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The Urban Geographies of Occupational Segregation

Manuel Garcia Dellacasa[1]

Abstract
Occupational segregation by sex is a persistent driver of labor market inequality, particularly in its horizontal form—the concentration of men and women in different sectors. This paper develops a structural account grounded in urban feminist political economy, emphasizing how segregation is sustained by the interaction of gendered mobility constraints and the uneven geography of economic activity. Using Santiago de Chile as a case study, we integrate georeferenced 2017 census data, commuting patterns, and satellite nightlight imagery to operationalize local labor market intensity and residential marginalization. We test two hypotheses—(H1) that segregation declines with economic activity, and (H2) that it rises with residential marginalization—using a suite of econometric methods, including OLS, spatial error models, and instrumental variables leveraging the historical incorporation of urban tracts. We further validate results through robustness checks and policy simulations that relocate social housing into advantaged areas. Our findings show that economic activity reduces segregation, while marginalization amplifies it; simulated housing integration policies yield effects comparable to decades of educational expansion. These results highlight the value of urban policy as a tool for advancing gender equity in labor markets.

Keywords: Occupational Segregation, Gender Inequality, Urban, Labor Markets, Uneven Geographies

JEL classification: J10, J16, R10, R23

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1 Introduction

Occupational segregation by sex is one of the most persistent drivers of gender inequality. While this phenomenon is often associated with *vertical* segregation, where men hold positions of authority and women are allocated into more subordinate roles, gender wage gaps are more strongly influenced by *horizontal* segregation. The overrepresentation of women in sectors like healthcare, education, and domestic services is the most crucial factor in explaining the resilience of gender disparities in labor markets (Blau and Kahn, 2017). In this paper, we examine the urban character of horizontal occupational segregation.

Grounded in urban feminist political economy, we advance a structural explanation of this phenomenon. We argue that horizontal occupational segregation is embedded in the geography of cities and sustained by the interaction of two structural forces. The first is the simultaneous pressure on women to engage in paid work while continuing to provide unpaid domestic and care labor. This *dual compulsion* limits women's mobility and intensifies their reliance on local labor markets (LLM)–that is, employment opportunities close to home. Since men are not subject to this mobility constraint, their job-search scope is much wider. As a result, men and women may not experience the same labor market even while living in the same household. Furthermore, women's higher reliance on LLM means not only fewer job opportunities available to them, but also a lower diversity of employment possibilities.

The second structural force is the *uneven geography* of economic activity. Unevenness shapes and differentiates LLM in terms of quantity and diversity across the urban fabric. Agglomeration forces entail that central LLM are thicker and more diversified than peripheral LLMs. In this context, women residing in central areas experience labor markets that resemble those experienced by their male counterparts, even while facing higher mobility constraints. In contrast, the gendered experience of labor markets diverges more sharply in peripheral regions. From this follows our first hypothesis (H1): horizontal occupational segregation decreases with the intensity of local economic activity, reflecting the uneven geography of urban development.

This structural account of horizontal occupational segregation stands in contrast to more traditional interpretations. In particular, it challenges human capital theories that attribute this phenomenon to gendered differences in educational endowments (Becker, 1985), as well as pure discrimination theories tracing its origins to preferences and norms Weichselbaumer and Winter-Ebmer (2005). Furthermore, our analysis foregrounds the role of *the social production of the city* and urban policy in mediating occupational segregation–a dimension often overlooked in traditional accounts. More concretely, we argue that processes of residential marginalization foster occupational segregation by concentrating marginalized communities in areas with thin and homogeneous LLMs. Our second hypothesis (H2), therefore, is that occupational segregation is positively associated with residential marginalization. If the latter is true, inclusive housing policy has the potential to reduce occupational segregation and the inequalities it sustains.

To test these hypotheses, we take Santiago de Chile as our case study. While prior research has examined the geographical determinants of occupational segregation (Perales and Vidal, 2015; Petrongolo and Ronchi, 2020), such work has typically relied on large regional units of analysis. To our knowledge, this is the first study to investigate the spatial determinants of horizontal occupational segregation within a single metropolitan area. Moreover, Santiago provides a compelling setting to examine these dynamics. The city combines high female educational attainment with stark patterns of gender and residential inequality, making it well-suited for testing whether urban structure and marginalization can explain the persistence of segregation despite human capital convergence.

Our empirical strategy draws on georeferenced 2017 census data to measure occupational segregation and residential marginalization, and commuting data in combination with satellite nightlight data to observe the size and intensity of LLM. The hypotheses are tested using a variety of econometric methods. These encompass OLS, spatial econometrics, and instrumental variables, complemented by a wide range of robustness checks. Furthermore, we use these models to simulate the impact of inclusive housing policy on occupational segregation. Concretely, we simulate the effect of relocating affordable housing units to more advantageous areas of the city.

Our findings confirm both hypotheses. In our more conservative estimations, a one standard deviation increase in local economic activity is associated with a 3.7% decrease in segregation among less-educated (LE) workers and a 1.9% decrease among more-educated (ME) workers. A comparable increase in marginalization is associated with a 4.9% and 1.9% increase, respectively. Our policy simulation predicts that inclusive housing policy could reduce occupational segregation up to 6.3% among LE workers and 9.3% among ME workers–effects comparable to those achieved by decades of educational expansion in Chile.

The remainder of the paper is structured as follows. Section 2 develops our conceptual framework. Section 3 introduces Santiago as our case study. Section 4 maps the spatial distribution of horizontal segregation. Section 5 details our empirical methods. Section 6 presents results, and Section 7 concludes.

2 Conceptual Framework: The Urban Geographies of Occupational Segregation

Traditional accounts of horizontal occupational segregation emphasize the role of individual attributes and preferences. Supply-side theories, such as the human capital theory, argue that segregation results from gendered differences in educational endowments and from exogenous norms shaping individual occupational choices (Becker, 1985). Yet, as educational gaps have narrowed globally, empirical research has found the explanatory power of this approach to be inconclusive and limited at best (Borrowman and Klasen, 2020). On the other hand, demand-side explanations emphasize the role of discriminatory hiring practices in reproducing segregation (Weichselbaumer and Winter-Ebmer, 2005). However, empirical research likewise suggests that discrimination alone offers limited explanatory power, as it is far less systematic than occupational segregation itself (Bravo et al., 2008).

Feminist political economists have long criticized the overemphasis on individual characteristics and preferences for explaining this phenomenon. While acknowledging that gender norms play an evident role in producing a gendered division of labor, feminist theory underscores the importance of structural forces. In particular, it highlights the role of patriarchal systems in simultaneously shaping women's experience of both paid and unpaid work (Folbre, 2021). In this framework, occupational segregation–rather than simply being a product of market forces–emerges from the structural interaction of patriarchal and capitalist systems.

Our framework builds on this approach by introducing the role of space and urban development in mediating this structural interaction.

2.1 Dual Compulsion and Gendered Local Labor Markets

We focus on a key spatial mechanism: women's limited mobility under patriarchal and capitalist demands for their work. Our concern here is with horizontal rather than vertical segregation, since the mechanisms we examine shape the kinds of jobs and sectors that women can access, not their hierarchical advancement within them.

Political economists hold that the binding of workers to labor markets does not occur through direct and explicit coercion. Rather, workers are compelled to sell their labor power as a condition for their own social reproduction. This operates as a *mute compulsion*: a form of domination embedded in economic dependence itself, requiring no explicit force (Mau, 2023).

Feminist political economists have long identified a second axis of labor compulsion. Patriarchal systems allocate the brunt of unpaid domestic and care labor to women, often through naturalized gender norms that associate femininity with reproductive work. Crucially, these systems are sustained and reproduced by positioning women in conditions of social and material dependence on family structures, compelling their continued provision of unpaid labor (Folbre, 2021).

Increasingly, capitalist and patriarchal compulsions converge in the lives of women as they are often subjected to a *dual compulsion*: they are required to sell their labor power while continuing to bear the primary responsibility for unpaid domestic work.[2]

This dual compulsion not only constrains women's time but also restricts their spatial mobility (Massey, 1994; Kwan, 2000). Because unpaid domestic work is anchored to the home, women's access to paid employment often depends on the proximity between the home and the workplace. This results in well-documented gender gaps in commuting distances, with women consistently travelling shorter distances than men (Le Barbanchon et al., 2020).

Consequently, women's participation in labor markets is more sensitive to the structure of localized labor markets (Garcia Dellacasa, 2023). These local labor markets (LLM)—defined by the jobs accessible within commuting range—are smaller than those available to men. Men, through heightened mobility, access more economically intensive labor markets–both in terms of employment opportunities and variety. Consequently, labor markets are segmented along gendered lines: men and women do not compete in the same spatial arenas but are exposed to distinct geographies of employment shaped by their mobility through the city.

