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CARE WORK IN CHILE’S SEGREGATED CITIES

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CARE WORK IN CHILE’S SEGREGATED CITIES

A Dissertation Presented

by

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DEDICATION

To all who care.

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Writing a dissertation is emotionally taxing. I sincerely do not know if I would have finished it without a strong support network. Family and friends are essential components in the production of knowledge. Kritika, my partner, deserves a lot of credit for my work. Our never-ending and illuminating discussions forged the building blocks of this project. She taught me perseverance, encouraging me when things looked grim. And her presence made every day more exciting.

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ABSTRACT

CARE WORK IN CHILE'S SEGREGATED CITIES

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This project combines diverse theoretical and methodological tools to examine the relationship between space and care work in Chile. The chapters are stand-alone articles that come together to tell a single story. The social production of urban space has marginalized thousands of female caregivers from the labor market as Chile's care system unravels. I argue that community caregiving could simultaneously improve the conditions of caregivers and dependents.

Chapter 1 examines the role of residential segregation in reproducing Chile's meager female labor market participation rates. I use spatial and econometric analysis to show that the social forces that segregate Santiago create a landscape that penalizes the labor market participation of individuals with mobility constraints. Unpaid care is especially restrictive to mobility. Hence, caregivers residing in economically marginalized regions are significantly less likely to participate in the labor market. Thanks to the gendering of care, female caregivers' participation is the most negatively affected by the city's residential configuration.

In Chapter 2, I use political economy analysis to examine the capability of the Chilean system to meet the growing demand for adult care in a rapidly aging population. Moreover, the care system continues to rely excessively on unpaid family members (i.e., women) to care for adult dependents. However, Chile's demographic transition has also led to transformations in dependents' family structures. With the help of econometric analysis, I show that dependents living in households where the patriarchal division of labor is unfeasible are significantly less likely to receive assistance. Additionally, using Machine Learning methods, I demonstrate that dependents are increasingly living in these types of households.

Chapter 3 explores the possibility of replacing the family as the primary space of adult care for the community. It uses theoretical tools to analyze the economic implications of a state-funded program hiring caregivers to assist adult dependents in their communities. Since adult dependency rates are higher in economically marginalized communities, the program would disproportionately benefit the urban poor, especially women. Additionally, the program would boost aggregate demand and aggregate supply, leading to real economic growth. A crucial factor determining the program's success is trust in community care.

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INTRODUCTION TO THE PROJECT

This dissertation is the product of four years of thinking about space and work. A project combining various analytical and methodological frameworks in stand-alone articles which, together, tell a single story. The narrative illustrates that the social production of space is fundamental in the accumulation of gender and economic inequalities. Therefore, it should play a central role in overcoming them.

The project is centered in Chile. A country where profound economic inequality has solidified in residentially segregated cities (Garreton et al., 2020). This urban configuration entails remarkably different experiences for the poor and the rich, beyond their distinct economic capabilities. In the pages that follow, I argue that this landscape thoroughly conditions the experience of providing and receiving care.

Care is an essential activity. Without it, any social order is unfeasible. However, unlike other essential activities, most care work goes unpaid. Centuries of patriarchal conditioning have naturalized us into relying on women's free supply of care. Moreover, since care is a public good, its benefits are not accrued by those who bear the costs of producing it (Folbre, 2021). Patriarchal systems, however, do not operate in a void. They interact with other social and spatial structures producing differences in the experience of caregiving. Therefore, not all women experience caregiving in the same way.

The first article in this project, "*Residential segregation and female labor market participation*," is a testament to these differences. The paper underscores the economic implications of caring in different neighborhoods of Santiago. The concentration of employment opportunities in the more affluent regions of town characterizes the city. Mobility, thus, is an asset for those living in lower-income peripheral neighborhoods.

Care entails *coupling* constraints to mobility (Hagerstrand, 1970; Kwan et al., 2000). Caring takes place *somewhere*, at *some time*, with *someone*. The restrictive nature of coupling constraints severely penalizes caregivers' urban mobility. Hence, as the paper shows, female caregivers in peripheral communities are significantly less likely to participate in the labor market than any other social group.

Using spatial and econometric analysis, I show that the interaction between the patriarchal system and economic segregation fuels two types of inequality. On the one hand, it enforces gender inequalities within lower-income peripheral households. On the other, it deepens economic inequalities between those living in wealthier regions of the city and the urban poor.

My second paper, *"The limits to care,"* examines the conditions of those who need care. Specifically, I use political economy analysis to evaluate the capability of the Chilean care system to meet the growing demand for adult care. The article finds that the system's over-reliance on unpaid female provision severely limits its ability to supply care. Without structural reform, an adult care crisis looms on the horizon.

Space is integral to this paper's analytical framework. Spatial configurations are not only concrete, as is the case of cities, but also abstract and imagined. For instance, the division of labor, economics most fundamental category, is limited by abstract space. Its operation becomes difficult outside certain imagined boundaries (e.g., the market, the nation, the household). Hence, when the space for the division of care labor is tight or shrinking, it is unlikely for the system to increase its care supply.

Currently, the system relies almost exclusively on a patriarchal division of labor limited by the family space. Using econometric analysis, I show that dependents living in households where the patriarchal division of labor is severely limited are far less likely to receive any assistance. Moreover, with the help of Machine Learning prediction methods, I show that dependents are increasingly living in these households. This pattern is likely to continue as population aging drives growing dependency rates.

This project's first and second papers underscore the role of space in the production of social afflictions. The third one, "An economic case for community care aides," ventures into the theoretical to highlight space as part of the antidote for these afflictions. Adult dependency rates are higher in lower-income neighborhoods. Hence, there is a spatial correspondence between low female labor market participation rates and growing care needs. In this context, I propose the implementation of a Community Care Aides (CCA) program.

CCAs are caregivers hired and paid by the state to provide care for adult dependents in their communities. The CCA stimulates female labor participation through two channels. First of all, it allows lower-income women to outsource care to a qualified network of caregivers, reducing the coupling constraints of care. Secondly, if they choose to continue caring, the program creates local job opportunities that are not far from home.

Since it would disproportionately benefit lower-income women, the CCA program would reduce inequalities even as it boosts economic growth. Therefore, the program is not only a good strategy for increasing the coverage and quality of adult care. Its economic implications entail that CCAs can contribute to the inclusive development of the Chilean economy

CHAPTER 1

RESIDENTIAL SEGREGATION AND FEMALE LABOR MARKET PARTICIPATION

THE CASE OF SANTIAGO DE CHILE

I. Introduction

Every weekend, Gabriela walks Santa Rosa avenue to sell windows. She looks for homes displaying cracked or missing windows to offer her services. Her clients are often surprised by this 61-year-old Window Repair Woman. *"People tell me that this is a man's job"*—she says. Marcela, Gabriela's 31-year-old daughter who has a cognitive disability, walks beside her. Marcela's care is solely Gabriela's responsibility, so she has always had to bring her daughter along. *"We can only work on spacious avenues; otherwise, Marcela gets lost"*—Gabriela tells me. Gabriela and Marcela live in La Pintana, Santiago's poorest municipal jurisdiction. Given Marcela's condition, Gabriela has had to find ways to provide for her family without moving too far away from home. The challenge, however, is that there are very few jobs in La Pintana. Hence, window-repair.[1]

Gabriela's experience illustrates the struggle of many low-income caregivers in Santiago, Chile's capital city. The burden of balancing paid and unpaid activities is compounded by an urban environment that agglomerates employment opportunities

[1] I interviewed Gabriela in July of 2019.

far from their homes. This article analyzes the effects of residential segregation on Santiago's exceptionally low female labor market participation by examining the joint constraints of unpaid caregiving and distance to work.

Chile ranks second to last in female labor market participation among South American countries (Serrano et al. 2019). Within the poorest 20% of population, less than a third of working-age women provided labor for pay and nearly half of non-participants are unable to enter the labor market due to unpaid domestic and care labor responsibilities. [2] The different explanations for this phenomenon, as outlined in Section II, have failed to account for residential segregation's role. This is a serious oversight considering that over 90% of Chileans live in economically segregated cities (Garreton et al. 2020).

I address this oversight by presenting theoretical and empirical evidence on how residential segregation disproportionately affected the labor market participation of less educated female caregivers. In doing so, I underscore the intersectional nature of Santiago's segregation, which thus far has been mostly studied from an economic lens (Sabatini and Brain 2008; Garreton 2017).

Section III introduces our theoretical framework. The sexual division of unpaid care labor entails mobility constraints which limit women's ability to travel long distances for employment. Moreover, a public transportation system which is not designed for the balancing paid and unpaid responsibilities complicates the logistics for

[2] These values were calculated using the 2017 CASEN. The survey can be found at http://observatorio.ministeriodesarrollosocial.gob.cl/encuesta-casen-2017

combining these activities (Hanson and Pratt 1995, Kwan 2000, Loukaitou-Sideris 2016). Under these conditions, local markets are a more viable option for female labor market participation. The concentration of employment opportunities in wealthy neighborhoods, hence, presents an unfavorable landscape for low income caregivers' participation. In economic geography, this phenomenon is known as a spatial mismatch (Kain 1968; Fernandez and Su 2004; Gobillion et al. 2007).

Sections IV through VI compose the empirical analysis of spatial mismatch effects over less educated women's labor market participation. Section IV contextualizes Santiago's residential sorting, highlighting the events that led to the location of the urban poor in regions distant from the city's economic center. Section V introduces the primary dataset for analysis, the variables of interests, and some methodological issues regarding the quantitative analysis of spatial variables.

Our primary dataset is the 2012 Origin Destination Survey (ODS). This survey contains geo-referenced information for over 60,000 individuals' households and more than 23,000 employment locations for the greater Santiago region allowing us te measure local job density. Job density, our independent variable of interest, is defined as the ratio of employment opportunities to working-age residents in a given locality (Hellerstein et al. 2008). This variable will vary according to different labor market assumptions and, for robustness purposes, this article considers three different models. Additionally, Section V shows job density's spatial distribution in Santiago, underscoring the geographical matching of high-density regions with high income and high schooling neighborhoods.

Section VI culminates the empirical assessment through the econometric analysis of spatial mismatch effects. Considering possible self-selection problems, I show that less educated female caregivers are unlikely to sort themselves into high density regions. As a result, I restrict the primary analysis to this subpopulation. Avoiding self-selection problems allows us to perform OLS (with municipal fixed effects) analysis. The wide use of this technique makes these findings transparent and accessible. As a secondary analysis, spatial mismatch effects are calculated for other subpopulations, including non-caregivers and more educated individuals. Moreover, I analyze if spatial mismatch affects accessing formal and full-time employment.

My findings show that less educated female caregivers' participation in the labor market is significantly lowered in regions with low job density. No other subpopulation is affected by residential segregation in this manner. Therefore, I conclude that the residential sorting of the city intensifies gender inequalities within less educated household even as it reproduces economic inequalities between low- and high-income regions of the city. Section VII discusses the implications of our main findings.

II. Chile's low female labor market participation in the literature

Chile's low female labor market participation has received an important deal of scholarly attention. During the first decade of the 2000s, cultural explanations dominated this discussion. Since 2010, however, more structural arguments have emerged.

Paredes (2003) finds that significant increases in female labor market participation rates have only occurred in long durations of high-economic growth. Since prolonged periods of economic growth are sporadic, the author predicts that it is unlikely to observe sustained growth's in participation. Larrañaga (2006) offers an idiosyncratic reason for low participation rates. He argues that decreasing fertility and marriage rates during the 1990s prompted an increase in female participation among middle- and high-income families over the same time period. Ferrada and Zarzoza (2010) add that age is a determining factor. This line of argumentation holds that younger women are more likely to participate in the labor market due to cultural changes regarding women's relationship to paid work. Finally, Contreras and Plaza (2010) argue that patriarchal values are more prevalent among low-income families, contributing to the low participation rate among women in these households.

Structural explanations regarding the uneven distribution of care responsibilities have emerged in the last decade (Encina and Martinez 2009; Contreras et al. 2012; Martinez and Perticara 2017). Contreras and his co-authors (2012) find that access to private care services has increased women's labor supply in the middle and upper levels of the income distribution. Martinez and Perticara (2017), furthermore, carried out a randomized control trial evaluating an after-school program. They found that the program increased female participation and employment by 7% and 5%, respectively. Although these programs are not available to most of the Chilean population, this research underscores how the temporal constraints of unpaid care work penalize female labor supply.

The spatial constraints to participation have received far less attention. Two undertakings have made original contributions in this regard. Puga and Soto (2018) argued that the segmented nature of social space plays a significant role in determining low-income and less educated women's participation. In particular, they show that unequal access to employment information networks (social capital) has reinforced the gap in participation rates between women in different economic classes. Asahi (2015), on the other hand, found that improvements to Santiago’s public transportation network presented more favorable conditions for less educated women’s participation. However, none of these works consider the spatial constraints emerging from residential segregation for women’s participation in the labor market.

III. Spatial mismatch and gender

Residential segregation is the spatial clustering of a subpopulation sharing one or more personal attributes. Race, class, ethnicity, or a combination of these categories are often identified as the basis of this phenomenon (Davis 2007; Rothstein 2017). Therefore, scholars have analyzed the effects of segregation on labor market outcomes from the perspective of these categories (Kain 1968; Wilson 1997; Zenou 2013).

Gender inequalities emerging from segregation have received far less attention. Gender, after all, is rarely the basis of segregation. However, this does not mean that segregation is not a gendered experience. People experience class, race, and ethnicity in distinctive ways. The mutual constitution of social categories entails that the rearticulation of one category will result in the reconfiguration of the rest. Hence, if segregation is a racial/class/ethnic phenomenon, it must also be a gendered one.

This section presents the theoretical mechanisms by which segregation conditions labor market access across class and gender.[3] In a nutshell, I argue that residential segregation fragments the urban landscape across education levels. Less educated workers are often located in regions where employment opportunities are scant, generating a *spatial mismatch* between their households and job-places. Moreover, the geographical representations of the patriarchal division of labor and gender norms accentuate the spatial mismatch penalties for less educated female workers, especially caregivers, limiting their access to labor markets.

a. The spatial mismatch hypothesis

The spatial mismatch hypothesis connects residential segregation to poor labor market outcomes. Its original proposition argued that segregation imposes spatial barriers to employment opportunities in the form of higher job-search costs. Additionally, by placing similarly educated workers in close proximity to each other, segregation

[3] The focus on class rather than in race is due to the nature of the case study analyzed in subsequent sections. Santiago's residential segregation, unlike most cities in the United States, has been primarily defined across economic rather than racial attributes (Sabatini 2000; Hidalgo 2007; Agostini et al. 2016; Garreton 2017).

intensifies competition for local employment (Kain 1968; Fernandez and Su 2004; Gobillion et al. 2007).[4]

The hypothesis emphasizes the role of distance to work and mobility in mediating the relationship between segregation and labor market outcomes. Highly mobile workers can mitigate spatial mismatch effects. However, not all individuals share similar capacities for mobility. Mobility is informed by our position within multiple social hierarchies, including gender.

b. *Engendering the spatial mismatch hypothesis*

Female labor market participation has increased significantly over the last decades. However, the masculinization of unpaid activities has proceeded at a much slower pace (Folbre 2021). The persistence of the patriarchal division of labor bears substantial consequences for women's mobility. Unpaid activities are performed in a given place and at a particular time. Cooking meals, housework, and grocery shopping are all activities that, for the most part, cannot be performed from the job place. Moreover, activities like setting up the table for lunch, picking up the children from school, or going

[4] The logic behind commuting and search costs effects is straightforward. People take into consideration the monetary cost of traveling to work; if this is too high, the net benefits from employment are lower (Zenou 2009). The spatial barriers to information have also been addressed through the significance of social networks for facilitating employment opportunities. The social composition of these networks is mediated by space. One application of this notion contends that segregated residents tend to have 'strong-ties' networks (close relations), with very few weak nodes (acquaintances). In close relations networks, information on job opportunities may be quickly flooded by the many close members of the network (Zenou 2013).

to PTA meetings occur at a particular location and at a specific time. These unpaid tasks penalize women's participation in labor markets as they are often incompatible with the workplace and the working-day. Therefore, unpaid work constraints women's mobility beyond monetary search-costs (Kwan 2000; Ta et al. 2016).

Domestic work's spatial and temporal requirements strengthen the household's gravitational pull on women's mobility (Hanson and Pratt 1995, Duberley and Carrigan 2013). Additionally, balancing paid and unpaid activities is seldom considered by public transportation authorities. This leads to a male-bias in transportation design, intensifying spatial mismatch effects (Loukaitou-Sideris 2016).

Mobility is also informed by gendered norms and expectations. For example, the socialization of modern ideals around 'responsible motherhood' encompass employment location. Mothers who work far away from their children often feel anxious, irresponsible, and judged (Duberley and Carrigan 2013). Furthermore, commuting is a gendered experience. Male dominance over the public domain between the household and the job place frequently results in psychological and physical harassment. In this context, women's mobility strategies entail avoiding specific places, or refraining from traveling during particular times of the day (Jiron 2007, Almahmood et al. 2017).

c. Caregiving as a "coupling" constraint

Since caregiving often involves the participation of dependents with limited mobility, it is exceptionally restrictive to caregivers' mobility. Additionally, dependents' needs may not have a regular schedule. Some dependents may require help with asynchronous activities like using the bathroom, moving within the household, or stepping out on to the streets. Thus, caregivers frequently have to be "on-call" in close proximity to dependents. Caregiving, moreover, includes a great deal of supervisory work.

The combination of spatial and temporal constraints with such associative requirements are known as "coupling constraints" (Hägerstrand 1970). Feminist literature on economic geography has underscored care as one of the most restrictive coupling constraints to female labor market supply (Kwan 2000; Ta et al. 2016). Against the backdrop of a spatial mismatch, therefore, caregivers in segregated communities may be systematically excluded from the labor market.

d. Occupational segregation and co-location of employment opportunities

Thus far, in line with the original proposition of the spatial mismatch hypothesis, I have underscored supply-side constraints for female labor market participation. However, spatial constraints may also arise from labor demand. Prior works have qualified the spatial mismatch hypothesis by incorporating employers' preferences and biases in hiring that segregate the labor market (Blumenberg 2004; Hellerstein et al. 2008).[5]

[5] Certainly, occupational segregation also emerges from supply-side factors. Gendered self-selection into different jobs significantly contributes to the gendered segmentation of paid labor.

Stereotypes associating authority to masculinity contribute to the allocation of women to lower-paid and less secure jobs (Elson 1999). The image of *glass ceilings* is often invoked to characterize this form of occupational segregation. However, people also face *glass walls* when selling their labor power. The gendering of particular occupations allocates similarly skilled men and women to different jobs (Johnson and Crum-Cano 2011; Nasser 2018).[6]

Gender occupational segregation may also be reflected in a geographical division of job opportunities (Massey and McDowell 1984). Some industries tend to agglomerate in space to lessen transaction costs and take advantage of knowledge spillovers (Malmberg and Maskell 2002). A gendered co-location of employment opportunities would imply that "women's jobs" are geographically separate from "men's jobs." Therefore, spatial barriers to employment may be gendered beyond mobility considerations. In an economically segregated city, paid domestic work may be an example of the co-location of gendered employment since more affluent households are more likely to hire domestic workers.

e. Historical and political context of the spatial mismatch

The empirical analysis of spatial mismatch effects on female labor market participation requires methodological qualifications. The residential organization of a city is the

[6] Women are more likely to be hired in sectors involving care work, education, and tourism. Male-dominated activities include economics, finance and the military.

outcome of place-specific political and historical processes (Brenner and Theodore 2002). Additionally, gendered differences in mobility and employment accessibility vary across space and time (Massey and McDowell 1984). The centrality of segregation and mobility in determining spatial mismatch effects, thus, calls for an empirical examination that thoughtfully considers the context under which it takes place.

The inclusion of contextual elements in the empirical analysis is relevant for at least two additional reasons. First of all, from a quantitative analysis perspective, it is important to highlight the structural determination of low skilled workers' residential location. If individual employment preferences are the main determinants of residential location, the econometric analysis would suffer from self-selection bias. Secondly, a contextual analysis of residential segregation unveils the systemic sources of labor market inequalities.

IV. The social production of a spatial mismatch

In magnitude, Santiago's economic segregation is similar to the most racially segregated cities of the United States (Agostini et al. 2017). The city's residential organization concentrates less educated (and low-income) workers in the southern and western banks of the city. In contrast, more affluent and higher-skilled households populate the northeastern quadrant of the city (see Figure 1). These regions, moreover, offer diametrically opposed conditions for mobility. While the wealthier areas connect to the city's economic center through high-speed highways, 40% of affordable housing residents—and 70% of slum-dwellers—have little to no access to public transportation (Shirahige & Correa 2015).

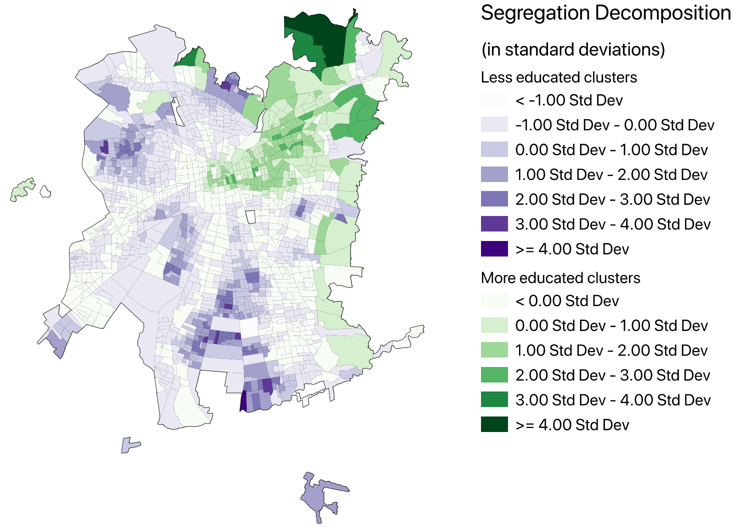

Figure 1: The economic segregation of Santiago. Using the Generalized Neighborhood Sorting Index (Jargowky and Kim, 2005), I have decomposed Santiago's residential segregation across the 2012 census tracts. Neighborhoods with above-average mean schooling are green (over 11.5), and neighborhoods that have below-average mean schooling are purple. The intensity of each color represents how much of the city's overall segregation is explained by each neighborhood (in standard deviations). Thus, the more intense green/purple neighborhoods, the higher segregation levels for high/low skilled segregated neighborhoods. Source: 2012 Census.

Santiago's residential distribution emerges from market-oriented reforms that trace back to the late 1970s.[7] Back then, under the authoritarian rule of Augusto Pinochet (1973-1990), a combination of ideological, economic, and political factors set in motion the sorting of the city. The return of democratic governments in 1990 did not change this trajectory. In fact, Santiago's segregation would peak several years into democratic rule (Agostini et al. 2017).

[7] The transformation of the urban landscape due to market-oriented reforms is otherwise known as the *neoliberalization* of the city (Brenner and Theodore 2002)

Pinochet’s policymaking style was well-known for its reliance on a reduced and selected crew of political and economic advisors (Silva 1996). Among these privileged voices, a group of Chicago trained economists were particularly relevant in restructuring the economic role of the Chilean state. These economists argued that the state’s intrusion in economic affairs fostered rent-seeking behavior (Krueger 1974), thus advocating for steep market deregulation and the privatization of publicly owned enterprises. The dogmatic character of the Chicago Boys’ economic agenda was, perhaps, best illustrated by the residential market reforms of 1979.

In that year, Neil Smith published an article underscoring that unregulated residential markets induce rent-seeking behavior among real estate entrepreneurs (Smith 1979). Yet, this did not bar the Chilean government from swiftly deregulating the residential sector by eliminating landholding and property-transaction taxes, as well as auctioning a significant share of state property. In line with Smith’s predictions, deregulation led to the spike of residential prices in regions with greater accessibility to Santiago’s economic center (Sabatini 2000; Garreton 2017).

Prior to Pinochet’s dictatorship, a significant number of informal settlements had spawned in these areas. Salvador Allende’s government (1970-1973) had promised not to evict settlers, leading many working-class families to occupy undeveloped lands in otherwise wealthy neighborhoods (Hidalgo et al. 2016). The deregulation of residential markets, however, turned these lands into profit opportunities for rent-seeking entrepreneurs (Sabatini 2000). Moreover, the slum-dwellers’ central role in the popular resistance to the dictatorship motivated the government to dissolve their communal settings (Morales 1990). The complementarities between the rent-seekers' economic interests and the dictatorship's political interests, thus, facilitated the resettlement of nearly 165,000 people between 1979 and 1985 (Garreton 2017).[8]

Most families were relocated to the southern and western peripheries of the city (Morales 1990; Garreton 2017). At the time, these regions were scarcely populated, poorly connected to the rest of the city, and notably unfit to host large human settlements (Hidalgo 2007).[9] This eviction process was instrumental in initiating Santiago's segregationist trajectory.

The 1980 constitutional reform would transform the role of the state in the provision of affordable housing, consolidating the segregation process. Before the reform, the state was an active supplier of social housing. Thereafter, the state would assume a subsidiary role. Instead of publicly providing affordable housing, the state would subsidize individual families to participate in the private housing market. The state's new role made private builders the *de facto* providers of affordable housing. Simultaneously, the government loosened restrictions for the construction of affordable housing projects. Among other reforms, it became permissible to build these projects in regions that were not fully urbanized (Hidalgo et al. 2016).

The new affordable housing market led private companies to cluster projects in the cheaper lands located west and south of the city's center, furthering Santiago's

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[8] According to the 1982 census, nearly 5% of people were relocated during this period.

[9] At the time of the evictions, the resettled regions presented poor to no access to clean water, poor access to electricity, and low levels of transportation connectivity to the rest of the city (Hidalgo 2007).

segregation (Sabatini and Brain 2008). Nevertheless, the urban poor faced significant barriers in accessing housing subsidies. Among its requirements, these subsidies required to demonstrate savings. Back then, however, very few low-income families had a bank account, let alone savings. These difficulties contributed to Santiago's housing deficit reaching nearly 40% by 1989 (Garreton 2017).[10]

In 1990, when democracy was reinstated, the newly elected government of Patricio Aylwin (1990-1994) promised to decrease Santiago's housing deficit. They did so by loosening the requirements on housing subsidies and increasing government spending. By the year 2000, this policy managed to reduce the deficit to nearly 10%. However, the elected governments did not transform the role of the state and private companies in the provision of affordable housing. Thus, the market continued to allocate the urban poor to the southern and western banks of the city. Consequently, by 2002, the city was significantly more segregated than it was in 1990 (Agostini et al. 2017).

Throughout the 21st century, the structural determinants of Santiago's segregation have not changed much. Residential markets continue to lack government oversight. Additionally, the role of the state in subsidizing the demand for affordable housing has persisted up until the writing of this article. More recently, some initiatives at the municipal level have attempted to integrate some sectors of the city by building

[10] The housing deficit in Chile is measured according to the number of families who share the same household with other families.

affordable housing in wealthy regions of the city. The magnitude of these initiatives, however, pales in comparison to the Santiago's segregation levels.

V. Methodological issues: Spatial autocorrelation and calculating the spatial mismatch

Spatial mismatch calculations require the geographical coordinates of both households and job places. Additionally, in calculating the spatial mismatch effects on labor market participation, the definition of *local* markets is crucial. Here local markets are defined as all employment opportunities between the household and the average point of indifference between walking (or cycling) and taking a motored mean of transportation. Since not all individuals have access to the same means of motored transportation, individual local markets differ according to the ownership of private vehicles. Finally, given that gender occupational segregation may be spatially represented, individuals may not be able to access local gendered employment opportunities. In this section, I assess these issues and present the data used for subsequent econometric estimations.

a. The Data

The primary dataset in this study's empirical analysis is the 2012 Origin-Destination Survey (ODS) for the greater Santiago.[11] The ODS provides coordinates for households and job places, as well as individual demographic and socio-economic data. Furthermore, this dataset has a large sample size at over 60,000 individual observations, including more than 23,000 employment locations.[12] Even though labor market analysis is not among the survey's primary objectives, the construction of individual survey weights considers employment and locational information that match the 2012 census.[13]

Additionally, the 2012 census is utilized for identification purposes. High omission rates in this census led to its repetition in 2017. However, omission rates were lower in Santiago (lower than 10%) and no systematic bias was found regarding socio-economic characteristics (Garreton et al. 2020). Therefore, at the very least, the 2012 census may be considered as a robust and reliable survey that accounts for over 90% of the city's population.

b. *The spatial autocorrelation of female labor market participation*

The quantitative studies of Chilean female labor market participation mentioned in Section II share a relevant methodological oversight. They fail to address the spatial

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[11] Encuesta de Origen Destino, executed by the sub-Secretary of Transport in the Ministry of Transport and Telecommunications.
[12] Around 53,000 observations reside in the greater Santiago area. The dataset is representative to census zones, an area that is smaller than the municipal jurisdiction.

[13] See annex for comparison between weighted statistics in the ODS and the 2012 census.

autocorrelation of labor market participation. Spatial autocorrelation is the co-variation of some characteristics—in this case, labor market participation—within a geographical region. By itself, it is not a problem for econometric calculations. If geographical variations are captured by the model's independent variables there shouldn't exist any identification problems. However, if the model's residuals continue to be spatially autocorrelated, then the model's parameters may be inconsistent and/or biased.[14]

Table 1 shows the degree and significance of labor market participation's spatial autocorrelation by gender and education level. Here, spatial autocorrelation is measured through Moran's I, a global indicator of spatial association that ranges between negative-one and one, where zero indicates no clustering and one or negative one perfect clustering. If Moran's I is statistically different from zero, then we can argue that labor market participation is spatially autocorrelated.[15]

Table 1: Labor market participation rate and spatial autocorrelation of LMP by gender and education level. Less educated is defined as having at most a high school degree, while more educated is defines ad having at least some years of tertiary education. Source: 2012 ODS.

