0059***	0.0092***	0.0029	0.0534	0.0563	0.0028	0.0329	0.0357
			(9.57)	(7.87)	(11.04)	(0.63)	(0.11)	(0.11)	(0.36)	(0.09)	(0.09)
		Child	-0.0095*	-0.0173*	-0.0267*	-0.0110	-0.2005	-0.2115	-0.0087	-0.1025	-0.1112
			(-2.41)	(-2.43)	(-2.47)	(-0.50)	(-0.11)	(-0.11)	(-0.23)	(-0.09)	(-0.09)
		Population density	-0.0000004	-0.000001	-0.000001	-0.00004	-0.0006	-0.0007	-0.00003	-0.0004	-0.0004
			(-0.25)	(-0.24)	(-0.24)	(-0.59)	(-0.11)	(-0.11)	(-0.18)	(-0.10)	(-0.10)
	Women	SDI	0.0026***	0.0032***	0.0057***	0.0024***	0.0041***	0.0065***	0.0031***	0.0025***	0.0056***
			(4.42)	(3.30)	(3.73)	(4.80)	(3.68)	(3.68)	(7.01)	(3.97)	(5.43)
		AI	-0.0176***	-0.0215***	-0.0391***	-0.0250***	-0.0438***	-0.0688***	0.0082**	0.0068**	0.0150**
			(-10.91)	(-10.07)	(-11.95)	(-9.14)	(-9.19)	(-9.19)	(2.72)	(2.63)	(2.75)
		Education	-0.0237***	-0.0290***	-0.0527***	-0.0199***	-0.0348***	-0.0547***	-0.0182***	-0.0152***	-0.0334***
			(-31.99)	(-10.46)	(-17.50)	(-21.98)	(-10.80)	(-10.80)	(-22.72)	(-6.14)	(-11.93)
		Age	0.0022***	0.0027***	0.0049***	0.0025***	0.0044***	0.0070***	0.0029***	0.0024***	0.0054***
			(4.17)	(4.93)	(4.65)	(6.49)	(5.26)	(5.26)	(3.68)	(4.28)	(4.12)
		Child	0.0180	0.0221	0.0401	0.0105	0.0185	0.0290	0.0103	0.0085	0.0188
			(1.23)	(1.25)	(1.25)	(1.61)	(1.73)	(1.73)	(1.59)	(1.74)	(1.67)
		Population density	-0.0001***	-0.0001***	-0.0002***	-0.0001***	-0.0002***	-0.0004***	-0.0001***	-0.0001***	-0.0003***
			(-12.34)	(-8.91)	(-11.47)	(-13.43)	(-8.43)	(-8.43)	(-13.49)	(-6.89)	(-12.33)
Informal employment rate	Total	SDI	0.0176***	0.0152***	0.0328***	0.0098	0.0752	0.0850	0.0038***	0.0059***	0.0097***
			(19.89)	(15.84)	(26.54)	(0.96)	(0.13)	(0.15)	(7.29)	(6.35)	(6.96)
		AI	0.0184***	0.0159***	0.0342***	0.0709	0.5427	0.6135	-0.0137**	-0.0211**	-0.0348**
			(7.25)	(6.05)	(6.89)	(1.09)	(0.15)	(0.17)	(-2.71)	(-2.62)	(-2.67)
		Education	-0.0149***	-0.0129***	-0.0277***	-0.0152	-0.1161	-0.1312	-0.0375***	-0.0577***	-0.0952***
			(-22.51)	(-11.80)	(-19.53)	(-1.00)	(-0.14)	(-0.15)	(-38.93)	(-11.76)	(-18.49)
		Age	0.0059***	0.0051***	0.0110***	0.0061	0.0471	0.0532	-0.0073***	-0.0113***	-0.0187***
			(11.06)	(8.84)	(10.83)	(1.04)	(0.14)	(0.15)	(-12.10)	(-8.57)	(-10.39)
		Population density	-0.00002*	-0.00002*	-0.00004*	0.0001	0.0004	0.0005	-0.00003*	-0.00004*	-0.0001*
			(-2.32)	(-2.32)	(-2.33)	(0.88)	(0.10)	(0.11)	(-2.17)	(-2.16)	(-2.17)
	Men	SDI	0.0175***	0.0167***	0.0341***	0.0130	0.2461	0.2591	0.0045***	0.0067***	0.0112***
			(18.50)	(15.54)	(24.54)	(0.20)	(0.08)	(0.08)	(8.13)	(6.26)	(7.18)
		AI	0.0196***	0.0187***	0.0383***	0.0743	1.4070	1.4813	-0.0205***	-0.0308***	-0.0514***
			(8.51)	(6.71)	(7.90)	(0.20)	(0.08)	(0.08)	(-4.09)	(-3.87)	(-4.02)
		Education	-0.0135***	-0.0129***	-0.0264***	-0.0180	-0.3407	-0.3587	-0.0347***	-0.0521***	-0.0868***
			(-21.11)	(-10.90)	(-17.17)	(-0.19)	(-0.08)	(-0.08)	(-37.71)	(-11.54)	(-18.69)
		Age	0.0047***	0.0045***	0.0092***	0.0072	0.1359	0.1430	-0.0075***	-0.0113***	-0.0188***
			(9.03)	(7.26)	(8.56)	(0.18)	(0.08)	(0.08)	(-11.04)	(-8.02)	(-9.68)
		Population density	0.00002**	0.00002**	0.00005**	0.0001	0.0017	0.0018	0.00001	0.00001	0.00002
			(2.70)	(2.64)	(2.69)	(0.23)	(0.08)	(0.08)	(0.39)	(0.39)	(0.39)
	Women	SDI	0.0173***	0.0167***	0.0341***	0.0094***	0.0149***	0.0243***	0.0052***	0.0079***	0.0131***
			(18.50)	(15.54)	(24.54)	(10.98)	(4.59)	(6.65)	(6.90)	(5.83)	(6.48)
		AI	0.0196***	0.0190***	0.0386***	0.0720***	0.1142***	0.1862***	-0.0027	-0.0042	-0.0069
			(8.51)	(6.71)	(7.90)	(14.13)	(5.07)	(7.81)	(-0.40)	(-0.40)	(-0.40)
		Education	-0.0136***	-0.0132***	-0.0268***	-0.0152***	-0.0242***	-0.0395***	-0.0399***	-0.0601***	-0.1000***
			(-21.11)	(-10.90)	(-17.17)	(-18.96)	(-4.94)	(-7.75)	(-34.29)	(-10.28)	(-16.34)
		Age	0.0048***	0.0046***	0.0094***	0.0076***	0.0119***	0.0195***	-0.0061***	-0.0092***	-0.0153***
			(9.03)	(7.26)	(8.56)	(12.92)	(5.46)	(8.64)	(-8.08)	(-6.25)	(-7.21)
		Population density	0.00002**	0.00002**	0.00005**	-0.00001	-0.00001	-0.00002	-0.0001***	-0.0001***	-0.0002***
			(2.70)	(2.64)	(2.69)	(-0.39)	(-0.31)	(-0.34)	(-4.95)	(-4.97)	(-5.12)
ln w	Total	SDI	-0.0506***	-0.0323***	-0.0829***	-0.0181***	-0.0747	-0.0927	-0.0047*	-0.0046*	-0.0092*
			(-16.94)	(-13.61)	(-20.92)	(-4.13)	(-0.49)	(-0.56)	(-2.13)	(-2.03)	(-2.11)
		AI	-0.0456***	-0.0291***	-0.0746***	-0.3137***	-1.2973	-1.6110	0.1393***	0.1363***	0.2756***
			(-5.55)	(-4.50)	(-5.19)	(-6.18)	(-0.49)	(-0.55)	(5.10)	(5.26)	(5.65)
		Education	0.0632***	0.0403***	0.1035***	0.0542***	0.2243	0.2785	0.1157***	0.1132***	0.2289***
			(22.47)	(10.15)	(17.99)	(3.83)	(0.40)	(0.45)	(24.06)	(6.32)	(11.56)
		Age	0.0019	0.0012	0.0031	-0.0110	-0.0457	-0.0567	0.0232***	0.0226***	0.0458***
			(0.95)	(0.95)	(0.96)	(-1.87)	(-0.31)	(-0.34)	(10.36)	(5.96)	(8.83)
		Population density	-0.0007***	-0.0004***	-0.0011***	-0.0004***	-0.0017	-0.0021	-0.0002***	-0.0002***	-0.0004***
			(-19.46)	(-11.72)	(-19.81)	(-4.57)	(-0.50)	(-0.57)	(-3.69)	(-3.51)	(-3.76)
	Men	SDI	-0.0535***	-0.0415***	-0.0950***	-0.0191***	-0.0368**	-0.0560***	-0.0081***	-0.0067**	-0.0147***
			(-16.08)	(-13.42)	(-19.75)	(-7.26)	(-3.26)	(-4.33)	(-3.63)	(-3.15)	(-3.58)
		AI	-0.0505***	-0.0391***	-0.0896***	-0.3059***	-0.5884***	-0.8942***	0.1300***	0.1077***	0.2376***
			(-5.11)	(-4.18)	(-4.74)	(-14.55)	(-3.65)	(-5.28)	(4.63)	(4.54)	(5.14)
		Education	0.0658***	0.0510***	0.1169***	0.0461***	0.0886**	0.1347***	0.1100***	0.0911***	0.2012***
			(21.91)	(10.20)	(17.22)	(9.72)	(2.79)	(3.68)	(21.54)	(4.95)	(9.64)
		Age	-0.0023	-0.0018	-0.0041	-0.0058*	-0.0112	-0.0171	0.0181***	0.0150***	0.0330***
			(-1.16)	(-1.15)	(-1.16)	(-2.07)	(-1.37)	(-1.54)	(7.51)	(4.31)	(6.33)
		Population density	-0.0007***	-0.0006***	-0.0013***	-0.0004***	-0.0007***	-0.0011***	-0.0002**	-0.0001**	-0.0003**
			(-18.78)	(-11.53)	(-18.59)	(-5.99)	(-3.57)	(-4.68)	(-2.90)	(-2.70)	(-2.92)
	Women	SDI	-0.0521***	-0.0219***	-0.0739***	-0.0191***	-0.0722*	-0.0913*	-0.0065*	-0.0096*	-0.0160*
			(-20.92)	(-10.82)	(-23.66)	(-5.18)	(-2.15)	(-2.50)	(-2.22)	(-2.00)	(-2.12)
		AI	-0.0111	-0.0046	-0.0157	-0.2859***	-1.0830*	-1.3689**	0.1220***	0.1801***	0.3022***
			(-1.44)	(-1.39)	(-1.42)	(-11.99)	(-2.38)	(-2.87)	(3.83)	(3.91)	(4.14)
		Education	0.0589***	0.0248***	0.0837***	0.0449***	0.1702	0.2152*	0.1025***	0.1513***	0.2538***
			(22.35)	(9.60)	(20.79)	(7.32)	(1.87)	(2.17)	(21.08)	(5.03)	(7.72)
		Age	0.0142***	0.0060***	0.0202***	-0.0051	-0.0194	-0.0245	0.0224***	0.0331***	0.0555***
			(7.18)	(7.27)	(7.71)	(-1.45)	(-0.90)	(-0.96)	(8.17)	(4.99)	(6.73)
		Population density	-0.0005***	-0.0002***	-0.0006***	-0.0004***	-0.0014*	-0.0018**	-0.0002*	-0.0003*	-0.0004*
			(-14.89)	(-9.56)	(-15.66)	(-4.99)	(-2.43)	(-2.84)	(-2.42)	(-2.32)	(-2.42)

t statistic in parenthesis. * p <0.05, ** p <0.01, *** p <0.001.

Table IV.A.14: SARAR/SAC panel model

	Random Effects			Fixed Effects			Fixed Effects(twoways)		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate (U)									
SDI	0.0024***	0.0014***	0.0127***	0.0004	-0.0002	0.0028**	0.0006	-0.0004	0.0033***
	(8.43)	(4.26)	(23.02)	(0.83)	(-0.50)	(3.25)	(1.18)	(-0.73)	(3.93)
AI	-0.0047***	0.0012	0.0209***	-0.0008	0.0067	-0.0172***	0.0014	0.0023	0.0032
	(-5.92)	(1.79)	(17.65)	(-0.24)	(1.66)	(-3.39)	(0.35)	(0.58)	(0.55)
Education	-0.0135***	-0.0093***	-0.0055***	-0.0133***	-0.0040***	-0.0192***	-0.0124***	-0.0042***	-0.0186***
	(-28.62)	(-19.82)	(-7.78)	(-13.54)	(-6.68)	(-13.03)	(-12.57)	(-6.12)	(-12.57)
Age	0.0054***	0.0075***	-0.0137***	0.0037***	0.0015***	0.0019*	0.0047***	0.0017*	0.0022
	(15.21)	(16.86)	(-20.77)	(6.62)	(4.33)	(2.21)	(4.58)	(2.15)	(1.53)
Child	0.0276***	-0.0299***	-0.0117	-0.0014	-0.0057**	0.0082	-0.0018	-0.0052**	0.0084
	(9.88)	(-22.87)	(-1.30)	(-0.41)	(-2.87)	(0.81)	(-0.68)	(-2.82)	(0.81)
Population density	-0.00003***	0.000003	0.00003***	-0.0001***	-0.00002	-0.0002***	-0.0001***	-0.00002	-0.0002***
	(-7.76)	(0.92)	(5.80)	(0.32)	(-0.04)	(0.55)	(-5.50)	(-1.33)	(-8.37)
Constant	0.0380**	-0.1337***	0.9195***						
	(50.33)	(14.16)	(24.26)						
W*U (λ)	0.6187***	0.6441***	0.2963***	0.6873***	0.9672***	0.6406***	0.6754***	0.9556***	0.4204***
	(3.25)	(-12.78)	(34.69)	(18.62)	(22.52)	(15.48)	(13.62)	(15.24)	(6.13)
ρ	-0.00003***	0.000003	0.00003***	0.5058	-0.1702	0.4920	-0.0094	0.0012	-0.0366**
	(-7.76)	(0.92)	(5.80)	(0.32)	(-0.04)	(0.55)	(-1.30)	(0.31)	(-2.97)
R^2	0.8532	0.3818	0.8702	0.9379	0.7263	0.9642	0.9380	0.7291	0.9658
$Corr^2$	0.7453	0.1153	0.6776	0.5665	0.0315	0.8189	0.5821	0.0899	0.8420
Informal employment rate (I)									
SDI	0.0163***	0.0247***	0.0233***	0.0095***	0.0098***	0.0104***	0.0067***	0.0070***	0.0084***
	(23.07)	(32.12)	(21.37)	(6.67)	(6.57)	(6.11)	(5.67)	(5.53)	(5.25)
AI	-0.0144***	0.0009	-0.0045	0.0369***	0.0341***	0.0314*	-0.0075	-0.0109	0.0007
	(-7.73)	(0.48)	(-1.80)	(3.65)	(3.36)	(2.55)	(-0.74)	(-1.11)	(0.05)
Education	-0.0382***	-0.0359***	-0.0392***	-0.0189***	-0.0181***	-0.0211***	-0.0334***	-0.0318***	-0.0342***
	(-41.24)	(-37.08)	(-32.61)	(-11.45)	(-11.03)	(-11.62)	(-19.86)	(-18.24)	(-16.80)
Age	0.0063***	-0.0218***	0.0095***	0.0028*	0.0029*	0.0019	-0.0059***	-0.0054***	-0.0062***
	(7.49)	(-23.56)	(8.57)	(2.25)	(2.30)	(1.30)	(-4.34)	(-3.84)	(-3.89)
Population density	0.0001***	0.0001***	-0.0002***	-0.00006	-0.00003	-0.0001*	-0.0001*	-0.0001	-0.0001**
	(11.34)	(7.78)	(-14.63)	(-1.82)	(-1.00)	(-2.49)	(-2.51)	(-1.72)	(-2.67)
Constant	0.6103***	1.8576***	0.4819***						
	(-9.60)	(-46.08)	(-1.97)						
W*I (λ)	-0.1651***	-0.8968***	-0.0402*	0.4130**	0.5584***	0.0594	0.5985***	0.6123***	0.5445***
	(25.47)	(66.79)	(15.35)	(2.95)	(3.96)	(0.55)	(11.76)	(11.01)	(10.90)
ρ	0.5659	0.6816	0.6228	1.2398	1.2449	0.7119	0.7750	0.7715	0.6619
	(1.36)	(1.73)	(1.00)	(1.27)	(1.26)	(0.55)	(1.07)	(1.05)	(0.72)
R^2	0.7655	0.6489	0.7843	0.9183	0.9071	0.8998	0.9287	0.9213	0.9040
$Corr^2$	0.4555	0.3844	0.5112	0.0037	0.0008	0.0207	0.2564	0.2435	0.1898
ln w									
SDI	-0.0538***	0.0697***	-0.1078***	-0.0140***	-0.0065	-0.0121*	-0.0017	-0.0061	-0.0015
	(-21.24)	(26.04)	(-37.51)	(-3.54)	(-1.55)	(-2.44)	(-0.42)	(-1.49)	(-0.26)
AI	0.1569***	-0.2747***	-0.0648***	-0.2436***	-0.0870*	-0.1773***	0.2605***	0.2177***	0.2029**
	(15.94)	(-25.05)	(-6.65)	(-6.68)	(-2.25)	(-4.34)	(5.66)	(4.46)	(3.22)
Education	0.0821***	0.1968***	-0.1049***	0.0422***	0.0206***	0.0296***	0.0799***	0.0842***	0.0636***
	(20.00)	(44.48)	(-27.13)	(7.59)	(3.57)	(5.19)	(10.62)	(10.09)	(7.70)
Age	-0.0411***	0.0038	0.1327***	-0.0088*	-0.0080*	-0.0063	0.0174***	0.0137***	0.0145**
	(-12.75)	(1.11)	(44.47)	(-2.26)	(-1.99)	(-1.37)	(4.54)	(3.39)	(2.83)
Population density	-0.0011***	-0.0002***	-0.0008***	-0.0003**	-0.0001	-0.0002*	-0.0002*	-0.0002*	-0.0001
	(-29.55)	(-4.56)	(-20.53)	(-3.12)	(-1.00)	(-2.11)	(-2.13)	(-1.99)	(-1.13)
Constant	6.4586***	1.7820***	9.7061***						
	(14.66)	(27.31)	(-19.59)						
W*ln w (λ)	0.3421***	0.5921***	-0.5484***	0.8559***	1.0422***	0.9277***	0.6060***	0.5546***	0.7225***
	(34.41)	(9.71)	(48.24)	(10.73)	(11.06)	(12.16)	(8.89)	(6.73)	(8.91)
ρ	0.5336	0.5709	0.3921	0.0317	-0.0675	-0.3376	-0.2634	-0.2015	-0.9990
	(0.83)	(0.82)	(0.41)	(0.02)	(-0.03)	(-0.11)	(-0.10)	(-0.10)	(-0.27)
R^2	0.6361	0.6018	0.2475	0.8263	0.8476	0.7874	0.8441	0.8616	0.8072
$Corr^2$	0.3973	0.2618	0.2008	0.0111	0.0025	0.0160	0.2100	0.1552	0.1950

t statistic in parenthesis. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table IV.A.15: Impacts of SARAR/SAC panel model