This distinction, in the context of spatially uneven economic activity, is crucial for understanding the structural character of horizontal occupational segregation.

2.2 Agglomeration and the Uneven Urban Geographies of Occupational Segregation

The spatial unevenness of local labor markets is neither anomalous nor indicative of inefficient market dynamics. Profit-seekers locate near consumers, suppliers, competitors, or large employment pools to reduce or share costs and facilitate revenue. As a result of these agglomeration forces, economic activity tends to concentrate in some regions of the city (Glaeser, 2007), giving rise to monocentric urban structures (Liotta et al., 2022).

While urban cores support thick labor markets with high sectoral diversity, peripheral regions tend to offer thinner, more homogeneous employment opportunities (Thisse, 2018). In other words, the spatial unevenness of economic activity under capitalism results in a geography where the intensity of LLM differs both quantitatively (in terms of total jobs) and qualitatively (in their industrial composition).

If the dual compulsion intensifies women's reliance on local labor markets for employment, spatial unevenness determines the geography of employment opportunity. Those residing near agglomeration centers benefit from more diverse local employment structures, whereas those in peripheral areas face more limited options. In contrast, men's greater mobility allows them to access a broader range of job opportunities regardless of residential location. As a result, as women reside closer to agglomeration centers, the diversity of employment opportunities increasingly resembles that of men's. As their labor market options converge, the likelihood of participating in similar industries rises, thereby reducing horizontal occupational segregation.

[2]Despite rising female labor force participation, men's contribution to unpaid domestic labor has remained largely stagnant (Folbre, 2021)

This leads to our first hypothesis (H1): the intensity of horizontal occupational segregation should decline with the level of local economic activity and reflects the geographic unevenness of urban economic activity. This hypothesis underpins a structural explanation of horizontal occupational segregation. When patriarchal and capitalist compulsions are generalized, segregation is likely to emerge regardless of preferences and attributes.

2.3 The Social Production of the City and Occupational Segregation

While urban economic activity tends to follow a monocentric logic, not all areas outside the economic core offer the same LLM conditions. The capacity to access diverse employment opportunities from a given residential location is not simply a geographic fact—it is socially produced (Massey, 1994). This is particularly evident in the case of residential marginalization, which frequently stems from exclusionary housing policies that limit, by accident or by design, the economic options available to marginalized communities (Rothstein, 2018; Garreton, 2017). In this regard, marginalization creates spatial conditions that are particularly conducive to occupational segregation.

Although often linked to broader patterns of residential segregation, marginalization goes beyond the mere spatial clustering of homogeneous social groups. Often, marginalized neighborhoods tend to suffer from poor public infrastructure and limited institutional investment (Hidalgo Dattwyler, 2007). Therefore, these areas are not only poorly connected to urban employment centers but also tend to attract fewer businesses and offer thinner local labor markets (Gobillon et al., 2007). These limitations compound dual compulsion by making it even harder to balance paid and unpaid work under marginalization.[3]

Second, limited employment opportunities in marginalized areas affect both less- and more-educated women. For those with lower levels of education, available jobs are often scarce and concentrated in low-paid, service-oriented roles, many of which are highly feminized (García et al., 2024). More-educated women may access professional work, but often in sectors with broader spatial dispersion, such as education, health, and other public services. As Petrongolo and Ronchi (2020) show, industries with wider geographic reach tend to employ more women—a pattern that reflects the spatial logic of dual compulsion.

From this follows our second hypothesis (H2): the intensity of horizontal occupational segregation is positively associated with the intensity of residential marginalization. H2 underscores that the social production of the city can deepen the structural tensions driving horizontal occupational segregation. However, it also implies that urban policy—and inclusive urban policy in particular—can mitigate these dynamics.

3 Case Study: Santiago de Chile

To test H1 and H2, we examine Santiago de Chile–the country's largest and capital city. Santiago provides a valuable empirical setting because it combines high female educational attainment with persistent gendered inequalities in the labor market. Chile enjoys one of the highest rates of female schooling in Latin America, and gender gaps in education have been virtually eliminated (Urquidi and Chalup, 2023). Yet, despite these gains, the country continues to report one of the widest gender wage gaps in South America (Ibid.).

Research attributes much of this gap to horizontal occupational segregation (Sanchez et al., 2022). Moreover, this pattern has proved strikingly resilient to economic development. Borrowman and Klasen (2020) show that between 1987 and 2009 segregation declined by only three

[3] Research shows that marginalization tends to be negatively associated with women's labor force participation, especially when they have caring responsibilities Garcia Dellacasa (2023).

percentage points—even as real GDP per capita grew by nearly 150%.

Importantly, such persistence cannot be fully explained by discriminatory hiring. Bravo et al. (2008), employing quasi-experimental methods, found no significant evidence of employer discrimination in the city.

More broadly, the city illustrates how national-level advances in gender equality, particularly in education, can coexist with entrenched inequalities in the labor market even in the absence of systematic discriminatory practices.

3.1 Gendered Local Labor Markets in Santiago

In line with our framework, we examine commuting patterns in Santiago as evidence of the city's gendered LLM. Figure 1 presents the distribution of commuting distances among employed men and women, based on the 2012 Origin-Destination Survey (ODS)–a citywide representative survey conducted by the Ministry of Transportation and Communication.[4] The figure shows that women's median commuting distance—slightly higher than 5.2 kilometers—is about 20% shorter than men's.

[Insert Figure 1 here]

These commuting differences reflect the gendered segmentation of LLM. In what follows, we define the areal size of LLM as a circumference centered at the worker's residence, with a radius equal to the median commuting distance. While stylized, this definition provides a tractable approximation of LLM. An additional advantage of this approach is that it allows us to conceptualize LLM as overlapping rather than as strictly contiguous units.

We further distinguish between less-educated (LE) workers, defined as those with at most a secondary education degree, and more-educated (ME) workers, defined as those with some tertiary education or higher. Although commuting gaps between men and women exist across both groups, they are slightly larger among LE workers. This likely reflects the more intense pressures of dual compulsion faced by LE women, who often have fewer resources to outsource domestic work. For this reason, we treat LE and ME LLM as analytically distinct.

Under our definition, the LLM area of LE women is about 58% the size of their male counterparts, pointing to particularly stark mobility inequalities within this group. Among ME workers, the figure increases to 72%. Although the gender gap is smaller for this group, it is still significant, reflecting that education does not fully eliminate gendered mobility constraints.

3.2 The Social Production of Residential Segregation and Marginalization in Santiago

Like most large cities, Santiago exhibits a predominantly monocentric structure in terms of economic activity. Nightlight data show that employment opportunities and economic intensity are concentrated in the central districts, while activity falls sharply toward the periphery (See Figure 2 below. Yet, these peripheries are not homogeneous.

On the one hand, the affluent northeast—known as the *Barrio Alto*–concentrates some of the wealthiest households in Chile. On the other hand, the southern and western peripheries host the urban poor in areas popularly known as *Comunas Dormitorio*. These are largely residential with limited local jobs, making Santiago one of the most segregated cities in Latin America (Roberts and Wilson, 2009).

This peripheral divide was largely produced during Augusto Pinochet's dictatorship (1973–1990). Earlier, Chile's developmentalist policies had spurred rural–urban migration and the growth of informal settlements, which under Salvador Allende (1970–1973) increasingly appeared in central

[4]This data is publicly available at https://www.sectra.gob.cl/encuestas_movilidad/encuestas_movilidad.htm

and northeastern districts. The dictatorship reversed this trajectory: starting in 1979, informal settlements—viewed as both economic liabilities and political threats—were dismantled, and around 165,000 residents were forcibly relocated to underdeveloped peripheries in the south and west (Morales and Rojas, 1986). These expulsions did not simply displace communities but actively created the *Comunas Dormitorio*, cementing the city's stark spatial divide (Garreton, 2017).

Neoliberal reforms further entrenched this geography. Deregulation of land markets spurred speculation and rising central land values (Sabatini, 2000). At the same time, the state shifted from direct public housing provision to subsidies for private developers, who increasingly built on cheaper peripheral land (Garreton, 2017). As a result, subsidized housing concentrated poverty on the urban fringe. Democratic governments of the 1990s, rather than reversing this pattern, expanded subsidies and deepened peripheral marginalization.

Figure 2 illustrates these dynamics. The *Comunas Dormitorio* are marked by low education and minimal economic activity, while the *Barrio Alto* combines high education with relatively low economic activity due to its residential character. By contrast, Santiago's central districts combine both high education and strong economic intensity, confirming the city's monocentric structure.

[Insert Figure 2 here]

Santiago thus exemplifies the processes outlined in our framework. Women's mobility constraints interact with the uneven geography of economic activity, making access to diverse employment opportunities highly dependent on residential location. Authoritarian displacement and market-driven housing policy together produced spatial marginalization, reinforcing the structural conditions for gendered occupational segregation.