		Less Educated		More Educated	
		Women	Men	Women	Men
LMP (%)	Full Population	39.09%	76.19%	60.25%	77.21%
	Caregiving Pop.[1]	37.44%	75.90%	55.41%	77.92%
Moran's I [2]	Full Population	0.014***	0.015***	0.013*	0.011
	Caregiving Pop.	0.013**	0.007	0.010*	0.010*

Note: *p<0.1; **p<0.05; ***p<0.01

[1] The caregiving population are those who reside with dependents. here, we identify two types of dependents: children under 14 years of age and adults with mobility and cognitive disabilities.

[2] A single random observation from each household was chosen for calculating Moran's I.

[14] For an extensive discussion on these issues, see Gibbons, Overman and Pattacchini (2015), p. 124-136.

[15] See annex 2. for the mathematical expression of Moran's I and how it was utilized in this article.

The Table shows that spatial autocorrelation in labor market participation is especially acute among less educated women. While there are significant levels of spatial autocorrelation levels among less educated men, this does not include all men. The participation of those that reside with dependents, defined here as the caregiving population, does not co-variate with geography. The table also shows labor market participation rates in the ODS. Of all groups, women's participation is the lowest and most geographically concentrated.

c. *Operationalizing the spatial mismatch through job density*

Following Hellerstein et al. (2008), I use job density as a local measurement of spatial mismatch. Job density is defined as the total number of job-places in a locality relative to the sum of working-age residents in the same area.[16] The ODS, however, does not allow us to use this exact definition since the survey weights do not factor-in employment location. In fact, unweighted employment locations minimize the difference between relative municipal job availability between the ODS and the 2012 census (See Table 2).[17]

[16] People who are enrolled in schooling institutions are not considered as potential competitors for local employment opportunities. This is because these people may appear as non-participant, but they are not necessarily spatially constrained.

[17] The census offers employment location information only at the level of municipal jurisdiction.

Table 2: Relative municipal employment mean error between the 2012 ODS and the 2012 census.

	All Workers	Less Educated	More Educated	Less Educ. (Men)	More Educ. (Men)	Less Educ. (Women)	More Educ. (Women)
Weighted	0.0032	0.0035	0.0037	0.0042	0.0048	0.0043	0.004
Unweighted	0.003	0.0032	0.0032	0.0038	0.004	0.0034	0.0026

Thus, job density calculations consider the (unweighted) standardized local job places over the (weighted) standardized local presence of working-age residents.[18] Highly segregated low-income regions presenting poor access to employment display job density values close to zero, while non-residential sectors that employ high amounts of people have a high hob density ratio.

Localities are calculated as a radius around each individual household. To avoid issues of mechanic endogeneity, I deduct one unit from the total pool of local employment opportunities from the individual observations who work locally.[19] Considering these qualifications, the job density measurement for individual i residing in the local area A takes the following functional form:

[18] Local competitors are defined below.

[19] On the left-hand side of the econometric equation (labor market participation) the observation would signal participation. Moreover, the local job that is held by the individual would marginally increase job density on the right-hand side of the equation. For every individual that is locally employed, this marginal increase in job density would always be associated with participation, thus leading to biases in the calculation of coefficients.

$$JD_{iA} = \frac{(E_A - e_{iA}) \big/ SD(\sum_i^n (E_A - e_{iA}))}{Rw_A \big/ SD(\sum_i^n Rw_A)}$$

$$Where\ E_A\ is\ the\ sum\ of\ job\ locations\ in\ local\ area\ A,$$

$$e_{iA} = \begin{cases} 1, & If\ individual\ i\ resides\ and\ is\ employed \\ & \qquad in\ local\ area\ A \\ 0, & Otherwise \end{cases}$$

$$and\ Rw_A\ is\ the\ weighted\ sum\ of\ potential\ competitors\ residing\ in\ local\ area\ A.$$

Job density varies according to two exogenous assumptions. First of all, we need to define a locality radius. The larger the radius (i.e., the bigger the locality), the more homogeneous will job density be across households. Secondly, the numerator and denominator will vary with the assumed segmentation of the labor market. If, for example, we assume that all individuals can access all job places, then all job locations (numerator) and every working age individual (denominator) in the same locality are considered for the calculation of job density. On the other hand, if we assume segmentation in labor markets across education levels, then we would only consider the local job locations that hire individuals with similar schooling levels (numerator) and local residents with the same characteristic (denominator). Both of these assumptions are qualified in the following sub-sections.

d. Defining local markets

Local boundaries must bear actual consequences on employment decisions. If not, Modifiable Areal Unit Problems (MAUP) may bias the analysis of spatial mismatch effects (Wong 2004). The MAUP arises when using artificial boundaries to capture a geographical effect. It is a common problem in spatial mismatch analysis. For example, prior works often rely on census tracts to define local markets (e.g., Hellerstein et al. 2008). Census tract boundaries, however, do not necessarily carry employment-search consequences for those who live within them.[20]

For this article, locality thresholds are defined as the distance between the household and the average point of indifference between motored and non-motored travel (walking or cycling).[21] Since not all individuals have access to the same means of motored transportation, the average point of indifference between motored and non-motored travel differs according to car ownership.

There are theoretical and empirical reasons to use this parameter. First of all, public transportation design does not consider the balancing of paid and unpaid activities, so employment opportunities which are not within walking distance may entail higher logistical costs for those conducting unpaid work (Loukaitou-Sideris 2016). Second, motored transportation involves higher economic search-costs than non-

[20] Imagine a household located in a mostly residential zip code area which is adjacent to a zip code area populated by multiple employment opportunities. Since the household's zip code area is mostly residential, the calculated job density for that observation would be relatively low. This would not be a problem if the household was located in the middle of the zip code area. However, what would happen if the household was located at the edge of the zip code area nearing the business district?

[21] This entails that we have as many localities as we have households and that localities overlap with each other.

motored transportation.[22] Finally, public transportation is also a gendered space and, as such, presents deterrent conditions for female travel. According to the 2019 National Survey of Urban Safety, Chilean women feared victimization significantly more than men while waiting for or while using public transportation.[23]

I calculate this indifference point using the ODS. On average, people who own automobiles walk to their destinations when they are within a one-kilometer radius from their homes. On the other hand, those whose means of motored transportation are limited to carpooling or public services, on average, walk up to 1.4 kilometers from their place of residence before taking a motored mean of transportation.[24] [25] According to these thresholds, nearly 20% of employed people in Santiago work within their local boundaries. This is more likely for less educated workers, with 21.7% of them being locally employed. Among these, women are disproportionately represented. While 18.4% of less educated men are locally employed, 27.1% of less educated women work within non-motored distance from their home.[26]

e. Labor market segmentation and three models of job-density

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[22] In Santiago, the high costs of public transportation sparked national-level protests in October 2019.

[23] According to the National Survey on Urban Safety by the National Institute of Statistics (INE, for its acronym in Spanish). In Spanish, the survey is *Encuesta Nacional Urbana de Seguridad Nacional* (ENUSC).

[24] For adults between 18 and 65 years of age.

[25] For greater detail in how these averages were calculated, please refer to the annex.

[26] These numbers do not consider live-in domestic workers.

Not every local resident will qualify for the same job opportunities. Due to labor market segmentation, some jobs will only be available for people who meet particular criteria. Taking this into account, and for robustness purposes, three different job density models are listed below.

i. *Economic activity model*

In this model, labor market stratification is not a factor. It considers all working-age local residents (denominator) who are not enrolled in schooling institutions as potential competitors. Similarly, all employment positions held in the locality are considered as potential job opportunities (numerator), regardless of the skill and gender of individuals in these positions. The rationale behind this model is that overall economic activity may generate employment opportunities for all workers in the form of multiplier effects (Moretti 2010). In this model, every member of the household faces the same job density.

ii. Education stratification model

In this model, relevant local employment opportunities are held by workers in the same education bracket as the observed individual (numerator). Similarly, relevant local competitors share the same education level as the individual observation (denominator). Hence, less and more educated job densities are calculated for every locality and ascribed to individuals according to their education level. The less educated job density measure includes people who hold at most a high-school degree while skilled job density comprises people having at least some college education. Individuals within the same household face the same job density only if they share education levels.

iii. Education and gender stratification model

Earlier, I argued that gendered occupational segregation in the labor market can entail different geographical landscapes for women's and men's work. This model seeks to capture these differences. While maintaining the distinction between less and more educated labor, this model also accounts for gender in the calculation of job densities. Therefore, individuals within the same household will face the same job density only if they share education level and gender.

Table 3 shows descriptive statistics for these three models. The most salient features in Table 3 are the outliers illustrated by the large discrepancy between job density at the 99th and 100th percentiles. The concentration of less educated employment opportunities in regions where few less educated workers reside partially explains these outliers. Nevertheless, they may also be a byproduct of the calculation of local boundaries.[27] Hence, they must be addressed in the subsequent econometric analysis.

[27] Even though the ODS considers a region larger than the greater Santiago area, some observations are located in peripheral localities of the dataset. This means that, for some localities, the observation of potential competitors may be censored leading to high job density values. Six observations were dropped

Table 3: Descriptive statistics for different models of job density using the 2012 ODS.

	Econ. Activity	*Education strat.*		*Education and Gender strat.*			
Stat\JD	All Jobs	Less Educated	More Educated	Less Educ. (Wom.)	More Educ. (Wom.)	Less Educ. (Men)	More Educ. (Men)
Mean	0.33	0.6	0.38	0.58	0.41	0.66	0.41
Median	0.18	0.27	0.21	0.23	0.25	0.29	0.19
Std. Dev	0.44	0.92	0.72	1.02	0.63	1.03	0.94
Min	0.02	0.03	0.01	0.01	0	0	0
1%	0.05	0.06	0.03	0.06	0.02	0.04	0.02
99%	2.21	4.68	2.23	4.73	2.35	4.67	2.71
Max	13.46	71.29	23.44	86.03	26.88	96.97	21.42

f. Visualizing job density clusters

Job density is a geographical variable that can help explain spatial autocorrelation in the labor market. If this is the case, we should expect for job density to be spatially autocorrelated as well. If our main thesis is correct, job density's distribution should also reflect Santiago's residential segregation.

Moran's I is a global indicator. In other words, just a number that does not communicate the location of job density clusters. Therefore, I decompose Moran's I into Local Indicators of Spatial Association (LISA). Following the literature, observations presenting statistically significant (p-values<0.01%) high measures of job density that neighbor other observations with high job density values are classified as part of a *high-High* cluster (statistically high job density neighboring other statistically high values). Conversely, observations with low local measures of job density in proximity to other

due to not having any observations for the denominator. For example, in some localities there were no skilled female residents.

low-dense localities are assigned to a *low-Low* group (Anselin 1995). [28] [29] Observations that do not meet any of these criteria are not clustered into any group, and thus are not depicted in the LISA maps.

Figure 2 illustrates the LISA maps for less and more educated job density measures. On the top-left corner of the figure is the Moran's I global statistic. Moran's I confirms the clustering of job density in Santiago for both less and more educated workers. Moreover, as depicted by the red dots (each dot is a household), households in high-High neighborhoods are mostly clustered in the downtown and northeastern regions of the city, where more affluent families reside. Blue dots represent clusters of low job density localities. The LISA maps illustrate how Santiago's spatial mismatch is a reflection of the city's residential segregation.

[28] The mathematical expression for LISA can be found in annex 4.

[29] We could also find high-Low and low-High clusters. This would mean that a significantly job-dense locality neighbors significantly low-dense areas (high-Low), or that a significantly low-dense area Is surrounded by regions that are significantly dense.

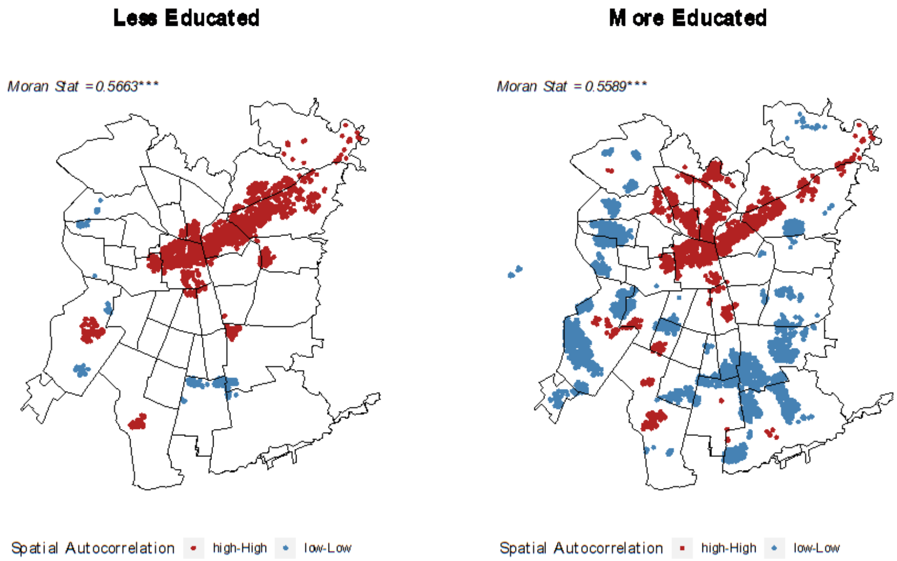

Figure 2: Spatial autocorrelation for less and more educated job density using the 2012 ODS. Red dots represent employment positions located in regions concentrating significantly high levels of job opportunities. Blue dots represent employment positions located in regions presenting significantly low levels of job opportunities. The left panel shows employment positions that are held exclusively by less educated individuals (who hold at most a high school degree). The right panel represents employment positions held by more educated individuals. Source: 2012 ODS.

Santiago's northeast concentrates employment opportunities for less and more educated workers. There are very few low-Low clusters for less educated workers, and more noticeable amount for more educated workers. This means that there are very few employment opportunities for more skilled workers outside the northeast. This does not imply a spatial mismatch for more educated workers, since they mostly reside in the northeast. However, it does entail few economic incentives for these workers to move outside the northeast.

VI. Spatial mismatch and female labor market participation

There are potential endogeneity problems when calculating spatial mismatch effects. Individuals may choose to live closer to employment opportunities if they have high preferences for participation. If this were the case, labor market preferences could contribute to Santiago's segregation, making job density coefficients endogenous and possibly biased. Nevertheless, as outlined in section III, the urban poor's residential location is born out of structural transformations rather than personal preferences. This is more evident when observing residential mobility patterns among less educated women.

a. Endogeneity issues I: Residential mobility patterns

While the ODS does not inform on residential mobility patterns, the 2012 census does. The census asks every citizen about their mothers' birth location (unfortunately, not their fathers'). Therefore, we get can observe residential mobility patterns for female caregivers currently living with their children. Narrowing the data to working mothers we can examine mobility patterns for those who have revealed their preferences for labor market participation.

In the census, job density is calculated at the municipal level. I group each of Santiago's thirty-six municipalities into six groups (each comprising six municipalities) ranked from lowest to highest density. If caregivers with higher preferences for participating in the labor market were able to choose their residential location freely, a significant flow of working women would move from low-dense areas to high-dense regions. However, this is not the case.

Over 83% of less educated working mothers born in the lowest-dense regions still live there. In fact, among all density groups, this one is the least mobile. Furthermore, those born in the highest-dense regions were the most mobile. Nearly 45% of less educated working mothers born in high-dense regions moved away.

Figure 3 depicts these mobility patterns. Here, Santiago's segregationist development is most evident. A small percentage of less educated women born into low dense groups moved into higher dense groups. Those born in higher dense areas moved into lower dense regions at a significantly larger rate. This evidence suggests that less educated women with preferences to work are not able to self-select into regions with high job density.

Figure 3: Fraction of less educated working mothers who moved away from their place of residence. The x-axis shows their new place of residence, in parenthesis is the average job density for each group. Source: 2012 census.

Additionally, residential mobility patterns for less educated participant and non-participant mothers are not significantly different from each other. Table 4 summarizes the percentage point differences between these two groups for all possible mobility combinations. A positive value entails that the percentage of labor market participants moving between density groups is higher than that of non-participants. For instance, the rate of labor market participants who were born in density group 1 but currently reside in density group 2 exceeds the rate for non-participants with the same mobility pattern by 0.8 percentage points. The diagonal bolded numbers represent percentage point differences between participant and non-participant mothers who did not move.

Out of thirty-six possible combinations, thirty-four show no significant differences in residential mobility patterns. The two combinations that are significantly different in statistical terms (G1 to G4, and G1 to G6) are not economically significant. Only a very small fraction of the population born in the lowest density group moved to groups four and six (2% and 1%, respectively). These statistics reaffirm that labor market preferences are not a significant driving force in the residential location of less educated households.

Table 4: Percentage point differences in residential mobility between less educated participant mothers and non-participant mothers, t-test for significance levels (Census 2012).

Born in:	*Current residence:*					
	G1	G2	G3	G4	G5	G6
G1	**-4.4**	0.8	2	0.7^{**}	0.4	0.5^{***}
G2	0.6	**-3**	0.4	1.5	0	0.4
G3	0.7	−0.1	**-1.2**	0.2	−0.1	0.4
G4	−1.8	0.7	−0.3	**1.2**	−0.1	0.2
G5	−0.9	−0.4	−0.6	0.9	**1.1**	−0.1
G6	−1.1	−1.1	−2.7	0	−1.4	**6.3**
Note:						*p<0.1; **p<0.05; ***p<0.01

The scenario is slightly different for more educated workers (Figure 4). In this case, groups two and three are the most mobile (23% and 24%, respectively) and nearly 14% of more educated women born in group two now reside in the city's densest region. This means that OLS coefficients for spatial mismatch effects for more educated female caregivers may be positively biased. Considering this endogeneity issue, our primary analysis is restricted to less educated caregivers.

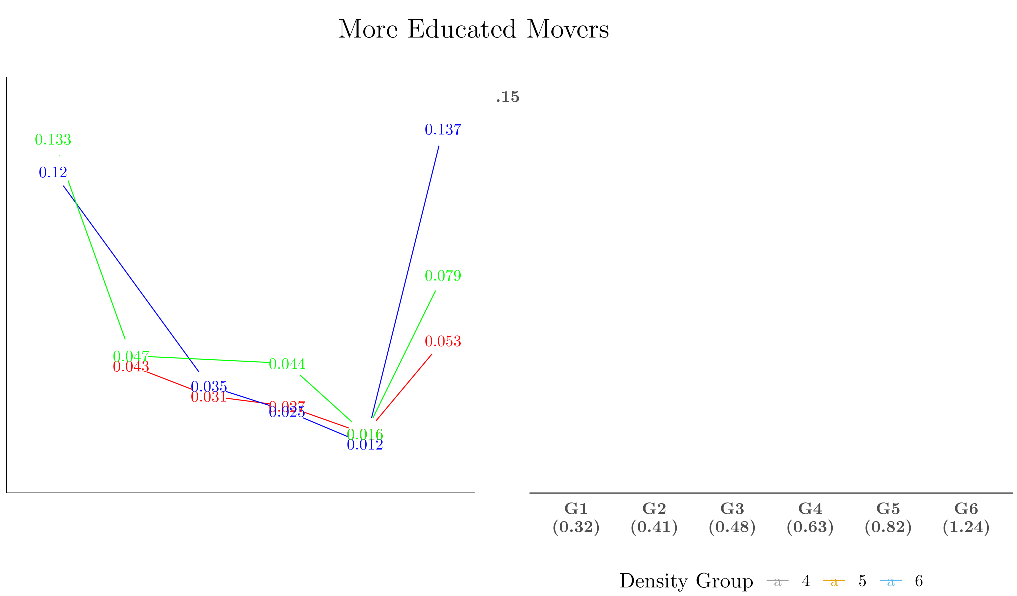

Figure 4: Fraction of skilled working mothers who moved away from their place of residence. The X-axis shows their new place of residence, in parenthesis is the average job density for each group. Source: 2012 census.

b. *Endogeneity issues II: Individual and household characteristics do not predict job density*

If the identifying assumption is correct, and less educated caregivers are unable to sort into job-dense locations, individual and household characteristics should not predict job density.[30] Table 5 shows that this is the case. Conditional on municipal fixed effects, OLS regressions show that individual and household characteristics are not significant predictors of job density, especially in the presence of dependents.

Table 5: OLS regression for job density measures on individual and household characteristics for less educated women. These calculations consider municipal fixed effects and standard errors clustered at the municipal level.

	Dependent variable: Job Density					
	All Women			Caregivers		
	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)
Schooling (Years)	0.0004	0.002	0.001	−0.00000	0.001	0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Age	0.002^{*}	0.004^{*}	0.004^{*}	0.001	0.002	0.001
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)
Age^2	−0.00002	−0.00003	−0.00004	−0.00001	−0.00001	0.00000
	(0.00001)	(0.00003)	(0.00002)	(0.00003)	(0.00004)	(0.00004)
Pregnant	−0.009	−0.019	0.022	0.001	−0.003	0.050
	(0.040)	(0.060)	(0.078)	(0.052)	(0.078)	(0.104)
Children (0-3 YO, Total)	0.007	0.010	0.013	0.012	0.018	0.020
	(0.020)	(0.031)	(0.031)	(0.027)	(0.043)	(0.043)
Children (4-6 YO, Total)	−0.002	−0.002	0.008	0.001	0.005	0.014
	(0.010)	(0.010)	(0.018)	(0.011)	(0.018)	(0.016)
Children (7-14 YO, Total)	-0.007^{*}	-0.015^{*}	-0.015^{**}	−0.003	−0.005	−0.005
	(0.004)	(0.004)	(0.008)	(0.011)	(0.006)	(0.012)
Adult Dependents (Total)	−0.020	−0.033	−0.038	−0.015	−0.022	−0.028
	(0.021)	(0.021)	(0.034)	(0.024)	(0.040)	(0.043)
Driver's License	0.036^{*}	0.079^{*}	0.106^{**}	0.041	0.071	0.089
	(0.019)	(0.012)	(0.052)	(0.028)	(0.050)	(0.056)
Constant	0.151^{***}	0.190^{***}	0.159^{***}	0.172^{**}	0.235	0.207
	(0.046)	(0.066)	(0.063)	(0.095)	(0.147)	(0.148)
Munic. F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,536	13,536	13,536	7,294	7,294	7,294
R^2	0.461	0.463	0.389	0.487	0.488	0.391
Adjusted R^2	0.459	0.461	0.387	0.484	0.485	0.387
Note:						*p<0.1; **p<0.05; ***p<0.01

[30] I would like to acknowledge and appreciate the anonymous reviewer who pointed this out.

c. Econometric model

In line with prior works on Chile, labor market participation is modeled as a function of individual and household level determinants (Larrañaga 2006, Contreras et al. 2011).[31] Additionally, two mobility variables are considered: the presence of a metro station within the observation's locality, and a dummy variable indicating if the individual holds a driver's license and owns a vehicle. Descriptive statistics for individual and household level regressors are summarized in Table 6.

[31] At the individual level we control for: schooling, age (and age squared), total number of other adult women in the household (this variable may be relevant since the presence of other non-dependent adults may ease domestic and caregiving responsibilities, and thus facilitate labor market participation), total number of other adult males in the household, the log of the household's income per capita discounting the observation's personal income, physical conditions that might affect participation (pregnancy, cognitive and physical disabilities). At the household level we control for: number of children between 0 and 3, 4 and 6, and, 7 and 14 years old separately; number of people who might need intensive care (cognitive and physical disabilities), and if there is a paid domestic worker in the household.

Table 6: Descriptive statistics (means, standard deviations in parentheses) for individual and household level regressors.

	Less Educated				More Educated	
	Caregivers (Women)	Caregivers (Men)	Women	Men	Women	Men
Schooling (Years)	10.365	10.549	10.09	10.449	16.233	16.542
	(0.058)	(0.056)	(0.046)	(0.042)	(0.042)	(0.047)
Age	41.357	41.16	46.81	44.621	42.149	42.817
	(0.332)	(0.361)	(0.273)	(0.289)	(0.344)	(0.341)
Driver license	0.108	0.462	0.112	0.453	0.635	0.836
	(0.008)	(0.013)	(0.006)	(0.009)	(0.012)	(0.008)
HH Income per capita*	12.349	10.571	11.443	10.135	12.207	10.438
	(0.053)	(0.117)	(0.071)	(0.093)	(0.095)	(0.134)
Domestic worker	0.001	0	0.002	0.001	0.043	0.038
	(0.001)	(0)	(0.001)	(0)	(0.006)	(0.005)
Adult men**	1.475	0.912	1.349	0.828	1.24	0.687
	(0.023)	(0.027)	(0.018)	(0.018)	(0.025)	(0.023)
Adult women**	1.023	1.778	0.846	1.533	0.902	1.406
	(0.022)	(0.023)	(0.017)	(0.018)	(0.03)	(0.025)
Children (0-3 YO)	0.402	0.375	0.223	0.204	0.158	0.147
	(0.014)	(0.015)	(0.009)	(0.009)	(0.01)	(0.011)
Children (4-6 YO)	0.331	0.325	0.184	0.178	0.103	0.102
	(0.012)	(0.014)	(0.007)	(0.008)	(0.008)	(0.008)
Children (7-14 YO)	0.823	0.79	0.457	0.431	0.31	0.305
	(0.017)	(0.019)	(0.012)	(0.013)	(0.017)	(0.017)
Dependent Adults	0.194	0.222	0.108	0.121	0.097	0.078
	(0.009)	(0.01)	(0.005)	(0.006)	(0.008)	(0.006)
Private Vehicles	0.524	0.607	0.532	0.62	1.354	1.405
(Total)	(0.021)	(0.025)	(0.016)	(0.018)	(0.027)	(0.025)
Subway in	0.233	0.242	0.255	0.249	0.408	0.442
locality (1km)	(0.01)	(0.01)	(0.007)	(0.007)	(0.012)	(0.013)
Observations	7,294	5,776	13,536	11,203	4,775	4,703

(*) Household income per capita does not consider the observations personal income.
(**) Total number of adults in the household do not consider the observation.

The Table shows some relevant differences across education and gender in means for urban mobility. Women and men with access to higher education are more likely to hold a driver license than less educated individuals. Female caregivers, moreover, are the least likely to have one. Additionally, more educated households have more than one private vehicle on average, even as their access to the subway network is higher. Less educated women, and especially caregivers, present the poorest conditions to travel across the city.

Municipalities play a central role in the provision of public child and health care services. Thus, the calculations include municipal fixed effects to account for geographical differences in accessing these services. Finally, job density measures are included to capture spatial mismatch effects. In line with Hellerstein et al. (2008), an interaction term between job density and schooling (in years) is included to capture differences in spatial mismatch effects across the education spectrum.[32]

$$LMP_{ihm} = \alpha + \beta X_i + \gamma Y_h + MunicFE_m + \theta JobDensity_{ih} + \delta(JobDensity_{ih} * Schooling_i) + \varepsilon_{ihm}$$

Where LMP_{ih} is a dummy variable equal to one if individual i in household h participates in the labor market, and zero otherwise. X_i, is a vector of individual variables, Y_h is a vector of household variables, and $MunicFE_m$ represents municipal level fixed effects.

To avoid endogeneiy issues, the primary sample for the analysis is restricted to less educated female caregivers [33] The model is calculated using OLS with standard errors clustered at the municipal level. For robustness purposes, the parameters of the model are recalculated after *winsorizing* job density measures by 1% and 5%.[34] Additionally, local job density is recalculated at double the walking-distance rate (2-

[32] The primary subset for analysis considers less educated caregivers. However, within the less educated group there is significant variation in schooling. Around 40% of less educated caregivers did not complete secondary education.

[33] Potential caregivers include adults who reside with children under 14 years of age and/or other adults who present severe mobility constraints. The ODS informs on people who face mobility constraints due to physical and cognitive disabilities.

[34] Winsorization is a mechanism for dealing with outliers that assigns less-extreme values to outliers. In this case, the observations that are in the first and last percentile of job density are assigned the values at 1% and 99% respectively.

kilometer radius for drivers and 2.8-kilometer for non-drivers) to test if results hold up when easing locality assumptions.

As a secondary analysis, and for comparison purposes, the model is calculated for all less educated women and men, as well as for more educated caregivers. Additionally, we examine if local job density has an effect on less educated female and male caregivers' access to formal and full-time employment.

d. Results for less educated caregivers

i. Spatial mismatch as a source of gender inequalities

The spatial mismatch effects for less educated female caregivers are summarized in the left three columns of Table 8. For this group, all specifications of local job density are positive and statistically significant. Furthermore, the interaction term between job density and schooling level is negative and statistically significant. Since schooling levels are, on average, higher than job density levels, this negative parameter entails than in places where job density is very low the net job density effect may be negative. In other words, when education levels are closer to complete secondary schooling, the likeliness of a caregiver participating in the labor market are significantly higher in job dense regions than in "job thin" localities.

Table 8: OLS estimations for working age less educated women and men residing with dependents and are not enrolled in any schooling institution.

	Dependent variable: Labor Market Participation					
	Less Educ. Women (Caregivers)			Less Educ. Men (Caregivers)		
	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)
Job Density (All)	0.321***			−0.126		
	(0.092)			(0.115)		
Job Density (LE[1])		0.198***			−0.081	
		(0.048)			(0.079)	
Job Density (LE, Gender)			0.228***			−0.057
			(0.037)			(0.065)
School∗Job Density (All)	−0.031***			0.010		
	(0.006)			(0.009)		
School∗Job Density (LE)		−0.018***			0.007	
		(0.004)			(0.006)	
School∗Job Density (LE, Gender)			−0.020***			0.005
			(0.003)			(0.006)
Constant	0.377***	0.380***	0.382***	0.472***	0.471***	0.466***
	(0.094)	(0.092)	(0.090)	(0.078)	(0.077)	(0.077)
Ind. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hh. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Munic. F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,294	7,294	7,294	5,776	5,776	5,776
R^2	0.161	0.161	0.162	0.264	0.264	0.264
Adjusted R^2	0.155	0.155	0.156	0.257	0.257	0.257
Residual Std. Error	4.635	4.634	4.633	2.255	2.255	2.256

Note: *p<0.1; **p<0.05; ***p<0.01

[1] LE is short for Less Educated. Job Density (LE) is the job density measurement that only considers individuals who at most have completed secondary education.