			Random Effects			Fixed Effects			Fixed Effects(twoways)		
			Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Non-employment rate	Total	SDI	0.0026***	0.0036***	0.0062***	0.0005	0.0009	0.0014	0.0007	0.0012	0.0019
			(8.86)	(7.74)	(8.31)	(0.79)	(0.80)	(0.80)	(1.16)	(1.10)	(1.14)
		AI	-0.0051***	-0.0072***	-0.0122***	-0.0008	-0.0016	-0.0024	0.0015	0.0027	0.0043
			(-5.76)	(-6.11)	(-6.02)	(-0.17)	(-0.14)	(-0.15)	(0.34)	(0.29)	(0.31)
		Education	-0.0147***	-0.0208***	-0.0355***	-0.0149***	-0.0278***	-0.0427***	-0.0138***	-0.0245***	-0.0383***
			(-31.07)	(-20.62)	(-28.86)	(-13.94)	(-5.83)	(-8.27)	(-12.88)	(-3.87)	(-5.43)
		Age	0.0058***	0.0083***	0.0141***	0.0041***	0.0076***	0.0117***	0.0052***	0.0092***	0.0144***
			(15.76)	(12.99)	(14.85)	(6.32)	(3.60)	(4.36)	(5.10)	(4.70)	(5.67)
		Child	0.0299***	0.0425***	0.0724***	-0.0015	-0.0029	-0.0044	-0.0020	-0.0036	-0.0056
			(10.61)	(10.83)	(11.14)	(-0.42)	(-0.46)	(-0.45)	(-0.62)	(-0.62)	(-0.62)
		Population density	-0.00003***	-0.00004***	-0.0001***	-0.0001***	-0.0002***	-0.0004***	-0.0001***	-0.0002***	-0.0003***
			(-8.18)	(-8.75)	(-8.69)	(-5.77)	(-4.52)	(-5.24)	(-5.48)	(-4.29)	(-5.31)
	Men	SDI	0.0015***	0.0024***	0.0039***	-0.0004	-0.0068	-0.0073	-0.0006	-0.0073	-0.0079
			(4.56)	(4.48)	(4.99)	(-0.08)	(0.11)	(0.10)	(-0.47)	(-0.003)	(-0.01)
		AI	0.0013	0.0021	0.0034	0.0119	0.1914	0.2033	0.0037	0.0471	0.0509
			(1.61)	(1.54)	(1.59)	(0.31)	(0.06)	(0.08)	(0.40)	(0.01)	(0.01)
		Education	-0.0101***	-0.0159***	-0.0260***	-0.0071	-0.1137	-0.1207	-0.0070	-0.0884	-0.0954
			(-24.96)	(-5.41)	(-8.95)	(-0.19)	(0.09)	(0.08)	(-0.94)	(0.02)	(0.01)
		Age	0.0082***	0.0128***	0.0210***	0.0027	0.0428	0.0455	0.0027	0.0345	0.0372
			(21.94)	(5.76)	(9.90)	(0.23)	(-0.08)	(-0.07)	(1.05)	(-0.01)	(-0.004)
		Child	-0.0327***	-0.0513***	-0.0841***	-0.0102	-0.1644	-0.1746	-0.0086	-0.1085	-0.1171
			(-20.87)	(-4.48)	(-6.65)	(-0.17)	(0.08)	(0.07)	(-0.91)	(0.04)	(0.04)
		Population density	0.000003	0.000004	0.00001	-0.00003	-0.0004	-0.0005	-0.00003	-0.0003	-0.0004
			(0.99)	(0.94)	(0.97)	(-0.11)	(0.11)	(0.09)	(-0.61)	(0.05)	(0.05)
	Women	SDI	0.0129***	0.0052***	0.0180***	0.0030***	0.0047*	0.0077**	0.0034***	0.0023*	0.0057***
			(22.83)	(12.20)	(19.31)	(3.36)	(2.53)	(2.85)	(4.00)	(2.41)	(3.35)
		AI	0.0212***	0.0085***	0.0297***	-0.0188***	-0.0291***	-0.0480***	0.0032	0.0022	0.0054
			(18.09)	(11.66)	(16.49)	(-3.52)	(-3.58)	(-3.74)	(0.40)	(0.35)	(0.38)
		Education	-0.0056***	-0.0022***	-0.0078***	-0.0210***	-0.0325***	-0.0535***	-0.0192***	-0.0129***	-0.0321***
			(-8.12)	(-7.95)	(-8.24)	(-13.26)	(-5.54)	(-8.26)	(-13.45)	(-3.37)	(-6.99)
		Age	-0.0139***	-0.0056***	-0.0195***	0.0021*	0.0033	0.0054*	0.0023	0.0015	0.0038
			(-19.46)	(-11.49)	(-17.04)	(2.38)	(1.89)	(2.08)	(1.65)	(1.63)	(1.69)
		Child	-0.0118	-0.0048	-0.0166	0.0090	0.0139	0.0229	0.0087	0.0059	0.0146
			(-1.43)	(-1.38)	(-1.41)	(0.77)	(0.69)	(0.73)	(0.76)	(0.63)	(0.72)
		Population density	0.00003***	0.00001***	0.00004***	-0.0002***	-0.0003***	-0.0004***	-0.0002***	-0.0001***	-0.0003***
			(6.05)	(5.33)	(5.88)	(-8.30)	(-5.05)	(-6.69)	(-8.12)	(-3.51)	(-6.70)
Informal employment rate	Total	SDI	0.0163***	-0.0024***	0.0140***	0.0098***	0.0064	0.0162**	0.0072***	0.0095***	0.0167***
			(22.50)	(-8.13)	(26.10)	(6.48)	(1.46)	(2.85)	(5.85)	(3.69)	(4.82)
		AI	-0.0145***	0.0021***	-0.0124***	0.0380***	0.0249	0.0628**	-0.0080	-0.0106	-0.0186
			(-7.88)	(6.24)	(-7.85)	(3.71)	(1.52)	(2.72)	(-0.84)	(-0.79)	(-0.82)
		Education	-0.0383***	0.0055***	-0.0328***	-0.0194***	-0.0127	-0.0321**	-0.0359***	-0.0472***	-0.0832***
			(-40.63)	(9.44)	(-42.94)	(-10.27)	(-1.42)	(-2.79)	(-21.45)	(-4.57)	(-7.52)
		Age	0.0064***	-0.0009***	0.0054***	0.0029*	0.0019	0.0048	-0.0064***	-0.0084**	-0.0148***
			(7.51)	(-6.02)	(7.48)	(2.23)	(1.13)	(1.76)	(-4.13)	(-2.90)	(-3.50)
		Population density	0.0001***	-0.00001***	0.00007***	-0.00006	-0.00004	-0.0001	-0.0001*	-0.0001*	-0.0002*
			(11.02)	(-8.93)	(10.40)	(-1.76)	(-1.19)	(-1.65)	(-2.46)	(-2.22)	(-2.39)
	Men	SDI	0.0268***	-0.0138***	0.0130***	0.0104***	0.0118	0.0223	0.0076***	0.0105***	0.0181***
			(30.02)	(-23.80)	(35.60)	(6.13)	(1.03)	(1.57)	(5.71)	(3.41)	(4.52)
		AI	0.0010	-0.0005	0.0005	0.0363***	0.0410	0.0773	-0.0117	-0.0163	-0.0280
			(0.49)	(-0.49)	(0.49)	(3.44)	(1.21)	(1.86)	(-1.22)	(-1.10)	(-1.16)
		Education	-0.0390***	0.0200***	-0.0189***	-0.0193***	-0.0218	-0.0411	-0.0344***	-0.0476***	-0.0820***
			(-35.21)	(27.58)	(-39.38)	(-8.48)	(-1.11)	(-1.69)	(-20.06)	(-4.07)	(-6.53)
		Age	-0.0236***	0.0121***	-0.0115***	0.0030*	0.0034	0.0065	-0.0058***	-0.0080**	-0.0138**
			(-23.03)	(21.18)	(-22.99)	(2.32)	(1.05)	(1.46)	(-3.68)	(-2.70)	(-3.22)
		Population density	0.0001***	-0.00004***	0.00004***	-0.00004	-0.00004	-0.0001	-0.0001	-0.0001	-0.0002
			(7.67)	(-7.78)	(7.49)	(-1.03)	(-0.68)	(-0.84)	(-1.75)	(-1.63)	(-1.72)
	Women	SDI	0.0233***	-0.0009	0.0224***	0.0105***	0.0007	0.0111***	0.0089***	0.0096***	0.0185***
			(21.11)	(-1.83)	(24.34)	(5.85)	(0.66)	(5.22)	(5.59)	(3.96)	(5.07)
		AI	-0.0045	0.0002	-0.0044	0.0314*	0.0020	0.0334*	0.0007	0.0007	0.0014
			(-1.84)	(1.25)	(-1.84)	(2.53)	(0.60)	(2.50)	(-0.03)	(-0.03)	(-0.03)
		Education	-0.0392***	0.0015	-0.0377***	-0.0211***	-0.0013	-0.0225***	-0.0362***	-0.0389***	-0.0751***
			(-32.09)	(1.85)	(-32.30)	(-12.04)	(-0.68)	(-7.02)	(-17.05)	(-4.90)	(-8.63)
		Age	0.0095***	-0.0004	0.0091***	0.0019	0.0001	0.0020	-0.0066***	-0.0070**	-0.0136***
			(8.49)	(-1.80)	(8.40)	(1.49)	(0.48)	(1.51)	(-4.12)	(-2.98)	(-3.60)
		Population density	-0.0002***	0.00001	-0.0001***	-0.0001*	-0.00001	-0.0001*	-0.0001*	-0.0001*	-0.0002*
			(-14.29)	(1.82)	(-15.03)	(-2.38)	(-0.57)	(-2.44)	(-2.49)	(-2.32)	(-2.48)
ln w	Total	SDI	-0.0548***	-0.0270***	-0.0818***	-0.0179	-0.0792	-0.0970	-0.0018	-0.0024	-0.0042
			(-20.93)	(-9.81)	(-19.92)	(-0.01)	(0.01)	(0.01)	(-0.33)	(-0.34)	(-0.34)
		AI	0.1598***	0.0786***	0.2384***	-0.3113	-1.3788	-1.6901	0.2811***	0.3801***	0.6612***
			(16.21)	(8.55)	(14.67)	(-0.001)	(-0.01)	(-0.01)	(5.81)	(3.52)	(5.05)
		Education	0.0837***	0.0411***	0.1248***	0.0539	0.2387	0.2926	0.0862***	0.1165**	0.2027***
			(20.42)	(10.23)	(20.62)	(-0.01)	(-0.01)	(-0.01)	(10.55)	(3.22)	(4.98)
		Age	-0.0419***	-0.0206***	-0.0625***	-0.0113	-0.0500	-0.0613	0.0188***	0.0254**	0.0442***
			(-13.21)	(-7.13)	(-11.25)	(0.02)	(0.03)	(0.03)	(4.42)	(2.89)	(3.76)
		Population density	-0.0012***	-0.0006***	-0.0017***	-0.0004	-0.0018	-0.0023	-0.0002*	-0.0003	-0.0005
			(-29.05)	(-9.22)	(-20.90)	(-0.02)	(-0.03)	(-0.03)	(-2.00)	(-1.78)	(-1.94)
	Men	SDI	0.0748***	0.0960***	0.1708***	-0.0052	0.1593	0.1541	-0.0065	-0.0072	-0.0137
			(23.96)	(8.96)	(12.96)	(-0.29)	(-0.09)	(-0.09)	(-1.61)	(-1.39)	(-1.54)
		AI	-0.2950***	-0.3784***	-0.6734***	-0.0702	2.1337	2.0636	0.2311***	0.2576**	0.4887***
			(-22.97)	(-8.82)	(-12.68)	(-0.43)	(-0.10)	(-0.10)	(4.73)	(2.83)	(4.24)
		Education	0.2113***	0.2711***	0.4825***	0.0166	-0.5048	-0.4882	0.0894***	0.0997**	0.1891***
			(49.07)	(11.66)	(20.01)	(0.32)	(0.08)	(0.08)	(10.44)	(2.67)	(4.46)
		Age	0.0041	0.0053	0.0094	-0.0064	0.1956	0.1891	0.0146**	0.0162*	0.0308**
			(1.17)	(1.17)	(1.18)	(-0.28)	(-0.06)	(-0.06)	(3.24)	(1.96)	(2.59)
		Population density	-0.0002***	-0.0003***	-0.0005***	-0.0001	0.0027	0.0026	-0.0002	-0.0002	-0.0004
			(-4.51)	(-4.42)	(-4.54)	(-0.26)	(-0.11)	(-0.11)	(-1.94)	(-1.65)	(-1.88)
	Women	SDI	-0.1113***	0.0417***	-0.0696***	-0.0178	-0.1495	-0.1673	-0.0017	-0.0036	-0.0053
			(-34.16)	(16.80)	(-39.67)	(-0.48)	(-0.20)	(-0.21)	(-0.15)	(-0.14)	(-0.15)
		AI	-0.0669***	0.0251***	-0.0418***	-0.2618	-2.1925	-2.4543	0.2307**	0.5005	0.7312
			(-6.70)	(6.66)	(-6.52)	(-0.71)	(-0.20)	(-0.21)	(3.16)	(1.48)	(1.92)
		Education	-0.1084***	0.0406***	-0.0678***	0.0436	0.3655	0.4091	0.0723***	0.1569	0.2292*
			(-28.82)	(22.78)	(-21.56)	(0.50)	(0.18)	(0.19)	(7.17)	(1.55)	(2.05)
		Age	0.1370***	-0.0514***	0.0857***	-0.0092	-0.0774	-0.0867	0.0165**	0.0357	0.0522*
			(43.90)	(-18.86)	(43.81)	(-0.31)	(-0.16)	(-0.17)	(2.80)	(1.71)	(2.11)
		Population density	-0.0008***	0.0003***	-0.0005***	-0.0004	-0.0031	-0.0034	-0.0002	-0.0003	-0.0005
			(-19.76)	(14.59)	(-19.43)	(-0.55)	(-0.20)	(-0.21)	(-1.02)	(-0.85)	(-0.93)

t statistic in parenthesis. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table IV.A.16: SLX - panel

	Random Effects			Fixed Effects			Fixed Effects(twoways)		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate									
SDI	0.0022***	0.0007	0.0037***	0.0006	-0.0004	0.0028***	0.0011*	-0.0003	0.0034***
	(4.93)	(1.68)	(5.30)	(1.28)	(-0.74)	(5.04)	(2.55)	(-0.65)	(6.49)
AI	-0.0119***	-0.0017**	-0.0214***	0.0017	0.0213***	-0.0162***	0.0139***	0.0142***	0.0056
	(-14.48)	(-3.24)	(-15.27)	(0.71)	(9.33)	(-4.87)	(5.28)	(6.22)	(1.66)
Education	-0.0182***	-0.0070***	-0.0270***	-0.0143***	-0.0064***	-0.0207***	-0.0124***	-0.0056***	-0.0189***
	(-32.93)	(-15.95)	(-29.04)	(-20.31)	(-11.46)	(-21.47)	(-19.77)	(-10.71)	(-21.27)
Age	0.0039***	0.0036***	-0.0022	0.0048***	0.0029***	0.0017	0.0055***	0.0034***	0.0021*
	(5.42)	(4.36)	(-1.77)	(7.73)	(5.42)	(1.83)	(8.97)	(6.28)	(2.40)
Child	0.0031	-0.0094	0.0175	0.0023	-0.0038**	0.0124	0.0005	-0.0037**	0.0099
	(0.92)	(-1.70)	(1.36)	(0.99)	(-2.74)	(1.89)	(0.27)	(-2.71)	(1.75)
Population density	-0.00001	0.00001***	-0.00004***	-0.0001***	-0.00004**	-0.0002***	-0.0001***	-0.00004**	-0.0002***
	(-1.88)	(5.36)	(-5.99)	(-6.14)	(-2.91)	(-13.29)	(-6.51)	(-2.75)	(-13.77)
W*SDI	-0.0017**	0.0055***	-0.0062***	-0.0100***	-0.0054***	-0.0059***	-0.0066***	-0.0058***	-0.0014
	(-2.73)	(8.95)	(-6.53)	(-11.84)	(-5.50)	(-6.20)	(-8.24)	(-5.89)	(-1.56)
W*AI	-0.0585***	-0.0086***	-0.1019***	0.0283***	0.1258***	-0.0764***	0.0935***	0.0852***	0.0416***
	(-33.96)	(-6.52)	(-34.13)	(7.88)	(33.72)	(-15.86)	(15.96)	(15.20)	(6.59)
W*Education	-0.0084***	-0.0018**	-0.0113***	-0.0233***	-0.0103***	-0.0209***	-0.0029**	-0.0042***	-0.0005
	(-11.29)	(-3.26)	(-10.36)	(-23.70)	(-11.30)	(-18.05)	(-2.77)	(-3.93)	(-0.35)
W*Age	0.0039***	0.0031***	0.0076***	0.0071***	0.0066***	0.0039***	0.0138***	0.0123***	0.0074***
	(5.57)	(3.75)	(6.35)	(10.49)	(9.83)	(4.32)	(17.09)	(14.54)	(8.14)
W*Child	0.0268***	-0.0202**	0.0965***	0.0493***	0.0105**	0.0865***	0.0218***	0.0133***	0.0493***
	(5.52)	(-3.15)	(7.09)	(10.84)	(2.95)	(9.83)	(5.81)	(3.63)	(7.33)
W*Population density	-0.0001***	-0.00002***	-0.0001***	0.00005	0.0001***	0.00003	0.0001*	0.0001***	0.00004*
	(-10.99)	(-4.11)	(-6.68)	(1.78)	(6.61)	(1.20)	(2.12)	(5.88)	(2.13)
Constant	0.3020***	-0.0578***	0.6769***						
	(24.05)	(-3.75)	(25.48)						
R^2	0.7414	-0.1690	0.8957	0.9037	0.5869	0.9593	0.9115	0.5963	0.9623
$Corr^2$	0.7796	0.1912	0.8762	0.6051	0.2926	0.8368	0.1991	0.1975	0.4579
Informal employment rate									
SDI	0.0087***	0.0086***	0.0122***	0.0078***	0.0084***	0.0091***	0.0067***	0.0074***	0.0081***
	(7.92)	(7.61)	(8.95)	(8.77)	(9.08)	(7.65)	(8.08)	(8.27)	(7.21)
AI	-0.0031	-0.0019	-0.0069**	0.0174*	0.0148*	0.0187*	-0.0139	-0.0203**	-0.0021
	(-1.33)	(-0.90)	(-2.63)	(2.28)	(2.22)	(1.98)	(-1.93)	(-3.29)	(-0.23)
Education	-0.0347***	-0.0345***	-0.0347***	-0.0321***	-0.0298***	-0.0344***	-0.0377***	-0.0350***	-0.0399***
	(-30.52)	(-30.78)	(-26.72)	(-26.84)	(-25.79)	(-23.90)	(-34.30)	(-31.77)	(-29.53)
Age	-0.0050***	-0.0056***	-0.0036**	-0.0036***	-0.0039***	-0.0024*	-0.0062***	-0.0062***	-0.0052***
	(-4.09)	(-4.57)	(-2.67)	(-3.78)	(-4.16)	(-2.10)	(-6.98)	(-7.14)	(-4.76)
Population density	-0.00003**	-0.000001	-0.0001***	-0.0001**	-0.00005*	-0.0001***	-0.0001***	-0.00007**	-0.0001***
	(-3.23)	(-0.09)	(-6.02)	(-3.03)	(-1.97)	(-3.57)	(-3.71)	(-2.59)	(-4.40)
W*SDI	0.0324***	0.0348***	0.0283***	-0.0044**	-0.0024	-0.0040*	-0.0109***	-0.0089***	-0.0096***
	(22.33)	(23.02)	(17.22)	(-3.02)	(-1.58)	(-2.11)	(-8.31)	(-6.55)	(-5.44)
W*AI	-0.0014	0.0027	-0.0159**	0.1391***	0.1337***	0.1123***	-0.0347**	-0.0604***	-0.0035
	(-0.28)	(0.62)	(-2.88)	(14.21)	(16.06)	(9.20)	(-2.73)	(-5.28)	(-0.21)
W*Education	0.0089***	0.0129***	0.0014	0.0163***	0.0192***	0.0102***	-0.0475***	-0.0413***	-0.0519***
	(5.33)	(7.77)	(0.78)	(9.40)	(11.46)	(4.93)	(-20.95)	(-20.02)	(-18.51)
W*Age	0.0181***	0.0155***	0.0212***	0.0128***	0.0084***	0.0186***	-0.0105***	-0.0122***	-0.0072***
	(12.07)	(10.26)	(12.64)	(10.23)	(6.87)	(12.39)	(-7.90)	(-9.00)	(-4.37)
W*Population density	-0.00004**	0.00003	-0.0001***	0.0001***	0.0002***	-0.00001	0.00003	0.0001***	-0.0001**
	(-2.66)	(1.81)	(-8.07)	(4.59)	(7.06)	(-0.18)	(0.93)	(3.31)	(-2.86)
Constant	0.1995***	0.2529***	0.1404***						
	(7.58)	(9.35)	(4.84)						
R^2	0.5302	0.5465	0.4658	0.8418	0.8473	0.8088	0.8724	0.8762	0.8317
$Corr^2$	0.5669	0.5549	0.5625	0.1336	0.1338	0.1079	0.0014	0.0013	0.0006
ln w									
SDI	-0.0097**	-0.0124***	-0.0199***	-0.0119***	-0.0142***	-0.0149***	-0.0092**	-0.0120***	-0.0123***
	(-3.17)	(-3.36)	(-7.37)	(-3.94)	(-4.56)	(-3.96)	(-3.16)	(-3.88)	(-3.46)
AI	0.0298***	0.0377***	0.0367***	-0.0749**	-0.0785**	-0.0698*	0.1147***	0.0939***	0.1314***
	(3.56)	(3.51)	(5.29)	(-3.00)	(-2.94)	(-2.55)	(4.33)	(3.39)	(4.43)
Education	0.1463***	0.1511***	0.1278***	0.1116***	0.1098***	0.0976***	0.1240***	0.1194***	0.1087***
	(29.57)	(26.93)	(28.28)	(22.37)	(20.08)	(19.31)	(24.83)	(21.52)	(21.99)
Age	0.0196***	0.0227***	0.0156***	0.0193***	0.0162***	0.0213***	0.0180***	0.0141***	0.0187***
	(4.43)	(4.82)	(3.72)	(6.31)	(5.01)	(6.30)	(6.18)	(4.49)	(5.76)
Population density	-0.0005***	-0.0006***	-0.0003***	0.00001	0.0001	0.00002	0.00002	0.0001	0.00002
	(-14.12)	(-13.89)	(-9.98)	(0.10)	(0.91)	(0.22)	(0.19)	(0.92)	(0.24)
W*SDI	-0.0967***	-0.1181***	-0.0634***	-0.0110*	-0.0147**	-0.0028	0.0147**	0.0085	0.0243***
	(-22.38)	(-22.89)	(-16.12)	(-2.13)	(-2.74)	(-0.47)	(2.92)	(1.61)	(4.22)
W*AI	0.1832***	0.2485***	0.1769***	-0.2793***	-0.2184***	-0.2823***	0.7644***	0.7304***	0.8253***
	(11.09)	(11.79)	(12.89)	(-7.78)	(-5.76)	(-7.34)	(15.05)	(13.74)	(14.55)
W*Education	-0.0842***	-0.0929***	-0.0672***	-0.1394***	-0.1284***	-0.1294***	-0.0003	-0.0190*	-0.0023
	(-13.68)	(-13.35)	(-11.62)	(-22.40)	(-19.39)	(-19.52)	(-0.04)	(-2.29)	(-0.28)
W*Age	-0.0006	-0.0064	0.0158**	0.0239***	0.0198***	0.0369***	0.0135**	0.0005	0.0140**
	(-0.12)	(-1.20)	(3.28)	(6.62)	(5.19)	(9.42)	(3.07)	(0.10)	(2.93)
W*Population density	-0.0009***	-0.0013***	-0.0005***	-0.0007***	-0.0007***	-0.0006***	-0.0004***	-0.0004***	-0.0003*
	(-18.51)	(-19.81)	(-11.41)	(-5.71)	(-5.48)	(-4.27)	(-3.31)	(-3.51)	(-2.31)
Constant	7.5665***	7.8159***	6.8847***						
	(121.86)	(117.59)	(104.04)						
R^2	0.4177	0.5100	0.2581	0.8118	0.8383	0.7460	0.8278	0.8479	0.7635
$Corr^2$	0.5298	0.5277	0.4987	0.1604	0.1276	0.1616	0.0057	0.0073	0.0185

t statistic in parenthesis. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table IV.A.17: Spatial durbin error model panel