4 Horizontal Occupational Segregation in Santiago

We draw from the 2017 Chilean census to analyze how spatial structures shape occupational segregation in Santiago. This section describes the measurement strategy and aggregation approach used to examine variation across the city's local labor markets.

4.1 Data and Occupational Segregation in Santiago

Our sample includes 1.7 million less-educated workers and 1.3 million more-educated workers, classified into 22 broad industry categories. Observations with missing values or non-employment status were excluded (See Table 1 below).

[Insert Table 1 here]

While 22 industries may seem like a limitation for analyzing segregation, it is on par with empirical literature on horizontal occupational segregation (Herranz et al., 2005; Herrera et al., 2019; Borrowman and Klasen, 2020). The reason for choosing broader categories is that segregation metrics often suffer from small-cell bias problems. As a product of each industry having fewer workers, disaggregating the data into more detailed categories can result in more unstable calculations (Herranz et al. 2005). This is particularly true of the most widely used measure of occupational segregation—and the primary measure used in this study—the dissimilarity index (DD).[5]

[5]For robustness purposes, all econometric estimations are cross-checked using Theil's H index (Reardon and Firebaugh, 2002) as a measure of occupational segregation. These results are presented in the appendix.

The DD is calculated as:

$$DD = \frac{1}{2}\sum_{i=1}^{I}\left|\frac{F_i}{F} - \frac{M_i}{M}\right|, \tag{1}$$

where:

- F_i is the number of women employed in industry i,
- M_i is the number of men employed in industry i,
- $F = \sum_{i=1}^{I} F_i$ is the total number of women employed,
- $M = \sum_{i=1}^{I} M_i$ is the total number of men employed,
- I is the total number of industries.

Ranging between zero and one, the index represents what percentage of women (or men) would need to switch industries to reach gender parity. Because the index is calculated upon industrial shares of total employment, when these are too small, a tiny variation in employment may result in a disproportional change in observed segregation.

According to the census data the dissimilarity index in Santiago is 34% of less-educated women and 22% of more educated women.

4.2 The Spatial Distribution of Horizontal Occupational Segregation

Our theoretical framework predicts that horizontal occupational segregation is unevenly distributed across the city. Therefore, we must estimate segregation at smaller levels of geographical aggregation to account for its spatial distribution.

The smallest spatial unit of aggregation in the data is the census tract. There are 1,648 tracts in Santiago, with an average of 1,827 employed resident workers and a mean land area of 0.48 km^2. Unfortunately, some of these tracts are inadequate for measuring segregation. With some tracts having fewer than 100 workers, the small-cell bias problem is likely to emerge.

To address this issue, we produce new units of spatial aggregation by merging small tracts to their nearest neighbor.[6] A tract is considered small if they have less than 500 less-educated or 500 more-educated workers. By educational group, we repeat this process until there are no tracts with fewer than 500 workers of each type. This process results in 1,336 'less-educated' tracts with an average of 1,249 less-educated working residents, and 1,106 'more-educated' tracts with an average of 1,101 more-educated workers. The new tracts have an average size of 0.6 and 0.72 km^2, respectively.

Using these revised tracts, we compute dissimilarity indices for each unit. The weighted average of tract-level DD values is 0.37 for less-educated workers and 0.26 for more-educated workers. The fact that this is higher than city-wide segregation may reflect small-cell problems in our calculation. Therefore, to mitigate this issue in our econometric assessment, regressions are replicated using tracts redrawn to include at least 1,000 workers per educational group.

After calculating dissimilarity indices for each tract, we assess whether occupational segregation follows a discernible spatial pattern across the city. This allows us to test a central claim of our theoretical framework: that segregation is not randomly distributed but structured

[6]Among less-educated workers, outliers in tract-level occupational segregation represent 5.4% of tracts when using original census data, but this share drops to 2.9% when we set a minimum floor of 500 working residents, and further to 1.97% with a floor of 1,000 workers. For more-educated workers, outliers are already rare, declining from 0.79% to 0.18% to 0.14% as tract floors increase. Outliers are identified using the interquantile range (IQR) method.

by Santiago's geography. We begin by computing Moran's I, a standard measure of spatial autocorrelation that ranges from –1 to +1. Values near zero indicate a random distribution, while significantly positive values suggest that tracts with similar levels of segregation—whether high or low—tend to cluster spatially.

To locate these clusters, we decompose Moran's I into Local Indicators of Spatial Autocorrelation (LISA). This method compares each tract's segregation level to that of its neighbors, identifying statistically significant local patterns. A tract is classified as high-high when it exhibits statistically high segregation and is surrounded by neighbors with similarly high values; low-low clusters reflect tracts with statistically low segregation levels surrounded by similarly low neighbors. High-low and low-high tracts are spatial outliers, displaying values that differ significantly from their surrounding areas. Tracts without significant local association are labeled non-significant.

Figure 3 presents the global Moran's I statistics and corresponding LISA maps for both less- and more-educated workers in Santiago.

[Insert Figure 3 here]

The spatial distribution of occupational segregation in Santiago is positively autocorrelated for both educational groups, with stronger clustering among more-educated workers. This confirms that segregation is not randomly distributed across space but exhibits clear geographic patterns. Clusters of low segregation tend to concentrate in central areas of the city, where access to a more diverse set of employment opportunities is likely. These areas show average dissimilarity index values of 0.32 for less-educated workers and 0.20 for more-educated workers.

High-segregation clusters follow distinct geographies depending on education level. Among LE workers, they are concentrated in the peripheral northeast and south. Although these regions differ socioeconomically, both share a predominantly residential character and limited local economic activity.

For ME workers, high-segregation clusters coincide largely with the city's *Comunas Dormitorio*. This suggests that even as educational attainment rises, residence in marginalized areas remains associated with high levels of occupational segregation.

On average, high-high clusters register a dissimilarity index of 0.46 among LE workers and 0.33 among ME workers.

These spatial patterns support the idea that horizontal occupational segregation in Santiago is not merely a function of individual characteristics or firm-level dynamics, but is deeply embedded in the geography of the city.

5 Methodology: Accounting for the Geographies of Horizontal Occupational Segregation

Our framework predicts that the uneven geographies of occupational segregation are explained, at least partially, by the level of economic activity in local labor markets (H1) and the degree of residential marginalization (H2). To test these hypotheses in our case study, we propose an econometric empirical strategy integrating these variables and other well-known determinants of occupational segregation.

5.1 Models and Variables of Interest

We estimate two linear models for both less-educated and more-educated samples. Model 1 includes our core geographic variables and controls. Model 2 builds on Model 1 by introducing controls for industrial composition among residents. This separation allows us to assess whether the effects of geography are explained by local employment structures or extend beyond the sectoral distribution of employment.

Model 1 is:

$$ln(DD_{t,ed}) = \alpha + \beta_1 \ln(NL_t) + \beta_2 H_t + \beta_3 LE_t + \beta_4 (H_t \times LE_t) \\ + \boldsymbol{\gamma}' \ln(\mathbf{X}_t) + \boldsymbol{\delta}' \ln(\mathbf{Z}_{t,ed}) + \varepsilon_{t,ed} \quad (2)$$

Where $DD_{t,ed}$ is the dissimilarity index for tract t among workers of education level ed (LE/ME), NL_t is the degree of nightlight activity around tract t as a proxy of LLM intensity, H_t is Theil's H index capturing residential segregation, and LE_t is a dummy equal to 1 if average education among heads of household is $\leq$ 12 years, and 0 otherwise. The interaction variable $H_t \times LE_t$ reflects residential marginalization. The vector X_t includes tract-level controls (child dependency ratio, distance to metro), while Z_{ed} captures educational group-specific controls (gender schooling ratio, women's labor force participation rate, average age, total working population). All continuous variables are in logs to enable elasticity interpretation.

Model 2 adds:

$$ln(DD_{t,ed}) = \alpha + \beta_1 \ln(NL_t) + \beta_2 H_t + \beta_3 LE_t + \beta_4 (H_t \times LE_t) \\ + \boldsymbol{\gamma}' \ln(\mathbf{X}_t) + \boldsymbol{\delta}' \ln(\mathbf{Z}_{t,ed}) + \sum_{i=1}^{I} \theta_i Share_{t,i} + \varepsilon_{t,ed} \quad (3)$$

Where $Share_{t,i}$ is the share of resident employment in industry i in tract t.

5.1.1 Operationalizing Local Labor Markets

In applying our definition, we use women's median commuting distance–calculated separately for LE and ME workers–as the defining radius for LLM areas. Since precise household coordinates are not available, each LLM is approximated as a circle centered at the centroid of the census tract. This procedure yields average LLM areas of 81.3 km^2 for LE workers and 94.3 km^2 for ME workers.