The unequal job density distribution generates gender inequalities between women and men residing with dependents. The last three columns on Table 8 display the job density coefficients for male caregivers. None of these is statistically significant from zero. Furthermore, job density effects are significantly different between men and women (See Table 9). Residential segregation, therefore, accentuates the gender inequalities emerging from the patriarchal division of labor.

Table 9: T-test for differences in job density effects between women and men residing with dependents.

Model	Difference (Women-Men)	T-value
Economic Activity	0.448***	2.393
Educ. Strat.	0.279***	2.662
Educ.+Gender Strat.	0.285***	3.163

Note: *p<0.1; **p<0.05; ***p<0.01

ii. Analyzing the magnitude of job density effects across Santiago's municipal jurisdictions

Interaction effects, as well as the tall number of localities, complicate the analysis of the magnitude of spatial mismatch effects. Additionally, since the different job density models vary in value, we cannot simply compare coefficients to analyze the differences between these measurements.

To address these issues, we analyze net job density effects for a less educated female caregiver of average schooling (10.3 years) facing the average job density level for their respective municipal jurisdiction. Figure 5 net municipal job density effects, highlighting the lowest and highest average effects.

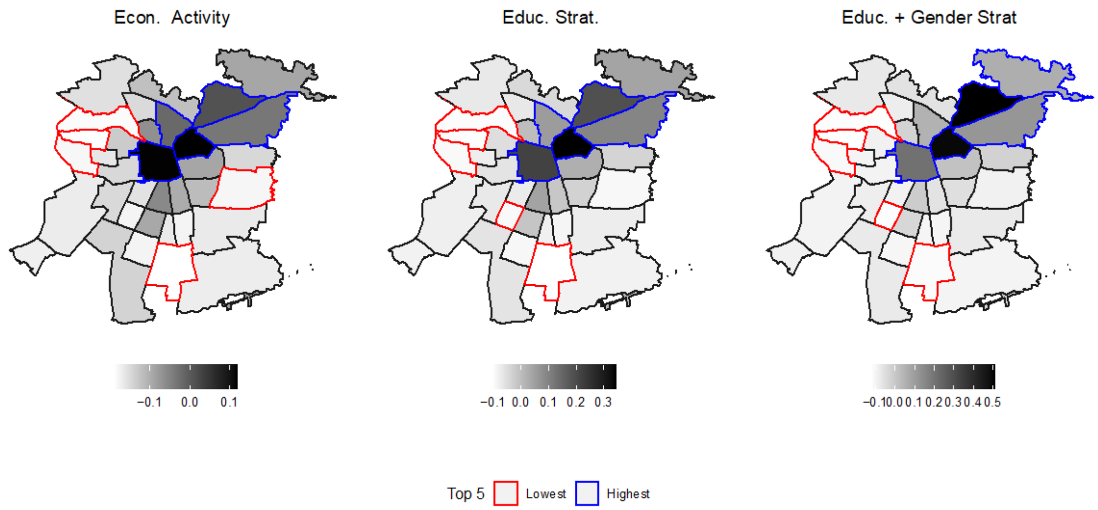

Figure 5: Municipal average job density effects over less educated women residing with dependents of average schooling. Outlined in red are the lowest net effects and in blue are the municipal jurisdictions with the highest net effects.

These maps once again reflect Santiago's residential segregation. The southern and western regions of the city that concentrate the urban poor (especially La Pintana, Cerro Navia, Renca, and Pudahuel) have the lowest net effects. On the other hand, the city's northeast (Santiago, Providencia, Vitacura, and Las Condes) concentrates the highest effects. In the *economic activity* model, the labor market participation of a less educated female caregiver of average schooling (and everything else equal) is 24% higher if she resides in the top 5 highest job dense municipalities vis-à-vis living in the top 5 less dense jurisdictions. The *education stratification* model and the *education and gender stratification* predict a 28% and 39% difference, respectively.

These differences in magnitude portray the interaction between occupational segregation and residential segregation. The regions that agglomerate wealthier households also provide gendered employment opportunities for less educated women, especially in the form of domestic service. Thus, the 'glass walls' of the labor market may in fact influence Santiago's spatial mismatch.

iii. Spatial autocorrelation of residuals

As outlined earlier, the spatial autocorrelation of labor market participation poses a potential problem for interpreting these results. If residuals continue to be spatially autocorrelated, then the model's parameters may be biased and/or inconsistent. Table 10 displays Moran tests for each model's residuals, showing that these are not spatially autocorrelated and that they explain the spatial distribution of labor market participation.

Table 10: Spatial autocorrelation for each of the models' residuals. Moran's I was calculated using lm.morantest from the R package spdep (set seed 123).

Model	*Moran test*	
	Moran's I	p-value
Economic Activity (residuals)	0.005	0.697
Educ. Strat. (residuals)	0.006	0.716
Educ.+Gender Strat. (residuals)	0.005	0.714

iv. *Robustness I: Winsorization of job density measures.*

Earlier, we saw that there are significantly high outlying job density values. To ensure that these are not driving the results, the data is transformed through *winsorization*. This process assigns less-extreme values to observations with especially high and low values. Here, we winsorize the top and bottom 1% values, as well as the top and bottom

5%. Table 11 summarizes OLS results after winsorization, indicating that the parameters' statistical significance holds after the transformation process.

Table 11: Winsorized coefficients for less educated women and men residing with dependents. Municipal fixed effects are considered, and standard errors are clustered to the municipal level.

	Dependent variable: Labor Market Participation (Female potential caregivers)					
	Winsor = 1%			Winsor = 5%		
	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)
Job Density (All)	0.316***			0.323**		
	(0.110)			(0.165)		
Job Density (LE[1])		0.202***			0.214**	
		(0.052)			(0.088)	
Job Density (LE, Gender)			0.229***			0.291***
			(0.037)			(0.090)
School∗Job Density (All)	−0.031***			−0.034***		
	(0.008)			(0.009)		
School∗Job Density (LE)		−0.019***			−0.020***	
		(0.004)			(0.006)	
School∗Job Density (LE, Gender)			−0.021***			−0.028***
			(0.003)			(0.007)

Note: *p<0.1; **p<0.05; ***p<0.01

[1] LE is short for Less Educated. Job Density (LE) is the job density measurement that only considers individuals who at most have completed secondary education.

v. Robustness II: Re-defining locality

Table 12 shows the coefficients for the different job density models when defining localities at double the walking-distance rate. That is, 2,800 meters for individuals who do not have access to private vehicles and 2,000 meters for those that do. The results show that the education stratification model and the gender and education stratification model are robust to the widening of local job markets, confirming that occupational segregation in the labor market may play a significant role in determining spatial mismatch effects.

Table 12: Job density coefficients for localities defined at double the walking distance (2,000 mts for individuals who drive, and 2,800 for those that do not).

	Dependent variable: LE[1] Female Labor Market Participation (Job density ratioX 2)		
	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)
Job Density (All)	0.450 (0.304)		
Job Density (LE)		0.280^{**} (0.133)	
Job Density (LE, Gender)			0.166^{**} (0.075)
School∗Job Density (All)	-0.058^{*} (0.030)		
School∗Job Density (LE)		-0.032^{**} (0.014)	
School∗Job Density (LE, Gender)			-0.018^{**} (0.008)

Note: *p<0.1; **p<0.05; ***p<0.01
[1] LE is short for Less Educated. Job Density (LE) is the job density measurement that only considers individuals who at most have completed secondary education.

e. *Secondary analysis: Access to high-quality jobs and spatial mismatch effects on other subpopulations*

i. *Informality and full-time employment*

The spatial mismatch may also affect caregivers' access to formal and full-time employment. Even though this question probably deserves an entire article, Tables 13 and 14 show preliminary evidence for these effects.[35] [36] The results show that when men reside with dependents in job-thin regions, they are more likely to participate in

[35] Informal job places are defined as the workplace of self-employed less educated workers. domestic workers (the law regulating domestic work in Chile did not come into place until 2014) and unpaid family workers. All other forms of employment are considered formal.

[36] The independent variables used for these regressions are the same as the ones used for predicting labor market participation.

the informal labor market and in part-time employment. For women, however, job density effects are not significantly different from zero. These results underscore the impoverishing effects of residential segregation on less educated caregiving families. While female caregivers are less likely to participate in the labor market due to the lack of available job opportunities, men are more likely to be employed in lower quality workplaces.

Table 13: Job density coefficients for spatial mismatch effects on access to formal employment for less educated women and men residing with dependents. Regressions consider municipal fixed affects and standard errors are clustered at the municipal level.

	Dependent variable: Formal Employment					
	Less Educ. Women (Caregivers)			Less Educ. Men (Caregivers)		
	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)
Job Density (All)	0.118^{*}			0.456^{*}		
	(0.070)			(0.241)		
Job Density (LE[1])		0.059			0.307^{**}	
		(0.039)			(0.144)	
Job Density (LE, Gender)			0.071			0.217^{**}
			(0.044)			(0.121)
School∗Job Density (All)	-0.019^{***}			-0.046^{**}		
	(0.006)			(0.019)		
School∗Job Density (LE)		-0.010^{***}			-0.029^{**}	
		(0.003)			(0.012)	
School∗Job Density (LE, Gender)			-0.009^{**}			-0.021^{**}
			(0.004)			(0.010)
Ind. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hh. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Munic. F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,039	3,039	3,039	4,920	4,920	4,920
R^2	0.159	0.159	0.158	0.126	0.126	0.124
Adjusted R^2	0.145	0.145	0.144	0.117	0.117	0.115

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

[1] LE is short for Less Educated. Job Density (LE) is the job density measurement that only considers individuals who at most have completed secondary education.

Table 14: Job density coefficients for spatial mismatch effects on access to full-time employment for less educated women and men residing with dependents. Regressions consider municipal fixed affects and standard errors are clustered at the municipal level.

	Dependent variable: Full Time Employment					
	Less Educ. Women (Caregivers)			Less Educ. Men (Caregivers)		
	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)
Job Density (All)	0.019 (0.076)			0.359*** (0.064)		
Job Density (LE[1])		0.013 (0.043)			0.231*** (0.037)	
Job Density (LE, Gender)			0.025 (0.043)			0.223*** (0.037)
School∗Job Density (All)	−0.012* (0.006)			−0.026*** (0.006)		
School∗Job Density (LE)		−0.007* (0.003)			−0.017*** (0.003)	
School∗Job Density (LE, Gender)			−0.006* (0.004)			−0.016*** (0.003)
Ind. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hh. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Munic. F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,039	3,039	3,039	4,920	4,920	4,920
R^2	0.096	0.096	0.094	0.093	0.094	0.095
Adjusted R^2	0.080	0.081	0.079	0.084	0.085	0.085

Note: *p<0.1; **p<0.05; ***p<0.01

[1] LE is short for Less Educated. Job Density (LE) is the job density measurement that only considers individuals who at most have completed secondary education.

ii. Spatial mismatch effects on less educated non-caregivers and more educated caregivers

Although our primary analysis focuses on less educated caregivers, it is worthwhile to show if residential segregation affects the labor market participation of other subpopulations. As argued above, unpaid domestic work can also be a source of mobility constraints at the same time as it is unevenly divided between men and women. Non-caregivers, therefore, may also be affected by spatial mismatch effects. Table 15 shows that this does not seem to be the case.

Restricting the population to less educated women and men who do not reside with any dependents, we observe that job density effects are not significantly different from zero for either group. For women, however, the parameters do maintain the same direction as before.

Table 15: Job density coefficients for spatial mismatch effects on labor market participation for less educated women and men who do not reside with dependents. Regressions consider municipal fixed affects and standard errors are clustered at the municipal level.

	Dependent variable: Labor Market Participation					
	Less Educ. Women (Non-Caregivers)			Less Educ. Men (Non-Caregivers)		
	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)
Job Density (All)	0.111			0.043		
	(0.092)			(0.134)		
Job Density (LE[1])		0.063			0.023	
		(0.050)			(0.070)	
Job Density (LE, Gender)			0.069			−0.008
			(0.051)			(0.066)
School∗Job Density (All)	−0.012			−0.003		
	(0.008)			(0.011)		
School∗Job Density (LE)		−0.006			−0.002	
		(0.004)			(0.006)	
School∗Job Density (LE, Gender)			−0.005			0.001
			(0.004)			(0.006)
Ind. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hh. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Munic. F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,242	6,242	6,242	5,427	5,427	5,427
R^2	0.270	0.270	0.270	0.412	0.412	0.412
Adjusted R^2	0.264	0.264	0.264	0.407	0.407	0.407
Residual Std. Error	4.173	4.173	4.174	2.825	2.825	2.825

Note: *p<0.1; **p<0.05; ***p<0.01

[1] LE is short for Less Educated. Job Density (LE) is the job density measurement that only considers individuals who at most have completed secondary education.

Even though this may be subject to self-selection problems, Table 16 shows that job density is not a significant determinant for more educated caregivers' labor market participation. The negligible spatial mismatch effects illustrate the economic inequalities emerging from residential segregation. Spatial mismatch effects are reserved only for less educated households.

Table 16: Job density coefficients for spatial mismatch effects on access to formal employment for more educated women and men residing with dependents. Regressions consider municipal fixed affects and standard errors are clustered at the municipal level.

	Dependent variable: Labor Market Participation					
	More Educ. Women (Caregivers)			More Educ. Men (Caregivers)		
	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)	(Econ. Activity)	(Educ. Strat.)	(Educ.+Gender Strat.)
Job Density (All)	0.096			−0.083		
	(0.245)			(0.102)		
Job Density (ME[1])		−0.017			−0.046	
		(0.105)			(0.184)	
Job Density (ME, Gender)			0.026			−0.072
			(0.065)			(0.074)
School∗Job Density (All)	−0.011			0.004		
	(0.016)			(0.006)		
School∗Job Density (ME)		−0.001			0.002	
		(0.006)			(0.003)	
School∗Job Density (ME, Gender)			−0.003			0.004
			(0.003)			(0.004)
Ind. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Hh. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Munic. F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,775	4,775	4,775	4,703	4,703	4,703
R^2	0.194	0.194	0.194	0.226	0.226	0.227
Adjusted R^2	0.186	0.186	0.186	0.217	0.218	0.219
Residual Std. Error	4.424	4.424	4.424	2.215	2.214	2.213

Note: *p<0.1; **p<0.05; ***p<0.01

[1] ME is short for More Educated. Job Density (ME) is the job density measurement that considers individuals who at least have some tertiary eduaction.

VI. Final remarks

This paper's findings underscore the entrenched relationship between residential segregation and labor market inequalities. Cities themselves are a structural product and, as such, take on an intermediary role between the forces that produce them and the labor market. The uneven urban geography generates dissimilar conditions for labor market participation across different subpopulations. In Santiago, market-oriented reforms alongside mass evictions produced an economically segregated city that offers unfavorable conditions for the less educated female caregivers' participation.

The mobility restrictions emerging from unpaid care labor, in conjunction to the agglomeration of employment opportunities in wealthy neighborhoods, are behind the adverse effects of segregation on less educated women's participation. The economic lives of women like Gabriela, who balance paid and unpaid responsibilities in areas with few employment opportunities, are a true testimony to our findings.

Segregation reinforces the economic inequalities between low-income and affluent families. In households where female adults are unable to participate in the labor market, families fail to augment their earnings pool with additional income from female employment. Additionally, working men in these residences are more likely to participate in more precarious labor markets. Secondly, segregation may also contribute to inequalities within low-income (heterosexual) households. In these households, women's economic dependence on male wages likely intensifies masculine control over females' work and bodies.

The scope of this article is limited to analyzing segregation's unequal effects on labor market participation. However, future research should address the relevance of residential segregation on gender inequalities within paid work. The fact that less educated women's labor market participation is disproportionately affected by segregation may be evidence of a more elastic labor supply at the level of the city. Nevertheless, at the local level mobility constraints could result in a more inelastic female labor supply when compared to men's (Schmid 2016). In line with emerging literature on monopsonistic labor markets, a lower labor supply elasticity increases the employer's wage-setting powers (Card 2018). Thus, segregation could potentially be an explanatory factor for the gender wage gap.

CHAPTER 2

THE LIMITS TO CARE

A POLITICAL ECONOMY ANALYSIS OF CHILE'S CARE SYSTEM AND ITS CRISIS

I. Introduction

Chile is aging rapidly. According to official estimates, nearly 30% of the working-age population (15+) will be 60 or more in 2035. Not only will Chile be the oldest country in Latin America, but it would have experienced one of the fastest demographic transitions in recent history (Villalobos Dintrans, 2018a). The pace of this transformation calls for a rapid understanding of its challenges. This article contributes to this endeavor by analyzing one of aging's most serious byproducts: rising adult dependency levels.

Adult dependents are working-age people who need assistance with daily living activities. In other words, they need care. Is the Chilean care system prepared to meet the increments in the demand for care? This paper utilizes political economy analysis to answer this question. I find that emerging heterogeneity in household structures is significantly complicating the system's ability to provide care. Furthermore, without structural reform, it is unlikely that adult dependents will receive the care they need.

The Chilean care system interlocks several subsystems of care, including state-provision, market-provision, and family-provision. The market and state subsystems, however, play a secondary role. The family is so essential to the Chilean care system that some have defined it as an *unsupported familial regime of care* (Martin, 2015; Palacios, 2016).

The centrality of the family in the provision of care entails that the system rests on the unpaid labor of family members to provide care. By 2017, nearly 70% of them were women. [37] The system, therefore, rests upon a patriarchal division of labor that disproportionately allocates unpaid work to women (Folbre, 2021). Like any other division of labor, space limits the patriarchal division of labor (Smith 1937 [1776), Ch. III; Weber, 2019). In this case, the family-space. In this article, I examine the care system's reliance on the patriarchal division of labor by calculating the significance of patriarchal limits in the overall provision of care.

Here, I identify two significant limits to the patriarchal division of labor: female presence and household size. Using OLS estimations and a large dataset from 2017, I show that dependents who reside in smaller households with less female presence are significantly less likely to receive any care whatsoever (even from secondary sources). My estimations show that dependents who reside with at least one non-dependent woman and one non-dependent man are more likely to receive care under the current system. On the other hand, adult dependents living without non-dependents are the least likely to receive any assistance. Considering that nearly 25% of adult dependents live in such conditions, this is a major cause for concern.

Additionally, my analysis shows that the proportion of dependents residing without non-dependents has increased significantly in the last decade, and it is likely to continue growing. Using Machine Learning (ML) prediction methods, I impute dependency levels to large surveys from 2006, 2009, 2011, 2013, 2015, and 2017. Until

[37] According to the 2017 CASEN.

now, such detailed information on dependency levels existed only from 2015 onwards. The ML predictions show that the share of dependents living with at least one female non-dependent and one male non-dependent has decreased from more than 42% in 2006 to less than 30% in 2017. The share of dependents residing without any non-dependents has increased from 19% to 25% in the same period.

Population aging is likely behind this transition. Older adults are more likely to reside in smaller households than average dependents. As a more significant proportion of dependents has become older, their family structure distribution has converged to that of the elderly. In this context, the familial care system is less likely to provide the necessary care supply. Hence, a profound restructuring of the care system that removes the family from its center is necessary to avoid a crisis.

The article is structured as follows. Section II introduces the current state of adult dependency in Chile. Section III frames this article's analysis in the literature of care crisis. Then, Section IV analyzes the political economy of adult care. Additionally, it analyzes the limits of the familial provision of care and how they affect the overall provision of care. Section V uses ML methods to analyze how dependents' family structures have evolved in the last decade. Section VI concludes the article by discussing the implications of this paper on the restructuring of the care system.

II. Adult dependency in Chile

Until recently, nationally representative surveys on adult dependency did not exist. In 2015, Chile's National Socioeconomic Characterization Survey (CASEN, for its acronym in Spanish) included adult dependence as a measurable variable for the first time.[38] Here, we use the 2017 CASEN survey to capture the social distribution of adult dependency. This dataset consists of 216,439 observations.

Adult dependency is defined according to individual capabilities for performing Basic Daily Activities (BDAs) and Instrumental Daily Activities (IDAs). BDAs include eating, bathing and grooming, moving within the household, using the bathroom, lying down or getting up from bed, and dressing. IDAs consider the capabilities to step out to the street, doing errands, doing housework, and making or receiving calls.

Dependency levels are defined according to the dependent's i) capability to perform an IDA or BDA, and ii) their need of assistance in performing an IDA or BDA (these are independent questions in the survey). Someone may present difficulties in performing an IDA or BDA, or they could completely lack the ability to do so. Similarly, someone could require help sometimes or always. Considering this, four dependency levels are defined in ascendant order: potential, mild, moderate, and severe. Table 7 describes each of these:

[38] http://observatorio.ministeriodesarrollosocial.gob.cl/encuesta-casen

Table 7: Dependency levels according to functional capabilities.

Dependency level	**Description**
Potential	Presenting difficulties in one BDA or one IDA, or sometimes needing assistance to perform one BDA or one IDA. [1]
Mild	Cannot perform one IDA, or always (or almost always) needing help with at least one BDA, or presenting difficulties for performing two IDA.
Moderate	Cannot bathe by themselves, or always need help to perform two or more BDA, or need help for three or more IDAs, or cannot perform one IDA and they need assistance for one BDA.
Severe	Cannot perform at least one BDA (except bathing), or cannot perform at least two IDAs

Source: Researcher's manual for 2017 CASEN.

According to the 2017 CASEN, there are 993,630 adult dependents in Chile. Over 7% of the total adult population. Age is a significant determinant of dependency. Almost 75% of adult dependents are 60 or more. A loss of functional abilities accompanies the natural decomposition of our bodies. Nearly 16% of adults between 60 and 80 years of age are dependent to some degree. For adults over 80, the dependency rate exceeds 50%. Figure 6 illustrates the exponential relationship between age and dependency rates. The severity of dependency is also a function of age. Figure 7 shows the distribution of dependency levels according to age.

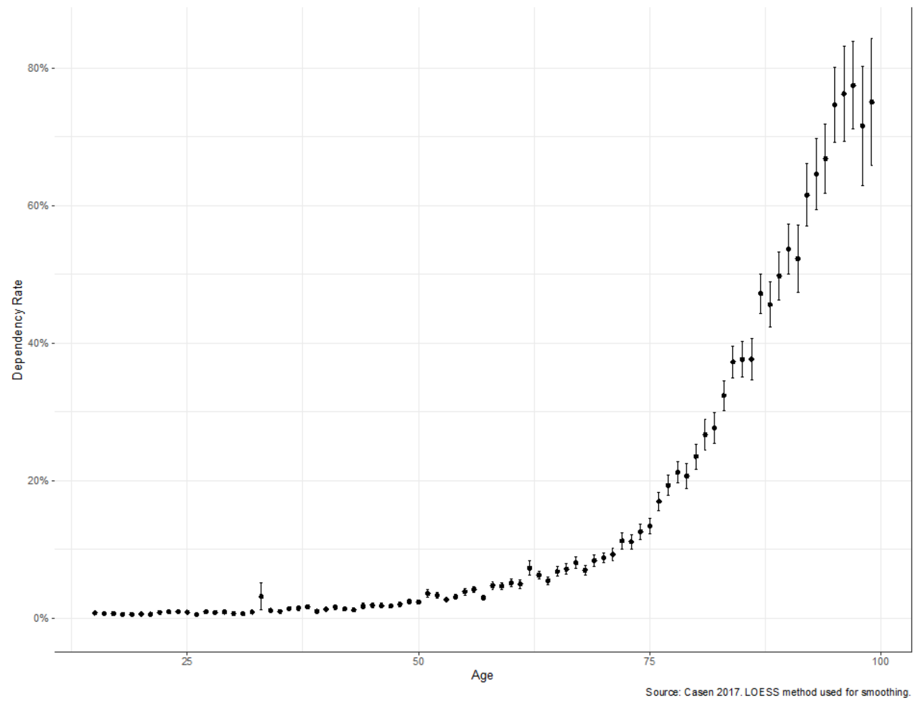

Figure 6: Dependency rates by age. LOESS method used for smoothing. Source: CASEN 2017

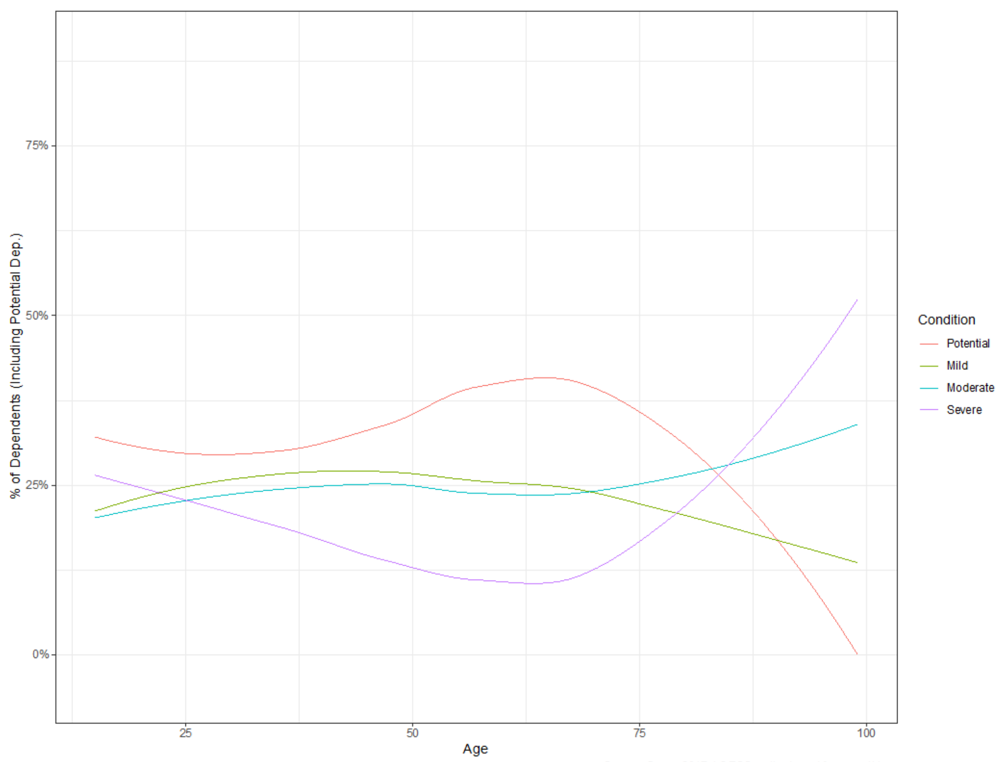

Figure 7: Dependency levels distribution by age. LOESS method used for smoothing. Source: CASEN 2017.

Age, however, is not the sole determinant of dependency. Socioeconomic factors also matter a great deal. For instance, income levels determine access to quality healthcare and healthy lifestyles. Strenuous physical work, vis-a-vis mental work, has been found to entail significantly higher levels of dependency in old age (Russo et al., 2006). Participation in recreational activities, also correlated with earnings, substantially improves cognitive health in old age (Verghese et al., 2003; Ferreira et al., 2015). For these reasons, dependency rates are significantly higher in the lower echelons of the income distribution. Figure 8 depicts dependency rates for individuals with different schooling levels. There is an evident contraction in dependency at higher schooling levels. This is especially true for people between 60 and 79 years of age, meaning that the less educated become dependent at an earlier stage.

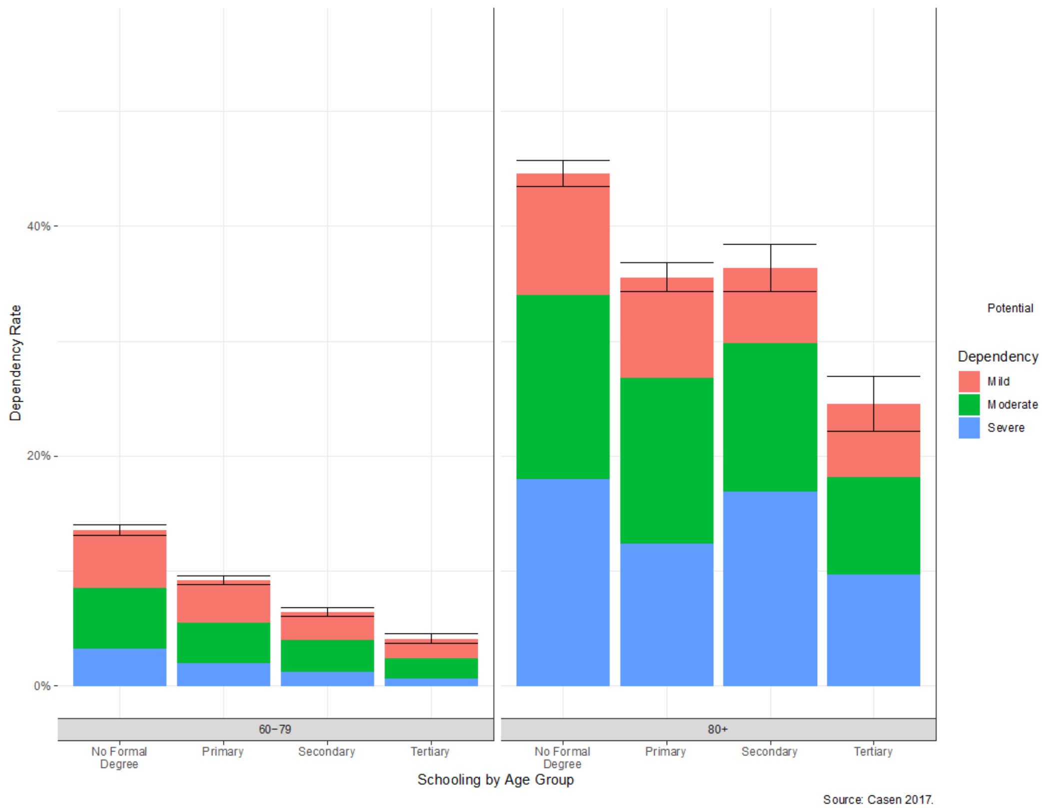

Figure 8: Dependency rates by age group and schooling. Source: CASEN 2017.