	Random Effects			Fixed Effects			Fixed Effects(twoways)		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate									
SDI	0.0035***	-0.0082***	0.0041***	0.0014	-0.0005	0.0036***	0.0017*	-0.0005	0.0040***
	(6.68)	(-14.17)	(5.98)	(1.85)	(-0.59)	(3.51)	(2.31)	(-0.54)	(4.16)
AI	-0.0023	0.0116***	-0.0031	-0.0083	0.0221***	-0.0241*	0.0017	0.0158***	-0.0011
	(-1.79)	(13.44)	(-1.77)	(-1.93)	(5.54)	(-2.03)	(0.08)	(3.98)	(-0.04)
Education	-0.0169***	-0.0103***	-0.0231***	-0.0136***	-0.0065***	-0.0206***	-0.0122***	-0.0057***	-0.0187***
	(-26.47)	(-18.71)	(-26.17)	(-11.19)	(-6.67)	(-11.50)	(-10.53)	(-6.19)	(-11.10)
Age	0.0021**	-0.0010	-0.0081***	0.0038***	0.0028**	0.0004	0.0048***	0.0035***	0.0015
	(2.73)	(-1.27)	(-7.54)	(3.54)	(3.01)	(0.21)	(4.21)	(3.72)	(0.89)
Child	-0.0039	0.0136***	0.0171	-0.0024	-0.0043	0.0083	-0.0034	-0.0042	0.0067
	(-1.03)	(6.99)	(1.64)	(-0.61)	(-1.77)	(0.71)	(-0.94)	(-1.80)	(0.64)
Population density	-0.00001	-0.0001***	-0.00003***	-0.0001***	-0.00004	-0.0002***	-0.0001**	-0.00004	-0.0002***
	(-1.38)	(-16.98)	(-4.80)	(-3.54)	(-1.82)	(-7.00)	(-3.02)	(-1.76)	(-3.92)
W*SDI	0.0055***	0.0239***	0.0045*	0.0009	-0.0037*	0.0010	0.0023	-0.0037*	0.0031
	(3.61)	(25.64)	(2.41)	(0.55)	(-2.25)	(0.31)	(0.98)	(-2.24)	(1.16)
W*AI	-0.0074	0.1100***	-0.0070	-0.0211**	0.1130***	-0.0937	0.0212	0.0830***	0.0047
	(-1.55)	(53.93)	(-1.06)	(-2.84)	(17.81)	(-1.83)	(0.22)	(8.51)	(0.04)
W*Education	-0.0021	-0.0215***	0.0045*	-0.0088***	-0.0086***	-0.0118*	-0.0017	-0.0038	-0.0021
	(-1.41)	(-27.41)	(2.39)	(-4.15)	(-5.17)	(-2.15)	(-0.48)	(-1.95)	(-0.45)
W*Age	-0.0008	0.0093***	-0.0101***	-0.0003	0.0055***	-0.0028	0.0050	0.0104***	0.0026
	(-0.44)	(11.37)	(-4.04)	(-0.23)	(4.56)	(-0.59)	(1.37)	(6.96)	(0.64)
W*Child	-0.0237	-0.1518***	0.0008	-0.0080	0.0029	0.0093	-0.0147	0.0038	-0.0026
	(-1.29)	(-34.03)	(0.03)	(-0.62)	(0.48)	(0.23)	(-0.64)	(0.58)	(-0.08)
W*Population density	0.00002	-0.0002***	0.00004	0.00002	0.0001***	-0.00005	0.00004	0.0001***	0.000005
	(1.12)	(-27.51)	(1.71)	(0.28)	(3.49)	(-0.49)	(0.14)	(3.39)	(0.01)
Constant	2.2677***	0.1651***	4.6792***						
	(18.12)	(12.25)	(38.31)						
ρ	-0.0023	0.0116***	-0.0031	-0.0080	0.0029	0.0093	1.0391	0.4960	1.0381
	(-1.79)	(13.44)	(-1.77)	(-0.62)	(0.48)	(0.23)	(0.20)	(0.37)	(0.56)
R^2	0.8929	-0.0018	0.9281	0.9425	0.6893	0.9668	0.9435	0.6910	0.9667
$Corr^2$	0.0004	0.1068	0.0007	0.5537	0.2913	0.8207	0.5996	0.3069	0.8421
Informal employment rate									
SDI	0.0023*	-0.0007	0.0063***	0.0072***	0.0077***	0.0082***	0.0067***	0.0072***	0.0076***
	(2.34)	(-0.73)	(4.46)	(4.65)	(4.73)	(3.98)	(4.55)	(4.59)	(3.85)
AI	-0.0173***	-0.0026	0.0329***	0.0149	0.0179	0.0138	-0.0062	-0.0012	-0.0086
	(-3.63)	(-0.81)	(9.82)	(0.81)	(1.09)	(0.84)	(-0.40)	(-0.07)	(-0.51)
Education	0.0248***	-0.0441***	-0.0374***	-0.0309***	-0.0295***	-0.0317***	-0.0344***	-0.0324***	-0.0359***
	(18.23)	(-34.60)	(-24.57)	(-14.26)	(-14.09)	(-12.69)	(-17.17)	(-15.76)	(-14.95)
Age	-0.0484***	-0.0069***	-0.0122***	-0.0034	-0.0033*	-0.0025	-0.0058***	-0.0053**	-0.0055**
	(-33.08)	(-5.18)	(-7.89)	(-1.95)	(-1.96)	(-1.24)	(-3.52)	(-3.20)	(-2.77)
Population density	0.0001***	-0.00003**	-0.0007***	-0.0001*	-0.0001	-0.0001*	-0.0001*	-0.0001	-0.0001*
	(7.96)	(-2.67)	(-49.35)	(-2.21)	(-1.58)	(-2.52)	(-2.16)	(-1.45)	(-2.51)
W*SDI	0.0599***	-0.0047*	0.0919***	0.0024	0.0022	-0.0005	-0.0005	-0.0001	-0.0040
	(20.06)	(-2.04)	(48.50)	(0.60)	(0.54)	(-0.14)	(-0.13)	(-0.01)	(-0.92)
W*AI	-0.2391***	-0.0008	0.1171***	0.0909	0.1144	0.0563*	-0.00001	0.0317	-0.0403
	(-12.18)	(-0.07)	(17.04)	(1.32)	(1.91)	(2.50)	(-0.0002)	(0.41)	(-0.87)
W*Education	0.0566***	-0.0377***	0.0642***	-0.0031	-0.0040	-0.0022	-0.0217***	-0.0193***	-0.0244***
	(12.65)	(-11.61)	(27.91)	(-0.53)	(-0.74)	(-0.56)	(-3.92)	(-3.32)	(-4.02)
W*Age	0.0204***	0.0035	-0.0340***	0.0084	0.0056	0.0147***	-0.0039	-0.0044	-0.0002
	(4.31)	(1.08)	(-16.64)	(1.93)	(1.32)	(5.07)	(-0.91)	(-0.90)	(-0.05)
W*Population density	-0.0022***	-0.00004	-0.0007***	0.000003	0.0001	-0.0002*	-0.00001	0.0001	-0.0002
	(-42.95)	(-1.35)	(-35.47)	(0.02)	(0.55)	(-2.28)	(-0.05)	(0.28)	(-1.85)
Constant	0.9692***	17.9222***	1.8365***						
	(4.73)	(46.59)	(51.29)						
ρ	-0.0173***	-0.0026	0.0329***	0.9990	0.9990	0.7727	0.9990	1.0234	0.9400
	(-3.63)	(-0.81)	(9.82)	(0.19)	(0.21)	(0.82)	(0.28)	(0.22)	(0.40)
R^2	0.5804	0.8658	0.6633	0.9356	0.9295	0.9059	0.9360	0.9297	0.9124
$Corr^2$	0.0968	0.00004	0.4059	0.0154	0.0144	0.0447	0.1892	0.1977	0.1608
ln w									
SDI	-0.1261***	-0.0921***	0.2877***	-0.0119*	-0.0137*	-0.0151*	-0.0088	-0.0115*	-0.0119
	(-38.83)	(-25.12)	(70.22)	(-2.26)	(-2.53)	(-2.30)	(-1.70)	(-2.11)	(-1.91)
AI	-0.0837***	-1.4230***	-0.3942***	-0.0888*	-0.0914*	-0.0850	0.0793	0.0982	0.1033*
	(-8.88)	(-54.75)	(-39.38)	(-2.04)	(-1.97)	(-1.79)	(1.68)	(1.49)	(2.00)
Education	0.0321***	-0.0848***	0.3713***	0.1079***	0.1072***	0.0937***	0.1247***	0.1197***	0.1088***
	(6.50)	(-15.88)	(69.79)	(12.54)	(11.40)	(10.68)	(14.15)	(11.54)	(12.64)
Age	-0.0785***	0.0617***	0.1073***	0.0199***	0.0173**	0.0222***	0.0195***	0.0146*	0.0194***
	(-17.84)	(14.17)	(23.09)	(3.76)	(3.10)	(3.79)	(3.80)	(2.51)	(3.44)
Population density	-0.0020***	0.0012***	0.0023***	-0.00002	0.00005	0.00001	0.00002	0.0001	0.00004
	(-44.11)	(22.65)	(45.51)	(-0.12)	(0.29)	(0.06)	(0.10)	(0.44)	(0.25)
W*SDI	-0.1441***	0.0038	-0.4251***	-0.0097	-0.0140	-0.0010	0.0083	0.0071	0.0185
	(-31.45)	(0.26)	(-77.53)	(-1.09)	(-1.51)	(-0.10)	(0.88)	(0.55)	(1.78)
W*AI	-0.4746***	-1.2819***	-0.3559***	-0.3469***	-0.2882***	-0.3488***	0.4257***	0.6933**	0.5254***
	(-23.39)	(-11.89)	(-17.53)	(-5.46)	(-4.30)	(-5.12)	(3.50)	(2.65)	(4.79)
W*Education	-0.2643***	-0.0239	-0.1095***	-0.1185***	-0.1074***	-0.1083***	-0.0048	-0.0194	-0.0009
	(-43.09)	(-1.29)	(-16.36)	(-11.13)	(-9.54)	(-9.41)	(-0.30)	(-0.78)	(-0.06)
W*Age	0.1811***	-0.0107	-0.1163***	0.0165**	0.0113	0.0287***	0.0108	0.0001	0.0082
	(37.44)	(-1.27)	(-22.33)	(2.66)	(1.72)	(4.23)	(1.30)	(0.01)	(0.96)
W*Population density	-0.0037***	-0.0063***	0.0006***	-0.0007**	-0.0006**	-0.0006*	-0.0004	-0.0004	-0.0004
	(-61.17)	(-25.11)	(9.15)	(-3.10)	(-2.78)	(-2.50)	(-1.48)	(-0.95)	(-1.63)
Constant	8.5864***	10.1593***	6.3030***						
	(150.80)	(70.25)	(100.33)						
ρ	-0.0837***	-1.4230***	-0.3942***	0.4782*	0.5161*	0.4460	0.8511	0.9962	0.6709
	(-8.88)	(-54.75)	(-39.38)	(2.12)	(2.43)	(1.50)	(0.94)	(0.58)	(0.90)
R^2	0.3737	-0.2778	-0.3249	0.8372	0.8591	0.7764	0.8405	0.8570	0.7836
$Corr^2$	0.0085	0.0510	0.2940	0.1592	0.1260	0.1607	0.2273	0.1794	0.2166

t statistic in parenthesis. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table IV.A.18: Spatial durbin panel model

	Random Effects			Fixed Effects			Fixed Effects(twoways)		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate (U)									
SDI	0.0017***	0.0003	0.0036***	0.0011***	-0.00004	0.0032***	0.0012***	0.00002	0.0033***
	(5.21)	(0.84)	(6.19)	(3.42)	(-0.11)	(6.44)	(3.80)	(0.06)	(6.75)
AI	-0.0044***	0.0006	-0.0089***	-0.0013	0.0001	-0.0058*	-0.0003	-0.0007	-0.0005
	(-5.21)	(0.99)	(-5.58)	(-0.71)	(0.04)	(-2.00)	(-0.15)	(-0.32)	(-0.16)
Education	-0.0166***	-0.0062***	-0.0249***	-0.0121***	-0.0052***	-0.0184***	-0.0117***	-0.0051***	-0.0181***
	(-33.14)	(-16.83)	(-31.51)	(-21.60)	(-11.70)	(-21.72)	(-21.32)	(-11.23)	(-21.55)
Age	0.0034***	0.0028***	-0.0015	0.0041***	0.0020***	0.0012	0.0041***	0.0019***	0.0014
	(5.43)	(4.56)	(-1.50)	(7.30)	(4.15)	(1.50)	(6.98)	(3.77)	(1.60)
Child	0.0008	-0.0070**	0.0116	-0.0016	-0.0050***	0.0071	-0.0020	-0.0053***	0.0069
	(0.24)	(-2.61)	(1.27)	(-0.89)	(-4.82)	(1.51)	(-1.19)	(-4.90)	(1.48)
Population density	-0.00002***	0.00001*	-0.0001***	-0.0001***	-0.0001***	-0.0002***	-0.0001***	-0.0001***	-0.0002***
	(-4.69)	(2.55)	(-8.65)	(-11.53)	(-4.31)	(-14.64)	(-11.80)	(-4.36)	(-14.73)
W*SDI	-0.0015***	0.0012*	-0.0028***	-0.0017***	-0.0005	-0.0023***	-0.0013**	-0.0001	-0.0018**
	(-3.67)	(2.32)	(-4.13)	(-3.57)	(-0.96)	(-3.61)	(-2.62)	(-0.26)	(-2.66)
W*AI	-0.0115***	0.0022*	-0.0219***	0.0072**	0.0072	-0.0101*	0.0103*	0.0048	0.0064
	(-6.93)	(2.06)	(-6.24)	(2.97)	(1.45)	(-2.40)	(2.16)	(1.04)	(1.14)
W*Education	0.0054***	0.0028***	0.0114***	0.0054***	0.0026***	0.0088***	0.0076***	0.0036***	0.0098***
	(6.07)	(4.04)	(7.93)	(5.23)	(3.57)	(6.39)	(8.94)	(4.75)	(7.29)
W*Age	-0.0004	-0.0010	0.0033***	-0.0019**	-0.0010	0.0004	-0.0016	-0.0014	0.0011
	(-0.61)	(-1.28)	(3.52)	(-3.06)	(-1.75)	(0.52)	(-1.89)	(-1.55)	(1.25)
W*Child	0.0065*	-0.0039	0.0201*	0.0040	0.0014	0.0092*	0.0076***	0.0036***	0.0098***
	(2.08)	(-1.38)	(2.44)	(1.64)	(0.73)	(2.15)	(8.94)	(4.75)	(7.29)
W*Population density	-0.00002*	-0.00001***	0.00002**	0.0001***	0.00005***	0.0002***	-0.0016	-0.0014	0.0011
	(-2.41)	(-3.59)	(2.91)	(7.77)	(4.36)	(9.33)	(-1.89)	(-1.55)	(1.25)
Constant	0.1119***	-0.0080	0.2226***						
	(9.61)	(-1.12)	(9.58)						
W*U (λ)	0.6500***	0.7406***	0.6843***	0.8862***	0.9623***	0.8073***	0.9263***	1.0228***	0.7497***
	(21.18)	(11.13)	(17.41)	(26.65)	(19.40)	(21.87)	(18.93)	(16.25)	(10.39)
R^2	0.9062	0.5588	0.9495	0.9434	0.7151	0.9675	0.9435	0.7133	0.9676
$Corr^2$	0.7777	0.1955	0.8733	0.0163	0.0004	0.0771	0.0015	0.0004	0.3199
Informal employment rate (I)									
SDI	0.0084***	0.0081***	0.0116***	0.0063***	0.0065***	0.0075***	0.0063***	0.0069***	0.0074***
	(11.05)	(10.66)	(10.39)	(7.52)	(7.94)	(6.47)	(9.07)	(9.27)	(7.63)
AI	0.0010	0.0011	-0.0007	-0.0165**	-0.0185***	-0.0031	-0.0100*	-0.0133**	-0.0023
	(0.60)	(0.68)	(-0.35)	(-3.18)	(-3.61)	(-0.51)	(-2.02)	(-2.75)	(-0.35)
Education	-0.0318***	-0.0316***	-0.0322***	-0.0286***	-0.0275***	-0.0293***	-0.0337***	-0.0313***	-0.0359***
	(-41.95)	(-39.96)	(-34.13)	(-28.74)	(-28.04)	(-24.83)	(-34.00)	(-31.19)	(-28.54)
Age	-0.0052***	-0.0053***	-0.0043***	-0.0055***	-0.0045***	-0.0063***	-0.0057***	-0.0053***	-0.0056***
	(-6.37)	(-6.20)	(-4.58)	(-7.15)	(-5.67)	(-6.55)	(-8.04)	(-7.32)	(-6.37)
Population density	-0.00004***	-0.00002*	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(-4.96)	(-2.02)	(-5.99)	(-5.70)	(-5.40)	(-3.92)	(-4.79)	(-3.81)	(-4.54)
W*SDI	-0.0013	-0.0019	0.0003	-0.0058***	-0.0067***	-0.0076***	-0.0063***	-0.0059***	-0.0064***
	(-0.99)	(-1.46)	(0.16)	(-5.14)	(-5.82)	(-5.14)	(-6.55)	(-5.94)	(-5.07)
W*AI	0.0143***	0.0131***	0.0119***	-0.0311***	-0.0307***	-0.0110	-0.0075	-0.0132	-0.0024
	(5.88)	(5.63)	(3.48)	(-3.74)	(-3.65)	(-1.24)	(-0.97)	(-1.69)	(-0.23)
W*Education	0.0259***	0.0270***	0.0219***	0.0307***	0.0282***	0.0313***	-0.0002	0.0028	-0.0040
	(24.14)	(25.34)	(14.80)	(23.46)	(23.14)	(17.28)	(-0.07)	(1.17)	(-1.21)
W*Age	0.0076***	0.0068***	0.0096***	0.0035***	0.0041***	0.0036**	-0.0009	-0.0016	0.0007
	(8.55)	(7.45)	(8.74)	(3.84)	(4.62)	(3.00)	(-0.94)	(-1.60)	(0.59)
W*Population density	0.00002	0.00002	-0.00001	0.0001***	0.00006*	0.00015***	0.0001**	0.0001***	0.00001
	(1.72)	(1.68)	(-0.45)	(4.82)	(2.47)	(4.99)	(2.90)	(3.81)	(0.26)
Constant	0.0323*	0.0328*	0.0292						
	(2.24)	(2.12)	(1.69)						
W*I (λ)	0.8464***	0.8831***	0.7216***	1.5247***	1.4924***	1.4141***	0.6624***	0.6907***	0.6114***
	(26.62)	(28.34)	(16.67)	(25.93)	(25.11)	(18.49)	(15.29)	(15.26)	(11.36)
R^2	0.8930	0.8857	0.8562	0.9092	0.9061	0.8917	0.9291	0.9257	0.9012
$Corr^2$	0.5466	0.5235	0.5559	0.00001	0.0001	0.00000005	0.0001	0.0001	0.0001
ln w									
SDI	-0.0080**	-0.0103***	-0.0195***	-0.0085**	-0.0101***	-0.0134***	-0.0085**	-0.0103***	-0.0133***
	(-2.92)	(-3.34)	(-7.19)	(-2.99)	(-3.38)	(-4.06)	(-3.09)	(-3.53)	(-4.07)
AI	-0.0120	-0.0122	0.00004	-0.0105	-0.0252	-0.0127	0.0104	-0.0134	-0.0056
	(-1.60)	(-1.36)	(0.005)	(-0.46)	(-1.04)	(-0.49)	(0.37)	(-0.43)	(-0.17)
Education	0.1375***	0.1412***	0.1182***	0.1216***	0.1192***	0.1045***	0.1222***	0.1199***	0.1052***
	(31.56)	(29.98)	(26.90)	(24.77)	(22.11)	(21.00)	(26.57)	(23.55)	(22.54)
Age	0.0167***	0.0189***	0.0158***	0.0138***	0.0131***	0.0139***	0.0167***	0.0148***	0.0166***
	(5.07)	(5.50)	(4.57)	(4.85)	(4.36)	(4.26)	(6.08)	(5.03)	(5.32)
Population density	-0.0003***	-0.0004***	-0.0002***	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(-8.64)	(-8.90)	(-6.51)	(0.93)	(1.54)	(1.49)	(0.71)	(1.49)	(1.40)
W*SDI	-0.0075	-0.0153**	-0.0039	0.0090*	0.0089	0.0145**	0.0076	0.0074	0.0138**
	(-1.48)	(-2.59)	(-0.76)	(2.13)	(1.93)	(3.06)	(1.91)	(1.74)	(2.99)
W*AI	-0.0198	-0.0001	-0.0106	0.0114	0.0057	0.0047	0.0831	0.0469	0.0283
	(-1.50)	(-0.004)	(-0.78)	(0.31)	(0.15)	(0.12)	(1.26)	(0.65)	(0.38)
W*Education	-0.1229***	-0.1238***	-0.1024***	-0.1084***	-0.1082***	-0.0901***	-0.0813***	-0.0899***	-0.0748***
	(-24.30)	(-22.15)	(-19.38)	(-21.40)	(-19.83)	(-16.27)	(-8.30)	(-8.64)	(-7.60)
W*Age	-0.0175***	-0.0192***	-0.0106**	-0.0230***	-0.0196***	-0.0258***	-0.0073	-0.0099*	-0.0129**
	(-4.97)	(-5.22)	(-2.63)	(-5.69)	(-4.63)	(-5.06)	(-1.74)	(-2.37)	(-2.67)
W*Population density	0.0001	0.00003	0.00002	-0.00001	-0.00011	-0.0001	-0.0001	-0.0002	-0.0001
	(1.93)	(0.38)	(0.29)	(-0.11)	(-0.98)	(-0.88)	(-1.02)	(-1.42)	(-1.30)
Constant	0.7819*	1.3039***	1.4675***						
	(2.21)	(3.36)	(3.82)						
W*ln w (λ)	0.9026***	0.8410***	0.7931***	1.1462***	1.0918***	1.1444***	0.8570***	0.9177***	0.9654***
	(19.48)	(17.12)	(14.26)	(14.51)	(11.56)	(13.53)	(9.73)	(8.70)	(10.10)
R^2	0.7700	0.8017	0.6655	0.8301	0.8536	0.7668	0.8399	0.8586	0.7762
$Corr^2$	0.4563	0.4916	0.4825	0.0006	0.0007	0.0002	0.0001	0.00005	0.00002