This definition offers two advantages. First, it mitigates the well-known Modifiable Areal Unit Problem (MAUP) by avoiding the use of administrative boundaries that may have no bearings on LLMs. Second, it reflects the overlapping nature of LLMs, which span beyond single tracts, as emphasized in the empirical literature (Manning and Petrongolo, 2017).

Because the Chilean census does not report workers' employment locations, we use satellite-based nightlight radiance (VIIRS, 2017) as a proxy for local economic activity. While it does not capture absolute employment levels, this measure has been widely used to reflect spatial variation in economic intensity, particularly in contexts with limited administrative data (Henderson et al., 2012). Given our focus on elasticities and relative differences across labor markets, nightlight radiance is an appropriate and informative proxy. LLM nightlight intensity is normally distributed and it reflects the city's monocentric structure.[7]

5.1.2 Residential Segregation and Marginalization

We measure residential segregation at the tract level using Theil's H index, the normalized between-group component of Theil's multigroup entropy measure. In our case, groups are defined by the educational attainment of household heads, classified as less-educated (LE) or more-educated (ME). Theil's H quantifies how much of Santiago's overall educational diversity is explained by differences between tracts, relative to the metropolitan average (Theil's M).[8]

[7] LLM nightlight distribution and maps are included in the appendix (Figure A-1).

[8] We calculate Theil's H using the `segregation` package in R.

The index ranges from zero to one. A value of zero means that the distribution of household heads' education in each tract exactly mirrors that of the city as a whole. A value of one means that a tract contains only household heads from a single educational category (all LE or all ME).

Importantly, high H values do not automatically indicate marginalization. For example, an affluent enclave in the *Barrio Alto* composed exclusively of ME household heads would also display high segregation. To distinguish marginalization from other forms of homogeneity, we interact each tract's Theil H with a dummy variable identifying low-education areas. This "LE dummy" equals one when the average years of schooling among household heads in a tract is less than or equal to 12 years (the equivalent of a secondary education degree), and zero otherwise.

5.1.3 Descriptive Statistics

[Insert Table 2 here]

Table 2 presents summary statistics for the main variables included in the analysis, separately for the less- and more-educated tract samples. On average, nightlight intensity is moderately higher in tracts associated with more-educated workers, though the variation is comparable across groups (coefficients of variation[9] around 25%). In contrast, Theil's H index displays significantly higher dispersion—coefficients of variation are 86.7% and 94.7% for the less- and more-educated samples, respectively—indicating substantial differences in local residential segregation across the metropolitan area.

The share of low-education tracts (LE dummy equal to 1) is 67% in the less-educated sample and 42% in the more-educated sample. Control variables also show expected contrasts: the average rate of women's labor force participation is 60% among less-educated tracts and 76% among more-educated tracts. The average distance to the nearest metro station is 2.41 kilometers for the less-educated sample and 2.07 kilometers for the more-educated one, although values range considerably across tracts. Child dependency ratios average approximately 25% in both groups.

Gender schooling ratios exhibit minimal variation and are close to parity, consistent with national patterns. Average age of the workforce differs slightly between samples, suggesting intergenerational changes in access to higher education.

5.2 Econometric Approach

5.2.1 Baseline Regressions: OLS and Spatial Econometrics

Our econometric analysis tests whether structural features of Santiago's geography are systematically associated with horizontal occupational segregation. We begin with OLS estimations to analyze structural associations under the assumption of residual independence (IID). However, since horizontal occupational segregation is spatially autocorrelated, this assumption may be violated unless our model fully accounts for the spatial structure of this phenomenon.

Hence, we use Moran's I to detect whether OLS residuals are spatially autocorrelated.[10] In case of spatial dependence, we estimate the models using Spatially Autoregressive (SAR) and Spatial Error Model (SEM) specifications.[11] The SAR specification captures spatial spillovers in

[9] Coefficient of variation is calculated as $CV\% = \frac{SD}{Mean} * 100$

[10] Residual spatial autocorrelation is tested using the *lm.morantest* function from the *spdep* package in *R*. This test is specifically designed to assess spatial dependence in residuals from a fitted linear model (Anselin, 1988).

[11] SAR and SEM specifications are estimated via maximum likelihood using the eigenvalue method in the *spatialreg* package in *R*.

the outcome variable, assuming occupational segregation in tract A influences occupational segregation in neighboring tract B. By contrast, the SEM model assumes that spatial dependence arises from unobserved factors that are spatially clustered, affecting the error term rather than the outcome directly. For brevity, we present only SEM results in the main text, and SAR results are presented in the appendix (this is because Lagrange Multiplier tests indicate that SEM models are more appropriate for addressing residual autocorrelation in our models (Anselin, 1988)).

5.2.2 Instrumental Variables and Self-Selection

Our conceptual framework posits structural constraints, rather than preferences, as the primary drivers of segregation. However, if individuals holding strong gendered views about work also systematically sort into neighborhoods with low economic activity or high segregation, baseline estimations may suffer from self-selection biases.

To address this potential issue, we re-estimate our models using an instrumental variable (IV) approach (2-stage least squares). Following other applications of IV regressions in urban settings, we exploit the path-dependent nature of urban activity to address self-selection (Bleakley and Lin, 2012). In our case, we use the historical incorporation period of each tract—that is, the stage when the area was first urbanized and integrated into Santiago's metropolitan fabric–as an instrument for LLM intensity (nightlights), residential segregation (Theil H), and marginalization (Theil H $\times$ LE).

The periodization is defined according to the developmental strategies that Chile was pursuing at the moment of incorporation. As the literature shows, the current residential structure of Santiago is a direct product of these developmental strategies ((Hidalgo Dattwyler, 2007; Garreton, 2017)). Furthermore, economic activity continues to concentrate in the older sections of the city ((Garreton, 2017)). Finally, and crucially, it is unlikely for historical patterns of urban growth to affect occupational segregation by gender, except through their impact on local economic activity and socioeconomic composition.

GIS data on historical incorporation is obtained from the Observatorio de Ciudades (Cities Observatory) at the Pontifical Catholic University of Chile and merged into our main dataset.[12] We classify tracts into five developmental periods: (1) colonial-liberal era (pre-1920); (2) early import-substitution industrialization (ISI) (1920–1960); (3) late ISI (1960–1982); (4) early neoliberal reform (1982–1998); and (5) mature neoliberal urbanization (post-1998). Therefore, we have four binary indicators (with the earliest category omitted as the reference group) for our three potentially endogenous variables.

5.2.3 Robustness

We conduct a series of robustness checks to assess the sensitivity of our results to alternative measurement strategies and spatial definitions. First, we re-estimate all models using Theil's H index to measure occupational segregation, rather than the dissimilarity index. Second, we address the potential bias arising from small-cell problems in tract-level segregation measures by redrawing tract boundaries to ensure that each tract contains at least 1,000 LE or ME workers, respectively. Finally, we test the sensitivity of our results to the definition of local labor markets. Instead of relying on median commuting distances as the areal radius, we define alternative LLMs using the 25th and 75th percentiles of women's commuting distance for each education group.

[12] Shapefiles can be downloaded at https://ideocuc-ocuc.hub.arcgis.com/datasets/ebf66c46b1b1475c82fef27d8bded651_0/explore?showTable=true.

5.3 Policy Simulation: Inclusive Social Housing and Occupational Segregation

We contend that occupational segregation is a structural issue when the dual compulsion on women's work interacts with the spatial unevenness of urban economic activity. However, the social processes by which the city is produced can amplify or minimize the impact of this interaction. In this regard, and since we have identified residential marginalization as an amplifier of horizontal occupational segregation, it is worth testing if processes of residential inclusion have the opposite effect.

To evaluate the impact of residential inclusion, we simulate the relocation of social housing units from donor tracts, defined as those where more than 10% of the housing stock consists of social housing, to more advantaged recipient tracts. We consider two relocation scenarios: (1) into tracts in the top decile of LLM intensity (measured by nightlight activity), and (2) into tracts in the top decile of average educational attainment.

We use social housing data from the Chilean Ministry of Housing and Urbanism (MINVU) to identify donor tracts.[13] Since the census does not identify individual social housing units, we approximate relocation by randomly selecting households within each donor tract in proportion to its share of social housing. These sampled households are then reassigned to the set of eligible recipient tracts in each scenario. To reduce the potential bias from drawing households not actually residing in social housing, we repeat this simulation 100 times and average the results. To further isolate the spatial effect of relocating households specifically from high social housing areas, we conduct a placebo test by reallocating an equivalent number of randomly selected households from across the city to the same set of recipient tracts.

This procedure simulates the relocation of approximately 10% of all housing units in each case: 334 donor and 134 recipient tracts for the less-educated sample, and 245 donor and 111 recipient tracts for the more-educated sample.