Less-educated individuals are also poorer. Therefore, adult dependency rates are disproportionately high in low-income neighborhoods. The spatial distribution of adult dependency marks a crucial difference between the childcare and adult care systems. Table 8 shows the linear correlation between adult and child dependency rates and municipally averaged per capita income (in logs). Child dependency is defined here as children under 14, and dependency rates are the total population of dependents to total adults. A 1% increase in average income is associated with a 3.3% decrease in adult dependency rates. There is no statistical relationship between child dependency rates and income.

Table 8: Linear regression for adult and child dependency rates. Dependency rates are calculated as the fraction of dependents over the total adult population.

	Dependency Rate:	
	Adults	Children
	(1)	(2)
Average Income (Municipal level, log)	-0.033^{***} (0.005)	0.010 (0.008)
Observations	324	324
R^2	0.113	0.005
Note:	*p<0.1; **p<0.05; ***p<0.01	

The CASEN survey offers another critical piece of information regarding the conditions of adult dependents: whether they receive assistance or not. Dependents can be cared for by household members (internal care), out-of-household individuals (paid and unpaid external care), or both. They can also not receive any care whatsoever. Figure 9 shows the distribution for each of these categories. Most dependents receive care exclusively from household members. Moreover, of the near one-million adult dependents in Chile, almost 30% do not receive any assistance. The considerable mismatch between the demand for care and its supply begs the question: is Chile undergoing a crisis in adult care?

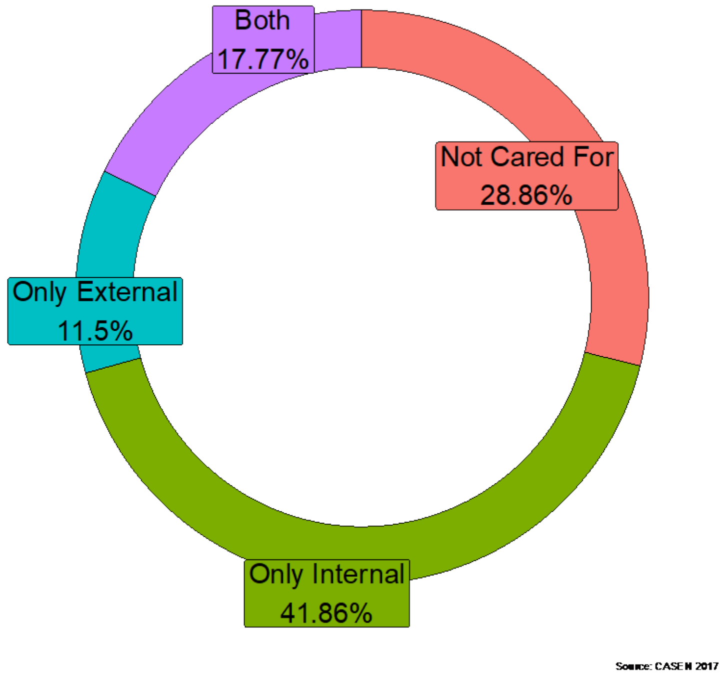

Figure 9: Distribution of caregiving. Internal care is defined as care provided by household members. External care is defined as care provided by out-of-household individuals.

III. Analytical framework: A crisis of care?

Most countries have a formal definition for an economic crisis. Economic breaking points are clearly defined to capture the beginning and end of a crisis. They are tracked and measured. Care crises, in contrast, do not enjoy such treatment (even less for adult care crises). The measurement of care activities is, at best, preliminary. State officials have not seriously considered the definition of official care breaking points. Nevertheless, scholars and activists are paying increasing attention to the care crisis.

Emma Dowling (2021) and others (Thorne, 2004; Himmelweit, 2007) define the care crisis as a simultaneous process that lowers access to care even as it raises the barriers to provide it. Similarly, Beneria (2008) and Fraser (2017) argue that the collapse of specific social structures has constrained care provision, making it less available. These definitions depict the care crisis in quite a similar light to an economic crisis. During an economic crisis, the mode of production's capability to produce is severely restricted. In a care crisis, the care system does not care enough. Both types of crises, moreover, are originated at the systemic level.

The systemic nature of care crises underscores their complexity. Care systems have an intricate architecture of multiple interlocking and interdependent social structures (Folbre, 2021, p.10). Furthermore, social structures are composed of human relations that are, more often than not, based on hierarchies of contradictory interests. The hierarchical nature of these structures stabilizes them. Contradictory interests, on the other hand, are sources of instability. When people in the lower echelons of a given social structure gain power, the hierarchy loses its ability to stabilize the structure. If the social structure is fundamental to the system's inner workings, then the whole system might be destabilized and enter into crisis.

The interlocking and interdependent nature of social structures adds another layer of complexity to care crises. The normal functioning of one social structure may create instability in another. Once again, this is similar to an economic crisis. Extensive scholarship describes how the institutional arrangements that regulate social life, the *mode of regulation*, periodically tensions the essential hierarchies in the capitalist mode of production (Boyer, 1990; Aglietta, 1998). This is true even as regulation and production can complement each other. Similarly, the interlocking structures that compose the care system may simultaneously complement and contradict each other (Folbre, 2021). Changing conditions transform the balance between contradictory and stabilizing forces. Systemic crises occur when the system is unable to adapt to these changes (Ibid.).

The complexity of care crises can be periodized into an ongoing cycle of different moments (Archer, 1995). The first moment is that of structural conditioning. Caregivers, non-caregivers, and dependents find themselves in a network of pre-existing social structures. Then, there is a moment of social interaction. Here, agents and pre-existing structures interact to condition a third moment: social elaboration. At this third moment, individual and collective agencies can either reproduce or transform the pre-existing social structures, thus creating new structural conditions.

This article's analysis of the adult care crisis examines these moments in an inductive manner. We start by analyzing the current structural conditions to care. Then, we contextualize the current conditions as part of an ongoing process of structural elaboration. By examining the evolution of structural changes in the care system over the past decade, we can identify if the system's care provision has become weaker or stronger. This process of structural elaboration sheds light on the system's abilities to meet increments in the demand for care and its capacity to overcome a care crisis.

IV. Structural conditions to care: The political economy of adult care and its limits

The care system is composed of interlocking subsystems of care. There are at least three subsystems of care in Chile: state-provided care, market-provided care, and family-provided care. Each of these subsystems presupposes a particular division of labor, which allocates care work and distributes costs. However, divisions of labor have limits that affect the subsystem's care supply. Hence, the capability of each subsystem to provide care informs the overall capacity of the system to supply care. This section will analyze each of these subsystems and their limits, emphasizing the familial subsystem of care.

Limits to the division of labor are an essential component of care supply. Limited space for expanding the division of care labor reduces the likelihood of the subsystem's care supply to meet rising care demand. The fundamental emergent property of the division of labor is that it allows for specialization. Individuals will carry out more specialized tasks as the division of labor is deeper, increasing social productivity (Weber, 2019). Conversely, a restricted division of labor incentives individuals towards diversification. Since combining care provision with other economic activities is difficult (Kwan, 2000; Loukaitou-Sideris, 2016), limited space for the division of labor will hardly be conducive to increasing the care supply. A reduction in the space for the division of labor may actually contract supply, leading to a care crisis.

a. Abstract social space, not just markets, limit the division of labor

The division of labor is a system of exchange. This led Adam Smith to famously claim that the size of the market limits the division of labor (Smith 1937 [1776), Ch. III). However, what is the market? Smith certainly did not mean that an actual concrete market would limit the division of labor. Instead, he speaks of an abstract place in our common imaginary, socially enforced by norms, institutions, regulations, and supply and demand. The forces that expand or contract the limits of the market-space are exclusive to this particular configuration. Divisions of labor can also take place outside this space.

For instance, an explicit chain of command structures the division of labor within most capitalist firms. Even though exchange exists within the firm, demand and supply mechanisms do not determine the firm-level division of labor limits (Simon, 1991). Rather, it expands or contracts according to the decisions of those at the top of the hierarchy.

Command mechanisms are present in other spaces as well, with varying qualities. The division of labor within the state, for instance, is the composite of multiple interdependent and inter-scalar chains of command at different scales. Existing institutions (e.g., the executive branch, democracy) and territorial boundaries establish its limits (Jessop, 2016). Within the family, patriarchal systems have historically commanded the division of labor. Biological and social reproduction limit the size of the household division of labor (Folbre, 2021).

The multiple spaces under which the division of labor takes place calls for a qualification of Smith's comment. It is abstract space, not markets, that limit the division of labor. We can find at least three of these spaces within the care system: the state, the market, and the family. The division of labor, and its limits, are particular to these places. Moreover, these limits also stamp the relevance of each subsystem within the overall care system. Abstract sites that are severely restricted will provide less care (i.e., secondary subsystems). On the other hand, more relevant to the system are places where the division of labor has provided ample supply of care (I.e., primary subsystems). A crisis in the care system, therefore, is more likely to originate in primary subsystems.

b. *The neoliberal state and its limits*

Since the 1980s, when a handful of military men controlled the state, three principles characterize Chile's welfare system: austerity, subsidiarity, and focalization (Valdivia Ortiz de Zarate, 2015). These are the pillars of the so-called neoliberal state. The principle of austerity portrays a 'fiscally responsible' state that significantly cuts down on discretionary expenditure.[39] Even though austerity is a common practice in

[39] The long-lasting characteristics of austerity in relation to the temporary nature of crises signals for some authors that austerity is inherently ideological (Jessop 2016, p.236).

neoliberal economies, Chile's fiscal spending is amongst the most restricted. Among OECD countries, Chile ranks second to last in public social expenditure as a percentage of GDP (11.4%).[40]

Fiscal spending is especially low in adult care (Palacios, 2016; Villalobos Dintrans, 2018b). Chile's most comprehensive adult care program is the Assistance and Care National Sub-system (ACNS),[41] implemented under the government of Michelle Bachelet (2012-2016). This program offers assistance to dependents and their caregivers by providing resources, information, and networks to facilitate home care. The ACNS, however, only covers 21 of the 345 municipal jurisdictions in the country. In 2017, the program served 937 adult dependents. That is 0.1% of adult dependents.[42]

The state also provides long-term care services, home care services, and day centers for elderly dependents. In line with focalization principles, these services are rigorously targeted. Benefactors must be elderly (60+) citizens in the poorest 60% of the population, abandoned or not receiving family care, and presenting at least moderate dependency levels. Together, these programs serve almost 3.400 dependent adults (0.35% of adult dependents). Public spending in ACNS plus these three caregiving services cost the state 0.004% of the country's GDP.

[40] https://www.oecd.org/centrodemexico/medios/gasto-publico-social-ocde.htm

[41] Sub-sistema Nacional de Apoyos y Cuidados (https://www.chilecuida.gob.cl/).

[42] Information on budgets and total beneficiaries for every social program in Chile can be found at https://programassociales.ministeriodesarrollosocial.gob.cl/programas/

Finally, the state also offers subsidies[43] to municipalities and NGOs to provide long-term care services to low-income older adults with moderate to severe dependency. These subsidies actually represent the state's highest-spending account in adult care. In 2017, these subsidies benefited 5.634 adult dependents. These subsidies accounted for over 47% of the state's total spending in care provisioning.

The pillars of neoliberalism limit the expansion of the state's care supply. The neoliberal ideal of a 'small' state is perhaps the clearest in adult care. In total, the state only provides care to about 10,000 people or 1% of adult dependents. Today, the number of dependents who do not receive any assistance exceeds the state's supply by almost thirty times. The more than forty years of neoliberal rule have assigned the state to a secondary role in the care system.

c. *The limits to the care market*

Here, we will consider the market provision of care in its broadest possible sense. Any form of commodified care, including paid domestic workers, is regarded as a part of the market. Under this definition, the limits of the market could be ample. Global care chains, for example, cut across international borders to cover the demand for care in one place by contracting care somewhere else (Hochschild, 2014). Demand for commodified care is crucial for the expansion of the market. In Chile, even though nearly 30% of dependents do not receive care, market demand is low. Less than 8% of

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[43] Fondo Subsidio ELEAM.

adult dependents access the care market.[44] The fact that adult dependents are disproportionately poor is most likely behind this fact.

The care market is overrepresented by the wealthy. Although 9% of adult dependents are in the top quintile of the income distribution, 30% of dependents with access to the market belong to this group. The hiring of live-in domestic workers partially explains this overrepresentation. 42% of live-in domestic workers caring for adult dependents work in top quintile households. However, these workers only represent 7.7% of the care market.[45]

Unequal access to the care market is reflected in out-of-home care as well. The economic segregation of Chilean cities has facilitated long-term care providers to cluster in wealthy neighborhoods (Villalobos Dintrans, 2018a). Private medical services, moreover, are virtually inaccessible for adult dependents. The unregulated private health insurance market (ISAPRES) crowds out adult dependents by heavily raising their premiums (Villalobos Dintrans 2018b). Hence, the state ensures 96% of the adult dependent population (FONASA).[46]

In Chile, economic inequality and high poverty rates among adult dependents limit the market provision of care. Rising dependency rates will likely increment the market's care supply. However, in an unequal country like Chile, the market will probably continue to target wealthy individuals. The focalization of state- and market-provided

[44] According to the 2017 CASEN.
[45] According to the 2017 CASEN.

[46] In contrast, less than 85% of the national population is publicly insured.

care entails that the family and unpaid female caregivers are at the heart of the Chilean care system.

d. *The primary subsystem of care: The family*

According to the 2017 CASEN, household members care for 56.7% of adult dependents. Considering that 29% of dependents do not receive any assistance, almost 80% of assisted dependents are cared for by family members. The care system strongly relies on family caregivers, especially women. Hence, scholars have labeled the Chilean adult care system as an unsupported familial regime of care (Palacios, 2016).

A patriarchal system structures the division of care labor in most families. This system ensures an ample supply of unpaid care through the exploitation of women (Folbre, 2021).[47] However, it also structures care shortages. Here we analyze the basic structure of the patriarchal care supply and its influence on the overall provision of care. As we will see, the limits to the patriarchal division of labor severely affect the system's care supply.

i. *The patriarchal family structure and caregiving*

[47] Exploitation can be defined beyond the productive sphere. Nancy Folbre (2021) defines it as an unfair division of gains and costs.

Most classical economists dismissed the social character of the household division of labor.[48] Marx, for example, argued that the household division of labor was a product of nature rather than exchange (Marx 1990 [1867], p. 471-3). Smith was even less attentive, arguing that the division of labor was limited to the space of the market (Smith 1937 [1776), Ch. III). This omission is more than a couple of centuries old. Aristotle, for instance, argued that masculine rationality was the natural source of patriarchal rule over slaves and women.[49] What is perhaps more surprising is that this rationale persisted long after the works of classical economists. Neoclassical economists have defended the patriarchal division of labor on very similar grounds to Aristotle. According to them, its efficiency relied on the altruistic nature of male household heads (Becker, 1985). Their models explicitly assume that "men know best."

However, as feminist scholars have pointed out, the patriarchal division of labor is neither natural nor efficient. Patriarchal structures are systems of collective power that privilege mature heterosexual men over others (Folbre, 2021, p. 21). In household care, patriarchal structures enable men to enjoy the benefits of care without bearing the brunt of its costs. The patriarchal order, moreover, is not sustained on the altruistic or rational nature of men but by a complex ensemble of political, cultural, and economic forces (Ibid.).

Two kinds of power regulate patriarchal systems: bargaining power and normative power. Bargaining power represents the political, legal, and economic

[48] For a rigorous review, see (Folbre, 2009).
[49] Aristotle, Politics, Book I, Part V (http://classics.mit.edu/Aristotle/politics.1.one.html).

entitlements that an individual can wield to influence (care) labor allocation. Additionally, since a division of labor is an inter-dependent social structure, bargaining power is also determined by each household member's fallback positions or exit strategies (Folbre, 2021). On the other hand, normative power emerges from shared imaginaries and expectations around gender and work (Agarwal, 1997).

Women "doing gender" often implies caring for family members. The pervasiveness of gender norms explains why the distribution of unpaid work has remained asymmetrical even as women have entered the labor force (Bittman et al. 2003; Beneria et al. 2015, p.60).[50] Normative power affects the division of labor differently than bargaining power. Gender norms are internalized. Therefore, to meet gender expectations, women may supply more care than men even if they do not live under the same roof. In other words, normative power entails that the patriarchal system does not necessarily need a live-in patriarch to enforce it. The historically gendered character of bargaining and normative power has ensured women's provision of unpaid care. Hence, female presence is crucial to ensure the patriarchal care supply.

In addition to female presence, household size also matters. The patriarchal care supply relies on female exploitation. Since care is a public good, women assume caregiving costs while not ripping most of its benefits (Folbre, 2021). This is an internal contradiction within the patriarchal system: caregiving can impoverish caregivers. In larger households, however, this contradiction is partially alleviated. More sizeable

[50] In Chile, scholars have attributed Chile's particularly low female labor market participation to the prevalence of gender norms (Contreras et al., 2010).

homes provide more space for the division of labor and, therefore, more space for specialization. In turn, the specialization of some (male) household members in paid employment allows for income-pooling, leveling the material conditions of paid and unpaid workers. Income-pooling, then, characterizes the exchange element within the patriarchal division of labor. Without it, the internal contradictions of patriarchal systems become more apparent, rendering them unstable. Hence, household size also conditions the patriarchal care supply.

The factors that condition patriarchal supply provide evidence for the familial subsystem's reliance on patriarchal systems. Table 9 shows that households without female presence and/or smaller in size are less likely to internalize care provision. The table divides dependents' families into four different types: dependents residing with i) at least one non-dependent woman and one non-dependent man (32% of dependents live in this families), ii) at least one non-dependent woman and zero non-dependent men (22%), iii) at least one non-dependent man and zero non-dependent women (22%), and iv) zero non-dependent adults (24%).

Table 9: Household type distribution for adult dependents. The table summarizes average household size (according to the presence of adult non-dependents), care internalization rates, and the female share of unpaid household caregiving.

Household Type	Share (%)	Non-Dependent Adults (Average)	Household Care (%)	Female Share (%)[1]
Non-Dep. Women > 0 & Non-Dep. Men > 0	32.24%	2.9	77.52%	80.99%
Non-Dep. Women > 0 & Non-Dep. Men $= 0$	21.77%	1.36	71.62%	98.96%
Non-Dep. Women $= 0$ & Non-Dep. Men > 0	21.86%	1.33	56.40%	5.50%
Non-Dep. Women $= 0$ & Non-Dep. Men $= 0$	24.13%	0	15.76%	60.47%
All Hh. with Adult Dependents	100%	1.82	56.70%	68.00%

Source: CASEN 2017. Calculations use survey weights.

[1] Female care shares were calculated as the percentage of unpaid family caregivers who are women.

The conditions for the patriarchal division of labor are more fertile in households with at least one non-dependent woman and one non-dependent man. These households are larger in size and have a female presence. Therefore, it is not surprising that almost 80% of dependents residing in these households receive care from a family member. In more than 80% of these cases, that family member is female. Dependents who live with at least one non-dependent woman and zero non-dependent men configure smaller residencies that retain a female presence. These households internalize care at a slightly lower rate to that of larger configurations with male presence. The normative character of caregiving may be more evident when we compare these households with their counterparts: households with at least one non-dependent man and no women. Although similar in size, these households internalize care at a significantly lower rate (72% versus 56%). Households without any non-dependents, moreover, are the least likely to internalize care (16%).

Table 9 confirms the strict reliance of the familial subsystem of care on the patriarchal exploitation of women. When the conditions for it are not ripe, the subsystem's care supply decreases. Patriarchal systems, therefore, simultaneously ensure and limit the provision of care. The primary role of family care within the care system underscores the relevance of patriarchal limits for the current system to close the gaps in care.

e. Who doesn't receive care?

Under the current structural configuration, who doesn't receive care? Using the 2017 CASEN survey, we can calculate if the structural limits to the different subsystems of care determine who does and who doesn't receive assistance. Nearly 30% of dependents do not receive care. As one might expect, individuals with lower levels of dependency are less likely to receive assistance. Figure 10 shows the percentage of dependent adults receiving assistance by dependency level.

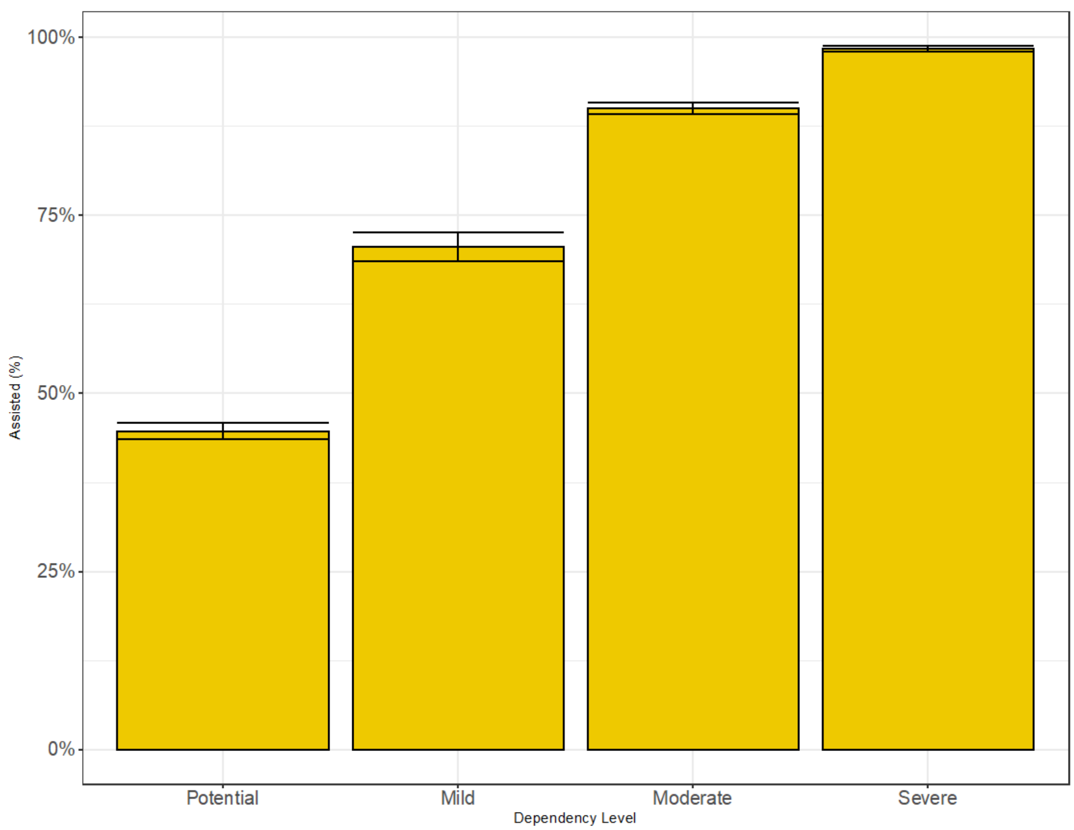

Figure 10: Percentage of dependents receiving care according to dependency levels.

45% of potentially dependent adults and 70% of mild dependents receive care. Most moderate and severely dependent adults receive some form of care (90% and 98%, respectively). Lack of assistance at the early stages of dependency can bring about serious public health concerns. Without proper care, individuals with low dependence levels may continue to lose functional abilities and accelerate severe dependency (Metz, 2000; Golinowska & Sowa, 2017).

The Chilean system of care is characterized by its inadequate provision of preventive care services (Palacios, 2016; Villalobos, 2018a). However, how much of this omission is owed to the familial subsystem of care? So far, we have seen that the Chilean care system is extremely reliant on family care. Different family types, moreover, internalize care responsibilities at different rates. Smaller and more masculinized households supply less care than larger households with a female presence. Hence, dependent adults residing in households with low care supply may be more likely to not receive any kind of care.

I test this hypothesis using the 2017 CASEN and OLS methods. The dependent variable takes the value of zero if the dependent adult does not receive any assistance and one if they do. Moreover, I use two population subsets. First of all, I calculate the determinants of being cared for for all adult dependents (12,660 individuals). Then, I limit the dataset to potential and moderate dependents (6,974).

I calculate two models for each population subset. Model 1 groups dependents into four family types, which are then used as categorical regressors. These categories are: dependents living with i) at least one non-dependent female and one non-dependent male, ii) at least one non-dependent woman and zero non-dependent men, iii) at least one non-dependent male and zero non-dependent females, and iv) with zero non-dependents. Model 2 considers the total of non-dependent women and non-dependent men as determinants for being cared for. This model captures the effects of household size on the likelihood of receiving care.

Both models also consider a series of household and individual determinants. These include the total number of children younger than 14 in the household, the household income per capita, dependency level, the dependent's gender, age, and schooling. The outcomes for each model are presented in Table 10:

Table 10: OLS regression output for all dependent adults and potential and mild dependents using the 2017 CASEN. Estimations were calculated using survey weights.

	Dependent variable:			
	Cared For=1			
	All Dependents		Potential + Mild	
	(1)	(2)	(1)	(2)
Family structure (Non-Dep. Women > 0 & Non-Dep. Men > 0 =0)				
Non-Dep. Women > 0 & Non-Dep. Men = 0	-0.017^{*}		-0.041^{**}	
	(0.010)		(0.017)	
Non-Dep. Women = 0 & Non-Dep. Men > 0	-0.055^{***}		-0.080^{***}	
	(0.010)		(0.017)	
Non-Dep. Women = 0 & Non-Dep. Men = 0	-0.182^{***}		-0.218^{***}	
	(0.010)		(0.016)	
Total Non-Dep. Women		0.055^{***}		0.075^{***}
		(0.004)		(0.008)
Total Non-Dep. Men		0.036^{***}		0.053^{***}
		(0.004)		(0.007)
Total Children	-0.004	-0.010^{*}	-0.014	-0.022^{**}
	(0.005)	(0.006)	(0.009)	(0.009)
Hh. Income per capita (Demeaned)	-0.009^{***}	-0.009^{***}	-0.018^{***}	-0.018^{***}
	(0.002)	(0.002)	(0.003)	(0.003)
(Hh. Income per capita (Demeaned))^2	0.0003^{***}	0.0003^{***}	0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Dependency (Pontential=0)				
Mild	0.250^{***}	0.251^{***}	0.248^{***}	0.247^{***}
	(0.009)	(0.009)	(0.011)	(0.011)
Moderate	0.414^{***}	0.421^{***}		
	(0.009)	(0.009)		
Severe	0.469^{***}	0.478^{***}		
	(0.010)	(0.010)		
Gender (Male=0)				
Female	0.027^{***}	0.025^{***}	0.050^{***}	0.050^{***}
	(0.008)	(0.008)	(0.013)	(0.012)
Age	0.002^{***}	0.002^{***}	0.003^{***}	0.003^{***}
	(0.0002)	(0.0002)	(0.0004)	(0.0004)
Schooling (Years)	-0.010^{***}	-0.009^{***}	-0.015^{***}	-0.015^{***}
	(0.002)	(0.002)	(0.004)	(0.004)
Schooling^2	0.0004^{**}	0.0003^{**}	0.001^{***}	0.001^{***}
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Constant	0.400^{***}	0.279^{***}	0.355^{***}	0.193^{***}
	(0.018)	(0.018)	(0.032)	(0.032)
Observations	12,660	12,660	6,974	6,974
R^2	0.265	0.257	0.116	0.111
Adjusted R^2	0.264	0.256	0.115	0.110
Residual Std. Error	3.384	3.402	4.141	4.152
Note:	*p<0.1; **p<0.05; ***p<0.01			

The regressions show that dependents living in family types that are less fertile for the patriarchal division of labor are significantly less prone to receive any care at all.

The difference between families with male and female non-dependents and households with only female non-dependents is the least significant. This result underscores the reliance of the Chilean care system on unpaid female labor. Moreover, dependents that only reside with male non-dependents are significantly less likely to receive care. Dependents residing without any non-dependent adults are the least likely to receive care. These results mimic the internalization rates for each household type presented in Table 9. Model 2 shows that family size matters for receiving care. The presence of non-dependent women and non-dependent men increases the likelihood of receiving care. However, the effects are higher for non-dependent women.[51] Model 2 further underscores the reliance of the system on unpaid female labor. Moreover, the effects are different for potential and mild dependents than for the average population. People at early stages of dependency are less likely to receive care if they reside in smaller households or without the presence of male and female non-dependents.[52]

When we analyze the remaining variables, we find some interesting results. Controlling for family types, the number of children in the household is not a significant determinant for receiving care. This is surprising since it has been observed elsewhere that children often help with taking care of dependent adults (Folbre, 2021). Moreover, household income per capita and the dependent's schooling level present an inverted-U relation with the likelihood of receiving care. This is in line with the political economy of

[51] T-tests for the differences between the effects of non-dependent women and non-dependent men are significant to 1% for all dependents, and 5% for mild and potential dependents.

[52] Statistical tests for these differences can be found in the annex (Section A.1).

the Chilean care system. The state targets the poorest households, while the market is hyper-focalized on the wealthiest families. However, income and education effects are very small.

The structural limits to the provision of care are significant predictors for receiving care. Therefore, the current structural conditions of the care system help explain the gap between the demand for adult care and its supply. However, has the care system always experienced these conditions? In the next section, we examine the last decade of structural elaboration. Our findings show that the structural environment has become increasingly adverse for the current system to provide care.