t statistic in parenthesis. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table IV.A.19: Impacts of panel durbin model

			Random Effects			Fixed Effects			Fixed Effects(twoways)		
			Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Non-employment rate	Total	SDI	0.0016***	-0.0010	0.0006	0.0007*	-0.0064	-0.0057	0.0010	-0.0021	-0.0011
			(4.85)	(-1.17)	(0.73)	(2.05)	(-1.52)	(-1.27)	(0.16)	(-0.07)	(-0.03)
		AI	-0.0069***	-0.0387***	-0.0455***	0.0013	0.0503	0.0516	0.0052	0.1301	0.1354
			(-7.29)	(-12.38)	(-12.43)	(0.49)	(1.75)	(1.72)	(0.11)	(0.21)	(0.25)
		Education	-0.0173***	-0.0147***	-0.0321***	-0.0140***	-0.0455**	-0.0595***	-0.0129	-0.0420	-0.0549
			(-34.80)	(-9.61)	(-19.52)	(-22.33)	(-3.06)	(-3.86)	(-0.28)	(-0.08)	(-0.13)
		Age	0.0037***	0.0050***	0.0088***	0.0046***	0.0147**	0.0194***	0.0052	0.0290	0.0342
			(6.01)	(5.78)	(10.74)	(9.00)	(2.71)	(3.46)	(0.19)	(0.13)	(0.20)
		Child	0.0020	0.0189**	0.0209**	-0.0004	0.0218	0.0214	-0.0026	-0.0160	-0.0186
			(0.63)	(2.90)	(2.86)	(-0.30)	(0.66)	(0.59)	(-0.13)	(0.09)	(0.07)
		Population density	-0.00003***	-0.0001***	-0.0001***	-0.0001***	0.000002	-0.0001	-0.0001	-0.000002	-0.0001
			(-6.32)	(-6.62)	(-8.40)	(-12.29)	(0.02)	(-1.19)	(-0.69)	(0.13)	(0.05)
	Men	SDI	0.0006	0.0050***	0.0056***	-0.0005	-0.0133	-0.0138	0.0001	0.0050	0.0051
			(1.75)	(3.94)	(4.16)	(-0.13)	(0.05)	(0.05)	(-0.07)	(0.01)	(-0.001)
		AI	0.0012	0.0096*	0.0108*	0.0060	0.1871	0.1931	-0.0035	-0.1748	-0.1783
			(1.74)	(2.21)	(2.25)	(0.33)	(0.15)	(0.15)	(-0.01)	(-0.02)	(-0.02)
		Education	-0.0065***	-0.0068***	-0.0132***	-0.0070	-0.0640	-0.0710	-0.0037	0.0652	0.0615
			(-19.06)	(-4.07)	(-7.49)	(-0.74)	(0.02)	(0.003)	(-0.44)	(0.10)	(0.07)
		Age	0.0030***	0.0041***	0.0071***	0.0026	0.0225	0.0251	0.0014	-0.0260	-0.0247
			(5.52)	(4.40)	(7.70)	(0.96)	(0.003)	(0.03)	(0.43)	(0.06)	(0.08)
		Child	-0.0090**	-0.0331***	-0.0421***	-0.0076	-0.0897	-0.0973	-0.0014	0.2211	0.2197
			(-3.12)	(-4.20)	(-4.86)	(-0.40)	(-0.01)	(-0.03)	(-0.28)	(0.08)	(0.07)
		Population density	0.00001	-0.00003*	-0.00002	-0.0001	-0.0001	-0.0002	-0.00004	0.0004	0.0003
			(1.84)	(-2.00)	(-1.44)	(-1.64)	(0.06)	(0.01)	(-0.92)	(0.20)	(0.14)
	Women	SDI	0.0034***	-0.0009	0.0025	0.0031***	0.0012	0.0043	0.0034***	0.0026	0.0060
			(5.53)	(-0.35)	(1.52)	(5.44)	(0.43)	(1.27)	(6.03)	(0.91)	(1.60)
		AI	-0.0141***	-0.0834***	-0.0975***	-0.0100***	-0.0727***	-0.0828***	0.0010	0.0227	0.0237
			(-8.04)	(-12.74)	(-13.24)	(-3.38)	(-4.78)	(-5.03)	(0.27)	(0.88)	(0.84)
		Education	-0.0256***	-0.0173***	-0.0428***	-0.0197***	-0.0303***	-0.0500***	-0.0185***	-0.0144	-0.0330**
			(-32.67)	(-7.58)	(-16.90)	(-21.95)	(-6.54)	(-10.48)	(-19.66)	(-1.67)	(-3.26)
		Age	-0.0010	0.0067***	0.0057***	0.0016*	0.0068***	0.0084***	0.0019	0.0081**	0.0099**
			(-1.20)	(5.96)	(5.05)	(2.08)	(3.41)	(4.01)	(1.76)	(2.85)	(2.96)
		Child	0.0169	0.0837***	0.1006***	0.0114*	0.0734***	0.0848***	0.0099	0.0497**	0.0597**
			(1.64)	(6.15)	(5.65)	(2.25)	(4.64)	(4.45)	(1.67)	(3.16)	(3.05)
		Population density	-0.0001***	-0.00004*	-0.0001***	-0.0002***	0.00002	-0.0002**	-0.0002***	0.00003	-0.0002**
			(-9.62)	(-2.26)	(-5.10)	(-14.79)	(0.23)	(-2.82)	(-16.20)	(0.59)	(-2.81)
Informal employment rate	Total	SDI	0.0102***	0.0359***	0.0460***	0.0059	-0.0068	-0.0009	0.0059***	-0.0056**	0.0002
			(13.15)	(8.46)	(10.68)	(0.20)	(-0.24)	(-0.47)	(8.86)	(-2.90)	(0.15)
		AI	0.0062**	0.0933**	0.0996**	-0.0226	0.1133	0.0907***	-0.0124**	-0.0394	-0.0518*
			(2.65)	(3.07)	(3.10)	(-0.04)	(0.26)	(8.80)	(-2.59)	(-1.94)	(-2.24)
		Education	-0.0310***	-0.0070	-0.0380***	-0.0264	0.0225	-0.0039*	-0.0372***	-0.0630***	-0.1002***
			(-40.94)	(-1.35)	(-5.69)	(-0.52)	(0.43)	(-2.16)	(-37.87)	(-8.84)	(-13.73)
		Age	-0.0040***	0.0193***	0.0153***	-0.0055	0.0094	0.0039***	-0.0065***	-0.0132***	-0.0196***
			(-5.14)	(5.36)	(4.06)	(-0.18)	(0.31)	(3.45)	(-9.25)	(-5.30)	(-7.40)
		Population density	-0.00004***	-0.0001	-0.0001*	-0.0001	0.0001	0.00001	-0.0001***	0.00001	-0.00007
			(-5.33)	(-1.90)	(-2.53)	(-0.29)	(0.33)	(0.32)	(-5.22)	(0.32)	(-1.73)
	Men	SDI	0.0099***	0.0423***	0.0522***	0.0059	-0.0055	0.0004	0.0065***	-0.0034	0.0031
			(12.71)	(5.07)	(6.15)	(0.99)	(-0.85)	(0.30)	(9.56)	(-1.27)	(1.27)
		AI	0.0069**	0.1142*	0.1211*	-0.0168	0.1167	0.0999***	-0.0175**	-0.0683**	-0.0858**
			(2.69)	(2.10)	(2.14)	(-0.002)	(0.27)	(9.89)	(-2.92)	(-2.79)	(-3.02)
		Education	-0.0307***	-0.0082	-0.0390***	-0.0247	0.0232	-0.0015	-0.0345***	-0.0579***	-0.0924***
			(-33.99)	(-0.99)	(-3.34)	(-1.27)	(1.18)	(-0.70)	(-35.86)	(-7.26)	(-11.27)
		Age	-0.0042***	0.0170**	0.0128*	-0.0040	0.0048	0.0008	-0.0063***	-0.0161***	-0.0224***
			(-5.11)	(2.98)	(2.18)	(-0.22)	(0.27)	(0.50)	(-8.68)	(-5.82)	(-7.67)
		Population density	-0.00001	0.00002	0.000001	-0.0001	0.0002	0.0001**	-0.0001***	0.0001*	0.00003
			(-1.78)	(0.18)	(-0.04)	(-0.19)	(0.41)	(2.80)	(-3.83)	(2.35)	(0.79)
	Women	SDI	0.0132***	0.0295***	0.0427***	0.0073	-0.0072	0.0001	0.0070***	-0.0043	0.0027
			(12.80)	(12.38)	(17.34)	(1.37)	(-1.21)	(0.01)	(7.80)	(-1.84)	(0.97)
		AI	0.0018	0.0384*	0.0401*	-0.0070	0.0410	0.0341	-0.0028	-0.0091	-0.0120
			(0.66)	(2.28)	(2.14)	(-0.08)	(0.48)	(1.66)	(-0.32)	(-0.41)	(-0.42)
		Education	-0.0318***	-0.0052	-0.0369***	-0.0281*	0.0231	-0.0050	-0.0394***	-0.0631***	-0.1025***
			(-36.09)	(-1.48)	(-9.02)	(-2.10)	(1.68)	(-1.35)	(-35.62)	(-8.11)	(-12.95)
		Age	-0.0028**	0.0219***	0.0190***	-0.0069	0.0133	0.0064**	-0.0059***	-0.0066**	-0.0125***
			(-3.11)	(8.57)	(7.27)	(-0.38)	(0.77)	(2.99)	(-6.48)	(-2.83)	(-4.77)
		Population density	-0.0001***	-0.0002***	-0.0002***	-0.0001	-0.0001	-0.0001**	-0.0001***	-0.0001**	-0.0002***
			(-6.99)	(-4.41)	(-5.80)	(-0.52)	(-0.33)	(-3.15)	(-5.52)	(-3.08)	(-5.25)
ln w	Total	SDI	-0.0145	-0.1442	-0.1588	-0.0079	0.0045	-0.0033	-0.0081	0.0015	-0.0066
			(-0.88)	(0.01)	(0.01)	(-0.27)	(0.07)	(0.06)	(-0.18)	(0.09)	(0.04)
		AI	-0.0259	-0.3006	-0.3265	-0.0101	0.0041	-0.0061	0.0438	0.6103	0.6541
			(-0.23)	(0.07)	(0.07)	(-0.09)	(0.11)	(0.11)	(0.08)	(0.17)	(0.31)
		Education	0.1324**	0.0167	0.1491	0.0842	-0.1744	-0.0902	0.1265	0.1591	0.2857
			(2.81)	(-0.08)	(-0.08)	(0.71)	(-0.15)	(-0.13)	(0.03)	(0.03)	(0.06)
		Age	0.0149	-0.0225	-0.0075	0.0246	0.0379	0.0625	0.0186	0.0466	0.0652
			(1.14)	(0.06)	(0.06)	(0.15)	(0.13)	(0.14)	(-0.02)	(0.03)	(0.02)
		Population density	-0.0004	-0.0017	-0.0021	-0.00003	-0.0004	-0.0005	0.00004	-0.0004	-0.0003
			(-1.68)	(0.02)	(0.02)	(0.01)	(0.08)	(0.08)	(0.06)	(-0.03)	(-0.02)
	Men	SDI	-0.0181***	-0.1427***	-0.1609***	-0.0101	0.0225	0.0124	-0.0109	-0.0242	-0.0350
			(-5.86)	(-4.17)	(-4.64)	(-0.16)	(0.12)	(0.07)	(-1.90)	(-0.07)	(-0.08)
		AI	-0.0153	-0.0618	-0.0772	-0.0331	0.2461	0.2129	0.0053	0.4031	0.4084
			(-1.18)	(-0.52)	(-0.57)	(-0.12)	(0.08)	(0.08)	(0.05)	(0.07)	(0.07)
		Education	0.1349***	-0.0252	0.1096	0.1183	-0.2386	-0.1203	0.1251***	0.2387	0.3638
			(27.56)	(-0.10)	(1.92)	(0.29)	(-0.09)	(-0.08)	(5.99)	(0.08)	(0.13)
		Age	0.0172***	-0.0189	-0.0017	0.0094	0.0617	0.0710	0.0161*	0.0441	0.0603
			(5.66)	(-1.02)	(-0.27)	(-0.01)	(0.09)	(0.09)	(2.56)	(0.09)	(0.12)
		Population density	-0.0005***	-0.0018**	-0.0023***	0.0001	-0.0005	-0.0003	0.0001	-0.0004	-0.0003
			(-11.12)	(-2.87)	(-3.55)	(0.01)	(0.07)	(0.07)	(0.88)	(-0.18)	(-0.16)
	Women	SDI	-0.0244***	-0.0889***	-0.1133***	-0.0122	0.0045	-0.0077	-0.0117	0.0267	0.0150
			(-9.71)	(-5.62)	(-7.12)	(-0.40)	(-0.08)	(-0.10)	(-0.78)	(0.21)	(0.13)
		AI	-0.0029	-0.0483	-0.0512	-0.0211	0.0765	0.0554	0.0141	0.6443	0.6584
			(-0.51)	(-0.69)	(-0.69)	(-0.05)	(0.05)	(0.05)	(0.09)	(0.19)	(0.19)
		Education	0.1126***	-0.0359	0.0766**	0.1197	-0.2193	-0.0996	0.1221	0.7567	0.8788
			(25.27)	(-0.90)	(2.61)	(0.74)	(-0.20)	(-0.13)	(0.86)	(0.05)	(0.08)
		Age	0.0159***	0.0095	0.0254	0.0014	0.0813	0.0827	0.0184	0.0903	0.1087
			(4.74)	(0.62)	(1.77)	(0.19)	(0.27)	(0.33)	(0.53)	(0.12)	(0.15)
		Population density	-0.0003***	-0.0008***	-0.0010***	0.0002	-0.0004	-0.0002	0.0001	-0.0007	-0.0006
			(-7.70)	(-3.89)	(-5.14)	(0.07)	(-0.07)	(-0.07)	(0.15)	(0.06)	(0.07)

t statistic in parenthesis. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table IV.A.20: General nesting spatial panel model