Expected occupational segregation is computed after each relocation by applying the coefficients from our baseline model 1 to the updated values of all independent variables. This reflects the predicted change in horizontal segregation under the assumption of spatial effects operating through access to new industries for relocated workers.

6 Results and Analysis

6.1 Baseline Results: OLS and SEM

[Insert Table 3 here]

Table 3 presents the OLS results for both models and samples. Although these regressions explain a substantial share of the spatial variation in occupational segregation, as reflected in low values of Moran's I, the residuals still exhibit statistically significant spatial autocorrelation.

[Insert Table 4 here]

Table 4 summarizes the SEM results for our main variables of interest, which address the issue of spatial autocorrelation in the residuals.

6.1.1 The Unevenness of Economic Activity as a Structural Component of Occupational Segregation

In line with Hypothesis 1, economic intensity at LLM level is significantly and negatively associated with occupational segregation across both OLS and SEM specifications (SAR specifications, presented in the appendix (Table A-1), also confirm this finding). In Model 1, the estimated

[13] Shapefiles are publicly available at https://ide.minvu.cl/datasets/catastro-de-condominios-sociales/explore.

elasticities of -0.14 and -0.07 indicate that a one SD increase in nightlight intensity is associated with a 3.7% decrease in occupational segregation among LE workers, and 1.9% reduction among ME workers. After controlling for industrial composition in Model 2, these effects decline to 0.8% and 1.2%, respectively, indicating that much of the relationship between local economic activity and occupational segregation is mediated by the spatial division of labor.

Furthermore, the persistence of statistically significant coefficients even after accounting for local industrial composition suggests that additional mechanisms may be at play. For instance, some authors argue that denser local labor markets reduce employers' monopsonistic power (Azar et al., 2022), thereby limiting the scope for discriminatory practices that sustain occupational segregation (Anker, 1997). Regardless of the precise channel, our findings support a structural interpretation: under gendered mobility constraints, the spatial unevenness of economic activity translates into an uneven geography of occupational segregation.

Finally, the results suggest that access to education mitigates the association between local labor market conditions and horizontal segregation. However, its continued significance highlights the limits of education alone in addressing gender inequalities in the labor market.

6.1.2 The Social Production of the City: Residential Marginalization as a Reinforcing Mechanism

Residential segregation alone (Theil's H) shows a weak and negative association to occupational segregation. However, the interaction term between segregation and the LE dummy variable, signaling marginalization, displays a stronger and positive coefficient.

Even without considering the high baseline effect associated to living in LE neighborhoods, a one SD increase in marginalization increases segregation by 4.9% in Model 1 and 2.2% in Model 2. For more-educated workers, the effect is 1.9% in Model 1 and becomes statistically insignificant after adjusting for industrial composition.

These results suggest that industrial composition is the main mechanism by which marginalization is associated to occupational segregation. LLM in marginalized areas are not only less intense than elsewhere in the city, but they might also be more homogeneous in their industrial structure—deepening occupational sorting among workers with limited mobility. That marginalization remains significant in the LE sample even after controlling for industrial composition indicates that other mechanisms may also be present. One such possibility is the negative impact of marginalization on social capital, which has been shown to negatively affect labor market outcomes (Zenou, 2013).

Our baseline results, in line with Hypothesis 2, highlight how the social production of the city can amplify (or mitigate) horizontal occupational segregation. In the case of Santiago, the processes that led to the residential marginalization of the urban poor, may have inadvertently entrenched gender inequalities in the labor market.

6.1.3 Other Covariates

Other covariates exhibit mostly expected patterns. Perhaps, most surprising is that distance to the nearest metro station is not significantly associated with segregation. However, as other authors have pointed out, access to public transportation does not necessarily favor women over men, as its design does not usually consider the spatial logistics associated with the patriarchal compulsion (Loukaitou-Sideris, 2016). Child dependency ratios and average age are both positively associated with occupational segregation across education groups, supporting the hypothesis that reproductive burdens constrain women's access to a broader range of employment opportunities. Meanwhile, women's labor force participation exhibits a bifurcated pattern: it is positively associated with segregation among less-educated workers but negatively among more-educated workers. This divergence suggests that integration into the labor market alone does not guarantee equitable labor market outcomes. Finally, gender schooling ratios show inconsistent effects. Nevertheless, given their low variation in the data, coefficient magnitudes should be interpreted with caution.

6.2 Robustness

We conduct several robustness checks to validate the consistency of our findings. First, we re-estimate all models using Theil's H index as the dependent variable. The magnitude and direction of effects remain stable, though the response to local economic activity is stronger among more-educated workers under this specification.

Second, to minimize small-cell bias in segregation measures, we repeat all estimations using redrawn tracts that contain at least 1,000 workers per educational group. Results are highly consistent with our baseline estimations.

Third, we redefine local labor markets using the 25th and 75th percentiles of women's commuting distances to test sensitivity to spatial scale. Across both thresholds, nightlight activity remains a statistically significant predictor of occupational segregation. However, the magnitude of the coefficients consistently declines in absolute value as we move away from the median commuting distance. This attenuation suggests that using women's median commuting distance to define local labor markets, derived from our theoretical framework of gendered mobility constraints, is not only conceptually appropriate but also empirically justified.

All robustness checks can be found in the appendix (Tables A-2 to A-4).

6.3 IV Regressions: Structural Constraints or Self-Selection?

What if people with strict preference/aversion for a gendered division of labor also prefer to live in residential areas with low/high economic activity or with high/low levels of segregation? If workers can 'vote with their feet', then the structural interpretation of our findings can suffer from self-selection bias.

To address this concern, we must first note that residential mobility in Santiago is not strongly associated with changes in occupational segregation. 16.7% of less-educated workers and 28.4% of more-educated workers changed residences between 2012 and 2017. While this is not a negligible amount, the difference in the occupational segregation of their origin and destination municipalities is very small.[14] The average difference in local occupational segregation experienced after moving is just 0.05 percentage points lower for LE workers, and 0.2 percentage points for ME workers (See Table 5).

[Insert Table 5 here]

These mobility patterns are consistent with findings that residential relocation in Santiago is highly proximity-based (Escolano Utrilla et al., 2020) and often driven by kinship responsibilities (Araos and Siles, 2021).

To further rule out endogeneity, as foreshadowed in our methodological framework, we implement an instrumental variable (IV) approach using the historical period of tract incorporation as an instrument for economic activity, segregation, and marginalization. The instruments are statistically strong in all specifications (See Table 6). In line with our residential mobility analysis, Wu-Hausman tests suggest no evidence of endogeneity among LE workers, so OLS and SEM models are more appropriate in explaining their segregation. While there is modest evidence of selection for ME workers, the IV results reinforce the substantive conclusions of the OLS and SEM models for this group.

[14] The municipal jurisdiction is the smallest unit of analysis for residential mobility analysis using the census.

[Insert Table 6 here]

6.4 Reimagining the Social Production of the City through Inclusive Social Housing

The final stage of our empirical analysis examines the potential for urban policy, and in particular social housing, to disrupt occupational segregation. Specifically, we simulate the relocation of social housing from marginalized neighborhoods to more economically advantaged areas. This exercise should not be interpreted as a recommendation to displace existing residents, as such moves could sever important kinship ties and support networks. Rather, our goal is to illustrate the possible labor market benefits of policies that promote greater residential integration.

As discussed in the methodological section, we identify donor tracts with $\geq$ 10% social housing and simulate the relocation of their respective share of social housing into tracts in the top decile of (1) local labor market intensity and (2) educational attainment. Each simulation relocates approximately 10% of the city's housing units and is repeated 100 times. Then, using Model 1 baseline coefficients, we predict the average impact of these simulations on average occupational segregation.

[Insert Table 7 here]

The results in Table 7 show that relocation would result in substantive reductions in expected occupational segregation. Case 1 relocations would result in 1.3 percentage points reduction in average occupational segregation among less-educated workers and 2.2 percentage points among more-educated workers. Interestingly, the effects are stronger in case 2, where social housing is relocated into the more-educated regions of the city. In this case of residential inclusion, average local occupational segregation is reduced by 2.3 and 2.4 percentage points for less- and more-educated workers respectively. These declines are equivalent to 6.3% and 9.4% of the baseline estimations of segregation for each respective group. All results are significantly different from zero and, in all cases but one (sim 1, for LE), the effects are statistically higher (in absolute values) than those observed from placebo estimations.

To contextualize how substantive these results are, we can compare them with estimates from Borrowman and Klasen (2020) on the evolution of horizontal occupational segregation in Chile. They calculate that, between 1987 and 2009, it decreased by 3 percentage points. Mind you, this period was marked by an extreme and unrepeatable growth in women's access to tertiary education. While 16% of women had access in 1987, this number had nearly quadrupled to 62% by 2009. Furthermore, while at the beginning of this period the gender gap in tertiary access favored men over women—women's access was about 80% of the level of men's access—relative access was higher for women in 2009 (62% vs 58% for men).