V. How did we get here and where are we going? Trajectories in adult dependent family structures and the structural elaboration of a care crisis

The limits to the patriarchal division of labor play a significant role in reducing the system's care provision. Hence, shrinking limits to the patriarchal division of labor would signal a loss in the system's capability to provide care. Our analysis here shows that this is the case. Moreover, if this trajectory continues, it is unlikely for the current care system to meet increments in demand. A care crisis may then be forming on the horizon.

a. *The shrinking of Chilean family structures: Internal and external factors*

Instability in social systems may arise from internal contradictions and external factors (Folbre, 2021). The exploitative nature of patriarchal systems is a source of internal instability. Exploited groups (i.e., women) are more likely to contest existing structures when they gain collective power. Conversely, external factors may obstruct the exploitation of women. The demographic transition, and its effects on the structural conditions of the care system, are most likely a result of both internal and external factors.

Household-size reduction is expected in growing economies. However, in Chile, it has been strikingly fast. Since the turn of the century, Chilean households have reduced from an average of 3.6 members to 3.1.[53] To contextualize, in the United States, the average household size was 3.6 in 1970, and it is yet to reach 3.1.[54] The fast reduction of Chilean homes has been associated with declining fertility and marriage rates (Salinas 2011). In turn, the internal weakening of patriarchal structures partially explains these declining rates.

In terms of bargaining power, women have made important strides over the last couple of decades. For instance, Before the COVID-19 pandemic hit, women had

[53] From 3.6 in 2002 to 3.1 in 2017, according to the census (https://www.censo2017.cl/wp-content/uploads/2018/05/presentacion_de_la_segunda_entrega_de_resultados_censo2017.pdf).

[54] https://www.statista.com/statistics/183657/average-size-of-a-family-in-the-us/

significantly increased their labor market participation. In 2000, 36.5% of working-age participated in the labor market.[55] This number rose to 48.9% by 2017. Additionally, there have been considerable improvements in family law. In 2004, Chile was the last country to legalize divorce, decreasing male power over women's bodies (Salinas, 2016). Reproductive contraception has also become more widely available in the past 20 years. For example, since 2013, all public health institutions are obligated to stock and distribute the "morning-after" pill.

However, as other authors have pointed out, the explanatory power of internal factors needs to be nuanced (Salinas, 2016; Ramm, 2016). First of all, gender norms continue to be an essential factor in allocating unpaid work, especially in lower-income households. Research has shown that "traditional" values that associate women to unpaid work have weakened among the younger and more educated people but remain strong among older and less educated individuals (Contreras & Plaza, 2010; Gómez-Urrutia et al., 2017). Since low-income and elderly homes have higher adult dependency rates, it is less likely to observe the transgression of gender norms in such spaces. Moreover, the masculinization of unpaid care provision has been much slower than the feminization of paid employment. Alejandra Ramm (2016) observes that women are still more likely to take on the lion's share of unpaid childcare responsibilities (Ramm, 2016). Our analysis shows a very similar trend for adult dependents. When there are non-

[55] https://www.ine.cl/docs/default-source/ocupacion-y-desocupacion/publicaciones-y-anuarios/publicaciones/mujeres-en-chile-y-mercado-del-trabajo---participaci%C3%B3n-laboral-femenina-y-brechas-salarialesa.pdf?sfvrsn=ade344d4_3

dependent women in the household, the likelihood of them becoming the primary caregiver exceeds 80%.

The limits to the internal explanation have led scholars to look for explanations to the demographic transition in external factors. In Chile, women born in wealthy households) are significantly more likely to marry than those born in lower-income homes. Therefore, lower-income women are far more likely to be born into single-mother or non-married couples' households, further decreasing their likelihood of marrying (Salinas, 2011). Persistent economic inequality has reproduced and deepened this pattern over time, as lower-income households are increasingly conformed around more unstable structures (cohabitation) or become smaller (Ibid., Ramm & Salinas, 2019). Since dependents tend to be from lower-income backgrounds, external economic factors may be reducing their household size.

Have dependent households reduced in size? The literature has paid little attention to this question. The lack of reliable data on adult dependency may be behind this omission. The Chilean authorities began to measure adult dependency in the CASEN only in 2015. Therefore, until now, we have not had reliable information on the evolution of families with adult dependents.

b. How to analyze the distribution of dependent's family structures over time?

Over 90% of dependents in 2017 are disabled people. However, less than half of the adult disabled population is dependent (42%). Analyzing the family distribution of disabled individuals may not provide an accurate depiction of the actual distribution of adult dependents. Similarly, as presented above and elsewhere (Villalobos Dintrans, 2018a), age is not the sole determinant of dependency. Hence, examining the family composition of the elderly may also lead to a misguided analysis of the condition and evolution of dependent family structures. Figure 11 compares the actual family distribution of adult dependents in 2015 and 2017 to that of the elderly (75+) and disabled adults.

Disabled people are more likely to live in large households, while the elderly usually live in smaller households. As we can see, people with disabilities are significantly more likely to reside with at least one non-disabled woman and one or more non-disabled men than dependents. Conversely, elderly individuals are more likely to reside without any other non-elderly adults than any other group. The actual distribution of adult dependents lies somewhere in between the distribution of the elderly and the disabled.

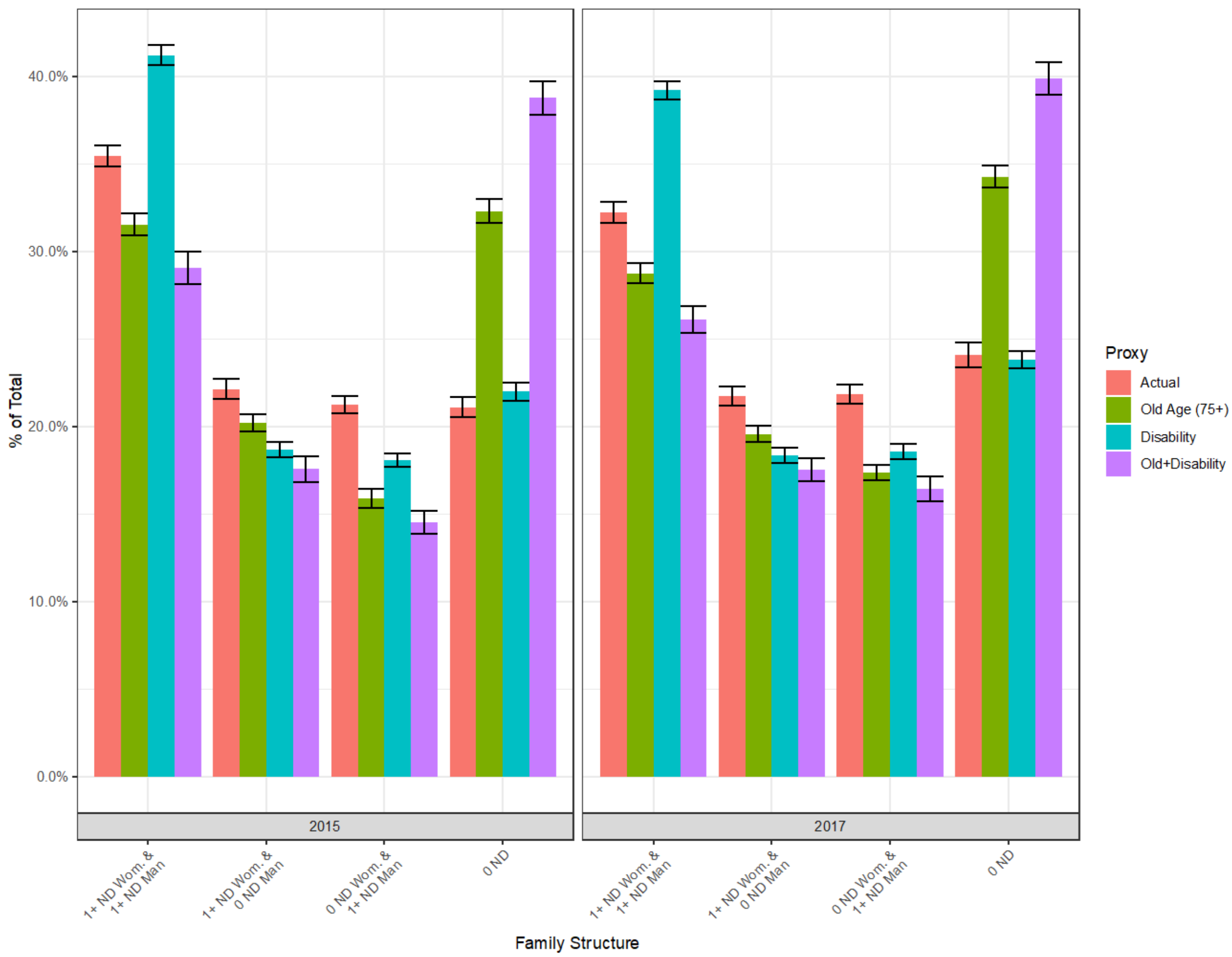

Figure 11: The family type distribution of dependents, disabled people, elderly people, and elderly disabled individuals in 2015 and 2017.

The distributional differences between elderly and disabled populations pose a challenge for analyzing the trajectories of the care system's capability to meet increments in demand. If disability drives dependency rates, the distributional pressures towards larger families may facilitate the familial system's care provision. On the other hand, if the aging population is pushing dependency levels, then the system may be entering a crisis.

As an initial approach, we can statistically compare the family distribution of dependents to that of old age, disability, and a combination of both. Paerson's Chi-squared and the Log likelihood ratio are two commonly used goodness of fit tests in the analysis of categorical data distribution. The null hypothesis for both tests is that the distribution of dependent family structures equals the distribution of disabled or elderly peoples' family structures. Tables 11 and 12 summarize the outcomes of the tests for each distribution in 2015 and 2017, respectively. None of these groups accurately represents dependency. The family distributions of disabled people, however, do have lower coefficients. This means that their distribution is closest to that of dependents. Interestingly, the coefficients for elderly distribution decreases from 2017 to 2015, and those for families with disabled members increases.

Table 11: Goodness-of-fit tests comparing the actual distribution of dependents to that of the elderly, disabled people, and elderly disabled in 2015. Survey weights were included in the calculations.

Proxy	Goodnes of Fit Test	Coef.	F-value	P-value
Old Age (75+)	Paerson's Chi-squared	1182.423	139.9133	0.0000
	Log likelihood ratio	1079.706	127.7590	0.0000
Disability	Paerson's Chi-squared	485.2142	52.0398	0.0000
	Log likelihood ratio	487.4047	52.2747	0.0000
Old Age + Disabled	Paerson's Chi-squared	1155.632	170.9435	0.0000
	Log likelihood ratio	1000.892	148.0541	0.0000

Table 12: Goodness-of-fit tests comparing the actual distribution of dependents to that of the elderly, disabled people, and elderly disabled in 2017. Survey weights were included in the calculations.

Proxy	Goodnes of Fit Test	Coef.	F-value	P-value
Old Age (75+)	Paerson's Chi-squared	770.4329	129.1262	0.0000
	Log likelihood ratio	716.3899	120.0685	0.0000
Disability	Paerson's Chi-squared	645.2752	65.8287	0.0000
	Log likelihood ratio	634.586	64.7383	0.0000
Old Age + Disabled	Paerson's Chi-squared	803.9841	134.4372	0.0000
	Log likelihood ratio	718.887	120.2078	0.0000

c. *Using machine learning to predict dependency since 2006*

Since dependent's family structures cannot be proxied through disability or age, I turn to Machine Learning. Machine learning is nothing more than different statistical and probabilistic techniques that optimize prediction. Its use has gotten particular attention in the medical community, where observers have noted that machine learning significantly improves our capacities to predict different medical conditions (Cruz & Wishart 2006; Weng et al. 2017; Blomberg et al. 2019). To my knowledge, there have not been any attempts to predict dependency using these techniques.

Overfitting is one of the most significant issues when using machine learning methods (Foster, Kropowski & Skufca, 2014). For this reason, we must consider a series of precautions. First, the dataset used for training the predictive model must be sufficiently large relative to the number of predicted categories. Here, we pooled individual data from the 2015 and 2017 CASEN surveys (212,730 and 175,076 observations, respectively) for predicting only two categories: non-dependency and dependency.[56] After dropping the observations that do not possess complete

[56] Dependency includes potentially dependent individuals.

information, we are left with 374,513 observations. The predictors were chosen according to a range of medical and socio-economic variables. All CASEN surveys since 2006 share these.[57]

For validation purposes, I randomly sample the pool data into a training and a testing dataset.[58] The training dataset consists of 187,769 observations (50,1% of total observations) and the testing dataset is comprised of 187,769 observations (49.9%). I use six different algorithms to predict dependency and then choose the superior combination of precision and accuracy. In the annex, you can find an explanation for each algorithm (Section A.2). Also, you will find the methodology for choosing the Random Forest algorithm as the most appropriate for our analysis. The annex also presents Paerson's Chi-Squared tests showing that the model accurately predicts the distribution of dependents' family structures (Section A.4). Having chosen the appropriate predicting model, I predict adult dependency for six different CASEN surveys between 2006 and 2017.

d. Adult dependency since 2006

The predictions show a clear increment in dependency rates over the past decade (Table 13). In 2006, a little over 4.5% of adults were dependents. This number rose to 7.4% in

[57] Hence, I will predict dependency for the years 2006, 2009, 2011, 2013, 2015, and 2017. The 2003 CASEN has very similar medical data with differences in the periodization of the data. 2003 was not considered due to this reason. The list of predictors can be found in the annex, Section A.3.

[58] Using set seed (12345) in R.

just eleven years. In the same period, the fraction of adults over 60 years of age increased significantly. In 2006, according to estimates from the National Institute of Statistics[59], people over 60 represented 15.9% of adults. The same estimates show that this number rose to 20.2% in 2017. The simultaneous increments in dependency rates and older population are not a coincidence.

Table 13: Predicted dependency rates since 2006.

Year	Predicted Dependency Rate	Standard Error
2006	4.54%	0.001
2009	5.35%	0.001
2011	5.68%	0.001
2013	5.39%	0.001
2015	6.85%	0.001
2017	7.42%	0.001

Figure 12 shows the predicted distribution of dependents according to age bracket between 2006 to 2017. Here, dependents between 15 and 59 years of age fall under the category of younger dependents. In eleven years, older dependents have increased their share by almost 10%. This more than doubles the increment in the share of 60+ individuals over the total adult population. Furthermore, by 2035 the fraction of 60+ adults will graze 30%. The dramatic increase in the older population will most likely entail a similarly momentous increment in dependency levels.

[59] Instituto Nacional de Estadisticas (INE), https://www.ine.cl/ .

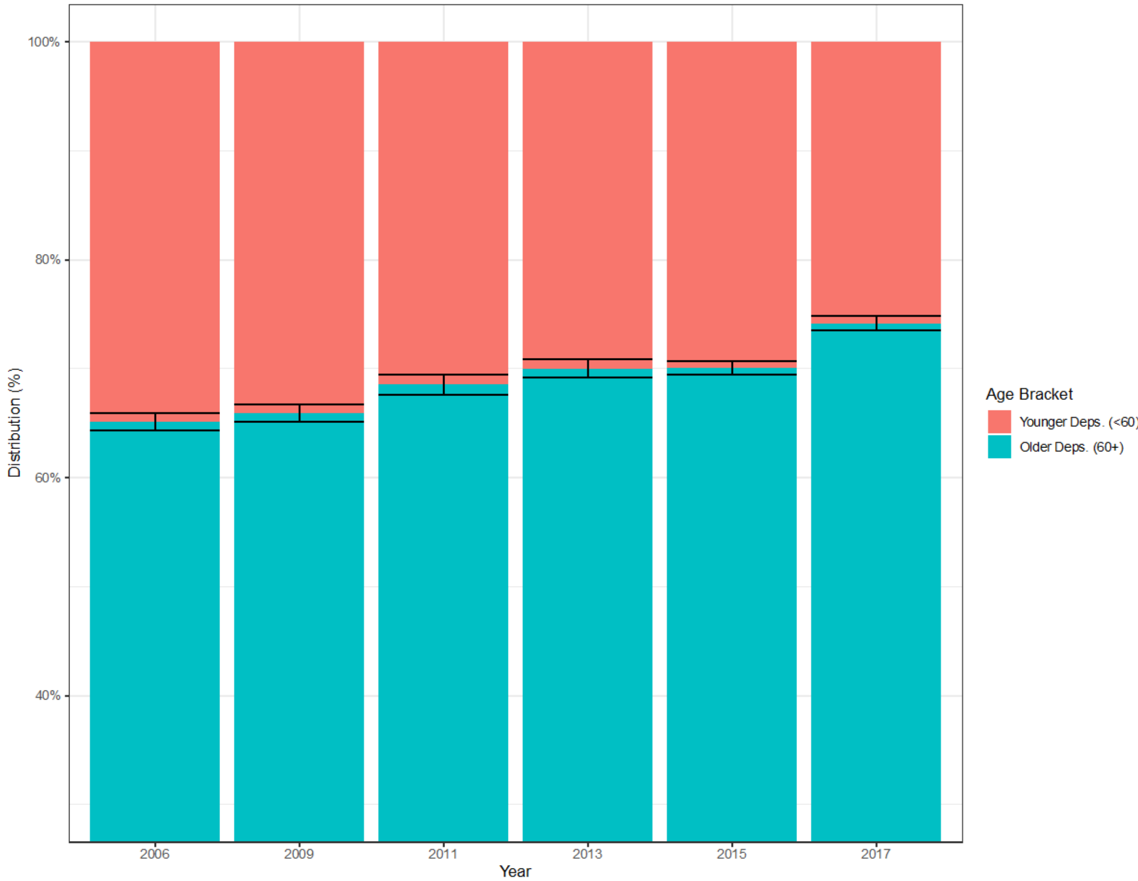

Figure 12: Growth in the share of older (60+) dependents between 2006 and 2017.

e. *Changes in dependents' family structures since 2006: A crisis in the horizon*

As dependents become increasingly older, their family structures change as well. Older people are more likely than the disabled population to reside in small households. The predictions show a convergence in the household structure distribution of dependents and older adults. Figure 13 depicts this convergence since 2006. That year, more than 42% of dependents resided with at least one non-dependent woman and one non-dependent man. The rate of dependents in these households has continuously decreased to around 30% in 2017. Moreover, dependents living without non-dependents have increased from under 20% to around 25%. The rate of dependents residing with one non-dependent man has slightly increased as well.

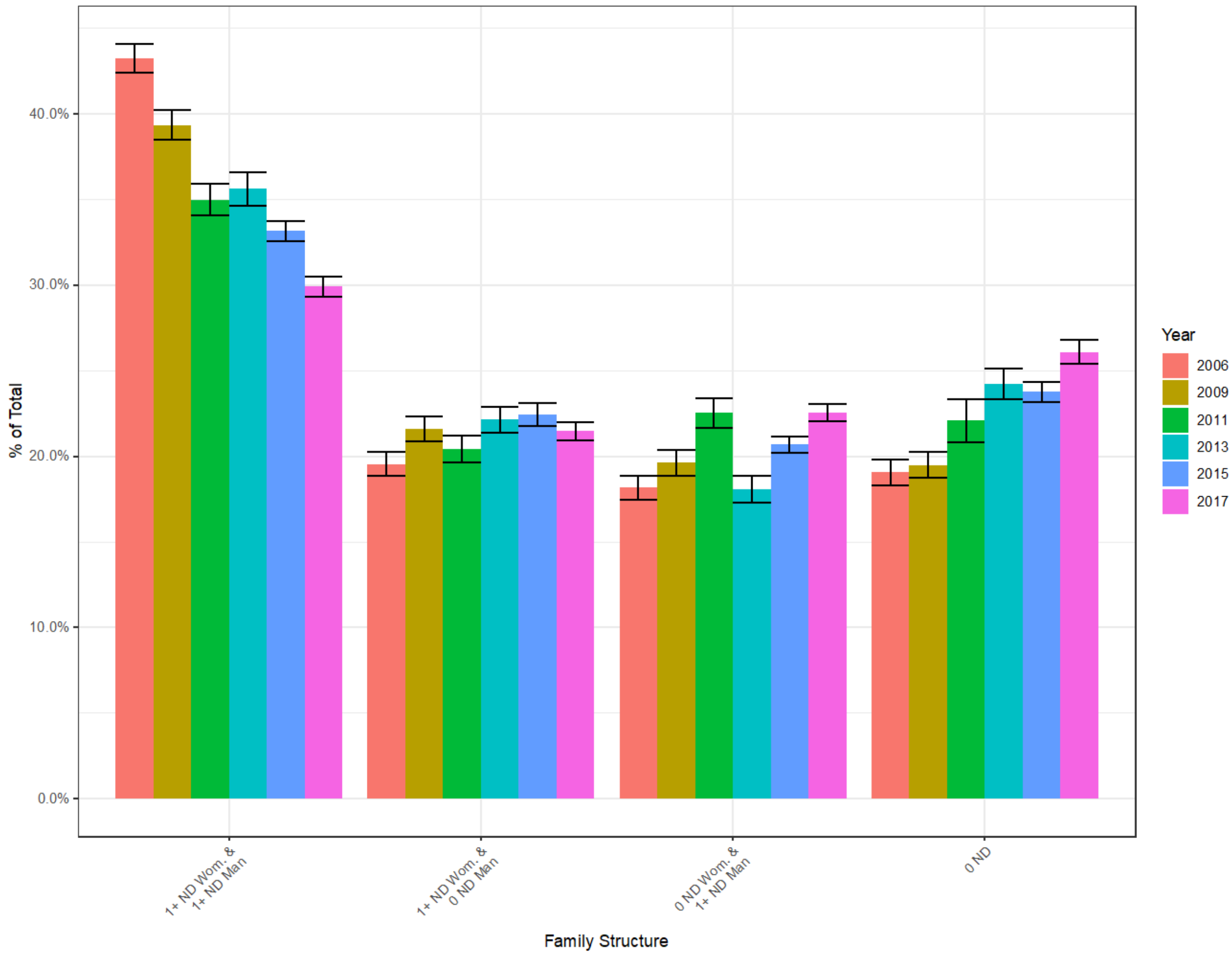

Figure 13: Machine learning predictions for the share of dependents in each family type between 2006 and 2017.

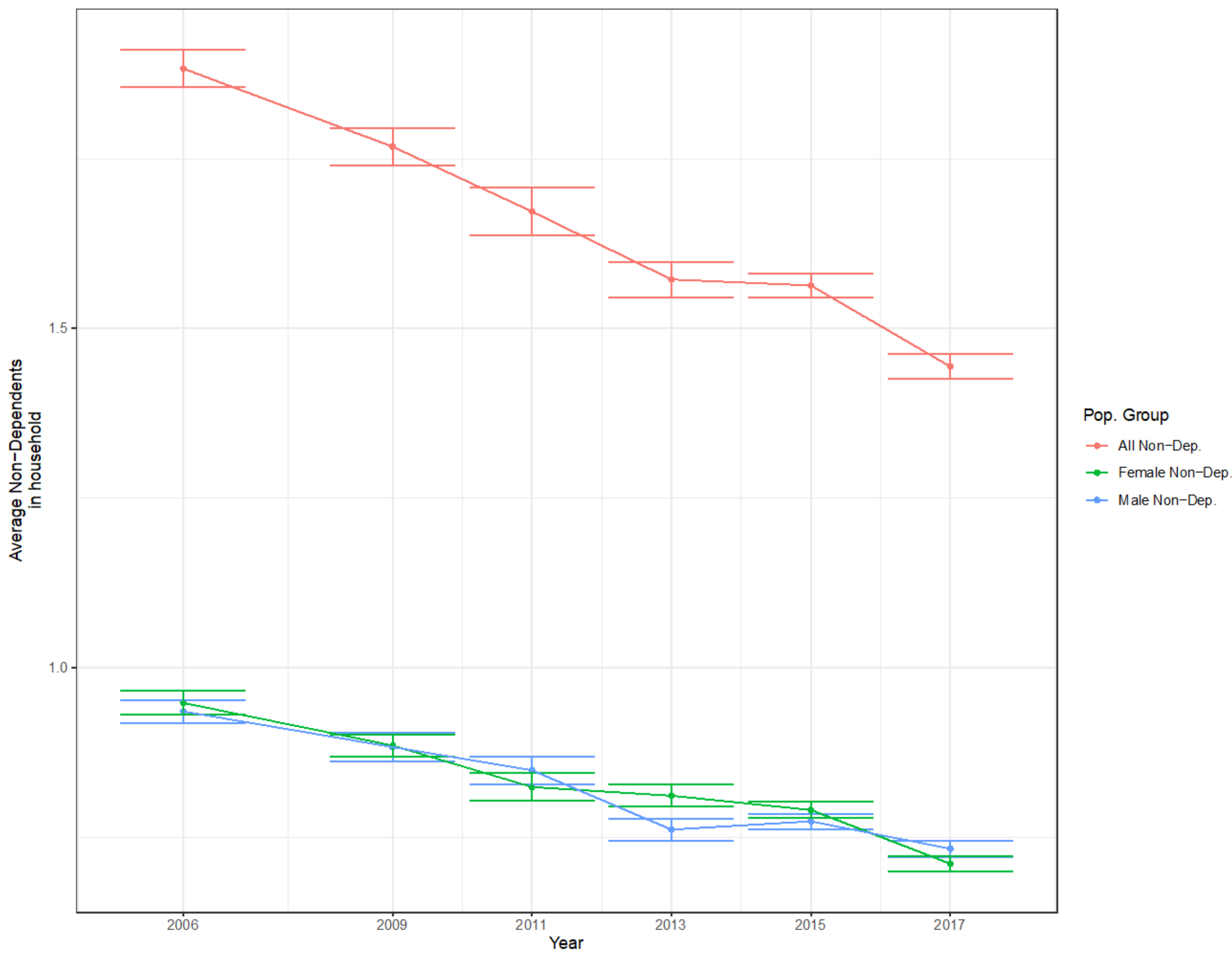

Figure 14: Average number of non-dependents residing with dependents according to machine learning predictions.

The trajectories presented in Figures 13 and 14 reflect a severe obstacle for the familial subsystem of care. As dependents' families become increasingly smaller, the likelihood of receiving unpaid care decreases. In other words, the shrinking limits of the family-space are increasingly complicating providing adequate care under the current system. Female presence, moreover, has not counteracted household shrinkage (Figure 14). Therefore, both essential elements to the patriarchal division of labor are increasingly missing. By insisting on the female unpaid provision of care, the system is trading women and ghosts.

The shrinkage of dependents' household size is ubiquitous across the income distribution. However, it is especially dramatic in lower-income homes. Figure 15 shows the average magnitude of non-dependent adults in households with at least one dependent by income quintile. Households in the poorest 20% of the population (or first quintile) have continuously decreased in size from having an average of nearly 1.9 non-dependent adults to less than 1.3 in 2017. This represents the most significant decrease among all income groups. Since dependency rates are higher in the lower echelon of the income distribution, household reduction in this group places additional concerns on the system's capability to supply necessary care.

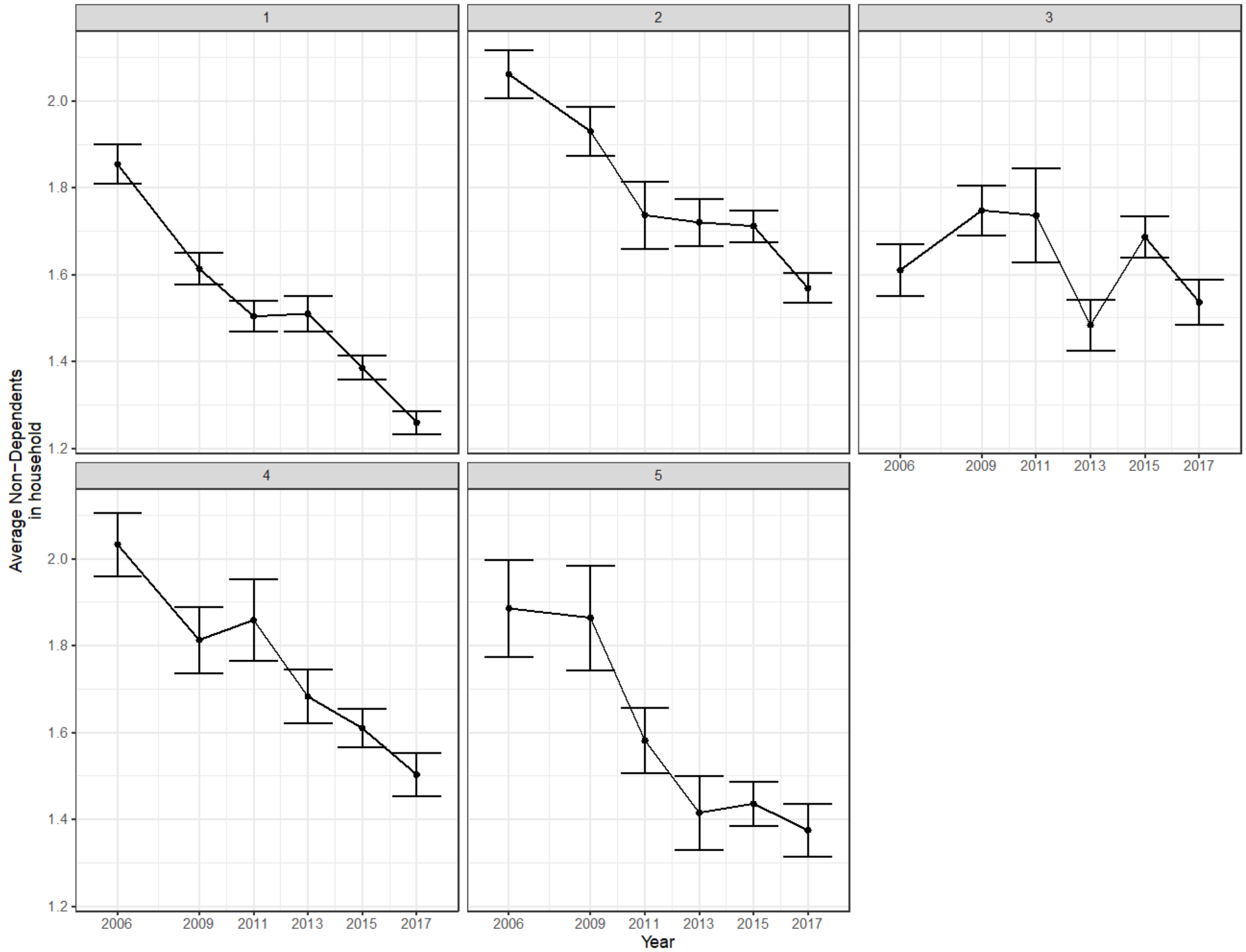

Figure 15: Average number of non-dependents residing with dependents by income quintile according to machine learning predictions.