	Random Effects			Fixed Effects			Fixed Effects(twoways)		
	Total	Men	Women	Total	Men	Women	Total	Men	Women
Non-employment rate (U)									
SDI	0.0021***	0.0042***	0.0069***	0.0011	0.00001	0.0032***	0.0011*	0.0001	0.0033***
	(5.52)	(10.15)	(11.29)	(1.90)	(0.02)	(3.72)	(2.11)	(0.12)	(3.93)
AI	-0.0062***	0.0053***	-0.0002	-0.0013	0.0003	-0.0060	-0.0003	-0.0007	-0.0007
	(-7.47)	(7.44)	(-0.14)	(-0.40)	(0.06)	(-1.19)	(-0.06)	(-0.17)	(-0.13)
Education	-0.0149***	-0.0079***	-0.0159***	-0.0123***	-0.0052***	-0.0186***	-0.0119***	-0.0050***	-0.0184***
	(-28.97)	(-16.63)	(-21.44)	(-12.68)	(-6.72)	(-12.61)	(-12.51)	(-6.47)	(-12.64)
Age	0.0078***	0.0033***	-0.0034***	0.0040***	0.0020*	0.0012	0.0041***	0.0020*	0.0014
	(11.59)	(4.83)	(-3.72)	(4.20)	(2.45)	(0.85)	(4.01)	(2.22)	(0.91)
Child	0.0494***	-0.0542***	-0.0670***	-0.0015	-0.0050**	0.0074	-0.0019	-0.0053**	0.0072
	(18.07)	(-54.62)	(-9.21)	(-0.50)	(-2.78)	(0.90)	(-0.66)	(-2.81)	(0.89)
Population density	-0.0001***	0.00001*	-0.000001	-0.0001***	-0.0001*	-0.0002***	-0.0001***	-0.0001*	-0.0002***
	(-14.65)	(2.38)	(-0.26)	(-6.57)	(-2.45)	(-8.43)	(-6.70)	(-2.50)	(-8.41)
W*SDI	-0.0008	-0.0038***	-0.0035***	-0.0014	-0.0006	-0.0018	-0.0009	-0.0003	-0.0009
	(-1.66)	(-5.76)	(-4.73)	(-1.59)	(-0.69)	(-1.64)	(-1.06)	(-0.30)	(-0.81)
W*AI	-0.0227***	-0.0026*	-0.1761***	0.0066	0.0076	-0.0112	0.0096	0.0046	0.0042
	(-13.89)	(-2.08)	(-74.05)	(1.57)	(0.88)	(-1.53)	(1.20)	(0.55)	(0.43)
W*Education	-0.0020*	0.0117***	0.0096***	0.0049**	0.0026*	0.0082***	0.0070***	0.0037**	0.0083***
	(-2.45)	(14.50)	(9.03)	(2.76)	(2.08)	(3.46)	(4.70)	(2.72)	(3.57)
W*Age	-0.0041***	-0.0025**	0.0084***	-0.0017	-0.0011	0.0005	-0.0013	-0.0014	0.0011
	(-6.25)	(-3.22)	(9.19)	(-1.61)	(-1.05)	(0.35)	(-0.87)	(-0.93)	(0.73)
W*Child	-0.0226***	0.0819***	0.1667***	0.0023	0.0020	0.0070	-0.0007	0.0010	0.0046
	(-6.97)	(24.41)	(26.40)	(0.56)	(0.58)	(0.94)	(-0.21)	(0.28)	(0.62)
W*Population density	0.00001*	-0.00001	0.0002***	0.0001***	0.00005*	0.0002***	0.0001***	0.00004*	0.0001***
	(2.39)	(-1.92)	(22.82)	(4.37)	(2.49)	(5.22)	(4.72)	(2.47)	(4.29)
Constant	0.2495***	-0.0967***	0.1329***						
	(21.84)	(-9.61)	(7.55)						
W*U (λ)	0.2810***	1.0635***	0.4906***	0.8794***	0.9596***	0.7997***	0.9168***	1.0198***	0.7300***
	(10.82)	(13.40)	(23.64)	(15.10)	(11.11)	(12.57)	(10.70)	(9.21)	(5.84)
ρ	-0.0211	-0.2162	0.0293	0.1731	-0.1244	-0.0686	0.2186	-0.2578	0.0089
	(-0.01)	(-0.01)	(0.02)	(0.07)	(-0.03)	(-0.04)	(0.08)	(-0.05)	(0.01)
R^2	0.7966	0.3574	0.8360	0.9413	0.7247	0.9679	0.9406	0.7341	0.9676
$Corr^2$	0.7416	0.0003	0.7569	0.5998	0.1228	0.8382	0.6024	0.0009	0.8454
Informal employment rate (I)									
SDI	0.0335***	0.0170***	-0.0124***	0.0065***	0.0068***	0.0079***	0.0070***	0.0072***	0.0084***
	(38.99)	(20.02)	(-9.81)	(4.60)	(4.92)	(3.97)	(5.48)	(5.32)	(4.84)
AI	0.0240***	-0.0035	0.0299***	-0.0213*	-0.0210*	0.0002	-0.0088	-0.0126	-0.0033
	(13.35)	(-1.91)	(14.14)	(-2.21)	(-2.43)	(0.01)	(-0.90)	(-1.37)	(-0.23)
Education	0.0030**	-0.0253***	-0.0424***	-0.0298***	-0.0281***	-0.0302***	-0.0334***	-0.0319***	-0.0351***
	(2.96)	(-25.29)	(-34.98)	(-17.53)	(-17.02)	(-14.81)	(-18.80)	(-17.34)	(-16.72)
Age	-0.0072***	0.0048***	-0.0189***	-0.0057***	-0.0044***	-0.0060***	-0.0055***	-0.0053***	-0.0051**
	(-7.22)	(4.64)	(-15.87)	(-4.26)	(-3.35)	(-3.66)	(-4.25)	(-4.07)	(-3.16)
Population density	0.0002***	-0.0001***	-0.0001***	-0.0001**	-0.0001**	-0.0001	-0.0001***	-0.0001*	-0.0001**
	(18.22)	(-13.71)	(-9.61)	(-3.16)	(-3.12)	(-1.93)	(-3.35)	(-2.37)	(-3.13)
W*SDI	-0.0321***	-0.0044**	-0.0216***	-0.0058*	-0.0066**	-0.0068	0.0009	-0.0021	0.0003
	(-21.98)	(-3.01)	(-11.14)	(-2.49)	(-3.27)	(-1.94)	(0.36)	(-0.90)	(0.07)
W*AI	0.0416***	0.0033	0.1145***	-0.0418*	-0.0336*	-0.0039	-0.0087	-0.0107	-0.0127
	(14.39)	(1.15)	(33.30)	(-2.16)	(-2.36)	(-0.16)	(-0.42)	(-0.60)	(-0.38)
W*Education	-0.0233***	0.0290***	0.0255***	0.0314***	0.0282***	0.0291***	-0.0073	-0.0003	-0.0081
	(-17.19)	(21.93)	(14.68)	(10.96)	(13.32)	(7.00)	(-1.46)	(-0.07)	(-1.29)
W*Age	0.0267***	-0.0053***	0.0070***	0.0037*	0.0044**	0.0050*	-0.0006	-0.0014	0.0034
	(23.74)	(-4.61)	(5.23)	(2.00)	(2.94)	(1.98)	(-0.25)	(-0.57)	(1.14)
W*Population density	-0.0001***	0.000002	-0.000002	0.0001	0.00005	0.0001	-0.00005	0.00004	-0.0001
	(-7.05)	(0.16)	(-0.12)	(1.87)	(1.22)	(1.74)	(-0.86)	(0.77)	(-1.66)
Constant	-0.5312***	0.0691***	0.4493***						
	(-28.63)	(3.70)	(19.81)						
W*I (λ)	0.9887***	0.8389***	1.1465***	1.7597***	1.5903***	1.4849***	0.2366*	0.6137***	0.3386*
	(38.86)	(34.08)	(33.80)	(13.99)	(16.52)	(8.62)	(2.53)	(6.24)	(2.15)
ρ	0.1563	0.0238	0.1997	0.7489	0.4634	0.8228	1.3282	1.3932	0.9260***
	(0.03)	(0.004)	(0.02)	(0.26)	(0.16)	(0.30)	(1.18)	(0.79)	(21.29)
R^2	0.7589	0.8255	0.7158	0.9002	0.9000	0.8736	0.9244	0.9075	0.9039
$Corr^2$	0.0109	0.3200	0.000005	0.000001	0.0003	0.0003	0.1686	0.2686	0.0062
ln w									
SDI	-0.0657***	-0.0552***	0.0019	-0.0084	-0.0098	-0.0127*	-0.0085	-0.0103*	-0.0131*
	(-19.50)	(-15.79)	(0.51)	(-1.69)	(-1.88)	(-2.16)	(-1.78)	(-2.04)	(-2.30)
AI	0.1260***	0.1035***	-0.1767***	-0.0124	-0.0210	-0.0171	0.0144	-0.0090	-0.0076
	(13.97)	(10.61)	(-17.88)	(-0.31)	(-0.50)	(-0.39)	(0.31)	(-0.18)	(-0.14)
Education	0.0114*	0.3357***	0.0900***	0.1201***	0.1190***	0.1022***	0.1215***	0.1205***	0.1035***
	(2.27)	(65.40)	(16.44)	(14.43)	(12.95)	(11.95)	(15.22)	(13.67)	(12.76)
Age	0.0901***	-0.1010***	0.0476***	0.0140**	0.0131*	0.0136*	0.0165***	0.0150**	0.0161**
	(19.84)	(-21.96)	(10.12)	(2.79)	(2.44)	(2.35)	(3.46)	(2.95)	(2.94)
Population density	0.0012***	0.0028***	-0.000002	0.0001	0.0001	0.0001	0.00006	0.0001	0.0001
	(25.66)	(58.19)	(-0.04)	(0.50)	(0.92)	(0.62)	(0.38)	(0.84)	(0.71)
W*SDI	0.0437***	0.0714***	0.0301***	0.0100	0.0109	0.0145	0.0078	0.0071	0.0137
	(9.31)	(14.42)	(5.38)	(1.32)	(1.34)	(1.65)	(1.12)	(0.97)	(1.68)
W*AI	0.2396***	-0.1929***	0.0985***	0.0316	0.0310	0.0271	0.1047	0.0564	0.0399
	(14.91)	(-11.22)	(5.41)	(0.54)	(0.51)	(0.42)	(1.04)	(0.51)	(0.35)
W*Education	-0.0483***	-0.2495***	-0.0523***	-0.1087***	-0.1088***	-0.0908***	-0.0806***	-0.0862***	-0.0786***
	(-7.71)	(-38.09)	(-7.73)	(-11.67)	(-10.78)	(-8.83)	(-5.14)	(-5.18)	(-4.80)
W*Age	-0.0755***	0.0377***	-0.0621***	-0.0232***	-0.0212**	-0.0246**	-0.0072	-0.0091	-0.0132
	(-15.32)	(7.56)	(-11.53)	(-3.49)	(-3.03)	(-3.02)	(-1.00)	(-1.28)	(-1.59)
W*Population density	-0.0017***	-0.0032***	0.0004***	0.00002	-0.00007	-0.00004	-0.00011	-0.0002	-0.0001
	(-25.48)	(-46.90)	(6.60)	(0.11)	(-0.34)	(-0.19)	(-0.62)	(-0.86)	(-0.63)
Constant	0.3852	2.2832***	-0.2319						
	(1.53)	(9.11)	(-0.72)						
W*ln w (λ)	0.9227***	0.9091***	1.0377***	1.1606***	1.1534***	1.1443***	0.8350***	0.8899***	0.9645***
	(28.24)	(29.05)	(22.44)	(11.95)	(9.93)	(11.31)	(6.32)	(5.60)	(6.59)
ρ	-0.7146	-0.4672	-0.8241	-0.5175	-0.4984	-0.7320	-0.1670	0.0687	-0.3517
	(-0.14)	(-0.09)	(-0.14)	(-0.10)	(-0.11)	(-0.12)	(-0.04)	(0.02)	(-0.06)
R^2	0.5622	0.4135	0.6577	0.8537	0.8720	0.8133	0.8772	0.8565	0.7978
$Corr^2$	0.1014	0.0053	0.0003	0.00003	0.0001	0.0006	0.0018	0.1324	0.1174

t statistic in parenthesis. * p <0.05, ** p <0.01, *** p <0.001.

Table IV.A.21: Impacts of general nesting spatial panel model

			Random Effects			Fixed Effects			Fixed Effects(twoways)		
			Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Non-employment rate	Total	SDI	0.0021*** (5.62)	-0.0003 (-0.52)	0.0018*** (3.76)	0.0008 (0.88)	-0.0034 (-0.04)	-0.0025 (-0.03)	0.0012 (0.31)	0.0018 (-0.01)	0.0030 (0.01)
		AI	-0.0075*** (-8.83)	-0.0327*** (-19.93)	-0.0401*** (-19.61)	0.0010 (0.08)	0.0427 (0.21)	0.0437 (0.21)	0.0046 (0.01)	0.1080 (0.19)	0.1126 (0.19)
		Education	-0.0152*** (-31.45)	-0.0083*** (-12.41)	-0.0235*** (-33.79)	-0.0143** (-2.69)	-0.0469 (-0.23)	-0.0611 (-0.28)	-0.0134 (-0.37)	-0.0456 (-0.15)	-0.0590 (-0.20)
		Age	0.0077*** (11.50)	-0.0026*** (-3.71)	0.0051*** (11.91)	0.0046* (2.19)	0.0148 (0.19)	0.0194 (0.24)	0.0052 (0.37)	0.0288 (0.14)	0.0340 (0.17)
		Child	0.0488*** (17.23)	-0.0115*** (-3.50)	0.0373*** (10.63)	-0.0011 (-0.19)	0.0077 (-0.05)	0.0066 (-0.05)	-0.0031 (-0.06)	-0.0288 (-0.06)	-0.0319 (-0.06)
		Population density	-0.0001*** (-15.62)	-0.000004 (-0.67)	-0.0001*** (-11.34)	-0.0001*** (-5.63)	-0.00002 (-0.09)	-0.0001 (-0.19)	-0.0001 (-0.85)	-0.00002 (-0.12)	-0.0001 (-0.22)
	Men	SDI	0.0039 (1.18)	-0.0093 (0.003)	-0.0053 (0.03)	-0.0005 (0.0004)	-0.0144 (0.12)	-0.0148 (0.12)	-0.0018 (-0.06)	0.0122 (-0.07)	0.0104 (-0.08)
		AI	0.0053 (0.32)	-0.0466 (-0.04)	-0.0413 (-0.03)	0.0063 (0.13)	0.1873 (0.10)	0.1936 (0.11)	0.0362 (0.001)	-0.2372 (0.10)	-0.2010 (0.10)
		Education	-0.0068 (-0.27)	-0.0540 (-0.01)	-0.0608 (-0.03)	-0.0068 (-0.26)	-0.0579 (0.13)	-0.0647 (0.11)	-0.0168 (-1.35)	0.0825 (0.08)	0.0658 (0.07)
		Age	0.0033 (0.55)	-0.0169 (-0.002)	-0.0137 (0.02)	0.0026 (0.29)	0.0211 (-0.10)	0.0237 (-0.07)	0.0072 (0.59)	-0.0363 (0.14)	-0.0291 (0.20)
		Child	-0.0464 (-0.26)	-0.3899 (-0.01)	-0.4363 (-0.02)	-0.0070 (-0.20)	-0.0692 (0.10)	-0.0762 (0.08)	-0.0451 (-0.13)	0.2642 (0.08)	0.2191 (0.08)
		Population density	0.00001 (0.39)	-0.00001 (-0.07)	-0.00001 (-0.04)	-0.0001 (-1.17)	-0.00008 (0.14)	-0.0001 (0.11)	-0.0001 (-1.05)	0.0005 (0.09)	0.0004 (0.07)
	Women	SDI	0.0069*** (11.42)	-0.00004 (-0.02)	0.0068*** (6.04)	0.0033*** (3.87)	0.0034 (0.69)	0.0067 (1.01)	0.0036 (1.72)	0.0052 (0.09)	0.0088 (0.12)
		AI	-0.0194*** (-15.70)	-0.3266*** (-31.94)	-0.3460*** (-31.83)	-0.0105* (-1.96)	-0.0757* (-2.49)	-0.0861** (-2.62)	0.0002 (0.01)	0.0128 (-0.08)	0.0130 (-0.08)
		Education	-0.0156*** (-21.24)	0.0031* (2.13)	-0.0125*** (-7.56)	-0.0199*** (-13.34)	-0.0316* (-2.37)	-0.0516*** (-3.57)	-0.0191*** (-4.56)	-0.0180 (-0.11)	-0.0371 (-0.16)
		Age	-0.0027*** (-3.31)	0.0124*** (11.47)	0.0097*** (11.05)	0.0016 (1.22)	0.0068 (1.31)	0.0084 (1.50)	0.0018 (0.78)	0.0073 (-0.01)	0.0091 (0.01)
		Child	-0.0518*** (-7.57)	0.2475*** (33.96)	0.1957*** (25.11)	0.0108 (1.05)	0.0607 (1.05)	0.0715 (1.12)	0.0093 (0.71)	0.0347 (-0.02)	0.0440 (-0.003)
		Population density	0.00002** (3.08)	0.0003*** (15.84)	0.0003*** (15.50)	-0.0002*** (-8.51)	0.0000001 (-0.13)	-0.0002 (-1.38)	-0.0002*** (-6.74)	0.00001 (-0.07)	-0.0002 (-0.17)
Informal employment rate	Total	SDI	0.0330** (3.26)	0.0937 (0.09)	0.1268 (0.17)	0.0051 (0.90)	-0.0059 (-0.91)	-0.0009 (-0.24)	0.0071*** (5.78)	0.0032 (1.01)	0.0103** (2.75)
		AI	0.1196 (0.12)	5.6686 (0.08)	5.7882 (0.08)	-0.0039 (-0.07)	0.0870 (0.84)	0.0831*** (3.63)	-0.0093 (-0.79)	-0.0137 (-0.56)	-0.0230 (-0.72)
		Education	-0.0275 (-0.10)	-1.7670 (-0.08)	-1.7945 (-0.08)	-0.0244 (-1.89)	0.0222 (1.64)	-0.0022 (-0.67)	-0.0340*** (-21.15)	-0.0193*** (-5.17)	-0.0533*** (-12.84)
		Age	0.0223 (0.08)	1.6997 (0.08)	1.7220 (0.08)	-0.0042 (-0.35)	0.0068 (0.61)	0.0026 (1.23)	-0.0056*** (-4.18)	-0.0024 (-0.93)	-0.0080** (-2.64)
		Population density	0.0003 (0.22)	0.0064 (0.07)	0.0067 (0.08)	-0.00008 (-0.87)	0.0001 (0.95)	0.00002 (0.43)	-0.0001*** (-3.99)	-0.0001 (-1.42)	-0.0002*** (-3.38)
	Men	SDI	0.0197*** (24.20)	0.0581*** (8.07)	0.0779*** (10.54)	0.0061 (0.35)	-0.0063 (-0.37)	-0.0002 (-0.03)	0.0075*** (5.57)	0.0059 (0.85)	0.0134 (1.57)
		AI	-0.0032 (-1.30)	0.0020 (0.12)	-0.0012 (-0.04)	-0.0162 (0.11)	0.1087 (0.41)	0.0925*** (5.65)	-0.0153 (-1.58)	-0.0450 (-0.91)	-0.0603 (-1.07)
		Education	-0.0219*** (-20.34)	0.0445*** (5.46)	0.0227** (2.71)	-0.0254 (-0.88)	0.0252 (0.86)	-0.0002 (-0.10)	-0.0345*** (-18.91)	-0.0488*** (-3.54)	-0.0833*** (-5.73)
		Age	0.0042*** (4.39)	-0.0073 (-1.55)	-0.0031 (-0.62)	-0.0040 (-0.66)	0.0040 (0.65)	0.00004 (0.08)	-0.0060*** (-4.09)	-0.0114 (-1.92)	-0.0174** (-2.66)
		Population density	-0.0001*** (-15.12)	-0.0006*** (-4.42)	-0.0007*** (-5.28)	-0.0001 (-0.16)	0.0002 (0.53)	0.0001 (1.72)	-0.0001** (-2.89)	-0.00002 (-0.33)	-0.0001 (-0.95)
	Women	SDI	0.0052 (-0.03)	0.2262 (0.97)	0.2314*** (4.30)	0.0079 (0.82)	-0.0101 (-0.72)	-0.0022 (-0.32)	0.0086*** (4.73)	0.0045 (0.83)	0.0131* (2.02)
		AI	-0.0425 (0.01)	-0.9426 (-0.91)	-0.9851*** (-3.70)	-0.0009 (0.13)	0.0086 (-0.10)	0.0077 (-0.06)	-0.0042 (-0.26)	-0.0200 (-0.46)	-0.0242 (-0.44)
		Education	-0.0300 (-0.23)	0.1453 (1.00)	0.1153** (2.91)	-0.0291 (-1.85)	0.0314 (1.36)	0.0023 (0.31)	-0.0363*** (-17.98)	-0.0290** (-2.67)	-0.0653*** (-5.34)
		Age	-0.0113 (-0.16)	0.0924 (0.99)	0.0811*** (4.19)	-0.0061 (-0.81)	0.0083 (0.57)	0.0022 (0.13)	-0.0049** (-2.76)	0.0024 (0.38)	-0.0026 (-0.41)
		Population density	-0.00004 (-0.09)	0.0007 (0.93)	0.0007** (2.79)	-0.0001 (-0.75)	-0.00002 (0.02)	-0.0001 (-0.43)	-0.0001*** (-3.57)	-0.0002* (-2.08)	-0.0004** (-2.91)
ln w	Total	SDI	-0.0719*** (-5.97)	-0.2118 (-0.34)	-0.2837 (-0.41)	-0.0078 (-0.11)	-0.0022 (-0.10)	-0.0099 (-0.15)	-0.0080 (-0.63)	0.0036 (-0.05)	-0.0043 (-0.09)
		AI	0.3126 (1.21)	4.4132 (0.28)	4.7257 (0.29)	-0.0111 (0.04)	-0.1084 (-0.19)	-0.1196 (-0.19)	0.0527 (0.32)	0.6690 (0.36)	0.7217 (0.40)
		Education	-0.0095 (-0.41)	-0.4669 (-0.28)	-0.4763 (-0.28)	0.1109 (0.72)	-0.1823 (-0.29)	-0.0713 (-0.07)	0.1246* (2.09)	0.1232 (0.22)	0.2478 (0.39)
		Age	0.0902*** (7.44)	0.0987 (0.22)	0.1889 (0.30)	0.0127 (0.16)	0.0446 (0.26)	0.0573 (0.42)	0.0182 (0.62)	0.0382 (0.16)	0.0564 (0.21)
		Population density	0.0009** (3.14)	-0.0065 (-0.36)	-0.0056 (-0.33)	0.0001 (0.02)	-0.0007 (-0.15)	-0.0006 (-0.15)	0.00003 (0.25)	-0.0004 (-0.19)	-0.0003 (-0.18)
	Men	SDI	-0.0424*** (-4.70)	0.2207 (0.38)	0.1783 (0.34)	-0.0084 (-0.11)	0.0011 (0.05)	-0.0073 (-0.05)	-0.0108 (-0.16)	-0.0182 (0.02)	-0.0289 (-0.003)
		AI	0.0508 (1.13)	-1.0333 (-0.37)	-0.9825 (-0.36)	0.0012 (-0.001)	-0.0665 (-0.04)	-0.0653 (-0.04)	0.0124 (-0.02)	0.4181 (0.20)	0.4305 (0.20)
		Education	0.3489*** (15.20)	0.5986 (0.34)	0.9475 (0.45)	0.1622 (0.19)	-0.2290 (-0.22)	-0.0668 (-0.16)	0.1249 (1.35)	0.1861 (-0.03)	0.3110 (0.08)
		Age	-0.1234*** (-6.85)	-0.5732 (-0.38)	-0.6965 (-0.42)	-0.0055 (-0.06)	0.0586 (0.15)	0.0531 (0.28)	0.0163 (1.13)	0.0374 (-0.03)	0.0537 (0.01)
		Population density	0.0024*** (35.18)	-0.0066 (-0.86)	-0.0042 (-0.60)	0.0004 (-0.01)	-0.0009 (-0.10)	-0.0005 (-0.12)	0.0001 (0.42)	-0.0004 (-0.02)	-0.0003 (0.01)
	Women	SDI	-0.0078 (0.12)	-0.8425 (-0.01)	-0.8503 (0.02)	-0.0110 (-0.28)	-0.0013 (0.11)	-0.0123 (0.08)	-0.0115 (-0.15)	0.0297 (0.07)	0.0182 (0.07)
		AI	-0.1390 (-0.19)	2.2144 (0.005)	2.0755 (-0.02)	-0.0081 (-0.16)	-0.0611 (-0.10)	-0.0692 (-0.10)	0.0199 (0.06)	0.8904 (0.08)	0.9103 (0.08)
		Education	0.0714 (0.16)	-1.0711 (0.01)	-0.9997 (0.04)	0.1113 (0.82)	-0.1905 (-0.08)	-0.0793 (0.03)	0.1156 (0.70)	0.5849 (0.07)	0.7005 (0.07)
		Age	0.0481 (-0.04)	0.3365 (-0.03)	0.3846 (-0.03)	0.0037 (0.17)	0.0726 (0.05)	0.0763 (0.07)	0.0172 (0.50)	0.0647 (-0.07)	0.0819 (-0.07)
		Population density	-0.0001 (0.12)	-0.0117 (0.01)	-0.0119 (0.03)	0.0002 (-0.02)	-0.0006 (0.001)	-0.0004 (-0.0004)	0.0001 (0.06)	-0.0004 (0.03)	-0.0003 (0.03)

t statistic in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table IV.A.22: Summary of feedback effects