In this context, the effect of inclusive social housing (case 2) on horizontal occupational segregation is equivalent to 80% of the impact generated by a massive, decades-long expansion in women's human capital—suggesting that spatial policy can be nearly as consequential for gender equity in labor markets as educational advancement. Moreover, the stronger effects observed among more-educated workers indicate that urban and educational policies are not substitutes but complements: when pursued together, they can reinforce one another in reducing gendered labor market disparities.

7 Conclusion

This paper shows that horizontal occupational segregation is embedded in the spatial structure of our urban environments. Women's subjection to the dual compulsions of paid and unpaid work, in the context of uneven local labor market geographies, creates a basis for segregation that persists even as educational gaps between men and women narrow. Segregation, therefore, is not only a by-product of individual choices, human capital differences or firm-level discrimination, but a structural outcome of the interaction between gendered mobility constraints and the geographies of local labor markets.

Using Santiago de Chile as a case study, we find that segregation is negatively associated with local economic activity (H1) and positively associated with residential marginalization (H2). Simulations based on our estimates suggest that placing affordable housing in neighborhoods with highly educated residents could reduce occupational segregation by an amount comparable to the gains from decades of educational expansion for women. These results highlight the potential of spatial policy to achieve gender equity effects on par with major human capital investments.

Although Santiago's social and historical context is distinctive, the spatial dynamics underlying occupational segregation are not. Patriarchal divisions of labor and agglomeration economies encompass much our modern urban world, suggesting that the interaction we identify is relevant well beyond our case. Furthermore, while we highlight inclusive housing is an important lever for mitigating segregation, others—such as transport planning that accounts for the spatial logistics of unpaid work—could also contribute to expanding women's mobility and narrowing labor market gaps.

The relationship between labor market gender inequality and the social production of cities remains underexplored. Future research should examine wage outcomes and incorporate other axes of inequality including the dynamics of informality. Understanding these structural geographies is essential for designing cities that do not simply accommodate inequality but actively dismantle it. By reimagining and reshaping our urban environments, regional policy can address not only the symptoms but also the structural foundations of gendered disparities.

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Tables

Table 1: Descriptive statistics for 22 industry categories in Santiago de Chile, showing total employment and female employment shares by education group: less-educated (LE) and more-educated (ME) workers.

Industry (Code)	Total Workers	Total LE Workers	Total ME Workers	Share Women	Share Women of LE	Share Women of ME
Agriculture, forestry and fishing (A)	11,872	7,190	4,682	29.6%	27.9%	32.1%
Mining and quarrying (B)	16,880	5,598	11,282	20.6%	13.8%	23.9%
Manufacturing (C)	200,666	143,293	57,373	30.2%	28.3%	34.9%
Electricity, gas, steam ... (D)	10,700	4,511	6,189	19.6%	12.6%	24.7%
Water supply; sewerage, waste ... (E)	9,430	6,588	2,842	18.0%	13.4%	28.5%
Construction (F)	222,648	171,890	50,758	7.4%	4.5%	17.0%
Wholesale and retail trade ... (G)	502,926	338,550	164,376	45.4%	46.3%	43.6%
Transportation and storage (H)	205,410	153,248	52,162	15.9%	12.5%	26.1%
Accommodation and food service (I)	120,833	80,564	40,269	53.5%	57.0%	46.3%
Information and communication (J)	96,729	24,909	71,820	27.8%	27.7%	27.8%
Financial and insurance activities (K)	82,507	21,700	60,807	51.6%	57.3%	49.5%
Real estate activities (L)	23,114	8,238	14,876	45.1%	41.5%	47.1%
Professional, scientific activities (M)	155,545	31,073	124,472	42.7%	45.4%	42.0%
Administrative/support services (N)	180,906	139,658	41,248	48.7%	48.9%	47.9%
Public administration and defence (O)	130,868	49,257	81,611	45.2%	37.5%	49.8%
Education (P)	189,820	41,475	148,345	70.3%	76.5%	68.5%
Human health/social work (Q)	174,846	56,884	117,962	75.3%	82.2%	72.0%
Arts, entertainment, recreation (R)	33,797	13,761	20,036	37.6%	33.1%	40.6%
Other service activities (S)	71,655	52,618	19,037	50.1%	47.3%	57.7%
Household employers ... (T)	117,417	106,976	10,441	96.8%	97.2%	92.7%
Extraterritorial organizations (U)	1,755	292	1,463	52.1%	39.0%	54.7%
Other	410,771	252,000	158,771	44.9%	43.8%	46.7%
Total	2,971,095	1,710,273	1,260,822	44.4%	42.1%	47.5%

Table 2: Summary statistics for main variables used in the analysis, reported separately for LE and ME tract samples.

	Less-Educated				More-Educated			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max
LLM Nightlights	50.93	12.76	12.72	77.39	53.09	13.64	12.97	75.28
Theil's H	0.15	0.13	0.00	0.76	0.19	0.18	0.00	0.78
Less Educated	0.67	0.47	0.00	1.00	0.42	0.49	0.00	1.00
Distance to Metro	2.41	2.21	0.06	12.43	2.07	2.11	0.08	12.48
Child Dependency	0.27	0.06	0.06	0.53	0.25	0.07	0.03	0.57
Gender Schooling Ratio	1.01	0.03	0.85	1.15	1.00	0.01	0.96	1.04
Women's Labor Participation	0.60	0.07	0.35	0.87	0.76	0.06	0.56	0.93
Age	43.49	2.68	33.39	53.43	38.30	3.42	30.12	48.49
N	1248.78	477.95	500.00	3453.00	1101.37	481.42	500.00	3029.00
Total Observations	**1,336**				**1,106**			

Table 3: OLS estimates of the association between local economic activity, residential marginalization, and horizontal occupational segregation, for LE and ME tract samples. The dependent variable is log(DD); Model 2 adds controls for industrial composition.

	Dependent variable: log(DD)			
	LE Sample		ME Sample	
	(M1)	(M2)	(M1)	(M2)
LLM Nightlights (log)	-0.146^{***}	-0.030^{***}	-0.069^{***}	-0.042^{**}
	(0.017)	(0.011)	(0.019)	(0.018)
Theil H (log)	-0.004	-0.007^{***}	-0.021^{***}	-0.010^{***}
	(0.003)	(0.002)	(0.002)	(0.003)
Less Educated	0.268^{***}	0.125^{***}	0.276^{***}	0.125^{***}
	(0.018)	(0.018)	(0.026)	(0.031)
Theil H (log) $\times$ Less Educated	0.056^{***}	0.024^{***}	0.039^{***}	0.015^{**}
	(0.006)	(0.004)	(0.007)	(0.007)
Distance to Metro (log)	-0.005	0.001	-0.012^{**}	-0.006
	(0.005)	(0.004)	(0.006)	(0.005)
Child Dependency (log)	0.227^{***}	0.078^{***}	0.176^{***}	0.117^{***}
	(0.020)	(0.014)	(0.016)	(0.017)
Gender Schooling Ratio (log)	-1.982^{***}	-0.249^{*}	4.086^{***}	2.285^{***}
	(0.160)	(0.136)	(0.428)	(0.443)
Women's Labor Participation (log)	0.335^{***}	-0.056^{*}	-0.482^{***}	-0.411^{***}
	(0.044)	(0.034)	(0.070)	(0.069)
Age (log)	0.418^{***}	0.327^{***}	0.249^{***}	0.261^{***}
	(0.069)	(0.066)	(0.065)	(0.083)
Constant	-1.613^{***}	-3.243^{***}	-1.872^{***}	-3.750^{***}
	(0.259)	(0.275)	(0.250)	(0.413)
Observations	1,336	1,336	1,106	1,106
R^2	0.455	0.785	0.701	0.759
Adjusted R^2	0.452	0.780	0.698	0.752
Industrial Shares	No	Yes	No	Yes
Moran's I	0.247^{***}	0.071^{***}	0.055^{***}	0.026^{**}
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4: Spatial Error Model (SEM) estimates for LE and ME tract samples, focusing on key geographic predictors of log(DD). Model 2 adds controls for industrial composition.