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The predictions show that dependent households have followed a similar trend to the overall structure of Chilean family structures. Hence, the change in dependent family structures may also respond to internal and external structural pressures. More research is necessary to elucidate if this is the case. However, what is certain is that the emergent configuration of dependents' households is increasingly challenging the patriarchal division of labor. As the share of older dependents grows, the observed trajectory is likely to continue. This would further weaken the current care system. Without reform, a crisis in adult care is almost inevitable.

VI. Final remarks: New spaces for care

Chile's care system has historically relied on unpaid family caregivers (i.e., women) to meet the demands in adult care. The demographic transition, however, is a challenge that the system is unlikely to overcome. This article analyzes the current configuration of the care system through a political economy lens, showing that the system is not only exploitative but unsustainable as well. Machine learning predictions show that dependency rates are rising even as dependents increasingly reside without non-dependent family members. Through econometric analysis, moreover, this paper has shown that the patriarchal system that structures the familial provision of care fails to provide for dependents under these family conditions. Hence, for the Chilean care system to overcome the demographic challenge, it must undergo a profound structural transformation.

First of all, the family should no longer be at the center of the system. The shrinkage of the family complicates a division of labor capable of providing care. Moreover, the incentives for non-dependents to diversify rather than specialize in care are higher in these smaller settings (Weber 2019). Our findings show that trajectories dependent family structures have mimicked that of the overall population. Internal and external structural elements have shrunk the limits to the patriarchal division of labor.

As this continues to happen, the familial system will increasingly lose its ability to provide care.

Moreover, in the context of extreme economic inequality, the market is seldom an option for care. The few long-term care services that exist in Chile tend to focalize on higher-income dependents. Adult dependency, however, is more common in lower-income communities. Only when presented with state subsidies, the market provided care for this population (Villalobos Dintrans 2018b). It is also worth noting that international experience tells us that the market also penalizes caregivers (Folbre, 2018). Therefore, a market-centered approach may not be appropriate to meet the increments in the demand for adult care.

A new political accord regarding the role of the state in care may be needed to overcome the challenges of the demographic transition. It would undoubtedly require higher fiscal spending. However, most importantly, it would require the state to create an appropriate space for the division of care labor. The dangers in defining this new abstract space are plenty. The state, unlike the market, has fewer self-regulatory mechanisms to increase or decrease the size of the division of labor. Therefore, a hyper-centralized structure in the provision of care may result in an elongated and over-bureaucratized space. Such a space may result in the inefficient use of public revenue. On the other extreme, if the provision of the state is too localized, the limits to the division of labor may prevent it from effectively meeting the increments in demand (as is the case for families today). The challenge of the impending crisis of care is, therefore, to find a middle ground.

CHAPTER 3

THE ECONOMIC CASE FOR COMMUNITY CARE AIDES

I. Introduction

Dependency rates among Chilean adults will skyrocket in the upcoming decades (Villalobos DIntrans, 2018). However, the familial care system that has characterized Chile since its inception is unlikely to meet the current demand for adult care (Garcia Dellacasa, 2021, Ch. II). Without reform, increased levels of dependency will undoubtedly entail an economic toll, especially for those who currently bear the brunt of caregiving costs: women. This article analyzes the economic and gender implications of a reform seeking to replace the familial care system with a community-based care system.

In particular, I analyze the impact of institutionalizing *Community Care Aides* (CCA) at the heart of the care system. CCAs are home and out-of-home care aides that assist and accompany adult dependents in their communities. Furthermore, CCAs are (paid) municipal employees. The program, hence, redistributes the costs of caring from the family to the state. However, there are other economic implications to such a program.

In Canada and the United States, the evolving role of health care aides has significantly increased the sector's efficiency (Berta et al., 2013; Quinn et al., 2016).

Moreover, a recent study showed that investing in home care aides would significantly boost aggregate demand in the United States (Palladino, 2021). This economic boost is likely to be paired with inequality reduction. The home care aide position does not usually require tertiary education. Therefore, lower-income individuals will disproportionately benefit from the program.

Here, I examine the economic benefits of the CCA through a theoretical lens. This article uses neoclassical economic analysis to evaluate the program's theoretical repercussions on economic growth and inequality reduction. These parameters are particularly relevant for Chile. In 2019, millions took the streets to protest against neoliberal policies that produced economic growth at the cost of deepening and reproducing staggering inequalities. Then the Covid-19 pandemic hit and, in one year, GDP fell by almost 6%. Today, the country necessitates inclusive economic policies that can boost growth while simultaneously decreasing inequality.

In this paper, I present a consumption-leisure-caring model to analyze the impact of the CCA and two other programs: a Universal Basic Income (UBI) and a stipend for domestic workers. Using baseline data, the simulations of the model show that the CCA outperforms the other policies in both boosting the economy and reducing inequality. The program will create a disproportionate amount of employment opportunities in economically depressed regions, increasing consumption levels among lower-income households. Moreover, the program will allow thousands of caregivers, especially women, to increase their labor supply by trading away several hours of unpaid work. The increment in consumption and aggregate demand, together with the expansion of labor supply, help disperse the inflationary pressures often associated with fiscal spending.

However, the success of the program is not guaranteed. Trust is essential to the economic prospects of the CCA. If families do not trust the care of their loved ones on community caregivers, the benefits of the program dissipate. In this article, I examine the potential impact of the CCA in three different scenarios—low, medium, and high trust environments. The analysis shows that trust conditions the program's potential to boost growth and decrease economic and gender inequality. Trust, therefore, is a risk factor that needs addressing in the design and implementation of the CCA.

The paper is organized as follows. In Section II, I present the main characteristics of the CCA program. Then, in Section III, we discuss the theoretical framework used for our analysis, underscoring the role of temporal and spatial constraints on caregivers' labor supply. Section IV introduces a leisure-consumption-caring model with gendered expectations and exogenous residential location for individual maximizers. This model does not consider family-decision making processes (a later section addresses this shortcoming). Section V analyzes the CCA program through the model's lens, showing that the CCA will simultaneously increase local job density and decrease the domestic provision of care (conditioned on trust), boosting consumption and labor supply.

Then, in section VI, we review alternative policies through our model. Section VII offers a simplified parametric version of the model presented in Section IV comparing the effects of the CCA on economic growth, inequality, and the distribution of domestic care with those emerging from the UBI and paying domestic caregivers. We show that the potential economic benefits of the CCA exceed those of the alternative policies. Section VIII introduces a theoretical extension to our individual-maximization model that includes family-decision making processes through a Cournot-Nash non-cooperative equilibrium analysis. This model shows that the CCA can potentially help achieve a balanced distribution of unpaid domestic care in heterosexual extended households.

II. Community Care Aides Program

By 2035, nearly 20% of Chilean adults will be 65 or older.[60] One of the challenges arising from a rapid demographic transition is the higher need for adult care and its implications for the economy. Today, nearly 30% of adult dependents do not receive any assistance.[61] Elsewhere, I have observed that a critical component in Chile's lack of adult care supply is the system's over-reliance on family care. As families have become smaller, their ability to cover the incremental demands for care has dwindled (Garcia Dellacasa 2021, Ch. II). Restructuring the care system is required to meet the challenges of the demographic transition.

The *Community Care Aides* (CCA) program is an alternative to restructure Chile's care system. At a structural level, the CCA does two things. First, it reallocates the role

[60] According to estimates from the National Statistics Institute (INE, for its acronym in Spanish).

[61] According to the 2017 CASEN survey, Chile's largest publicly available dataset.

of primary adult caregiving provider from family members (i.e., women) to the community. The CCA is a universal caring service where adult dependents receive care from people in their communities, providing respite to their family members. Secondly, the CCA reassigns the costs of caregiving from families to the state. Community caregivers are not volunteers. They are state agents employed by local municipal health clinics (CESFAMs or CECOFs.) Hence, they are paid for their work with tax money.

The program seeks to increase the coverage of adult care by addressing one of the current system's most salient shortcomings. The increasing number of dependent adults residing in small households has rendered the familial system unsuitable for providing care (Garcia Dellacasa, 2021; Ch. II). The CCA program incentivizes people to provide care for their neighbors even when they reside alone. Moreover, the CCA may also generate efficiency gains for the health sector by preventing increments in dependency levels. People who receive care at early stages of dependency are less likely to worsen their condition (Thomas and Blanchard, 2009).

Trust is essential for the CCA to succeed. If people are unwilling to participate in the program, unpaid family members will continue to provide care. The community aspect of the program is crucial for trust-building. People tend to trust more in those more similar to them and have had more extended social interaction (Alesina & La Ferrara, 2002; Freitag & Traunmuller, 2009). However, experience is also crucial to trust (Ibid.). Therefore, the CCA must provide a quality service for which training caregivers is necessary. Since CCAs are nested in the Public Health system, they are required to go through formal training.[62] This way, the CCA program seeks to professionalize care provision while building trust in its services.

A crucial component of the CCA is that it improves the working conditions of caregivers. First and foremost, caregivers are paid for their work. Although this requires further research, elsewhere, I have proposed a sliding-scale payment based on employment flexibility.[63] Severely dependent adults require full-time supervision and assistance. Caregivers assisting them would earn 1.5 minimum wages.[64] Moderate dependents may not require full-time assistance, but they do need periodical visits. Part-time CCAs caring for moderate dependents would receive one minimum wage. Finally, moderate and potentially dependent adults may require help with occasional and sporadic activities. Sporadic CCAs would make 75% of the monthly minimum wage.[65]

The program would also improve caregivers working conditions in other ways. Caring alone, as is the case in most families, increases the subjective workload associated with caring (Sandoval et al., 2019). Caregivers who participate in social networks (like the church, for example) consistently have better mental health (Ibid.,

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[62] This should not increase the cost of the CCA too much. Fortunately, the training for community care aides already exists in Chilean health centers This is because the figure of the community caregiver is already present in the system. However, today, community caregivers are volunteers.

[63] ciperchile.cl/2021/03/02/desafios-de-la-transicion-demografica-hacia-un-sistema-de-cuidado-de-adultos-dependientes-remunerado-y-comunitario/

[64] In Chile, the minimum wage is established on a monthly basis.

[65] Under Chilean labor law, someone who works less than full-time is entitled to receive the direct fraction of the minimum wage corresponding to their workday. For instance, if someone works 50% of a full-time position (45 hours per week), they would be entitled to 50% of the minimum wage.

Villalobos Dintrans, 2019). The CCA program seeks to institutionalize these networks through regular meetings between caregivers and municipal authorities.

The CCA, therefore, has the potential of closing the adult care gap while simultaneously improving the conditions of those who care. However, this comes at a high cost for taxpayers. This is why it is essential to underscore the additional economic implications of the CCA program. In what follows, I will examine some of these implications in the context of Chile. A country where most of its population resides in economically segregated cities (Garreton et al., 2020).

III. Caring in segregated cities

In Chile, employment opportunities cluster in regions far away from lower-income neighborhoods. This *spatial mismatch* is especially problematic for the labor market participation of female caregivers who face the highest penalties for mobility (Garcia Dellacasa, 2021, Ch. I). Moreover, dependency rates are disproportionately high in low-income communities, further restricting female labor market participation (Garcia Dellacasa, 2021, Ch. II).

The coinciding problems of residential segregation and unequal dependency rates present us with a unique opportunity for inclusive development. The CCA program would create jobs in communities where employment opportunities are scant. Additionally, it would allow families to externalize care provision, effectively removing one of the most critical barriers to less educated women's participation in the labor market. To understand the effects effects of the CCA on growth and inequality, we must intengrate the spatial context of caregiving under the familial system of care.

a. *Temporal constraints on female labor supply*

The patriarchal division of labor disproportionately allocates unpaid domestic and care responsibilities to women. Whether it is due to lower bargaining power or enforcement of traditional gender roles, women continue to undertake most unpaid responsibilities (Folbre, 2021). Among these responsibilities, unpaid domestic care is particularly restrictive to labor market participation. In fact, in Chile, female caregivers spend around double the time on unpaid responsibilities than non-caregiving women.[66]

Some neoclassical theorists have underscored care's temporal constraints as a crucial component of women's labor supply (Carmichael and Charles, 1998; Heitmueller, 2007). In their models, informal caregiving affects labor supply in a contradictory manner. Since time is finite, and most jobs do not offer completely flexible working days, unpaid responsibilities increase the opportunity cost of labor market participation, contracting labor supply through substitution effects. On the other hand, dependents cannot always sustain themselves economically. Therefore, caregiving responsibilities may also entail income effects that expand labor supply. If substitution effects are higher than income effects, then informal care reduces labor market supply. If, on the

[66] According to the 2015 National Time Use Survey (ENUT 2015, for its acronym in Spanish), female caregivers spend 7.3 hours per day in unpaid work versus 4 for non-caregivers.

contrary, income effects exceed substitution effects, informal care would increment labor supply.

b. Spatial constraints to labor supply

If the temporal competition of paid and unpaid work determines substitution effects, then commuting times also affect labor supply. Therefore, women facing long commuting times present a more constrained labor supply. In economic geography, the geographical penalization to labor market outcomes is known as spatial mismatch effects, a theory that underscores the role of mobility and distance to work in determining labor supply (Kain, 1968; Kain, 2004).

In Chile and elsewhere, scholars have outlined that women face additional obstacles when moving across the urban space (Jirón, 2007; Almahmood et al., 2017). For example, male harassment often leads women to different strategies for urban mobility and labor market participation. Night jobs, for instance, may be out of consideration for women who reside in dangerous neighborhoods and rely on public transportation (Jirón, 2007). However, unpaid domestic and care labor is probably the most limiting factor to female mobility.

First of all, public transportation is not designed to balance paid and unpaid responsibilities, complicating the combination of these activities (Loukaitou-Sideris, 2016). Additionally, unpaid care involves the participation of dependents whose mobility is often limited. Care work pairs place-bound and people-bound constraints. In other words, care needs to take place somewhere (at some time) with someone, further complicating labor market participation.[67] [68]

c. *Residential segregation and female labor supply*

The spatial considerations for labor supply present a possible source of endogeneity in balancing paid and unpaid work. If people can self-select (a-la-Tiebout)[69] into regions were employment opportunities are widely available, then spatial and temporal constraints may not be a significant factor in determining the labor supply. Consequently, determining the exogeneity of residential location on employment decisions is a considerable challenge for spatial mismatch research (Hellerstein et al., 2008).

More often than not, however, residential segregation is the product of exogenous political and economic events that penalize the urban poor's locational capabilities (Nightingale, 2012, Rothstein, 2017). Extensive research has unveiled the political events that have led Chilean cities to become some of the most economically segregated in Latin America (Sabatini, 2000; Hidalgo, 2007; Sabatini and Brain, 2008;

[67] This is known as a *coupling constraint* (Hägerstrand, 1970) and is one of caregivers' most restrictive factors to mobility (Kwan, 2000; Ta et al., 2016).

[68] In terms of female labor supply, gendered mobility entails that substitution effects will grow faster for women than for men. Moreover, if we consider coupling constraints, substitution effects will likely grow the fastest for caregivers. Assuming that income effects will not drastically vary with distance, growing substitution effects entail that female labor supply will become less elastic with commuting distance and, eventually, negatively sloped until the point of not entering or dropping out of the labor force.

[69] In 1956, Charles Tiebout developed a theory of public goods where urban residents were able to locate their households according to their public goods preferences (Tiebout 1956).

Agostini et al., 2016; Garreton, 2017; Garreton et al., 2020). In my work, I have provided evidence for the inability of less-educated female caregivers to locate their households in regions with high availability of employment opportunities in Santiago, the country's capital and most populous city (Garcia Dellacasa, 2021, Ch. I).

Regularly, the economic segregation of urban space coincides with the sorting of the city across educational levels (Diamond 2016). The attractiveness of urban amenities attracts more educated and affluent households to particular sections of a city, increasing housing prices and effectively displacing or excluding lower income people from these regions. These areas, moreover, tend to be around the economic centers of the city, where employment opportunities are more widely available (Garcia Dellacasa, 2021, Ch. I).

Considering gendered mobility constraints, the sorting of urban spaces across educational levels further penalizes female labor market participation, especially for less-educated caregivers. This entails additional considerations for inclusive development strategies. In order to be successful, policies seeking to increase female labor market participation and reduce economic inequalities must seriously consider the locational characteristics of job creation.

IV. A simple model

I use a leisure-consumption-caring model to analyze the economic implications of the CCA program. In order to contextualize the CCA in Chilean cities, the model considers exogenous household location and gendered expectations. Moreover, in this initial setup, the model assumes that women and men residing with dependents make decisions independently. This is a strong assumption. After all, families do coordinate their division of work. I relax this assumption in a later section.

The model's initial setup bridges two bodies of theoretical literature. It considers both the temporal constraints of care and residential segregation for defining labor supply. The caring aspects of the model reflect the works of Carmichael and Charles (1998) and Fevang, Kverndokk, and Roed (2009). Similarly to these models, we assume that men and women have altruistic preferences for family dependents. However, we also consider that women can internalize social expectations that associate femininity with caregiving (i.e., gender norms).

Gender norms have sustained, and have been reinforced by, several centuries of patriarchal rule (Folbre, 2021). Scholars have observed that even when women enter the labor force, they take on the lion's share of domestic care responsibilities to live up to social expectations (Bittman et al., 2003; Beneria, 2010). Social narratives of 'good working mothers'—women who balance paid and unpaid responsibilities—have become increasingly prevalent (Duberley and Carrigan, 2016). On the other hand, 'Good working fathers' narratives are much less present in the social imaginary (Ranson, 2012). Chile's low female labor market participation in lower-income households, moreover, has been associated with prevalent gender norms (Contreras & Plaza, 2010).

Regarding adult care, gender norms are perhaps the clearest in households where dependents reside with single non-dependent adults (Garcia Dellacasa, 2021; Ch. II). The likelihood of adult dependents residing with single women or single men is similar. In 2017, around 22% of dependents lived with single women and 22% with single men. Nevertheless, single women provide care at a significantly higher rate than single men. Almost 72% of dependents residing with single women receive care from them. On the other hand, less than 57% of dependents living with single men receive care from their family members.

Previous works theorizing spatial effects on labor supply have focused on mobility constraints (Gutierrez-i-Puigarnau and van Ommeren, 2010). The model presented here integrates residential segregation in this form. As mentioned earlier, residential segregation is associated with a spatial mismatch between home and job place. The regions that host lower-income segregated communities are often economically depressed and, therefore, lack employment opportunities. Hence, people in segregated communities are less likely to be employed locally and travel longer distances to find employment. The effects of residential segregation on mobility constraints can be operationalized through the relationship between job density and commuting time.

Job density is the relative availability of employment places to working-age residents in a given locality. Following Garcia Dellacasa (2021, Ch. I), this model assumes that local job density is exogenous to labor supply decisions. The 2012 Origin Destination Survey for the greater Santiago region shows the relationship between job density and commuting time. Defining job density similarly to Garcia Dellacasa (2021, Ch. I), Table 14 summarizes this linear relationship for less-educated full-time workers on a typical workday.[70] The dependent variable is the ratio of commuting time over total hours spent at the job place (i.e., the commuting share).[71] Table 14 shows that a unit of job density decreases the commuting share by over 5% for public transportation users.

Table 14: OLS regression for less-educated workers in a typical day using 2012 ODS.

	Dependent variable:	
	Commuting Share	
	Public Transp.	Private Transp.
Job Density	-0.052^{***}	-0.016^{*}
	(0.007)	(0.009)
Observations	3,790	1,113
Note:	*p<0.1; **p<0.05; ***p<0.01	

a. *The basic setup: Utility maximization under gendered expectations*

Considering gender norms; and decision-making as independent from other non-dependent adults; our model assumes that non-dependent women and men residing with dependents maximize the following utility function:

$$\begin{aligned} U_w &= u(X, L) + \beta A(N) - \gamma S(N) \\ U_m &= u(X, L) + \beta A(N) \end{aligned} \tag{1}$$

[70] Less educated workers are those that at most hold a high school degree.

[71] According to the ODS, the commuting share is 25.7% for workers using public transportation and 15.1% for people who travel using private means of transportation.

Where *X* represents the bundle of goods and services consumed by the individual and bought in the market, and *L* illustrates the number of hours spent on leisure activities. Following Fevang et al. (2009), *A* denotes an altruistic function informed by the dependent's wellbeing (*N*), and β is the individual valuation of the dependent's care status ($\beta > 0$). Hence, A is positively correlated with *N.* S, on the other hand, is a function denoting the gendered expectations to provide care. Its negative coefficient is interpreted here as a psychological penalty for not meeting gendered expectations. Therefore, as dependents have their needs met, the gendered penalty decreases. In other words, *S* is inversely related to total care received by the dependent (*N*). γ is its respective discount factor ($\gamma > 0$).

The dependent's wellbeing is assumed to depend entirely on total care received, such that:

$$N = Z + \eta\overline{Z} \tag{2}$$

Where Z is the total amount of informal care received from household members and $\bar{Z}$ is the total hours of care received from out-of-household individuals. η is a discount factor associated with the degree of trust in out-of-household care ($0 < \eta < 1$). As mentioned above, people may be less trusting in non-familiar individuals. Therefore, the dependent's psychological wellbeing is assumed to improve less from one hour of outside care than one hour of in-home care. Replacing (2) in (3), non-dependents maximize the following utility functions:

$$
\begin{aligned}
U_w &= u(X,L) + \beta A(Z+\eta\overline{Z}) - \gamma S(Z+\eta\overline{Z}) \\
U_m &= u(X,L) + \beta A(Z+\eta\overline{Z})
\end{aligned}
$$

Additionally, we make the following assumptions:

$$
u'_X > 0, u'_L > 0, A'_N > 0, S'_N < 0, u''_{XX} < 0, u''_{LL} < 0, u''_{XL} > 0, u''_{LX} > 0, A''_{NN} < 0, S''_{NN} > 0 \tag{3}
$$

b. Spatio-temporal budget constraint: Introducing residential segregation as an income penalty

In leisure-consumption models, individual consumption is constrained by their budget and time. Here, we add a spatial element (disguised as a temporal one) to individual constraints. Our model includes job density's effect over commuting shares as a constraint to labor supply. Considering the commuting share, we define total time available (T) as being made up of:

$$
\begin{aligned}
&T = LS(1+t(j)) + L + Z \\
&with \\
&t(j) > 0, t'_j < 0
\end{aligned} \tag{4}
$$

Where *LS* is the total labor supply, and *t(j)* is the commuting share, which is negatively correlated with job density (j). On the other hand, after normalizing commodity prices (P=1), the individual's budget constraint can be defined as:

$$X = \hat{Y} + w * LS \tag{5}$$

Where $\hat{Y}$ is the non-labor income and w represents the real wage. Replacing (4) in (5), we obtain the following spatio-temporal budget constraint:

$$X = \hat{Y} + \frac{w}{(1+t(j))}(T - L - Z)$$

The commuting share, hence, acts as a discount factor on wages.

In summary, individuals face the following optimization problem:

$$\begin{array}{rcl} Max_{x,l,z} & & U_w = u(X,L) + \beta A(Z + \eta\overline{Z}) - \gamma S(Z + \eta\overline{Z}) \\ or & & \\ Max_{x,l,z} & & U_m = u(X,L) + \beta A(Z + \eta\overline{Z}) \\ s.t. & & \\ X & = & \hat{Y} + \dfrac{w}{(1+t(j))}(T - L - Z) \end{array} \quad ($$

Hence, women's optimal allocation will be determined by:

$$\begin{array}{l} X_w^* = X_w^*(\beta, \gamma, w, \hat{Y}, \overline{Z}, j) \\ L_w^* = L_w^*(\beta, \gamma, w, \hat{Y}, \overline{Z}, j) \\ Z_w^* = Z_w^*(\beta, \gamma, w, \hat{Y}, \overline{Z}, j) \\ LS_w^* = \dfrac{1}{1+t(j)}\,(T - L_w^* - Z_w^*) \end{array}$$

And men's:

$$
\begin{aligned}
X_m^* &= X_m^*(\beta, w, \hat{Y}, \overline{Z}, j) \\
L_m^* &= L_m^*(\beta, w, \hat{Y}, \overline{Z}, j) \\
Z_m^* &= Z_m^*(\beta, w, \hat{Y}, \overline{Z}, j) \\
LS_m^* &= \frac{1}{1+t(j)}\left(T - L_m^* - Z_m^*\right)
\end{aligned} \tag{8}
$$

The first- and second-order conditions for the female caregivers' optimization problem are in Section 1.1 in the Appendix. Men's optimization is the same, with the difference being

$\gamma = 0$. Hence, any gendered difference in individual maximization can be evaluated by how maximization equilibria change with respect to γ. If, in equilibrium, women's care provision is positively affected by γ, they will provide more care than men.

V. CCA's effects through the lens of our model

The model presented above can help us analyze the CCA's effects on female and male consumption, leisure time, domestic care provision, and labor supply. The program influences at least two variables. First of all, the communal factor in the program entails that job density (j) will increase according to local dependency rates. Secondly, the socialization of care from the family to the state will increase individual access to out-of-household care (increase in $\bar{Z}$).

a. Increasing job density effects on total consumption, leisure, care provision, and labor supply

Under certain assumptions, an increase in job density will carry positive effects over total consumption and leisure. No additional assumptions are necessary for capturing job density's negative effects over the provision of care. Section 1.2 in the Appendix shows the calculations for obtaining the equilibrium allocation after increasing job density. For female caregivers, job density effects are:

$$\begin{aligned}
\frac{dX_w^*}{dj} &= \frac{(\beta A''_{NN} - \gamma S''_{NN})(t'_j u'_L w - b\Theta(1+t(j))) + wt'_j u'_L u''_{LL}}{(\beta A''_{NN} - \gamma S''_{NN})(aw - b(1+t(j))} && > 0 \\
\frac{dL_w^*}{dj} &= \frac{(\beta A''_{NN} - \gamma S''_{NN})(a\Theta + t'_j u'_L)(1+t(j)) - wt'_j u'_L u''_{LX}}{(\beta A''_{NN} - \gamma S''_{NN})(aw - b(1+t(j))} && > 0 \qquad (6) \\
\frac{dZ_w^*}{dj} &= \frac{t'_j u'_L b}{(\beta A''_{NN} - \gamma S''_{NN})(aw - b(1+t(j))} && < 0
\end{aligned}$$

With:

$$\begin{aligned}
a &= wu''_{XX} - (1+t(j))u''_{LX} && < 0 \\
b &= wu''_{XL} - (1+t(j))u''_{LL} && > 0 \\
\Theta &= \frac{t'_j w}{(1+t(j))^2}(T - L - Z) && < 0
\end{aligned}$$

Conversely, men's equilibrium allocation is affected in the same way as women's, but with $\gamma = 0$:

$$
\begin{aligned}
\frac{dX_m^*}{dj} &= \frac{\beta A''_{NN}(t'_j u'_L w - b\Theta(1+t(j))) + wt'_j u'_L u''_{LL}}{\beta A''_{NN}(aw - b(1+t(j))} &> 0 \\
\frac{dL_m^*}{dj} &= \frac{\beta A''_{NN}(a\Theta + t'_j u'_L)(1+t(j)) - wt'_j u'_L u''_{LX}}{\beta A''_{NN}(aw - b(1+t(j))} &> 0 \\
\frac{dZ_m^*}{dj} &= \frac{t'_j u'_L b}{\beta A''_{NN}(aw - b(1+t(j))} &< 0
\end{aligned}
\tag{7}
$$

Commuting shares act as a discount factor to wages. Therefore, as is common in leisure-consumption models, an increase in perceived wages has an ambiguous effect on consumption. However, job density effects on consumption will be negative only at high levels of labor market participation.[72] Since female caregivers present a priori low levels of labor participation, it is unlikely that consumption will decrease with higher job density. Men residing in low job density regions are also more likely to participate in the informal and part-time market (Garcia Dellacasa, 2021, Ch. I). Therefore, it is safe to assume that income effects will be stronger than substitution effects and consumption in regions where the CCA is instituted. Higher consumption signals an increase in labor supply that arises from decreased commuting time and less time allocated to domestic care activities. With higher job density, the opportunity cost of domestic care provision increases and, hence, its provision decreases.

Gendered differences in job density effects depend on how the parameter γ affects the equilibrium points. Since $(dZ_w^*/dj) - (dZ_m^*/dj) > 0$ (due to $\gamma > 0$),

[72] Since leisure and caring time are low at high levels of labor market participation, Θ will be large. This could possibly reverse job density effects.

women's provision of domestic care decreases less than men's provision. Therefore, at the social level, higher job density may create more significant inequalities in the distribution of unpaid domestic care while reducing the provision of domestic care for both men and women. Gendered expectations entail that women's labor supply is more inelastic than men's to changes in job density.

b. Higher access to public care and the importance of trust

Following Section 1.3 in the Appendix, we find that:

$$\begin{aligned}
\frac{dX_w^*}{d\overline{Z}} &= \frac{-bw\eta}{aw - b(1+t(j))} && > 0 \\
\frac{dL_w^*}{d\overline{Z}} &= \frac{aw\eta}{aw - b(1+t(j))} && > 0 \\
\frac{dZ_w^*}{d\overline{Z}} &= -\eta && < 0
\end{aligned} \tag{8}$$

These results underscore the importance of trust for determining the economic impact of the CCA. When trust in out-of-household care is high, female and male caregivers will be more willing to change caring hours for leisure and paid labor. Notice, moreover, that gendered expectations do not affect these results. We would observe gendered differences only if trust levels are different for men and women.