	Cross-section						Panel data	
	Men			Women				
	1990	2000	2010	1990	2000	2010	Men	Women
Non-employment rate								
SDI	–	–	–	–	–	–	–	–
AI	–	–	–	(37.6%, 38.5%)	(32.7%, 33.3%)	(35.0%, 35.8%)	–	(42.1%, 42.4%)
Education	–	–	–	–	–	–	–	(6.4%, 6.9%)
Age	–	–	(−14.1%, −12.2%)	–	–	–	–	–
Child	–	–	(0.4%, 2.3%)	–	(12.0%, 12.2%)	(4.0%)	–	–
Informal employment rate								
SDI	–	(11.1%, 11.6%)	(9.7%, 13.9%)	–	–	(5.2%, 5.3%)	–	–
AI	(17.2%, 30.0%)	(65.8%, 69.4%)	(19.7%, 23.4%)	–	–	(19.2%, 19.9%)	(17.8%, 23.9%)	–
Education	–	(1.8%, 2.0%)	(0.1%, 1.4%)	–	–	–	(7.7%, 9.1%)	(3.3%, 8.9%)
Age	–	(−19.0%, −17.8%)	–	(3.5%, 5.8%)	(−17.5%, −11.0%)	(8.1%, 8.7%)	(10.8%, 15.0%)	(−2.6%, 5.8%)
Wages								
SDI	–	–	(6.4%, 13.8%)	–	(5.3%)	–	–	–
AI	–	–	–	–	(18.6%, 18.6%)	(17.0%, 21.0%)	–	–
Education	–	–	–	–	–	–	–	–
Age	–	–	–	–	–	–	–	–

The percentage of feedback effects is the following ratio: (direct effect of X − estimated coefficient of X)/(direct effect of X). A negative percentage means that the feedback effect have a opposite impact that the direct effect does have. These results come from SDM and GNS models.

Dynamic spatial panel

We estimate the following dynamic spatial panel:

$$\mathbf{Y}_t = \tau \mathbf{Y}_{t-1} + \lambda \mathbf{W}\mathbf{Y}_t + \mathbf{X}_t \boldsymbol{\beta} + \boldsymbol{\mu} + \xi_t \boldsymbol{\iota}_N + \mathbf{u}_t \tag{IV.A.1}$$

There are three methodologies to estimate a dynamic spatial panel: quasi maximum likelihood, bias corrected least squares dummy variables (LSDV) and Arellano and Bond's estimator extended to a spatial autoregressive dynamic panel. We use this last methodology following Jacobs et al. (2009) because we have too few time periods (three years).

Table IV.A.23: Time-space simultaneous model

	GMM(oneway)			GMM(twoways)		
	Total	Men	Women	Total	Men	Women
Non-employment rate (U)						
L.U	0.1010***	0.1419***	0.2079***	0.0618***	0.1526***	0.1013**
	(4.86)	(3.58)	(5.47)	(3.35)	(3.44)	(2.83)
SDI	0.0014**	0.0005	0.0030***	0.0015**	0.0006	0.0033***
	(2.89)	(0.79)	(3.70)	(3.01)	(1.00)	(4.27)
AI	0.0134**	0.0030	0.0263***	0.0077	0.0003	0.0164*
	(3.00)	(0.69)	(3.44)	(1.91)	(0.06)	(2.49)
Education	-0.0086***	-0.0043***	-0.0128***	-0.0073***	-0.0033***	-0.0110***
	(-9.65)	(-5.30)	(-9.00)	(-8.61)	(-4.24)	(-8.17)
Age	0.0026***	-0.0004	0.0052***	0.0051***	0.0012	0.0073***
	(5.31)	(-0.66)	(4.41)	(5.72)	(1.69)	(4.96)
Child	-0.0021	-0.0226***	0.0223*	-0.0047	-0.0268***	0.0271*
	(-0.38)	(-3.71)	(2.10)	(-0.92)	(-4.29)	(2.53)
Population density	-0.0001***	-0.00005*	-0.0002***	-0.0001***	-0.00004*	-0.0002***
	(-6.34)	(-2.25)	(-5.53)	(-6.78)	(-1.98)	(-6.34)
W*U (λ)	0.5808***	0.7424***	0.3772***	0.4726***	0.6675***	0.2132*
	(10.36)	(10.91)	(4.62)	(8.27)	(9.62)	(2.31)
Informal employment rate (I)						
L.I	-0.1703*	0.3313*	-0.3148***	0.1271***	0.2258***	0.0281
	(-2.09)	(2.49)	(-6.19)	(3.55)	(4.61)	(1.23)
SDI	0.0065***	0.0034*	0.0094***	0.0029**	0.0031*	0.0032*
	(5.23)	(2.29)	(5.66)	(2.60)	(2.48)	(2.34)
AI	-0.0207*	-0.0283*	-0.0137	-0.0036	-0.0014	0.0086
	(-2.24)	(-2.22)	(-1.45)	(-0.38)	(-0.14)	(0.84)
Education	-0.0100***	-0.0173***	-0.0087***	-0.0268***	-0.0241***	-0.0276***
	(-6.29)	(-7.59)	(-5.56)	(-14.68)	(-12.25)	(-14.22)
Age	0.0023**	0.0025**	0.0025**	-0.0090***	-0.0055***	-0.0120***
	(3.08)	(2.77)	(2.67)	(-6.77)	(-3.71)	(-9.01)
Population density	-0.0001***	-0.0001**	-0.0002***	-0.0001**	-0.0001**	-0.0001
	(-3.83)	(-2.62)	(-3.53)	(-2.88)	(-2.80)	(-1.72)
W*I (λ)	0.6512***	0.9678***	0.4594***	0.8986***	0.8866***	0.8440***
	(6.53)	(7.73)	(4.83)	(27.83)	(25.62)	(26.11)
ln w						
L.LNW	-0.0254	-0.1075*	-0.0915**	0.1349***	0.1983***	0.0297
	(-0.72)	(-2.45)	(-2.59)	(4.48)	(5.33)	(1.58)
SDI	-0.0201***	-0.0241***	-0.0160***	-0.0227***	-0.0261***	-0.0186***
	(-5.23)	(-6.24)	(-3.92)	(-5.20)	(-5.32)	(-4.34)
AI	-0.0467	-0.0788	-0.0778	0.0033	0.0068	-0.0330
	(-1.01)	(-1.56)	(-1.71)	(0.07)	(0.13)	(-0.68)
Education	0.0979***	0.0756***	0.0910***	0.0976***	0.0717***	0.0906***
	(11.32)	(8.60)	(11.22)	(11.22)	(8.06)	(10.98)
Age	0.0090**	0.0070*	0.0103**	0.0026	-0.0061	0.0033
	(3.13)	(2.31)	(3.25)	(0.63)	(-1.18)	(0.89)
Population density	0.0005**	0.0006***	0.0006***	0.0003*	0.0002	0.0005**
	(3.28)	(3.90)	(3.67)	(2.18)	(0.87)	(3.21)
W*ln w (λ)	0.1779*	0.1996*	0.3351***	0.2135*	0.4730***	0.3404**
	(2.28)	(2.23)	(4.57)	(2.01)	(3.63)	(3.11)

t statistic in parenthesis. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Chapter V

Conclusions

V.1 Main results

The main goal of this thesis is to analyze the effects of the urban structure on the labor market outcomes of the individuals focusing on the case of the Metropolitan Area of Mexico City, one of the largest megacities in the World. Throughout the thesis we provide evidence of the existence of the relationship between urban structure and selected labor market outcomes, such as employment probability, the degree of informal employment, and the real wages.

Our analysis mainly focus on the separation between formal and informal labor conditions. In other words, attention must be paid to the distinction between formal and informal jobs in the job accessibility and the number of formal and informal workers in the household and in the neighborhood. In Chapter II, we conclude that the accessibility to different types of job opportunities (formal vs informal) is relevant to explain the probability of employment as an informal or formal worker. In Chapter III, we find that the effects of social interaction and family ties within social networks affect the probability of filling up a formal job depending on the composition of neighborhoods or households in terms of formal/informal workers.

In Chapter IV, it is relevant to stress that we find that job access generates the strongest spillover effects on non-employ-ment rates, informal employment rates and wages. Additionally, in this chapter we assess that there are spillover effects on non-employment rates, informal employment rates, and wages in intra-urban context. The adoption of different spatial econometric models allows us to distinguish between global and local spillover effects. The existence of global spillovers effects captures the possible presence of feedback effects or endogenous effects. Meanwhile, the existence of local spillover effects implies that the contextual effects or socioeconomic composition of neighborhoods go beyond the own neighborhood boundaries.

Moreover, the previous results are not identical for women and men. In Chapter II where we focus on the problem of disconnection between place of residence and job opportunities, our results state that the impact of job accessibility is more relevant to women than to men, above all when they are unskilled. In the wake of Chapter II and III centers on residential segregation. On the one hand, our conclusions emphasize that residential segregation has negative effects on labor-force participation in case of married women. On the other hand living in a deprived neighborhood decreases men's probability of being a formal worker. Chapters II and III provide partial insights of the effects of urban structure and gender issues in labor market because they deal with one time period. Instead, Chapter IV extends the temporal dimension of the analysis such to cover three decades: 1990, 2000 and 2010. Additionally, we move from using individual data to aggregated data at census tract level. In this new setting we are able to determine that, in general, neighborhood composition or exogenous (contextual) variables have greater effects on women's labor market outcomes than men's.

In summary, the main results of the thesis indicate that access to jobs have the strongest effects on employment and informal employment. Job accessibility increases the probability of being employed among women. The access to formal jobs increases the probability of being a formal worker; meanwhile the access to informal jobs decreases this probability among less-educated workers. In order to determine our labor market outcomes, another important variable is the poor living conditions in the neighborhood that decrease both the probability of being a formal worker in the case of men and the probability of being employed in the case of women. Last but not least, a third variable that strengthens the effects of the above mentioned variables on the three selected labor market outcomes is the social interactions or endogenous effects.

Our results may not be particular to Mexico City. Other Latin American Cities suffer from spatial disconnection, residential segregation, and job informality, as it was discussed in Chapter III.[1] Therefore it is important to understand how having access to jobs and living in deprived neighborhood affects labor market outcomes, especially informal employment.

V.2 Policy implications

The results of the thesis offer elements to ground a discussion on policy implications. Among the policies that could be implemented in order to reduce spatial disconnection and improve the conditions of poor individuals living in deprived neighborhoods are the facilitation of residential mobility, neighborhood regeneration policies, the development or subsidization of public and private transport, the spatial dissemination of information on available jobs, and the implementation of anti-discriminatory laws, among others.

Different policies have been put in place with a spatial focus. There has been central city repopulation policies in Mexico City. This type of policy can help to reduce the spatial mismatch or to decrease the distance between workplaces and residential locations. As the results of the Thesis show the access to job opportunities increases the employment probability of individuals. However, the price of housing is very high in the central area, hence low income households have no access to this central area housing. The incentives of residential mobility of low income households entails subsidizing the land prices or the price of housing which could be very costly. A better alternative could be to increase the public transport infrastructure connecting the most

[1] For an extensive review see the McKinsey Global Institute (2011) *Building globally competitive cities: The key to Latin American growth.*

remote peripheral residential places with the central workplaces.

In some cases, the urban infrastructure is unsuitable or insufficient, such as Mexico City. This city needs greater public-transport infrastructure to connect remote residential areas with employment centers, especially those offering formal employment. Moreover, the spatial disconnection affects microenterprises' access to human capital and the exploitation of agglomeration economies and the formation of individual human capital. A substantial proportion of these individuals becomes informal workers in domestic microenterprises because it is the only option. The development and improvement of urban infrastructure may help to increase the productivity of both domestic microenterprises and workers located in deprived zones.

Therefore, public-transport infrastructure investment that connects the employment centers with labor supply location may reduce effects of residential segregation, informal employment and unemployment. In recent years there has been investment in transport infrastructure in Mexico City. However, it is still lacking, especially in the periphery of the city where most people have only the bus as means of transport.

Additionally, policies can also be developed to create formal job subcenters close to the most densely populated areas through the formalization of informal jobs or the creation of formal jobs. Most of the people that lives in the periphery of the city becomes informal because informal workplaces are closer to them. One of the causes of informality is the lack of formal credit. [2]

Since 2007, a program to improve the urban environment in Mexico City has been implemented: the *Programa Comunitario de Mejoramiento Barrial*. This program aims to facilitate the association and organization of individuals within a deprived neighborhood in order to improve the internal urban public space. The goal is to strengthen the social network ties in these neighborhoods. This type of program should be implemented along with other job training programs for individuals and credit for micro-firms in order to integrate both firms and workers into the urban development of neighborhoods. This can help local firms to grow, develop, and legalize, and it could thus increase productivity. Additional results may be the reduction of social deprivation of these zones and the increase of the social network ties. Then informal employment could be reduced and the employment probability could be increased given the effects that we identify in this thesis.

Social programs based on social interactions can strengthen social network ties or produce new networks. This generates spillover effects that may increase the effects of macroeconomic policies, such as education, housing, employment, and social security. Social networks and social interaction effects may be relevant, as shown by the results of this thesis. The combination and integration of different public policies may yield stronger effects than non-integrated policies because the externalities of social interaction matter.

[2] The formalization of informal employment could be achieved through the programs that give some credit to informal firms on the condition that within a fixed term they become formal.

V.3 Future lines of research

The results of this thesis suggest possible extensions for future research. A first line of research will be to consider the existence of the heterogeneity of labor informality in a static and a dynamic framework. In this thesis, we only consider informality status selecting wage earners. Self-employment has not been included in the informality realm. This choice given by data availability constrains the heterogeneity of the informal workers in our sample. We did not study the heterogeneity of labor informality, and we only concentrated on informal salaried workers, because our available data did not allow us to discern which part of self-employment and employees are in the informal sector. This improvement in the quality of data can better the analysis in two directions. First, it may increase the variety of job options in the static analysis of the probability of being a formal/informal worker. And second, this additional variety of options will enrich the structure of the dynamic framework introducing the possibility of switching between different labor statuses.

A second extension is to bring the static analysis of Chapter IV to a dynamic framework according to the availability of further census waves by estimating different kinds of dynamic spatial panel models.

A third extension could be to compare our findings for Mexico City with other Latin American cities experiencing similar problems of connectivity and employment informality.

A final valuable extension, will be to build a theoretical model that incorporates different spatial frictions and urban agglomeration economies with two sectors, namely the formal and the informal. The scope is to explain the effects of urban structure on informal sector as a whole more precisely; that is including job informality. Moreover, this model will allow simulating the effects of different urban public policies on labor market outcomes. The idea is to build it by merging two strands of literature: the standard search and matching framework with an exogenous job-destruction probability (*à la Diamond-Mortensen-Pissarides)*, and an urban structure model (*à la Lucas and Rossi-Hansberg*).

Appendix A

Indexes

A.1 Social deprivation index

Social deprivation index (SDI) is constructed using CONEVAL's methodology. The used index of Chapter III is composed of 12 indicators. In the Table (A.1.1), we present each of these indicators.

Table A.1.1: Indicators of social deprivation index of Chapter III

Indicators
Education
Percentage of illiterate population aged 15 years and more
Percentage of population aged 6 to 14 who does not attend school
Percentage of population aged 15 and more with incomplete basic education
Access to social security
Percentage of population that has no access to social security
Quantity and quality of dwelling services
Percentage of inhabited dwellings with earth floor
Percentage of occupants per room (overcrowding)
Basic dwelling services
Percentage of inhabited dwellings that have no toilet or lavatory
Percentage of inhabited dwellings that have no access to piped water from a public network
Percentage of inhabited dwellings that have no drainage
Percentage of inhabited dwellings that have no access to electricity
Basic durable housing goods
Percentage of inhabited dwellings that do not have wash machine
Percentage of inhabited dwellings that do not have refrigerator

The social deprivation index of Chapter IV (SDI_t) is a composite index by 7 variables. These variables are presented in Table A.1.2. The social deprivation index of ChapterIV has fewer indicators than that of Chapter III due to two reasons. The first reason is data available, for the 1990 Population and Housing Census we do not have information about basic durable housing goods and social security. The second reason is that we have the mean education of working individuals in the estimations of Chapter IV, then we exclude percentage of illiterate population and percentage of population with incomplete basic education.

Table A.1.2: Indicators of social deprivation index of Chapter IV

Indicators
Education
Percentage of population aged 6 to 14 who does not attend school
Quantity and quality of dwelling services
Percentage of inhabited dwellings with earth floor
Percentage of occupants per room (overcrowding)
Basic dwelling services
Percentage of inhabited dwellings that have no toilet or lavatory
Percentage of inhabited dwellings that have no access to piped water from a public network
Percentage of inhabited dwellings that have no drainage
Percentage of inhabited dwellings that have no access to electricity

A.2 Job accessibility index

Power accessibility indexes are calculated using the following equation:

$$AI_{ik}(d) = \sum_{j} \frac{\mathit{Jobs}_{jk} f(d_{ij})}{\sum_s \mathit{Workers}_{sjk} f(d_{sj})} \tag{A.1}$$

where $f(d_{ij}) = d_{ij}^{-1}$ is the impedance function, d_{ij} is the distance in kilometers from zone i to zone j; Jobs_{jk} is the job of type k (formal or informal) in zone j; $\mathit{Workers}_{sjk}$ are the total occupied individuals of type k (or economically active population) that could commute from zone s to zone j. This index is a gravitational index that includes two friction terms, the first is the distance and the second is the labor competition or labor supply weighted by the distance that this supply has to commute.

In Chapter III, we use the Economic Census 2009 and the Population and Housing Census 2010 to calculate job accessibility indexes. The total number of workers or occupied individuals is obtained from the Census of the Federal District and the State of Mexico. To compute the total formal and informal workers, we assume that the distribution of economically active population by labor status is the same as the distribution occupied population by labor status in each *estrato*. The total formal and informal employment or jobs are calculated with data of Microcensus of the Federal District, the State of Mexico, Hidalgo, Morelos, Queretaro, Puebla and Tlaxcala, and the Economic Census 2009. We assume that the distribution of formal and informal jobs by sector in each *estrato* is the same as the distribution of formal and informal jobs by sector in each municipality. Centroids of *estratos* are selected considering the census track with the highest population density.

In Chapter IV, we use a variant of this index:

$$AI_{it}(d) = \sum_{j=1}^{N} \frac{\mathit{Jobs}_{jt} f(d_{ij})}{\sum_{s=1}^{N} \mathit{Workers}_{sjt} f(d_{sj})} \tag{A.2}$$

Jobs_{jt} is the total jobs in tract j in year t; $\mathit{Workers}_{sjt}$ are the total occupied individuals (or economically active population) that could commute from tract s to tract j in year t. We use the Economic Census of 1989, 1999 and 2009 and the Population and Housing Census of 1990, 2000 and 2010 to calculate job accessibility index by year.

A.3 Measures of spatial correlation

The formula to calculate the Moran's I is:

$$I = \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \tag{A.3}$$

where N is the total number of census tract or *estratos* indexed by i and j, X is the variable of interest, $\bar{X}$ is the mean of X and w_{ij} is an element of the spatial weight matrix.

The global G test, $G(d)$, is defined as a measure of spatial concentration of X and it is calculated as follows:

$$G(d) = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij} X_i X_j}{\sum_{i=1}^{N}\sum_{j=1}^{N} X_i X_j}, \qquad \forall i \neq j. \tag{A.4}$$

The global G test, $G(d)$, defined as a measure of spatial concentration of X is calculated as follows: The null hypothesis of $G(d)$ test is that there is no spatial autocorrelation. In the case of rejecting the null hypothesis, positive z-values indicates that high values for a given attribute are clustered in the city, while negative z-values reflects that low values of this attribute are clustered.