	Dependent variable: log(DD)			
	LE Sample		ME Sample	
	(M1)	(M2)	(M1)	(M2)
LLM Nightlights (log)	-0.136^{***}	-0.031^{**}	-0.078^{***}	-0.050^{***}
	(0.030)	(0.013)	(0.021)	(0.018)
Theil H (log)	-0.010^{***}	-0.006^{***}	-0.014^{***}	-0.008^{***}
	(0.003)	(0.002)	(0.002)	(0.003)
Less Educated	0.271^{***}	0.125^{***}	0.173^{***}	0.077^{**}
	(0.020)	(0.018)	(0.028)	(0.031)
Theil H $\times$ Less Educated	0.050^{***}	0.024^{***}	0.021^{***}	0.006
	(0.005)	(0.004)	(0.007)	(0.007)
λ	0.627^{***}	0.207^{***}	0.168^{***}	0.079
Observations	1,336	1,336	1,106	1,106
AIC	-2023.5	-3006.6	-1661.5	-1811
Moran's I	-0.04	-0.01	-0.00	-0.00
Note:				*p$<$0.1; **p$<$0.05; ***p$<$0.01

Table 5: Average occupational segregation (Dissimilarity Index, DD) for movers and non-movers, showing percentage differences between groups and mean individual-level changes from origin to destination tracts.

	Occupational segregation (Dissimilarity Index, DD)			
	Avg DD Non-Movers	Avg DD Movers	% Diff (Movers vs Non-Movers)	Mean Individual Diff (Dest – Origin)
Less Educated (LE)	0.349	0.343	-0.6%	-0.05%
More Educated (ME)	0.237	0.224	-1.3%	-0.2%

Note: Mean Individual Diff reports the average of individual-level differences in DD between destination and origin.

Table 6: IV estimates using historical tract incorporation period as instrument, for LE and ME tract samples. The dependent variable is log(DD); Model 2 adds controls for industrial composition.

	Dependent variable: log(DD)			
	LE Sample		ME Sample	
	(M1)	(M2)	(M1)	(M2)
LLM Nightlights (log)	-0.209^{**}	-0.085	-0.167^{*}	-0.036
	(0.087)	(0.112)	(0.099)	(0.102)
Theil H (log)	0.014	0.034	-0.068^{***}	-0.085^{**}
	(0.023)	(0.050)	(0.019)	(0.043)
Less Educated	0.074	-0.209	0.689^{***}	0.667^{**}
	(0.148)	(0.364)	(0.181)	(0.287)
Theil H × Less Educated	-0.011	-0.054	0.146^{***}	0.124^{**}
	(0.045)	(0.081)	(0.046)	(0.059)
Observations	1,334	1,334	1,105	1,105
R^2	0.389	0.699	0.572	0.585
Adjusted R^2	0.385	0.691	0.568	0.573
Diagnostic Tests				
Weak IV F-stat (logNight)	13.07^{***}	9.59^{***}	13.06^{***}	13.62^{***}
Weak IV F-stat (logTheilH)	12.15^{***}	7.38^{***}	7.07^{***}	2.49^{*}
Weak IV F-stat (logTheilH × LessEduc)	13.88^{***}	13.03^{***}	11.93^{***}	7.10^{***}
Wu-Hausman statistic	1.83	0.89	5.09^{***}	2.73^{**}
Sargan test	0.443	0.235	0.276	0.143
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table 7: Predicted changes in occupational segregation (DD) from simulated relocation of social housing to advantaged areas, for LE and ME workers, under two relocation scenarios.

Simulation	Group	Baseline Pred.	Placebo Pred.	Sim. Pred.	Mean Effect Effect	CI Effect 95%	Min	Median	Max
Sim 1	LE	0.365	0.358	0.352	−0.013	(−0.023, −0.003)	−0.0132	−0.0130	−0.0128
	ME	0.256	0.248	0.234	−0.022	(−0.030, −0.014)	−0.0226	−0.0223	−0.0219
Sim 2	LE	0.365	0.356	0.342	−0.023	(−0.034, −0.011)	−0.0229	−0.0225	−0.0221
	ME	0.256	0.248	0.232	−0.024	(−0.032, −0.016)	−0.0246	−0.0242	−0.0240

Figures

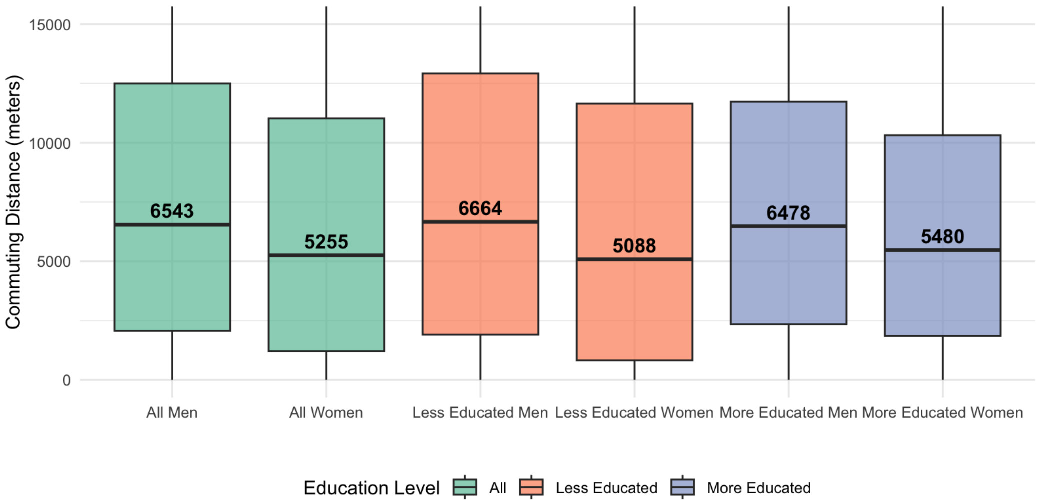
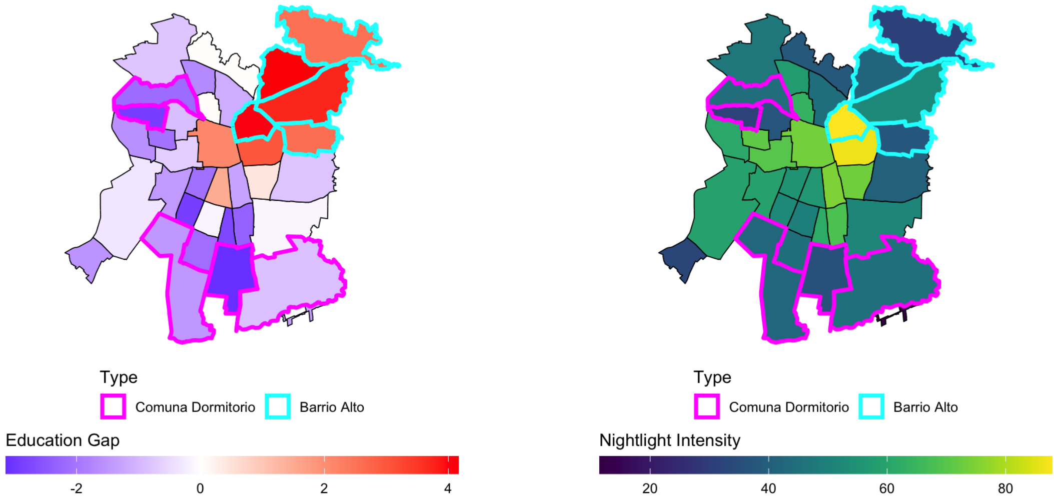
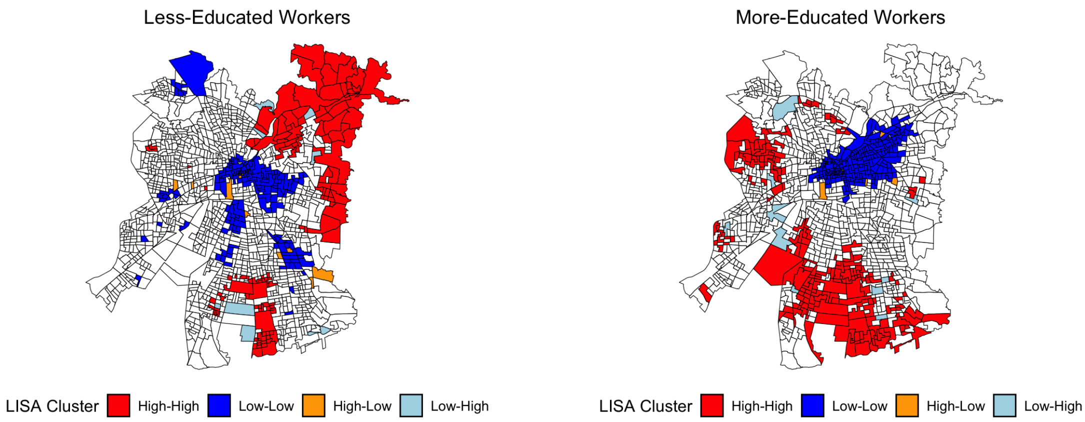


Figure 1: Weighted boxplots of commuting distance (in meters) by gender and education level. “Less Educated” refers to individuals with at most a secondary education degree and ”More Educated” to those having at least some tertiary education. Median values are displayed above each box. All calculations use survey weights. Data: Santiago Origin-Destination Survey 2012.