The economic performance of the CCA program depends on its ability to get people to trust it. The fact that the Care Aides will be a part of the dependent's community facilitates trust. However, this may not be enough. For this reason, allocating resources to trust-building and allowing local organizations to be a part of the planning process is of utmost importance.

VI. Alternative policies for economic reactivation and care provision

The CCA is an ambitious program. For this reason, it is necessary to evaluate it against the backdrop of other proposals that have similar goals. Here we have chosen two policies proposed in the current election year: a universal basic income (UBI) and paying domestic caregivers. The UBI's main objective is to reactivate the economy through a push in aggregate demand while paying domestic caregivers has been framed in the context of addressing patriarchal exploitation of female labor. Here, we evaluate these policies through the model presented above.

a. Universal Basic Income

The profound economic impact of the COVID-19 pandemic has led congress and other politicians to consider implementing a UBI.[73] [74] As of late, at least one presidential campaign has included a UBI that ensures a poverty line transfer as a part of their

[73] https://www.elmostrador.cl/destacado/2020/06/16/renta-basica-de-emergencia-para-chile-urgente-y-necesaria/

[74] https://www.t13.cl/noticia/politica/renta-basica-universal-emergencia-detalle-propuesta-12-05-2021

platform.[75] Supporters of the UBI claim that it is an effective tool for boosting aggregate demand and economic reactivation.[76] [77] UBI's effects on the distribution of unpaid work is absent from their discourse.

In our model, the UBI can is an increase in every individual's non-labor income ($\hat{Y}$). Following Section 1.4 in the Appendix, we find that female caregiver's response to the UBI is:

$$\begin{aligned} \frac{dX_w^*}{d\hat{Y}} &= \frac{-b(1+t(j))}{aw-b(1+t(j))} &> 0 \\ \frac{dL_w^*}{d\hat{Y}} &= \frac{a(1+t(j))}{aw-b(1+t(j))} &> 0 \\ \frac{dZ_w^*}{d\hat{Y}} &= \frac{(1+t(j))(au''_{LL}-bu''_{LX})}{(\beta A''_{NN}-\gamma S''_{NN})(aw-b(1+t(j))} &= 0 \end{aligned} \tag{9}$$

As expected, the UBI increases total consumption. Moreover, it bears no consequences over the provision and distribution of care. Therefore, an increment in leisure time entails that hours of labor supply will be crowded out of the market. Gendered expectations have no impact over UBI's effects.

b. Paying domestic caretakers

[75] https://boricpresidente.cl/programa/

[76] https://www.latercera.com/opinion/noticia/mas-alla-de-la-emergencia-pensar-una-renta-basica-universal-como-politica-permanente/F5Q2TYSYSBBDDHFVAXR2PNCEQA/

[77] https://www.cnnchile.com/pais/renta-basica-de-600-mil-la-propuesta-de-la-oposicion-para-la-agenda-de-minimos-comunes_20210512/

Another idea that has come up during this election year combines the CCA and the UBI. At least one presidential candidate has proposed to pay 75% of the monthly minimum wage to domestic caregivers in low-income households (poorest 40%).[78] The candidate and his allies have argued that this would be an effective policy "towards ending the patriarchal society."[79] However, the mechanisms through which this would happen are unclear.

To analyze this policy through the lens of our model, we need to slightly tweak budget constraints to:

$$X = \hat{Y} + Y^c Z + \frac{w}{(1+t(j))}(T - L - Z) \tag{10}$$

Where Y^c is the transfer associated with one hour of domestic care.

The effects of this program on women's total consumption, leisure, and caring time are:

$$\begin{aligned}
\frac{dX_w^*}{dY^c} &= \frac{-(1+t(j))bu'_L\,(w-(1+t(j))Y_c)}{w(\beta A''_{NN}-\gamma S''_{NN})(aw-b(1+t(j))} - \frac{(1+t(j))bZ_w^*}{aw-b(1+t(j))} \gtrless 0 \\
\frac{dL_w^*}{dY^c} &= \frac{(1+t(j))au'_L\,(w-(1+t(j))Y_c)}{w(\beta A''_{NN}-\gamma S''_{NN})(aw-b(1+t(j))} + \frac{(1+t(j))aZ_w^*}{aw-b(1+t(j))} \gtrless 0 \\
\frac{dZ_w^*}{dY^c} &= \frac{-u'_L(1+t(j))}{w(\beta A''_{NN}-\gamma S''_{NN})} > 0
\end{aligned} \tag{11}$$

[78] https://www.danieljaduepresidente.cl/wp-content/uploads/2021/06/PROGRAMA.pdf

[79] https://www.radionuevomundo.cl/2021/06/08/maria-e-puelma-propuesta-de-jadue-que-busca-remunerar-el-trabajo-domestico-de-la-mujer-es-un-avance-hacia-el-fin-de-una-sociedad-excluyente-y-patriarcal/

The effects on consumption and leisure depend on the relationship between the value of the domestic care transfer and the discounted wage rate. If $Y^c > {}^{w}\!/_{1+t(j)}$, total consumption and leisure time will increase with the program. Moreover, the effect on care provision also depends on the discounted wage rate. Although always positive, the lower the discounted wage rate, the higher the provision of care. Hence, paying for domestic caregiving may entail very different effects for lower-income and wealthy individuals. Lower-income people living in segregated communities face lower discounted wage rates. Therefore, they will increase their consumption by allocating more time to caregiving. They will also increase their leisure time. Hence, their labor supply will decrease. The effects of the program on wealthy individual's labor supply, on the other hand, is undetermined. The effect of paying domestic caregivers over labor supply marks a significant departure from paying community caregiving through the CCA.

These effects are also gendered. Due to gendered expectations, it is likely that $Z_w^* > Z_m^*$.[80] Moreover, ${}^{\partial(dX_w^*/dY^c)}\!/_{\partial\gamma} > 0$ and ${}^{\partial(dL_w^*/dY^c)}\!/_{\partial\gamma} > 0$, meaning that women's consumption and leisure time will increase at a higher rate (or decrease at a lower rate) than men's. Since ${}^{\partial(dZ_w^*/dY^c)}\!/_{\partial\gamma} < 0$, men will increase their provision of care at a higher rate than women. The program would increase the household provision of domestic care and equalize the social provision of care between men and women.

[80] Unless both men and women reach a ceiling of care provision. For example, if $Z_w^* > Z_m^* > T$, then men and women would provide the same amount of care.

VII. Comparing policies using a parametric model

We use a simplified parametric version of the model to compare the economic effects of the CCA, UBI, and paying domestic caregivers. The simulations only consider a segment of the population. Namely, non-dependent adults who reside with dependent adults. Additionally, the comparative analysis considers two aspects of each program for this subset of the population: their effects on economic growth (aggregate demand and aggregate supply) and their effects on economic inequality (average-income households versus high-income households and gender inequalities). We also analyze the effects of each program on the distribution of domestic care. The parameters of the model were chosen according to available baseline data.

Non-dependent women's optimization process is:

$$\begin{aligned} U_w &= X^{\alpha} L^{(1-\alpha)} + \beta Z^{\kappa} - \gamma(-Z^{\kappa}) \\ s.t. & \\ X &= \frac{w}{1+t(j)}(16 - L - Z) \end{aligned} \tag{12}$$

Men maximize the same function with $\gamma = 0$. In this parametric model, $A(N) = -S(N) = N^{\kappa}$. The model maintains the properties of the theoretical model presented above. Initially, we assume that there is no source of out-of-home care. Therefore, $N =$

Z. For simplicity, we assume $\alpha = \kappa = 0.5$. Real wages (w) were set according to the 2017 Family Budgets Survey (FBS), the most comprehensive income and spending survey in Chile.[81] Since we normalized prices before, we must do the same in our baseline model. Thus, we define real wages as the ratio between average income over average spending. According to the FBS, the average ratio between income and spending is 1.04. Hence, we define real wages at that level. The average commuting share ($t(j)$), as per the 2012 ODS, is 25%. Additionally, according to the 2015 National Time Use Survey[82] the average time spent in care by women residing with dependents is 3.27 hours while men spend 1.73 hours in active care. β and γ were adjusted accordingly to $\beta = 1.2$ and $\gamma = 0.45$.

This model is solved in Section 2.1 of the Appendix, giving the following equilibrium allocation for women and men, respectively:

$$\begin{array}{llllllllllll} Z_w^* & = & 3.27 & ; & X_w^* & = & 5.3 & ; & L_w^* & = & 6.37 & ; & LS_w^* & = & 5.1 \\ Z_m^* & = & 1.73 & ; & X_m^* & = & 5.94 & ; & L_m^* & = & 7.14 & ; & LS_m^* & = & 5.71 \end{array} \tag{13}$$

a. Caveats in simulation analysis

Before analyzing the economic potential of each program, we must address some caveats in the simulation exercise. First of all, the implementation of these programs will likely require tax reform. Although taxes may affect aggregate demand, the model

[81] https://www.ine.cl/estadisticas/sociales/ingresos-y-gastos/encuesta-de-presupuestos-familiares

[82] https://www.ine.cl/estadisticas/sociales/genero/uso-del-tiempo

presented above does not consider them. The analysis, therefore, assumes a post-reform scenario, where taxes are a sunk cost. This scenario is not unlikely. Most candidates, including the more economically conservative ones, have proposed to increase tax collection. The proposals range from increasing the tax collection by 3%[83] of GDP to 11%.[84]

The second caveat is that the programs' economic effects are only examined for the subpopulation of non-dependent adults living with dependent adults. However, CCA and UBI entail effects for additional fractions of the population. Job density effects associated with CCA, for instance, may also benefit the non-dependent population who does not live with any dependents. The universal nature of the UBI implies that every adult receives a stipend, irrespective of their family structure. Paying domestic caregivers, on the other hand, only targets non-dependent adults living with dependent adults. Hence, for comparative purposes, the analysis is reduced to this maximum common denominator.

Finally, in our model, men and women allocate their labor independently from each other. Given the current distribution of dependents' family structures, this is not a horrible assumption. 44% of dependents live with a single non-dependent adult, and less than 30% reside with at least one non-dependent woman and one non-dependent man (Garcia Dellacasa, 2021, Ch. II). Nevertheless, in a later section, we present a

[83] https://www.sumamosxsichel.cl/2021/05/15/propuesta-de-reforma-tributaria-de-sebastian-sichel-incluye-devolucion-de-iva-a-familias/

[84] https://www.danieljaduepresidente.cl/wp-content/uploads/2021/06/PROGRAMA.pdf

theoretical extension to our model analyzing the effects of the CCA in households with at least one woman and one man.

b. *Economic reactivation and cost analysis*

We measure the effectiveness of these policies for reactivating the economy in contrast to their estimated implementation costs. We use the 2017 CASEN survey, Chile's most comprehensive socioeconomic survey,[85] to make some back-of-the-envelope estimations for the policies' cost. These estimations do not consider implementation, administrative, or any other form of transaction costs.

The CCA gross cost is calculated by imputing the sliding-scale payment presented in Section II to adult dependents' unpaid caregivers in the 2017 CASEN. The CCA's estimated cost is 0.756% of GDP.[86] The UBI cost is calculated through a simple imputation of the poverty line income to every adult (18+) in a family with at least one dependent adult, making it 0.139% of GDP. Finally, the proposal to pay domestic caregivers is unclear on how many caregivers there might be in a household. However, if we impose a limit of one caregiver per household, the cost of paying 75% of the minimum wage to every unpaid caregiver is 0.789% of GDP.

[85] http://observatorio.ministeriodesarrollosocial.gob.cl/encuesta-casen

[86] We assume that the nearly 600,000 unpaid caregivers are enough to provide coverage for the entire dependent population (nearly a million). Almost the entirety of the moderate and severely dependent population receives care from family members. Hence, their unpaid caregivers are allocated one and one-and-a-half monthly minimum wages, respectively. The rest of unpaid caregivers are assumed to be sporadic workers.

We consider two factors to measure the effectiveness of these policies on boosting the economy. On the one hand, we calculate the effects on total consumption (aggregate demand) for non-dependents residing with dependents. Secondly, to assess if these policies may lead to inflationary pressures, we also calculate the effects on their labor supply (aggregate supply).[87] We know from equation 8 that CCAs impact on total consumption and labor supply depend on the degree of trust families have in out-of-household care provision. Therefore, we will consider three different scenarios to measure the impact of the CCA program: a low-trust scenario ($\eta = 0.3$), a medium-trust scenario ($\eta = 0.5$) and a high-trust scenario ($\eta = 0.7$).

i. Total consumption and aggregate demand in the examined subpopulation

Table 15 summarizes the effects of each program on total consumption for non-dependent adults residing with dependents. The last column in Table 15 shows the spending efficacy of each program in increasing total consumption. The Table shows that the CCA is the program that carries the most significant impact on total consumption.[88] However, its effectiveness depends on at least two variables. First of all, trust in the program is crucial. The more people trust in the program, the more likely

[87] The analysis for each program can be found in the Mathematical Appendix, Section 2.

[88] We have assumed that the CCA program offers six hours of care a day.

they will trade hours of unpaid care for hours of paid labor. Therefore, aggregate demand effects are significantly dependent on trust levels.

The second factor to consider is if there are minimum floors to the provision of care. CCAs may not be able to meet all caring needs. For instance, some dependents may need assistance in the middle of the night when CCAs will not be available to provide it. This would mean that the minimum floors for reducing the domestic care provision could be higher than zero. For simplicity, in this model, we have considered the floor to be zero. Due to gendered expectations, men reach that floor faster than women, and total consumption increments reach its ceiling at 12.48%. However, the higher the minimum floor for the provision of unpaid domestic care, the lower the program's effect on economic growth.

Table 15: Policy effects on total consumption percentage point change.

		Increase in total consumption (%)			
	Trust	Women	Men	Total	Increase/Cost[1]
CCA	Low ($\eta = 0.3$)	14.53%	12.48%	13.43%	17.76%
	Medium ($\eta = 0.5$)	23.96%	12.48%	17.88%	23.65%
	High ($\eta = 0.7$)	26.04%	12.48%	18.86%	24.95%
UBI		2.64%	2.36%	2.49%	17.91%
Paying domestic caregivers		7.12%	-4.71%	0.71%	0.90%

[1] This number shows the effectiveness of a 1% of GDP into the programs.

Another attractive characteristic of the CCA program is that even when economic reactivation is not its primary objective and trust in the program is low, it performs similarly to the UBI. When trust is higher, the CCA outperforms the UBI. Paying domestic caregivers is, by far, the less profitable program. The reason behind this very mild increase is an extreme crowding-out from the paid labor market into the newly paid domestic caregiving sector. Here, we have assumed a ceiling on the provision of domestic care to six hours. Since the pay is lower than the discounted wage rate, the effects on total consumption are positive but low. Men actually decrease their total consumption.

ii. Effects on labor supply and inflationary pressures

After the current economic crisis, it is unlikely that people will continue to step out of the labor force. Therefore, crowding-out effects are improbable in the short term. As the economy stabilizes, however, their likelihood becomes higher and inflationary pressures may arise. Table 16 shows significant differences between the programs' effects on labor supply.

Table 16: Policy effects on percentage point change in labor supply hours.

		Increase in total labor supply (%)			
	Trust	Women	Men	Total	Increase/Cost[1]
CCA	Low ($\eta = 0.3$)	14.51%	12.43%	13.41%	17.73%
	Medium ($\eta = 0.5$)	23.92%	12.43%	17.85%	23.61%
	High ($\eta = 0.7$)	25.88%	12.43%	18.78%	24.84%
UBI		−2.94%	−2.10%	−2.5%	−17.98%
Paying domestic caregivers		−49.80%	−55.17%	−52.63%	−66.71%

[1] This number shows the effectiveness of a 1% of GDP into the programs.

The CCA is the only program that increases the labor supply. Therefore, it is best suited to generate *real* impacts on the economy as it minimizes the likelihood of inflationary pressures. Paying domestic caregivers, on the other hand, generates the highest contraction in aggregate supply.

c. *Economic and gender inequality*

We can analyze two sources of economic inequality through our model: i) wage inequalities in the labor market and ii) territorial inequalities emerging from differences in job density. Additionally, we can analyze the policy effects in within- and between gender-inequality.[89]

Here we consider high-earning individuals to earn double the average wage rate. According to our model, and assuming equal job density between households, average wage earners consume 45.8% of high-earners consumption. This ratio assumes equal job density. If we assume that job density is higher in high-income neighborhoods, then inequality in consumption would be even more significant.[90]

i. *Policy effects over consumption inequalities:*

[89] In Section 2.1.1 in the Mathematical Appendix we find the base allocation for women and men who perceive wages at double the average rate.

[90] This means that unpaid care deepens inequalities in consumption.

Table 17 shows the change in the consumption ratio between average earners and high-earners. Here, we can see that the CCA and the UBI policy can decrease inequality in consumption. The CCA's effectiveness once again depends on the level of trust in the program. Inequality reduction will go hand-in-hand with trust levels. Paying domestic caregivers, on the other hand, may produce the opposite result. This is because wealthier households are less likely to trade paid labor market hours for paid domestic hours. In fact, as we can see in Section 2.4.1 in the Mathematical Appendix, the increase in domestic care hours for high-earners is minimal.

Table 17: Policy effects on percentage point change of the ratio between average consumption and high-earners consumption. A positive value indicates that the after-policy ratio is higher, meaning that the gaps in consumption have decreased.

	CCA (Trust)				
	Low (η=0.3)	Mid (η=0.5)	High (η=0.7)	UBI	Paying domestic caregivers
Percentage point change in total consumption ratio	1.88%	3.75%	4.16%	0.61%	−0.74%
Change/Cost[1]	2.49%	4.96%	5.50%	4.40%	−0.94%

[1] This number shows the effectiveness of a 1% of GDP into the programs.

ii. Territorial considerations for the CCA's inequality effects

CCA's effects on consumption depend on how much the program can reduce domestic care provision and increase job density. If job creation is proportional to total dependents, then increments in job density will be proportional to dependency rates.

Therefore, residents in places with higher dependency rates (the ratio of dependents to adults) will benefit more from the program.

Poorer municipalities are, on average, less job dense than wealthier municipalities (Garcia Dellacasa 2021, Ch. I). Table 18 shows the linear relationship between dependency rates (for adults and children) and average municipal income. We find that adult dependency rates are higher in lower-income municipalities, while there is no significant relationship for child dependency rates. This correlation indicates that lower-income jurisdictions will benefit more from the CCA than higher-income jurisdictions, further reducing territorial inequality.

Table 18: OLS regression for dependency on average municipal income using the 2017 Casen.

	Dependency Rate:	
	Adults	Children
	(1)	(2)
Average Income (Municipal level, log)	-0.033^{***} (0.005)	0.010 (0.008)
Observations	324	324
R^2	0.113	0.005
Note:	*p<0.1; **p<0.05; ***p<0.01	

iii. Gender inequalities in consumption

Given gendered expectations, men and women react differently to public policy. Hence, these policies will affect gender inequalities in consumption. Keeping in mind that inequality effects were calculates as if men and women allocate their labor independently of each other, columns three and four in Table 19 summarize the percentage point change in the ratio of total consumption for men and women (between-gender inequality). The ratio is defined as women's consumption over men's consumption. The results show that, in average income households, the higher the trust in the CCA program, the higher the ratio of total consumption. Thus, between-gender inequality would decrease. In high-income households, given that the program is less effective in decreasing hours of unpaid care, trust does not affect consumption inequality.

Table 19: Policy effects on percentage point change in female to male consumption ratio. A positive value indicates that gaps in consumption are lowered.

		Between Gender Ratio		Within Gender Ratio	
	Trust	Average Income	High Income	Women	Men
CCA	Low ($\eta = 0.3$)	1.64%	5.08%	1.05%	2.78%
	Medium ($\eta = 0.5$)	9.13%	5.08%	4.79%	2.78%
	High ($\eta = 0.7$)	10.77%	5.08%	5.61%	2.78%
UBI		0.25%	0.06%	0.64%	0.58%
Paying domestic caregivers		10.77%	1.49%	1.55%	−2.93%

[1] This number shows the effectiveness of a 1% of GDP into the programs.

Trust will affect within-gender inequality as well. Higher trust in the CCA will lead to lower consumption inequality between women of different economic backgrounds. Paying domestic caregivers will strongly reduce between-gender inequality in average income households. However, this is paired with an increase in men's within-inequality ratio, signaling that higher equality in average income households may not necessarily signal better material conditions for all homes.

iv. The distribution of domestic care work

Gendered expectations lead women to provide the lion's share of domestic work. Moreover, Chile's familial care system relies excessively on household members to provide care for adult dependents. According to our baseline data, female-led households provide 3.27 hours of domestic care, and male-led homes provide 1.73 hours. This means that women provide 65.4% of total domestic care.[91] The programs have very distinct effects on the distribution of unpaid care. The CCA socializes care to communities and the state, decreasing the load of domestic care. The UBI bears no effects on the distribution of care. Moreover, paying domestic caregivers increments the reliance of dependents on domestic care.

Table 20 summarizes the effects on the total provision of unpaid care and the female share of domestic care provision:

Table 20: Policy effects on the provision of domestic care.

		Change in domestic provision of care (%)			
	Trust	Women	Men	Total	Female share of domestic care provision
CCA	Low ($\eta = 0.3$)	-55.35%	-100%	-70.8%	100%
	Medium ($\eta = 0.5$)	-92.04%	-100%	-94.8%	100%
	High ($\eta = 0.7$)	-100%	-100%	-100%	–
UBI		0%	0%	0%	65.4%
Paying domestic caregivers		83.49%	246.82%	140%	50%

[91] This estimate is pretty close to the gender distribution of unpaid caregivers for adult dependents. According to the 2017 CASEN, 67.8% of unpaid caregivers are women.

The Table shows that paying domestic caregivers may be the best equalizer in the distribution of domestic work. It does so, however, by severely increasing the supply of domestic care. On the other hand, the CCA reduces the reliance on domestic care, but it makes its gender distribution more skewed at medium and low levels of trust.[92]

VIII. Allocation in families: A theoretical extension

Thus far, we have considered that men and women residing with dependents maximize their utility independent from each other. Although smaller households are becoming increasingly common, nearly 30% of adult dependents still reside in extended families.[93] In these households, family decision-making processes influence individual allocation.

Traditional neoclassical models of the family assume the household as a single-maximizing unit (Becker, 1985). Feminist economists have disputed this amicable perspective of the family, arguing that conflict and bargaining processes are crucial to family decision-making (Folbre, 2012; Beneria et al., 2015 Political, economic, and cultural factors inform bargaining power. However, fallback positions, or exit threats, have been syndicated as a crucial component (Chant and McIlwaine 2016, p.79; Folbre,

[92] It must be noted that the extreme change in distribution for the CCA program is due to our assumption of a zero-care floor. If people were to reduce their care to a fixed positive number of hours of care, the distribution would be less skewed (and the program would also be less effective in stimulating consumption).

[93] According to 2017 CASEN. See Garcia Dellacasa 2021, Ch. II.

2021).[94] Exit threats refer to the individual's resource allocation in case they were to exit the family relationship. This theoretical extension discusses how policies may affect the family decision-making process through changes in exit threats through a non—cooperative Cournot-Nash equilibrium analysis (Chen and Woolley, 2001).

The first thing to note is that the individual maximization presented above is the de-facto exit threat for men and women, i.e., how much care they would provide if they exited the relationship. If there are no barriers to exit, men and women can leave the relationship and allocate their time according to the individual maximization model. However, men and women may use their bargaining power to negotiate non-exit outcomes. The bargaining position, conversely, will depend on the degree of interdependence between the two parties.

We can slightly tweak our model to integrate interdependency into our model. Following a similar structure to equation 2, let us assume that in a heterosexual traditional extended family, the total provision of care is determined by:

$$\begin{aligned} N_w &= Z_w + \delta Z_m + \eta \overline{Z} \\ N_m &= Z_m + Z_w + \eta \overline{Z} \end{aligned} \tag{14}$$

N_w is the total provision of care perceived by non-dependent women, and N_m is the total provision of care perceived by non-dependent men. Note that the role of care provisioning in individual maximization has a slightly different interpretation. Now it is interpreted from the perspective of the caregiver. Furthermore, we assume that both

[94] Bargaining power is a complex social construct conditioned by Institutional, political, cultural, and social institutions (Elson 1999).

men and women value their personal provisioning of care at the highest (unitary) rate. However, due to gendered expectations, we will assume that women's trust in male care is lower than men's trust in female care ($\delta < 1$).[95]

Assuming a non-cooperative Cournot equilibrium, any change in exogenous factors is evaluated against the backdrop of the partner's respective reaction function. From equation 8 we know that:

$$\begin{aligned} \frac{dZ_w}{dZ_m} &= -\delta \\ &and \\ \frac{dZ_m}{dZ_w} &= -1 \end{aligned} \tag{15}$$

Therefore, the reaction functions can be written and rearranged as:

$$\begin{aligned} Z_w^N &= Z_w^{exit} - \delta Z_m^N \\ Z_m^N &= Z_m^{exit} - Z_w^N \end{aligned} \tag{16}$$

$$\begin{aligned} \Rightarrow Z_w^N &= \frac{Z_w^{exit} - \delta Z_m^{exit}}{1-\delta} \\ \Rightarrow Z_m^N &= \frac{Z_m^{exit} - Z_w^{exit}}{1-\delta} \end{aligned} \tag{17}$$

Where Z^N is the Nash equilibrium care provision. Equation 17 tells us that whenever men's exit provision is equal or greater than women's, male care will be equal to zero (or whatever the floor provision is). Additionally, if there are barriers to exiting the

[95] Possibly a result of social conditioning.

relationship, and women's exit provision is higher than men's, female provision of care may be higher than the value of the exit provision. Finally, the magnitude of women's care provision (and, hence, their labor supply) depends on the difference between feminine and masculine exit strategies. Since men's care provision is zero, women provide exit-threat level care, and a sexual division of labor emerges.

Due to gendered expectations, women's provision of care when exiting the relationship is always equal or higher than that of men for the policies analyzed above. Even though the CCA policy would increase female labor supply at a higher rate (the difference between exit strategies is less), it would still lead to a skewed distribution of domestic care.[96] There is, however, a theoretical possibility for the CCA to distribute domestic care work more equitably. To see this, we need to remember that the exit strategy is conditional on job density. When job density is higher, the exit provision of care decreases.

Thus far, we have assumed that men and women face similar job densities. However, gendered occupational segregation in the labor market may entail different local job densities for men and women in the same household (Garcia Dellacasa 2021, Ch. I). If the CCA were to create jobs at a higher proportion for women than for men, women's exit strategies would decrease faster. If female job density increases

[96] Furthermore, in contrast to the individual maximization process, paying domestic caregivers would most likely result in the most skewed distribution of all under the strategic allocation. If we assume δ=0.5 in our simplified model, the non-cooperative outcome would be for women to provide six hours of care and men to provide zero.

sufficiently, a balanced distribution of care becomes a credible threat. Figure 16 illustrates this argument:

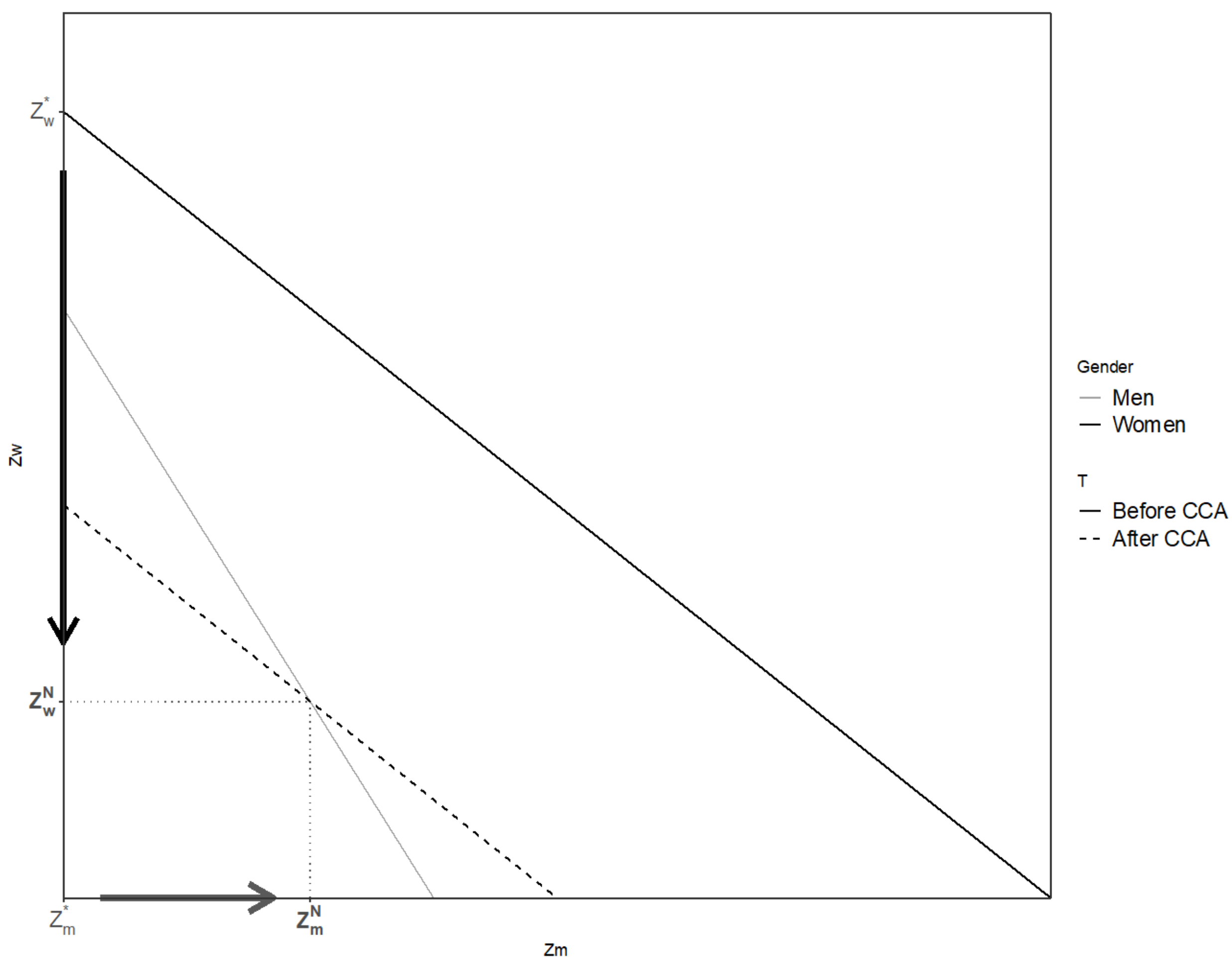

Figure 16: Cournot-Nash equilibrium for a sufficiently high increase in female job density.