The formula to calculate the local Moran's I is:

$$I_i = \frac{(X_i - \bar{X})}{\sum_{j=1, j\neq i}^{N} \frac{(X_j - \bar{X})^2}{N-1} - \bar{X}^2} \sum_{j=1, j\neq i}^{N} w_{ij}(Xj - \bar{X}). \tag{A.5}$$

A.4 Segregation Indexes

There are several quantitative indicators of residential segregation. The dissimilarity index (DI) measures the proportion of X and Y that would have to change residence/neighborhood in order to the proportion of X and Y would be the same in each neighborhood. In other words, it measures the distribution of a given group of population in urban space. It is calculated with the following formula:

$$DI = \frac{1}{2}\sum_{i=1}^{N}\left|\frac{X_i}{X} - \frac{Y_i}{Y}\right|, \qquad 0 \leq ID \leq 1 \tag{A.6}$$

A dissimilarity index equal to zero implies that the two distributions are the same in the space, while a dissimilarity index equal to one means the maximum of segregation where no distribution overlaps in space.

The isolation index (II) measures the probability that an individual share the same spatial unit with an individual of the same group.

$$II = \sum_{i=1}^{N}\left[\left(\frac{X_i}{X}\right)\left(\frac{X_i}{P_i}\right)\right]. \tag{A.7}$$

The isolation index corrected by asymmetry is equal to:

$$\eta^2 = \frac{II - p}{1 - p} \tag{A.8}$$

In all these indices X is the total number of individuals with a specific attribute and Y is the rest of individuals who do not have this attribute. For example, X would be the total number of non-employed persons, while Y would be the total number of employed persons in the city. N is the total number of tracts with indexed by i. X_i is the total number of individuals with an attribute that reside in tract i, and P_i is the total of individuals living in tract i, in this case P_i is equal to $X_i + Y_i$. p is the proportion of individuals with an attribute in the whole city, that is, $p = X/(X + Y)$.