(a) Residential Segregation **(b) Economic Activity**

Figure 2: Comparison of educational advantage and economic activity across Santiago's comunas. **Panel (a)** shows the difference between each comuna's average years of education among household heads and the citywide mean, based on the 2017 Chilean Census. Red areas indicate comunas where household heads have higher-than-average education levels, while blue areas reflect lower-than-average levels. **Panel (b)** displays nightlight intensity from VIIRS 2018 satellite imagery, used as a proxy for economic activity and measured in radiance units (nW/cm²/sr).

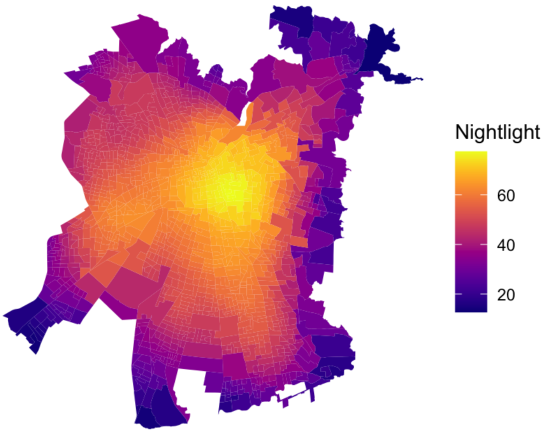


(a) Moran's I: 0.54^{***} **(b) Moran's I:** 0.65^{***}

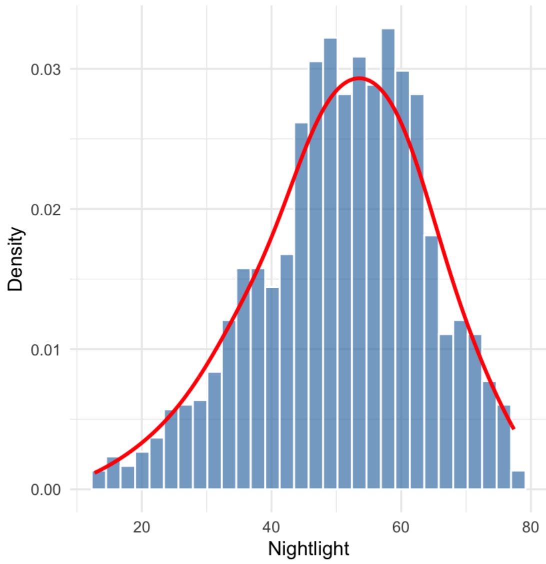
Figure 3: Local Indicators of Spatial Association (LISA) cluster maps of occupational segregation, measured by Duncan and Duncan dissimilarity index, for (a) less-educated and (b) more-educated workers. Each panel shows spatial clusters of high or low segregation values relative to their neighboring areas. Statistically significant clusters ($p < 0.05$) are categorized as High-High, Low-Low, High-Low, or Low-High. Non-significant areas are shown in white. Both maps reveal strong spatial autocorrelation, as indicated by the Global Moran's I statistics reported below each panel.

Appendix: The Urban Geography of Occupational Segregation

A-8 Nightlight distribution for tracts with at least 500 LE workers



(a) Geographical distribution of nightlight intensity



(b) Distribution of tract-level nightlight values

Figure A-4: Nightlight-based measures of local labor market intensity. Panel A maps tract-level buffers, each centered on an aggregated tract with at least 500 less-educated workers. Buffers are drawn with a radius equal to the median commuting distance of less-educated women (5.2 km). Nightlight intensity within each buffer is averaged and used as a proxy for local economic activity. Panel B shows the distribution of tract-level nightlight values across Santiago.

A-9 Spatial Autorregressive Model Results (Marginal Effects)

Table A-8: Total (marginal) effects from SAR models for LE and ME tract samples. Only main variables of interest are shown; other controls omitted for brevity. Simulated p-values are based on Monte Carlo simulations from the `impacts()` function in R.

	Dependent variable: log(DD)			
	LE Sample		ME Sample	
	(M1)	(M2)	(M1)	(M2)
LLM Nightlights (log)	-0.143^{***}	-0.025^{**}	-0.070^{***}	-0.042^{**}
	(0.030)	(0.013)	(0.023)	(0.021)
Theil H (log)	-0.010^{**}	-0.007^{***}	-0.012^{***}	-0.007^{**}
	(0.005)	(0.002)	(0.003)	(0.003)
Less Educated	0.398^{***}	0.136^{***}	0.160^{***}	0.070^{*}
	(0.038)	(0.020)	(0.035)	(0.037)
Theil H (log) × Less Educated	0.079^{***}	0.026^{***}	0.016^{*}	0.003
	(0.011)	(0.005)	(0.009)	(0.008)
ρ	0.513	0.123	0.251	0.172
LM test residual autocorr	7.05^{***}	3.58^{*}	13.89^{***}	9.15^{***}
AIC	−2038.6	−3006.0	−1700.4	−1830.1
Note:				*p<0.1; **p<0.05; ***p<0.01

A-10 Robustness

A-10.1 Theil's H as Dependent Variable

Table A-9: OLS estimates of the association between local economic activity, residential marginalization, and horizontal occupational segregation (Theil H), for LE and ME tract samples. The dependent variable is log(Theil H); Model 2 adds controls for industrial composition.

	Dependent variable: log(Theil $H_{occupation}$)			
	LE Sample		ME Sample	
	(M1)	(M2)	(M1)	(M2)
Nighttime Light (log)	-0.193^{***}	-0.029^{*}	-0.148^{***}	-0.100^{***}
	(0.025)	(0.016)	(0.032)	(0.031)
Theil H (log)	-0.012^{***}	-0.016^{***}	-0.043^{***}	-0.018^{***}
	(0.004)	(0.003)	(0.004)	(0.005)
Less Educated	0.413^{***}	0.159^{***}	0.411^{***}	0.143^{**}
	(0.028)	(0.025)	(0.048)	(0.056)
Theil H $\times$ Less Educated	0.081^{***}	0.026^{***}	0.061^{***}	0.016
	(0.008)	(0.006)	(0.012)	(0.013)
Observations	1,336	1,336	1,106	1,106
R^2	0.429	0.805	0.779	0.813
Adjusted R^2	0.424	0.800	0.777	0.808
Note:				*p<0.1; **p<0.05; ***p<0.01

A-10.2 Tracts with at least 1,000 workers of respective educational level

Table A-10: OLS estimates of the association between local economic activity, residential marginalization, and horizontal occupational segregation, for LE and ME tract samples. The dependent variable is log(DD); Model 2 adds controls for industrial composition. Tracts are constructed in order to have at least 1,000 LE workers in the LE sample and at least 1,000 workers in the ME sample.

	Dependent variable: log(DD)			
	LE Sample		ME Sample	
	(M1)	(M2)	(M1)	(M2)
LLM Nightlights (log)	-0.133^{***}	-0.025^{**}	-0.046^{**}	-0.031^{*}
	(0.017)	(0.012)	(0.020)	(0.019)
Theil H (log)	0.001	-0.004^{*}	-0.012^{***}	-0.002
	(0.003)	(0.002)	(0.002)	(0.003)
Less Educated	0.245^{***}	0.111^{***}	0.154^{***}	0.010
	(0.021)	(0.020)	(0.024)	(0.033)
Theil H (log) × Less Educated	0.044^{***}	0.018^{***}	0.020^{***}	-0.002
	(0.006)	(0.005)	(0.007)	(0.008)
Constant	-0.083	-2.049^{***}	-1.055^{***}	-2.197^{***}
	(0.102)	(0.131)	(0.121)	(0.416)
Observations	965	965	738	738
R^2	0.510	0.812	0.749	0.800
Adjusted R^2	0.506	0.806	0.746	0.791
Shares	No	Yes	No	Yes
Moran's I	0.277^{***}	0.104^{***}	0.086^{**}	0.03^{**}
Note:				*p<0.1; **p<0.05; ***p<0.01

A-10.3 Redefining LLMs to 25th and 75th percentile of commuting distances

Table A-11: OLS estimates of Models 1 and 2 using different definitions of Local Labor Markets.

	Dependent variable: log(DD)			
	LE Sample		ME Sample	
	(M1)	(M2)	(M1)	(M2)
LLM: 25th percentile of women's commuting distance				
Nighttime Light (log)	-0.101^{***}	-0.002	-0.050^{***}	-0.043^{***}
	(0.013)	(0.008)	(0.016)	(0.015)
LLM: 75th percentile of women's commuting distance				
Nighttime Light (log)	-0.119^{***}	-0.027^{**}	-0.057^{***}	-0.028^{*}
	(0.015)	(0.011)	(0.016)	(0.016)
Observations	1,336	1,336	1,106	1,106
Note:				*p<0.1; **p<0.05; ***p<0.01