Appendix B

R Code

```
library(sphet)
library(MASS)
library(coda)
library(Matrix)
library(Rcgmin)
library(corpcor)

spgmsdmsl <- function(formula, data=list(), listw=NULL, listw2=NULL, listw3=NULL, model=c("fixed","random"), twoways
     =FALSE, abs.tol=1e-20, rel.tol=1e-10, eps=1e-5, chol=FALSE, W3XI=TRUE, inst=FALSE) {

if(attr(terms(formula), "intercept") == 0 ) formula <- as.formula(paste(attr(terms(formula),"variables")[1+attr(
     terms(formula),"response")], paste(attr(terms(formula),"term.labels"), collapse="+"), sep="~"))

# Spatial weight matrix

  W <- listw2dgCMatrix(listw)          # Error
  W2 <- listw2dgCMatrix(listw2)        # Dependent variable
  W3 <- listw2dgCMatrix(listw3)        # Independent variable

# Sort the data by year

  index <- data[,1]
  tindex <- data[,2]

  data$index <- data[,1]

  names(index)<-row.names(data)
  ind <-index[which(names(index)%in%row.names(data))]
  tind<-tindex[which(names(index)%in%row.names(data))]
  spord <- order(tind, ind)
  data <- data[spord,]

# Labels of the model

  mt <- terms(formula, data = data)

# Variables of the model

  mf <- lm(formula, data, na.action = na.fail, method = "model.frame")

  y <- model.extract(mf, "response")
  x <- model.matrix(mt, mf)
  namesx <- colnames(x)

  N <- length(unique(ind))                          # Individuals
  k <- dim(x)[[2]]                                  # Variables
  T <- max(tapply(x[,1],ind,length))                # Time
  NT <- length(ind)                                 # Individuals*Time
  indic <- rep(1:N,T)                               # ID of individuals

# Creating the matrix transformations

  I_T <- Diagonal(T)
  I_N <- Diagonal(N)
  eT <- rep(1,T)
  JT <- eT%*%t(eT)
  Q1 <- kronecker(JT/T,I_N)            # Between transformation
  Q0 <- kronecker(I_T,I_N) - Q1        # Within transformation
  Q2 <- kronecker(JT,I_N)              # Sum by year

#  Spatial Weight Matrix

  Ws <- kronecker(I_T, W)
  Ws2 <- kronecker(I_T, W2)
  Ws3 <- kronecker(I_T, W3)

#  Lag of dependent variable
```

```
  wy <- as.matrix(Ws2 %*% y)
  colnames(wy) <- "lambda"

#  Lag of independent variables

  WX <- Ws3%*%x[,-1]
  colnames(WX) <- paste('W*', colnames(x[,-1]), sep='')

# Instruments

  if (inst) {
    WWX <- Ws3 %*% WX
    W3X <- Ws3 %*% WWX
  } else {
    WX2 <- Ws2 %*% x[,-1]
    WWX <- Ws2 %*% WX2
    W3X <- Ws2 %*% WWX
    }

  if (W3XI) HH <- cBind(WWX, W3X)
  else HH <- WWX

  # Transform y and X

  x2 <- x[,-1]
  ywithin <- as.matrix(Q0%*%y)
  Xwithin <- as.matrix(Q0%*%x2)
  wywithin <- as.matrix(Q0%*%wy)
  colnames(wywithin) <- colnames(wy)
  HHwithin <- as.matrix(Q0%*%HH)
  colnames(Xwithin) <- colnames(x[-1])

  WXwithin <- Ws3 %*% Xwithin

  xf <- cBind(x, WX)
  xf2 <- cBind(x2, WX)
  xfw <- cBind(Xwithin, WXwithin)

if (model=="fixed"){

  if (twoways) {

    k <- k + (T-1)
    time <- kronecker(Diagonal(T),rep(1,N))
    namest <- unique(tindex)
    colnames(time) <- namest
    time <- time[,-1]
    Xtime <- as.matrix(Q0%*%time)
    xf2 <- cBind(xf2, time)
    xfw <- cBind(xfw, Xtime)

  }

  # Step 1.a

  # Estimate a 2SLS
    res0 <- spgm.tsls(y=y, yend=wy, X=xf2, Zinst=HH, Y1=y, WY1=wy, X1=xf2, robust=FALSE)
    u0 <- res0$residuals

    Gg <- gammas(Ws=Ws, u=u0, N=N, T=T, Q0=Q0, Q1=Q1)

  # Initial values of Optimization
    wu <- as.matrix(Ws %*% u0)
    r.init <- solve(crossprod(u0),crossprod(u0,wu))
    mu.init <- 1/(N*T-N)*sum(crossprod(u0))
    pars <- c(as.numeric(r.init), as.numeric(mu.init))

  # Optimization function (1)
    estim1 <- nlminb(pars, arg, v = Gg, control = list(abs.tol=abs.tol,rel.tol=rel.tol), lower=c(-0.999,0), upper=c
         (0.999, Inf))

  # rho1 and sigma_mu
    param <- estim1$par

  # Step 1.b

  # Moment weighting matrix
    WV <- VGM(rho=estim1$par[1], sigmam=estim1$par[2], u=u0, Ws=Ws, W=W, Q0=Q0, Q1=Q1, N=N, T=T, eT=eT, H=cBind(xf2,
          HH), Z=cBind(wy, xf2),  Z1=cBind(wy, xf2), model="fixed", spatial=FALSE)

  # Optimization function (2)
    estim2 <- nlminb(param, arg1, lower=c(-0.999,0), upper=c(0.999, Inf), control=list(abs.tol=abs.tol,rel.tol=rel.
         tol), v=Gg, VC=WV$Vinv)
    if (estim2$convergence!=0){
        WV <- VGM(rho=estim1$par[1], sigmam=0, u=u0, Ws=Ws, W=W, Q0=Q0, Q1=Q1, N=N, T=T, eT=eT, H=cBind(xfw,
             HHwithin), Z=cBind(wywithin, xfw),  Z1=cBind(wywithin, xfw), model="fixed", spatial=FALSE)
        estim2 <- optim(par=param, fn=arg1, v=Gg, VC=WV$Vinv)
    }

    rhotilde <- estim2$par[1]
```

```
# Step 2

# Spatial transormations

  R <- Diagonal(NT) - rhotilde*Ws

  ys <- R%*%y
  Xs <- R%*%xf2
  Wys <- R%*%wy
  Hs <- R%*%HH
  colnames(Wys) <- "lambda"

  ysw <- R%*%ywithin
  Xsw <- R%*%xfw
  Wysw <- R%*%wywithin
  Hsw <- R%*%HHwithin
  colnames(Xsw) <- colnames(xf2)
  colnames(Wysw) <- "lambda"

# Estimate a GS2SLS
  res1 <- spgm.tsls(y=ys, yend=Wys, X=Xs, Zinst=Hs, Y1=y, WY1=wy, X1=xf2, robust=FALSE)
  u1 <- res1$residuals

  Gg <- gammas(Ws=Ws, u=u1, N=N, T=T, Q0=Q0, Q1=Q1)

# Moment weigthing matrix
  WV <- VGM(rho=rhotilde, sigmam=estim2$par[2], u=u1, Ws=Ws, W=W, Q0=Q0, Q1=Q1, N=N, T=T, eT=eT, H=cBind(xf2, HH),
        Z=cBind(Wys, Xs), Z1=cBind(wy, xf2), model="fixed", spatial=TRUE)

  pars <- estim2$par

# Optimization function (3)
  estim3 <- nlminb(pars, arg1, lower=c(-0.999,0), upper=c(0.999, Inf), control=list(abs.tol=abs.tol,rel.tol=rel.
       tol), v=Gg, VC=WV$Vinv)
  if (estim3$convergence!=0){
      WV <- VGM(rho=rhotilde, sigmam=0, u=u1, Ws=Ws, W=W, Q0=Q0, Q1=Q1, N=N, T=T, eT=eT, H=cBind(xfw, HHwithin), Z
           =cBind(Wysw, Xsw), Z1=cBind(wywithin, xfw), model="fixed", spatial=TRUE)
      estim3 <- optim(par=param, fn=arg1, v=Gg, VC=WV$Vinv)
  }

  rhohat <- estim3$par[1]
  names(rhohat) <- "rho"
  sigma_mu <- estim3$par[2]
  names(sigma_mu) <- "sigma_mu"

# Step 3

# Consitent estimate of betas

  res2 <- spgm.tsls(y=ysw, yend=Wysw, X=Xsw, Zinst=Hsw, Y1=ywithin, WY1=wywithin, X1=xfw, robust=TRUE)

  res3 <- spgm.tsls(y=ywithin, yend=wywithin, X=xfw, Zinst=HHwithin, Y1=ywithin, WY1=wywithin, X1=xfw, robust=TRUE
       )
  SS <- as(Diagonal(,as.vector(res3$residuals^2)),"sparseMatrix")

  NR <- Diagonal(NT) - rhohat*Ws
  Xswn <- NR%*%xfw
  Wyswn <- NR%*%wywithin
  ZN <- cBind(Wyswn, Xswn)

  WV <- VGM(rho=rhohat, sigmam=sigma_mu, u=u1, Ws=Ws, W=W, Q0=Q0, Q1=Q1, N=N, T=T, eT=eT, H=cBind(xfw, HHwithin),
       Z=ZN, Z1=cBind(wywithin, xfw), model="fixed", spatial=TRUE, Sigma=SS)

  Coef <- c(res2$coefficients, rhohat, sigma_mu)

# Variance and Covariance Matrix

  J <- matrix(nrow=3, ncol=2)
  J[,1] <- c(1, 2*rhohat, 0)
  J[,2] <- c(0,0, 1)
  J <- Gg$bigG%*%J

  if (chol) varb <- Omega(P=WV$P, Fv=WV$Fv, Tva=WV$Tva, J=J, Phi=WV$V, Phiv=WV$Vinv, N=N, T=T, Sigma=SS, sigmam=
       sigma_mu, model="fixed", chol=TRUE)
  else varb <- Omega(P=WV$P, Fv=WV$Fv, Tva=WV$Tva, J=J, Phi=WV$V, Phiv=WV$Vinv, N=N, T=T, Sigma=SS, sigmam=sigma_
       mu, model="fixed")

# Spatial Trasformations

  yF <- NR%*%y
  xF <- NR%*%xf2

# Spatial fixed effects

  nn <- nrow(res2$coefficients)
  WyF <- as.matrix(res2$coefficients[1]*Ws2%*%yF)
  y1 <- yF - WyF - xF%*%res2$coefficients[2:nn]
  mi <- as.matrix(Q1%*%y1)

# Goodness of fit measures
```

```
    error <- yF - WyF - xF%*%res2$coefficients[2:nn] - mi
    rsqr1 <- as.matrix(t(error)%*%error)
    ym <- y - mean(y)
    rsqr2 <- as.matrix(t(ym)%*%ym)

    IW <- solve(Diagonal(NT)-res2$coefficients[1]*Ws2)
    xtt <- xfw%*%res2$coefficients[2:nn]
    yhatw <-IW%*%xtt
    yy1 <- as.matrix(ywithin-mean(ywithin))
    yy2 <- as.matrix(yhatw-mean(ywithin))
    yya <- as.matrix(t(yy1)%*%yy2)
    yyb1 <- as.matrix(t(yy1)%*%yy1)
    yyb2 <- as.matrix(t(yy2)%*%yy2)

}
else{
# RANDOM EFFECTS

# Step 1a

  # Estimate a 2SLS

    res0 <- spgm.tsls(y=y, yend=wy, X=xf, Zinst=HH, Y1=y, WY1=wy, X1=xf, robust=FALSE)
    u0 <- res0$residuals

    Gg <- gammas(Ws=Ws, u=u0, N=N, T=T, Q0=Q0, Q1=Q1)

  # Initial values of Optimization

    wu <- as.matrix(Ws %*% u0)
    r.init <- solve(crossprod(u0),crossprod(u0,wu))
    mu.init <- 1/(N*T-N)*sum(crossprod(u0))
    pars <- c(as.numeric(r.init), as.numeric(mu.init))

  # Optimization function

    estim1 <- nlminb(pars, arg, v = Gg, control = list(abs.tol=abs.tol,rel.tol=rel.tol), lower=c(-0.999,0), upper=c
         (0.999, Inf))

  # rho1 and sigma_mu
    param <- estim1$par

# Step 1.b

    WV <- VGM(rho=estim1$par[1], sigmam=estim1$par[2], u=u0, Ws=Ws, W=W, Q0=Q0, Q1=Q1, N=N, T=T, eT=eT, H=cBind(xf,
         HH), Z=cBind(wy, xf), Z1=cBind(wy, xf), model="random", spatial=FALSE)

    estim2 <- nlminb(param, arg1, lower=c(-0.999,0), upper=c(0.999, Inf), control=list(abs.tol=abs.tol,rel.tol=rel.
         tol), v=Gg, VC=WV$Vinv)

    if (estim2$message=="singular␣convergence␣(7)" | (estim2$message=="false␣convergence␣(8)" & abs(estim2$objective
         )>=.01)){
      estimm <- estim2$message
      WV <- VGM(rho=estim1$par[1], sigmam=0, u=u0, Ws=Ws, W=W, Q0=Q0, Q1=Q1, N=N, T=T, eT=eT, H=cBind(xf, HH), Z=
           cBind(wy, xf), Z1=cBind(wy,xf), model="random", spatial=FALSE)
      bigG2 <- Gg$bigG[1:2,1:2]
      smallg2 <- Gg$smallg[1:2]
      Gg2 <- list(bigG = bigG2, smallg = smallg2)
      WV2 <- WV$Vinv[1:2,1:2]
      par2 <- estim1$par[1]
      estim2 <- nlminb(par2, arg2, lower=-1, upper=1, v=Gg2, VC=WV2)
          R <- Diagonal(NT) - estim2$par*Ws
          ys <- R%*%y
          Xs <- R%*%xf
          Wys <- R%*%wy
          Hs <- R%*%HH
          res1 <- spgm.tsls(y=ys, yend=Wys, X=Xs, Zinst=Hs, Y1=y, WY1=wy, X1=xf, robust=FALSE)
          u1 <- res1$residuals
          Gg <- gammas(Ws=Ws, u=u1, N=N, T=T, Q0=Q0, Q1=Q1)
          WV <- VGM(rho=estim2$par, sigmam=0, u=u1, Ws=Ws, W=W, Q0=Q0, Q1=Q1, N=N, T=T, eT=eT, H=cBind(xf, HH), Z=
               cBind(Wys, Xs), Z1=cBind(wy, xf), model="random", spatial=TRUE)
      estim2 <- nlminb(param, arg1, lower=c(-0.999,0), upper=c(0.999, Inf), control=list(abs.tol=abs.tol,rel.tol=rel
           .tol), v=Gg, VC=WV$Vinv)
      }

    rhotilde <- estim2$par[1]
    sigmatilde <- estim2$par[2]

# Step 2

  # Spatial transormations

    R <- Diagonal(NT) - rhotilde*Ws

    ys <- R%*%y
    Xs <- R%*%xf
    Wys <- R%*%wy
    Hs <- R%*%HH
    colnames(Xs) <- colnames(xf)
    colnames(Wys) <- "lambda"
```

```
# Estimate a GS2SLS
  res1 <- spgm.tsls(y=ys, yend=Wys, X=Xs, Zinst=Hs, Y1=y, WY1=wy, X1=xf, robust=FALSE)

  u1 <- res1$residuals

  Gg <- gammas(Ws=Ws, u=u1, N=N, T=T, Q0=Q0, Q1=Q1)

# Moment weigthing matrix
  WV <- VGM(rho=rhotilde, sigmam=estim2$par[2], u=u1, Ws=Ws, W=W, Q0=Q0, Q1=Q1, N=N, T=T, eT=eT, H=cBind(xf, HH),
       Z=cBind(Wys, Xs), Z1=cBind(wy, xf), model="random", spatial=TRUE)

  pars <- estim2$par

# Optimization function (3)
  estim3 <- nlminb(pars, arg1, lower=c(-0.999,0), upper=c(0.999, Inf), control=list(abs.tol=abs.tol,rel.tol=rel.
       tol), v=Gg, VC=WV$Vinv)

      if (estim3$message=="singular␣convergence␣(7)" | (estim3$message=="false␣convergence␣(8)")){
        sigmammt <- estim3$par[2]
        WV <- VGM(rho=rhotilde, sigmam=0, u=u1, Ws=Ws, W=W, Q0=Q0, Q1=Q1, N=N, T=T, eT=eT, H=cBind(xf, HH), Z=
             cBind(Wys, Xs), Z1=cBind(wy,xf), model="random", spatial=TRUE)
        estim3 <- optim(par=param, fn=arg1, v=Gg, VC=WV$Vinv)
        sigmatilde <- estim3$par[2]
        if (estim3$convergence!=0 & abs(estim3$par[1])>1 & sigmammt<1){
            WV <- VGM(rho=rhotilde, sigmam=sigmammt, u=u1, Ws=Ws, W=W, Q0=Q0, Q1=Q1, N=N, T=T, eT=eT, H=cBind(xf,
                 HH), Z=cBind(Wys, Xs), Z1=cBind(wy,xf), model="random", spatial=TRUE)
            estim3 <- Rcgmin(pars, arg1, lower=-0.999, upper=0.999, bdmsk=c(1,0), v=Gg, VC=WV$Vinv)
            sigmatilde <- estim3$par[2]
            }
        }

  rhohat <- estim3$par[1]
  names(rhohat) <- "rho"
  sigma_mu <- estim3$par[2]
  names(sigma_mu) <- "sigma_mu"

# Step 3

# Consitent estimate of betas

  uwithin <- Q1%*%u1
  sigma_vi <- Q2%*%(uwithin^2)
  sigma_vi <- (1/(T-1))*as.vector(sigma_vi)

  ystw <- Q0%*%ys
  ystb <- Q1%*%ys
  yst <- ystw/sqrt(sigma_vi) + ystb/sqrt(T*sigmatilde+sigma_vi)
  Wystw <- Q0%*%Wys
  Wystb <- Q1%*%Wys
  Wyst <- Wystw/sqrt(sigma_vi) + Wystb/sqrt(T*sigmatilde+sigma_vi)
  Xstw <- Q0%*%Xs
  Xstb <- Q1%*%Xs
  Xst <- Xstw/sqrt(sigma_vi) + Xstb/sqrt(T*sigmatilde+sigma_vi)
  HHstw <- Q0%*%Hs
  HHstb <- Q1%*%Hs
  HHst <- HHstw/sqrt(sigma_vi) + HHstb/sqrt(T*sigmatilde+sigma_vi)

  res2 <- spgm.tsls(y=yst, yend=Wyst, X=Xst, Zinst=HHst, Y1=yst, WY1=Wyst, X1=Xst, robust=TRUE)

  res3 <- spgm.tsls(y=ywithin, yend=wywithin, X=xfw, Zinst=HHwithin, Y1=ywithin, WY1=wywithin, X1=xfw, robust=TRUE
       )
  SS <- as(Diagonal(,as.vector(res3$residuals^2)),"sparseMatrix")

  NR <- Diagonal(NT) - rhohat*Ws
  Xsn <- NR%*%xf
  Wysn <- NR%*%wy

  Gg <- gammas(Ws=Ws, u=u1, N=N, T=T, Q0=Q0, Q1=Q1)
  WV <- VGM(rho=rhohat, sigmam=sigma_mu, u=u1, Ws=Ws, W=W, Q0=Q0, Q1=Q1, N=N, T=T, eT=eT, H=cBind(xf, HH), Z=cBind
       (Wysn, Xsn), Z1=cBind(wy, xf), model="random", spatial=TRUE, Sigma=SS)

  Coef <- c(res2$coefficients, rhohat, sigma_mu)

# Variance and Covariance Matrix

  J <- matrix(nrow=3, ncol=2)
  J[,1] <- c(1, 2*rhohat, 0)
  J[,2] <- c(0,0, 1)
  J <- Gg$bigG%*%J

  if (chol) varb <- Omega(P=WV$P, Fv=WV$Fv, Tva=WV$Tva, J=J, Phi=WV$V, Phiv=WV$Vinv, N=N, T=T, Sigma=SS, sigmam=
       sigma_mu, model="random", Fm=WV$Fm, Tma=WV$Tma, chol=TRUE)
  else varb <- Omega(P=WV$P, Fv=WV$Fv, Tva=WV$Tva, J=J, Phi=WV$V, Phiv=WV$Vinv, N=N, T=T, Sigma=SS, sigmam=sigma_
       mu, model="random", Fm=WV$Fm, Tma=WV$Tma)

# Transform the data

  yF <- NR%*%y
  theta <- 1 - sqrt(sigma_vi/(T*sigma_mu+sigma_vi))
  xp <- Xsn - theta*Q1%*%Xsn
```

```
    yp <- yF - theta*Q1%*%yF
    wyp <- (res2$coefficients[1])*Ws2%*%yp

  # Goodness of fit measures

    error <- yp - wyp - xp%*%res2$coefficients[-1]
    rsqr1 <- as.matrix(t(error)%*%error)
    ym <- as.matrix(y - mean(y))
    rsqr2 <- t(ym)%*%ym

    IW <- solve(Diagonal(NT)-res2$coefficients[1]*Ws2)
    xtt <- xf%*%res2$coefficients[-1]
    yhatw <-IW%*%xtt
    yy2 <- as.matrix(yhatw-mean(y))
    yya <- as.matrix(t(ym)%*%yy2)
    yyb1 <- rsqr2
    yyb2 <- as.matrix(t(yy2)%*%yy2)

}

   # Print Results

    result <- list(coefficients=Coef, var=varb, estim1=estim1, estim2=estim2, estim3=estim3)
    rest.se <- sqrt(diag(varb))
    result$Coef <- cbind(Coef, rest.se, Coef/rest.se, 2*(1-pnorm(abs(Coef/rest.se))))
    colnames(result$Coef) <- c('Estimate', 'SD', 'zvalue', 'pvalue')
    result$R2 <- data.frame(sigma2=rsqr1, R2=1-(rsqr1/rsqr2), corr2=(yya^2)/(yyb1*yyb2))
    colnames(result$R2) <- c('sse', 'R2', 'corr2')
    result

}

# Function of two least squares
spgm.tsls <- function(y, yend, X, Zinst, Y1, WY1, X1, robust=TRUE) {

  H <- cBind(X,Zinst)
  Z <- cBind(yend,X)
  df <- nrow(Z) - ncol(Z)
  HH <- solve(crossprod(H,H))
  P <- H%*%HH%*%t(H)
  Zp <- P%*%Z
  ZpZ <- solve(crossprod(Zp,Z))
  Zpy <- crossprod(Zp,y)
  biv <- as.matrix(ZpZ %*% Zpy)
  Z1 <- cBind(WY1,X1)
  yp <- Z1 %*% biv
  e <- as.matrix(Y1 - yp)
  names(biv) <- colnames(Z)

  if (robust) {

        sse <- c(crossprod(e,e))
        omega <- as.numeric(e^2)
        ZoZ<-crossprod(Zp,(Zp*omega))
        varb<-as.matrix(ZpZ%*%ZoZ%*%ZpZ)

                result <- list(coefficients=biv, var=varb, sse=sse, residuals=c(e), df=df)
                rest.se <- sqrt(diag(result$var))
                result$Coef <- cbind(coefficients=result$coefficients, rest.se, result$coefficients/rest.se, 2*(1-
                     pnorm(abs(result$coefficients/rest.se))))

        } else {

        sse <- c(crossprod(e,e))
        s2 <- sse / df
        varb <- ZpZ * s2
                result <- list(coefficients=biv, var=varb, sse=sse, residuals=c(e), df=df)
                rest.se <- sqrt(diag(result$var))
                result$Coef <- cbind(result$coefficients, rest.se , result$coefficients/rest.se, 2*(1-pnorm(abs(
                     result$coefficients/rest.se))))
                }
        result
}

# Parameters of the optimization function
gammas <- function(Ws, u, N, T, Q0, Q1) {

    WsWs <- t(Ws)%*%Ws

    A1 <- Q0%*%(WsWs)
    diag(A1) <- 0
    A2 <- Q0%*%Ws
    A3 <- Q1%*%(WsWs)
    diag(A3) <- 0
    A4 <- Q1%*%Ws

    ub <- Ws%*%u

# smallg

    g1 <- t(u)%*%A1%*%u          # gamma1
```

```
    g2 <- t(u)%*%A2%*%u          # gamma2
    g3 <- t(u)%*%A3%*%u          # gamma3
    g4 <- t(u)%*%A4%*%u          # gamma4

    smallg <- c(as.matrix(g1), as.matrix(g2), as.matrix(g3), as.matrix(g4))/(N*(T-1))

# bigG

    AA2 <- A2+t(A2)
    AA3 <- A2+t(A3)
    AA4 <- A4+t(A4)

    G11 <- 2*(t(ub)%*%A1%*%u)
    G12 <- t(ub)%*%A1%*%ub
    G21 <- t(ub)%*%AA2%*%u
    G22 <- t(ub)%*%A2%*%ub
    G31 <- t(ub)%*%AA3%*%u
    G32 <- t(ub)%*%A3%*%ub
    G33 <- T*sum(diag(WsWs))
    G41 <- t(ub)%*%AA4%*%u
    G42 <- t(ub)%*%A4%*%ub

    bigG <- matrix(0, 4, 3)
    bigG[, 1] <- c(as.numeric(G11)/(T-1), as.numeric(G21)/(T-1), as.numeric(G31)/T, as.numeric(G41)/T )/N
    bigG[, 2] <- -c(as.numeric(G12)/(T-1), as.numeric(G22)/(T-1), as.numeric(G32)/T, as.numeric(G42)/T)/N
    bigG[, 3] <- c(0, 0, G33, 0)

    list(bigG = bigG, smallg = smallg)
}

# Optimization function of step 1a

arg <- function(rhopar, v) {
    sys <- v$smallg - v$bigG %*% c(rhopar[1], rhopar[1]^2, rhopar[2])
    value <- sum(sys^2)
    value
}

# Optimization function of step 1b

arg1 <- function(rhopar, v, VC){
    sys <- v$smallg - v$bigG %*% c(rhopar[1], rhopar[1]^2, rhopar[2])
    value <- t(sys) %*%  VC  %*% sys
    value
}

# Optimization function of step 1b

arg2 <- function(rhopar, v, VC){
    sys <- v$smallg - v$bigG %*% c(rhopar, rhopar^2)
    value <- t(sys) %*%  VC  %*% sys
    value
}

# GMM Weighting Matrix
VGM <- function(rho, sigmam, u, Ws, W, Q0, Q1, N, T, eT, H, Z, Z1, model=c("fixed","random"), spatial=FALSE, Sigma=
     NULL) {

    WsWs <- t(Ws)%*%Ws
    WW <- t(W)%*%W

    A1 <- Q0%*%(WsWs)
    diag(A1) <- 0
    A2 <- Q0%*%Ws
    A3 <- Q1%*%(WsWs)
    diag(A3) <- 0
    A4 <- Q1%*%Ws

    Wu <- Ws%*%u
    urWu <- u-rho*Wu
    if(is.null(Sigma)) Sigma <- as(Diagonal(,as.vector(urWu^2)),"sparseMatrix")

    HH <- crossprod(H,H)/(T)
    HH <- solve(HH)
    HZ <- (t(H)%*%Z)/(T)
    QQ1 <- HH%*%HZ
    QQ2 <- solve(t(HZ)%*%HH%*%HZ)
    P <- QQ1%*%QQ2

    InvW <- (Diagonal(N) - rho*t(W))
    InvW <- solve(InvW)
    InvW <- kronecker(Diagonal(T), InvW)

    if (spatial) Fv <- (Diagonal(N*T) - rho*Ws)%*%H
    else Fv <- InvW%*%H

    D <- -t(Z1)%*%(Diagonal(N*T) - rho*t(Ws))
    Tv <- Fv%*%P

    A1S <- A1%*%Sigma
    A2S <- A2%*%Sigma
```

```
  tA2S <- t(A2)%*%Sigma
  A3S <- A3%*%Sigma
  A4S <- A4%*%Sigma
  tA4S <- t(A4)%*%Sigma
  A2A2 <- (A2S+tA2S)
  A4A4 <- (A4S+tA4S)

  a1 <- A1%*%urWu
  a1 <- D%*%a1
  a1 <- a1*(1/(T-1))
  a2 <- A2%*%urWu
  a2 <- D%*%a2
  a2 <- a2*(1/(T-1))
  a3 <- A3%*%urWu
  a3 <- D%*%a3
  a4 <- A4%*%urWu
  a4 <- D%*%a4

  Tva1 <- Tv%*%a1
  Tva2 <- Tv%*%a2
  Tva3 <- Tv%*%a3
  Tva4 <- Tv%*%a4

  A3vm <- kronecker(eT,WW)
  A4vm <- 1/2*kronecker(eT,(W+t(W)))

  A3m <- T*(WW)
  A4m <- T/2*(W+t(W))

# V11
  A1A1 <- A1S%*%A1S
  V11 <- 2*sum(diag(A1A1))/((T-1)^2)
  A1A1 <- t(Tva1)%*%Sigma%*%Tva1
  V11 <- V11 + as.numeric(A1A1)
# V12
  A1A2 <- A1S%*%A2A2
  V12 <- sum(diag(A1A2))/((T-1)^2)
  A1A2 <- t(Tva1)%*%Sigma%*%Tva2
  V12 <- V12 + as.numeric(A1A2)
# V13
  A1A3 <- A1S%*%A3S
  V13 <- 2*sum(diag(A1A3))/(T-1)
  A1A3 <- t(Tva1)%*%Sigma%*%Tva3
  V13 <- V13 + as.numeric(A1A3)
# V14
  A1A4 <- A1S%*%A4A4
  V14 <- sum(diag(A1A4))/(T-1)
  A1A4 <- t(Tva1)%*%Sigma%*%Tva4
  V14 <- V14 + as.numeric(A1A4)
# V21
  A2A1 <- A2A2%*%A1S
  V21 <- sum(diag(A2A1))/((T-1)^2)
  A2A1 <- t(Tva2)%*%Sigma%*%Tva1
  V21 <- V21 + as.numeric(A2A1)
# V22
  A2A22 <- A2A2%*%A2A2
  V22 <- sum(diag(A2A22))/(2*((T-1)^2))
  A2A22 <- t(Tva2)%*%Sigma%*%Tva2
  V22 <- V22 + as.numeric(A2A22)
# V23
  A2A3 <- A2A2%*%A3S
  V23 <- sum(diag(A2A3))/(2*(T-1))
  A2A3 <- t(Tva2)%*%Sigma%*%Tva3
  V23 <- V23 + as.numeric(A2A3)
# V24
  A2A4 <- A2A2%*%A4A4
  V24 <- sum(diag(A2A4))/(2*(T-1))
  A2A4 <- t(Tva2)%*%Sigma%*%Tva4
  V24 <- V24 + as.numeric(A2A4)
# V31 = V13
  A3A1 <- A3S%*%A1S
  V31 <- 2*sum(diag(A3A1))/(T-1)
  A3A1 <- t(Tva3)%*%Sigma%*%Tva1
  V31 <- V31 + as.numeric(A3A1)
# V32
  A3A2 <- A3S%*%A2A2
  V32 <- sum(diag(A3A2))/(T-1)
  A3A2 <- t(Tva3)%*%Sigma%*%Tva2
  V32 <- V32 + as.numeric(A3A2)
# V33
  A3A3 <- A3S%*%A3S
  V33 <- 2*sum(diag(A3A3))
  A3A3 <- t(Tva3)%*%Sigma%*%Tva3
  V33 <- V33 + as.numeric(A3A3)
  A3A3 <- t(A3vm)%*%Sigma%*%A3vm
  A3A3 <- 4*sigmam*(T/(T-1))*sum(diag(A3A3))
  V33 <- V33 + as.numeric(A3A3)
  A3A3 <- A3m%*%A3m
  A3A3 <- 2*(sigmam^2)*sum(diag(A3A3))
  V33 <- V33 + as.numeric(A3A3)
# V34
```

```
  A3A4 <- A3S%*%A4A4
  V34 <- sum(diag(A3A4))
  A3A4 <- t(Tva4)%*%Sigma%*%Tva4
  V34 <- V34 + as.numeric(A3A4)
  A3A4 <- t(A3vm)%*%Sigma%*%A4vm
  A3A4 <- 4*sigmam*(T/(T-1))*sum(diag(A3A4))
  V34 <- V34 + as.numeric(A3A4)
  A3A4 <- A3m%*%A4m
  A3A4 <- 2*(sigmam^2)*sum(diag(A3A4))
  V34 <- V34 + as.numeric(A3A4)
# V41
  A4A1 <- A4A4%*%A1S
  V41 <- sum(diag(A4A1))/(T-1)
  A4A1 <- t(Tva4)%*%Sigma%*%Tva1
  V41 <- V41 + as.numeric(A4A1)
# V42
  A4A2 <- A4A4%*%A2A2
  V42 <- sum(diag(A4A2))/(2*(T-1))
  A4A2 <- t(Tva4)%*%Sigma%*%Tva2
  V42 <- V42 + as.numeric(A4A2)
# V43
  A4A3 <- A4A4%*%A3S
  V43 <- sum(diag(A4A3))
  A4A3 <- t(Tva4)%*%Sigma%*%Tva3
  V43 <- V43 + as.numeric(A4A3)
  A4A3 <- t(A4vm)%*%Sigma%*%A3vm
  A4A3 <- 4*sigmam*(T/(T-1))*sum(diag(A4A3))
  V43 <- V43 + as.numeric(A4A3)
  A4A3 <- A4m%*%A3m
  A4A3 <- 2*(sigmam^2)*sum(diag(A4A3))
  V43 <- V43 + as.numeric(A4A3)
# V44
  A4A42 <- A4A4%*%A4A4
  V44 <- sum(diag(A4A42))/2
  A4A42 <- t(Tva4)%*%Sigma%*%Tva4
  V44 <- V44 + as.numeric(A4A42)
  A4A42 <- t(A4vm)%*%Sigma%*%A4vm
  A4A42 <- 4*sigmam*(T/(T-1))*sum(diag(A4A42))
  V44 <- V44 + as.numeric(A4A42)
  A4A42 <- A4m%*%A4m
  A4A42 <- 2*(sigmam^2)*sum(diag(A4A42))
  V44 <- V44 + as.numeric(A4A42)

  Tva <- cbind(Tva1, Tva2, Tva3, Tva4)
  Tma <- 0
  Fm <- 0

  if (model=="random") {

      Fm <- kronecker(t(eT),Diagonal(N))
      if (spatial) Fm <- Fm%*%(Diagonal(N*T) - rho*Ws)
      else Fm <- Fm%*%InvW
      Fm <- Fm%*%H

      Tm <- Fm%*%P
      Tma1 <- Tm%*%a1
      Tma2 <- Tm%*%a2
      Tma3 <- Tm%*%a3
      Tma4 <- Tm%*%a4

      A1A1 <- sigmam*t(Tma1)%*%Tma1
      V11 <- V11 + as.numeric(A1A1)
      A1A2 <- sigmam*t(Tma1)%*%Tma2
      V12 <- V12 + as.numeric(A1A2)
      A1A3 <- sigmam*t(Tma1)%*%Tma3
      V13 <- V13 + as.numeric(A1A3)
      A1A4 <- sigmam*t(Tma1)%*%Tma4
      V12 <- V12 + as.numeric(A1A4)
      A2A1 <- sigmam*t(Tma2)%*%Tma1
      V21 <- V21 + as.numeric(A2A1)
      A2A22 <- sigmam*t(Tma2)%*%Tma2
      V22 <- V22 + as.numeric(A2A22)
      A2A3 <- sigmam*t(Tma2)%*%Tma3
      V23 <- V23 + as.numeric(A2A3)
      A2A4 <- sigmam*t(Tma2)%*%Tma4
      V24 <- V24 + as.numeric(A2A4)
      A3A1 <- sigmam*t(Tma3)%*%Tma1
      V31 <- V31 + as.numeric(A3A1)
      A3A2 <- sigmam*t(Tma3)%*%Tma2
      V32 <- V32 + as.numeric(A3A2)
      A3A3 <- sigmam*t(Tma3)%*%Tma3
      V33 <- V33 + as.numeric(A3A3)
      A3A4 <- sigmam*t(Tma3)%*%Tma4
      V34 <- V34 + as.numeric(A3A4)
      A4A1 <- sigmam*t(Tma4)%*%Tma1
      V41 <- V41 + as.numeric(A4A1)
      A4A2 <- sigmam*t(Tma4)%*%Tma2
      V42 <- V41 + as.numeric(A4A2)
      A4A3 <- sigmam*t(Tma4)%*%Tma3
      V43 <- V41 + as.numeric(A4A3)
      A4A42 <- sigmam*t(Tma4)%*%Tma4
```

```
        V44 <- V44 + as.numeric(A4A42)

        Tma <- cbind(Tma1, Tma2, Tma3, Tma4)
        }

  V <- matrix(nrow=4, ncol=4)
  V[, 1] <- c(V11, V21, V31, V41)/N
  V[, 2] <- c(V12, V22, V32, V42)/N
  V[, 3] <- c(V13, V23, V33, V43)/N
  V[, 4] <- c(V14, V24, V34, V44)/N

  V <- as.matrix(V)
  Vinv <- solve(V)
  WM <- list(V = V, Vinv=Vinv, P=P, Fv=Fv, Tva=Tva, Tma=Tma, Fm=Fm)
  WM
}

# Variance and Covariance matrix
Omega <- function(P, Fv, Tva, J, Phi, Phiv, N, T, Sigma, sigmam, model=c("fixed", "random"), Fm, Tma, chol=FALSE){

  JPhJ <- t(J)%*%Phiv%*%J

  if (chol) JPhJ <- chol2inv(chol(JPhJ))
  else JPhJ <- solve(JPhJ)
  JJPhJ <- J%*%JPhJ
  PhJJPhJ <- Phiv%*%JJPhJ

  O1 <- Sigma%*%Fv
  O1 <- as.matrix(t(Fv)%*%O1)

  O21 <- Sigma%*%Tva[[1]]
  O21 <- 1/(N*(T^(1/2)))*t(Fv)%*%O21
  O22 <- Sigma%*%Tva[[2]]
  O22 <- 1/(N*(T^(1/2)))*t(Fv)%*%O22
  O23 <- Sigma%*%Tva[[3]]
  O23 <- 1/(N*(T^(1/2)))*t(Fv)%*%O23
  O24 <- Sigma%*%Tva[[4]]
  O24 <- 1/(N*(T^(1/2)))*t(Fv)%*%O24

  if (model=="random") {
  Om <- 1/(N*T)*sigmam*t(Fm)%*%Fm
  O1 <- O1 + Om
  Om <- 1/(N*(T^(1/2)))*sigmam*t(Fm)%*%Tma[[1]]
  O21 <- O21 + Om
  Om <- 1/(N*(T^(1/2)))*sigmam*t(Fm)%*%Tma[[2]]
  O22 <- O22 + Om
  Om <- 1/(N*(T^(1/2)))*sigmam*t(Fm)%*%Tma[[3]]
  O23 <- O23 + Om
  Om <- 1/(N*(T^(1/2)))*sigmam*t(Fm)%*%Tma[[4]]
  O24 <- O24 + Om
  }

  O1 <- as.matrix(O1)
  O2 <- cbind(as.matrix(O21), as.matrix(O22), as.matrix(O23), as.matrix(O24))

  OC1 <- rbind(O1, t(O2))
  OC2 <- rbind(O2, Phi)
  OC <- cbind(OC1, OC2)

  zero <- matrix(0, nrow=(nrow(PhJJPhJ)), ncol=(ncol(P)))
  OR1 <- rbind((1/(T^(1/2)))*as.matrix(P), zero)
  zero <- matrix(0, nrow=(nrow(P)), ncol=(ncol(PhJJPhJ)))
  OR2 <- rbind(zero, PhJJPhJ)
  OR <- cbind(OR1, OR2)

  vcov <- OC%*%OR
  vcov <- t(OR)%*%vcov
  vcov
}
```