At an initial stage, men's a women's reaction functions do not cross. The Nash equilibrium at this level is a sexual division of labor where women provide Z_w^* and men provide $Z_m^* = 0$ However, a sufficiently high increment in female job density contracts women's reaction function inwards. Now an internal solution is possible. Women can credibly threaten to provide Z_w^N, at which point men provide $Z_m^N > 0$. Even in the presence of gendered expectations, women's improvement in their fallback position may trigger a negotiation and a more just distribution of unpaid work. It is also worth noticing that if the changes in job density are too small, the sexual division will persist (no internal solution).

Since families do cooperate, a non-cooperative equilibrium is unlikely. However, this equilibrium replaces the exit strategy as a credible threat of non-cooperation (Chen and Woolley 2001). Job density, therefore, may induce a bargaining process that does not necessarily rely on the threat of or barriers to exiting the relationship.

This theoretical possibility also raises a possible moral conundrum for the CCA program. A gendered distribution of paid community care may lead to greater equality in the gender distribution of unpaid domestic care. It is not in the scope of this paper to discuss the implications of this trade-off, but it is important to acknowledge its theoretical feasibility.

IX. Final remarks

The CCA program is an ambitious idea to transform Chile's care system. The program is expected to the coverage and quality of adult care even as it improves the working conditions of caregivers. Moreover, the program's also entails economic benefits arising from increasing job density in economically depressed regions and decreasing unpaid work hours for caregivers, especially women. This article provides theoretical evidence for the mechanisms behind the program's economic impacts.

The CCA applies one of the oldest premises in the economics discipline. The community aspect of the program allows for a division of labor which is challenging if not impossible for households, especially for smaller ones. By expanding the limits of the division of labor, the CCA introduces efficiency to care provision, liberating thousands of unpaid hours of work. Additionally, the CCA targets the more temporally and spatially constrained communities, driving economic growth through inequality reduction.

The model presented in this article shows that decreasing unpaid care work will increase total consumption and labor supply, especially for women. Therefore, the CCA's simultaneous effects on aggregate demand and aggregate supply boost real economic growth without generating inflationary pressures often associated with high fiscal spending. Furthermore, given that the program will disproportionately benefit regions with high dependency rates, the CCA will decrease inequality between low- and high-income households and gender inequalities.

Within the assumptions of this model, the CCA program outperforms the UBI and paying domestic caregivers as an economic policy. However, the economic performance of the CCA is contingent upon people's trust in community caregiving. The significance of trust calls for planning and implementation methods that seriously consider local needs. Therefore, state authorities need to collaborate with local organizations throughout the process of transforming Chile's system of care.

APPENDIX A

APPENDIX TO CHAPTER 1

A.1 Comparison between ODS and 2012 census

Defining low-skilled potential workers as those who, at most, hold a high school degree, I compare the representativity of the ODS to the 2012 census in Table A-1. The table indicates that the weighted observations from the ODS dataset and the population parameters are similar in magnitude.

Table A-1: Summary of basic labor statistics comparing ODS 2012 and the 2012 Census. Calculations using survey weights. The working-age is between 15 and 65 years of age for the greater Santiago area.

	Total obs. ODS 2012		Census 2012	Labor market part.		Employment rate		% Less Educated*	
	Sample Size	Weighted	Population	ODS	Census	ODS	Census	ODS	Census
Women	19,233	2,125,613	2,091,881	52.36%	56.21%	93.90%	92.69%	67.22%	67.06%
Men	17,006	2,087,804	1,996,741	81.66%	79.70%	93.40%	93.40%	64.61%	65.67%
All	36,239	4,213,417	4,058,622	66.88%	67.60%	93.60%	93.10%	65.93%	66.40%

* Calculated for people who were not currently enrolled in an educational establishment at the time of the survey.
Calculations weighted using survey weights. Working age in Chile is considered between 15 and 65 years of age.

A.2 Moran's I

Moran's I is expressed as:

$$I = \frac{N}{\sum_{i=1}^{N}\sum_{j=1}^{N} W_{i,j}} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} W_{i,j}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{N}(y_i - \bar{y})^2}$$

Where N is equal to the number of observations, $W_{i,j}$ is the matrix which represents the degree of influence between observation i and observation j (usually known as the ‘distance weight matrix’), and y is the outcome or variable for which spatial correlation is tested. The numerator represents the covariance between observations and their neighbors, while the denominator is the global variance. The outcome is thus a normalized outcome, which takes the value of -1 when the data is negatively perfectly clustered, 1 when it is positively perfectly clustered and 0 when it is dispersed or random.

This indicator, especially when it comes to social and economic analysis, is not free from assumptions. A distance weight matrix defines the relationship between neighbors. However, how do we quantify this relationship? There are several ways in which one can specify this matrix (Gibbons, Overman and Patacchini 2015, p. 128-131), which often depends on the nature of the dataset. In the simplest of cases, a region that shares its borders with four other regions would have a matrix that allocated a weight of ¼ to each of the bordering regions. Thus, in this case, the assumption would be that all of the bordering regions have the same degree of influence over the region of interest. Regions that do not share a border, on the other hand, have no influence over each other.

Observations in the ODS are identified at the household level. This allows us for a more refined definition for spatial autocorrelation. Assuming that closer neighbors are more likely to experience similar alternatives to outsource care, the distance weight matrix is constructed according to an inverse distance weight structure. This means that neighbors that are closer are assigned larger weights than those who reside further away. Moreover, I have limited the definition of neighbor to the 50 closest neighbors at less than 1000 meters from the household coordinates.

A.3 Technical explanation for local boundaries

Our definition of locality is the point where people are indifferent between walking (or cycling) and taking a motorized form of transportation. Beyond this point, people are more willing to assume greater accounting costs in order to reach their destinations. This definition is particularly relevant in the Chilean case, where the cost of transportation is particularly high for low-income residents. In fact, according to the 2017 Family Budget Survey[97], out-of-pocket spending in transportation is only lower to expenditures in food and non-alcoholic drinks. Moreover, a subway fare hike of CLP$30 (US$0.05) in 2019 resulted in a social crisis which eventually led to a process of constitutional transformation.

The 2012 ODS recorded over 113,000 trips for that year. However, not all people face similar commuting costs. Chilean students' public transportation use is heavily subsidized by the state. For 2012, the bus fares costed $590 (CLP) for non-student users and $190 for students. Similarly, people over 65 years of age are beneficiaries of a subway subsidy. There are also individuals who face higher constrains to non-motorized

[97] https://www.ine.cl/estadisticas/sociales/ingresos-y-gastos/encuesta-de-presupuestos-familiares

mobility. People with disabilities may be indifferent between non-motorized travel and motorized travel at a much lower distance. Thus, to obtain the point of indifference we consider only adults between 18 and 65 years of age who are not enrolled in an educational institution and are not physically constrained by disability. For this sub-group, the ODS recorded 70,627 trips using motorized or non-motorized modes of transportation.

We define the indifference point as that one where the probabilities of using motorized transportation is equal to that of walking or cycling. Figure A-1 summarizes the trips recorded in the ODS using survey weights and bins all trips according to the Euclidean distance between origin and destination in 100-meter intervals. On the left panel we can see that short trips are much more common than longer trips. However, the variable of interest is in the right panel. At what distance are people indifferent between motorized and non-motorized transportation? On average, this seems to take place at the 1,000-meter difference between origin and destination of trip. At this point 51% of trips are non-motorized. Moreover, the steepest declines in non-motorized modes of transportation are between 900 and 1,000 meters, and between 1,000 and 1,100 meters. Together, the decline in preference for non-motorized modes of transportation amounts to 28% of total trips. Only 37% of trips between 1,000 and 1,100 meters are non-motorized. Hence, our first approximation to defining locality is a 1000-meter radius around the household.

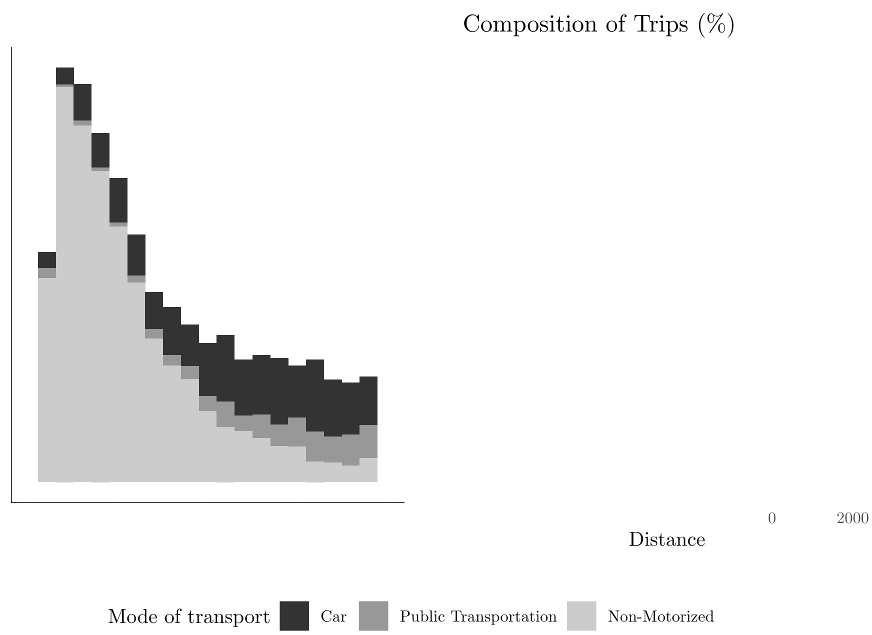

Figure A-17: Trips in the 2012 ODS. The left panel represents the total amount of trips categorized by one hundred-meter intervals and mode of transportation for working age adults. The right panel shows the distribution of utilized means of transportation per every one hundred-meter interval. When non-motored travel is at 50%, individuals are equally likely to travel through motored and non- motored means of transportation. Source: 2012 ODS.

There is, however, at least one caveat with this initial measure of locality: The point of indifference considers both public transportation and private vehicles. Nevertheless, there are families that do not possess private vehicles, so their choices are split between non-motorized and public transportation (and carpooling to a lesser extent). Nearly half of the aforementioned trips recorded by the ODS were taken by people who do not own a private vehicle (35,784). Unsurprisingly, the point of indifference for these travelers is higher (Figure A-2). At 1,400 meters, 49.5% of all trips are non-motorized. 100 meters later, only 37% percent of all trips take place under this mode of transportation. Public transportation, on the other hand, represent 53% of all trips at this point. In fact, the change in the percentual composition of total travel is the second largest only to the change between 1,000 and 1,100.

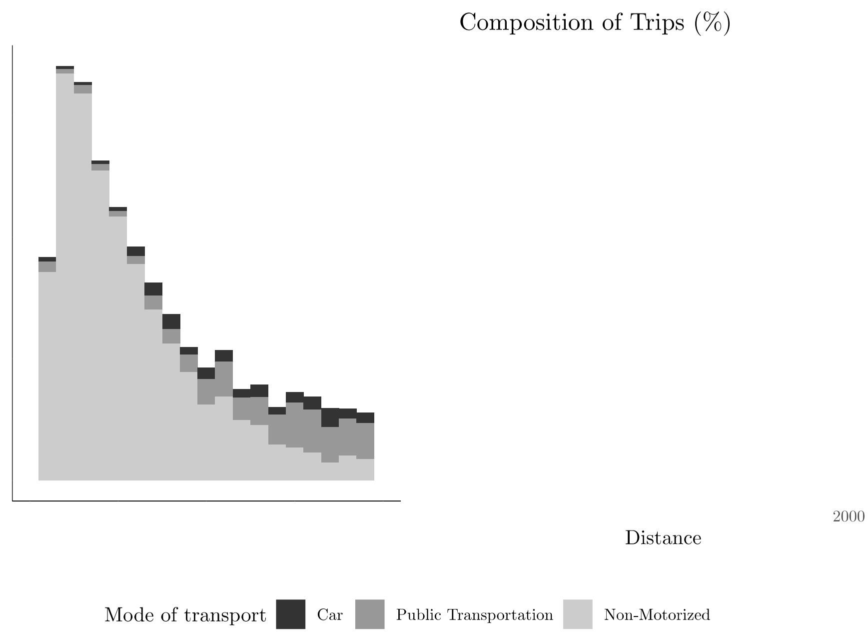

Figure A-18:Trips in the 2012 ODS for individuals who do not own private vehicles. The left panel represents the total amount of trips categorized by one hundred-meter intervals and mode of transportation for working age adults who do not own private means of motored transportation. The right panel shows the distribution of utilized means of transportation per every one hundred-meter interval. When non-motored travel is at 50%, individuals are equally likely to travel through motored and non-motored means of transportation. Source: 2012 ODS.

Thus, a larger radius of 1,400 meters will be considered for households that do not possess a vehicle. The walking-distance radius approach to defining local markets reduces the possibility of MAUP in at least two ways. First of all, our conceptualization of locality is directly related to the importance of local markets on employment decisions. Secondly, no observation is near the border of their own locality. Another important property of this definition of locality is that it allows for overlapping local markets. The radius approach allows for two workers may compete between each other without leaving their personal local markets even when they reside in different localities, a characteristic of local labor markets that has been stressed by the literature (Manning and Petrongolo 2017).

A.4 Local Indicators of Spatial Association (LISA)

The local Moran can be expressed in the following manner:

$$I_i = \frac{N(y_i - \bar{y})}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \sum_{j}^{N} W_{i,j}\,(y_j - \bar{y})$$

As Felkner and Townsend argue: “The statistic is a measure of the strength of the spatial correlation of an observation with its neighbors” (2013, p. 2054). If the spatial correlation is positive, both the observation and its neighbors are simultaneously beneath or above the mean when it comes to mobility. If the statistic is negative, on the other hand, the observation’s mobility and its neighbors will be intersected by the mean. The statistic is then tested for significance against the backdrop of complete spatial randomness. To identify spatial clusters, a conditional randomization/permutation approach is used to obtain pseudo significance levels (Hubert 1987 in Felkner and Townsend 2013). Through this approach these clusters can be visualized using GIS.

APPENDIX B

APPENDIX TO CHAPTER 2

B.1 Statistical differences in the determinants of being cared for between low dependency population and average dependent population.

Table B-1 presents t-tests for the difference in coefficients for the distinct population subsets (Low levels of dependency minus average dependency). T-tests for each difference show that these are more significant in households that are less likely to internalize care. Therefore, an extreme reliance in household care may result in a large fraction of the dependent population not receiving early care.

Table B-21: T-tests comparing the family type coefficients of being cared for between low dependency individuals and average dependents.

Variable	Difference	T-Value	P-value
Non-Dep. Women > 0 & Non-Dep. Men $= 0$	-0.024	1.212	0.113
Non-Dep. Women $= 0$ & Non-Dep. Men > 0	-0.026	1.337	0.091
Non-Dep. Women $= 0$ & Non-Dep. Men $= 0$	-0.036	1.954	0.0253
Non-dependent Women	0.020	2.251	0.012
Non-dependent Men	0.017	2.08	0.019

B.2 Machine Learning methods for predicting dependency

In order to predict dependency, I will choose the best model emerging from six different algorithms: Logistic regression, stepwise regression, ridge regression, lasso regression, over-grown tree, and a random forest algorithm. Brief descriptions of each of these algorithms can be found in Table B-2.

Table B-22: Short description of each predicting method used for the analysis of adult dependency.

Method	Algorithm (Type)	Description
Logistic Regression	Logistic	Probabilistic algorithm for classification that uses a logistic function to map predictions. Unlike a linear regression, a logistic regression predicts values between zero and one and different classes are sorted according to a threshold of probabilities.
Stepwise logistic regression	Logistic	A logistic regression that undergoes a variable selection process in order to maximize parsimony. Stepwise regressions combine forward and backward selection methods to simultaneously maximize goodness of fit and remove non-significant variables.
Ridge	Linear	A linear regression that uses a regularization method to prevent overfitting. The cost function for Ridge regressions penalizes increments in variance, thus reducing multicollinearity in the model and improving prediction capabilities. Regularization method does not eliminate coefficients.
Lasso	Linear	A linear regression that uses a regularization method that uses shrinkage, producing sparse models. This regularization method can eliminate certain coefficients.
Overgrown tree	Decision tree	An algorithm that uses decision trees to classify the data according to splits. A decision tree is a hierarchical structure that organizes predictive variables in a sequential manner, ultimately leading to a final classification. The algorithm construct different trees in a recursive manner until the combination between maximum accuracy and minimum number of splits has been reached.
Random forest	Decision tree	A large number of individual decision trees operating conjointly. Classification is decided upon the total number of trees predicting a particular class. Since these individual trees are different from each other, they compensate for each other's errors in prediction.

Traditionally, machine learning models are evaluated according to two alternative measurements. The ROCC curve represents the tradeoff between the true positive rate (also known as 'sensitivity') and the false positive rate (1-'specificity') of our predictions[98]. Ideally, a prediction would have a true positive rate of one and a false positive rate of zero, and the ROCC curve would take the shape of an inverted 'L'. An alternative to the ROCC curve is the 'Precision-Recall' curve. In this case, we evaluate models according to their capability to simultaneously maximize true positive rates (same as in the ROCC curve, now labeled 'recall') and precision.[99] Here, the ideal model would yield a precision and a recall equal to one, and the Precision-Recall curve would have its vertex in the top-right corner of a one-by-one graph.

We choose according to how close they are to perfect prediction. These curves also allow us to choose the optimal prediction threshold for dependency. Instead of arbitrarily choosing 0.5 as the cutting point for dependency predictions, we choose the threshold that minimizes the ROCC curve tradeoff and maximizes the Prediction-Recall curve. In other words, the thresholds by which we obtain the points closer to the top-left and top-right corners, respectively. These are calculated through the Youden Index (for ROCC curves) and F-1 scores (for Precision-Recall curves).

The ROCC curve and the Precision-Recall curve will most likely yield different thresholds as optimal. How do we choose between them? The answer lies in the nature of our classification and how affects the different. Dependency is an imbalanced

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98 $$True\ positive\ rate = \frac{True\ Positives}{True\ Positives + False\ negatives}$$

$$False\ positive\ rate = \frac{False\ Positives}{False\ Positives + True\ Negatives}$$

99 $$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

variable, as only 7% of the training dataset corresponds to dependents, Hence, it is likely that false positive rates will increase very slowly (true negatives will probably be very high). Precision, on the other hand, is unaffected by this imbalance, since it only focuses on positive values. For this reason, when we prioritize precision for choosing the appropriate threshold false positive rates do not shoot through the roof. Figures B-1 and B-2 illustrates both curves and their optimal threshold points.

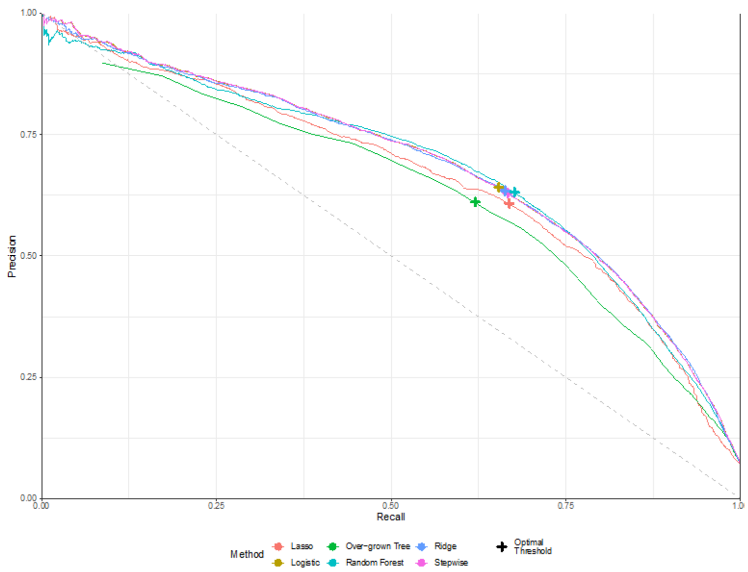

Figure B-19: Precision-Recall curve for different models. Optimal thresholds that maximize F-1 scores for each model are represented with a '+'. The dotted line represents a 'chance' prediction.

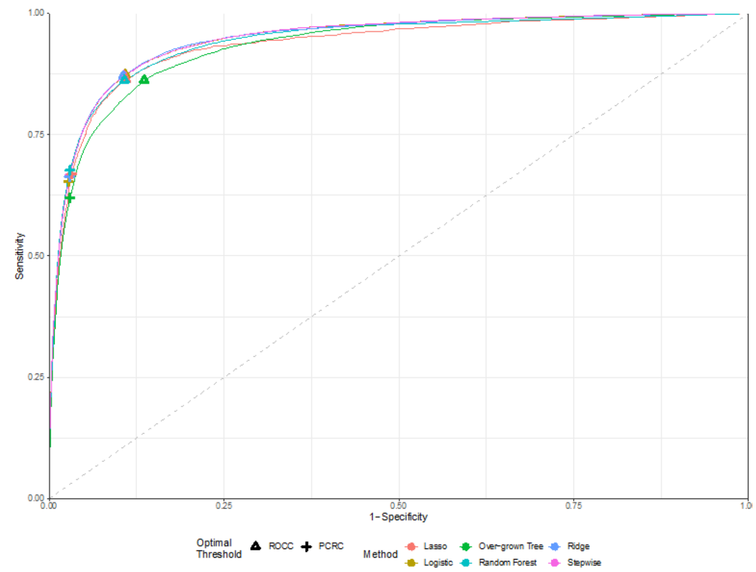

Figure B-20: ROCC curve for different models. Optimal thresholds that maximize the Youden Index for each model are represented with a triangle. Precision-Recall optimal thresholds are represented with a '+'. The dotted line represents a 'chance' prediction.

Table B-3 summarizes the performance for each model in predicting dependency on the testing data. Since precision is prioritized, we chose the model that yields the optimal thresholds with the maximum F-1 score. In this case, it is the random forest model. Coincidentally, when maximizing precision, the random forest model also yields the highest Youden-Index, signaling that it minimizes the tradeoff between true and false positive rates. This model also maximizes the accuracy of our predictions.[100]

Table B-23: Performance for each method in predicting adult dependency.

	Method:					
	Logistic	Stepwise	Ridge	Lasso	Over-grown Tree	**Random Forest**
Optimal Threshold	0.272	0.254	0.248	0.208	0.326	0.288
Precision	0.642	0.630	0.635	0.608	0.611	0.631
TPR (Recall)	0.654	0.667	0.663	0.669	0.620	0.677
FPR	0.028	0.030	0.029	0.032	0.030	0.030
F-1 Score	0.648	0.648	0.648	0.637	0.616	**0.653**
Youden Index	0.626	0.637	0.634	0.637	0.591	0.647
Accuracy	0.950	0.949	0.950	0.947	0.946	0.950

B.3 Predictors

Table B-4 summarizes the variables used to predict dependency, comparing the means for dependents and non-dependents in the training data.

[100] $Accuracy = \frac{True\ Positives + True\ Negatives}{True\ Positives + True\ Negatives + False\ Positives + False\ Negatives}$

Table B-24: Variables used as dependency predictors. Statistics are for the training data.

	Dependents *(N=13,078)*		*Non-Dependents* *(N=174,691)*			
Statistic	Mean	Std. Dev	Mean	Std.Dev	Type[1]	T-test (p-value)[2]
Physical Disability	0.572	0.495	0.025	0.156	Categorical	$p < 0.001$
Speaking Disability	0.075	0.264	0.012	0.107	Categorical	$p < 0.001$
Psychological Disability	0.049	0.215	0.005	0.073	Categorical	$p < 0.001$
Mental Disability	0.109	0.312	0.006	0.079	Categorical	$p < 0.001$
Hearing Disability	0.135	0.341	0.011	0.105	Categorical	$p < 0.001$
Vision Disability	0.150	0.357	0.017	0.130	Categorical	$p < 0.001$
Schooling (Years)	6.500	4.773	10.957	4.075	Discrete	$p < 0.001$
Labor Market Participation	0.151	0.359	0.594	0.491	Categorical	$p < 0.001$
General Medical App.[3]	0.783	2.104	0.272	1.063	Discrete	$p < 0.001$
Emergency App.	0.476	1.600	0.152	0.764	Discrete	$p < 0.001$
Medical Specialty App.	0.516	1.677	0.176	0.867	Discrete	$p < 0.001$
Dental App.	0.133	0.785	0.137	0.786	Discrete	$p > 0.1$
Lab Exams	1.306	2.899	0.475	1.712	Discrete	$p < 0.001$
X-Rays	0.393	1.429	0.137	0.773	Discrete	$p < 0.001$
Preventive App.	1.247	2.407	0.392	1.359	Discrete	$p < 0.001$
Age Group 40-59	0.195	0.396	0.338	0.473	Categorical	$p < 0.001$
Age Group 60-79	0.419	0.493	0.184	0.388	Categorical	$p < 0.001$
Age Group 80+	0.295	0.456	0.022	0.148	Categorical	$p < 0.001$
Female	0.629	0.483	0.525	0.499	Categorical	$p < 0.001$
Rural	0.224	0.417	0.206	0.405	Categorical	$p < 0.001$
Income Quintile (2)	0.244	0.429	0.227	0.419	Categorical	$p < 0.001$
Income Quintile (3)	0.193	0.394	0.209	0.407	Categorical	$p < 0.001$
Income Quintile (4)	0.138	0.345	0.188	0.390	Categorical	$p < 0.001$
Income Quintile (5)	0.081	0.273	0.158	0.365	Categorical	$p < 0.001$
Hospitalized (Disease/Surgery)[4]	0.082	0.275	0.032	0.175	Categorical	$p < 0.001$
Hospitalized (Disease/Treatment)	0.083	0.276	0.013	0.113	Categorical	$p < 0.001$
Hospitalized (Pregnancy)	0.0004	0.020	0.003	0.054	Categorical	$p < 0.001$
Hospitalized (Normal Childbirth)	0.001	0.023	0.005	0.069	Categorical	$p < 0.001$
Hospitalized (C-Section)	0.001	0.023	0.004	0.064	Categorical	$p < 0.001$
Hospitalized (Accident/Surgery)	0.009	0.096	0.003	0.052	Categorical	$p < 0.001$
Hospitalized (Accident/Treatment)	0.005	0.072	0.001	0.034	Categorical	$p < 0.001$
Hospitalized (Other Reasons)	0.004	0.062	0.002	0.041	Categorical	$p < 0.001$
Public Health Insurance (Fonasa B)	0.480	0.500	0.299	0.458	Categorical	$p < 0.001$
Public Health Insurance (Fonasa C)	0.043	0.202	0.125	0.330	Categorical	$p < 0.001$
Public Health Insurance (Fonasa D)	0.044	0.204	0.102	0.302	Categorical	$p < 0.001$
Public Health Insurance (Fonasa unknown)	0.041	0.198	0.051	0.220	Categorical	$p < 0.001$
Army/Police Insurance	0.022	0.148	0.022	0.148	Categorical	$p > 0.1$
Private Insurance (Isapre)	0.037	0.189	0.129	0.335	Categorical	$p < 0.001$
Uninsured	0.011	0.105	0.033	0.179	Categorical	$p < 0.001$
Other Insurance	0.004	0.062	0.007	0.081	Categorical	$p < 0.001$

[1] All categorical variables are dummies where 0 = No and 1 = Yes.
[2] T-tests were calculated for mean differences. Significant values reject the null hypothesis for dependents and non-dependents having the same distribution.
[3] All medical appointments are in the period of the last three months.
[4] All hospitalizations are in the period of the last three months.
Omitted variables: Age Group (15-39), Income Quintile (1), Public Health Insurance (Fonasa A).
Seed 12345 in R was used to produce the training data.

B.4 Capturing family distributions in testing data

Figure B-3 compares the actual distribution of dependents' family types with the predicted distributions in the testing data (divided into 2015 testing data and 2017 testing data). Since training and testing data were chosen at random, many households were split between the different datasets. Therefore, it is not strange that we have an overrepresentation of dependents living alone in the testing data. This is not something to worry about, since family types were not utilized as a predicting variable. Moreover, the Figure shows that the predictions accurately capture the dependents' family distributions. Tables B-5 and B-6 provide statistical reassurance to this visual inspection. The Pearson Chi-squared test and the Log likelihood ratio test show that Random Forest predictions are statistically equally distributed to the actual distribution.

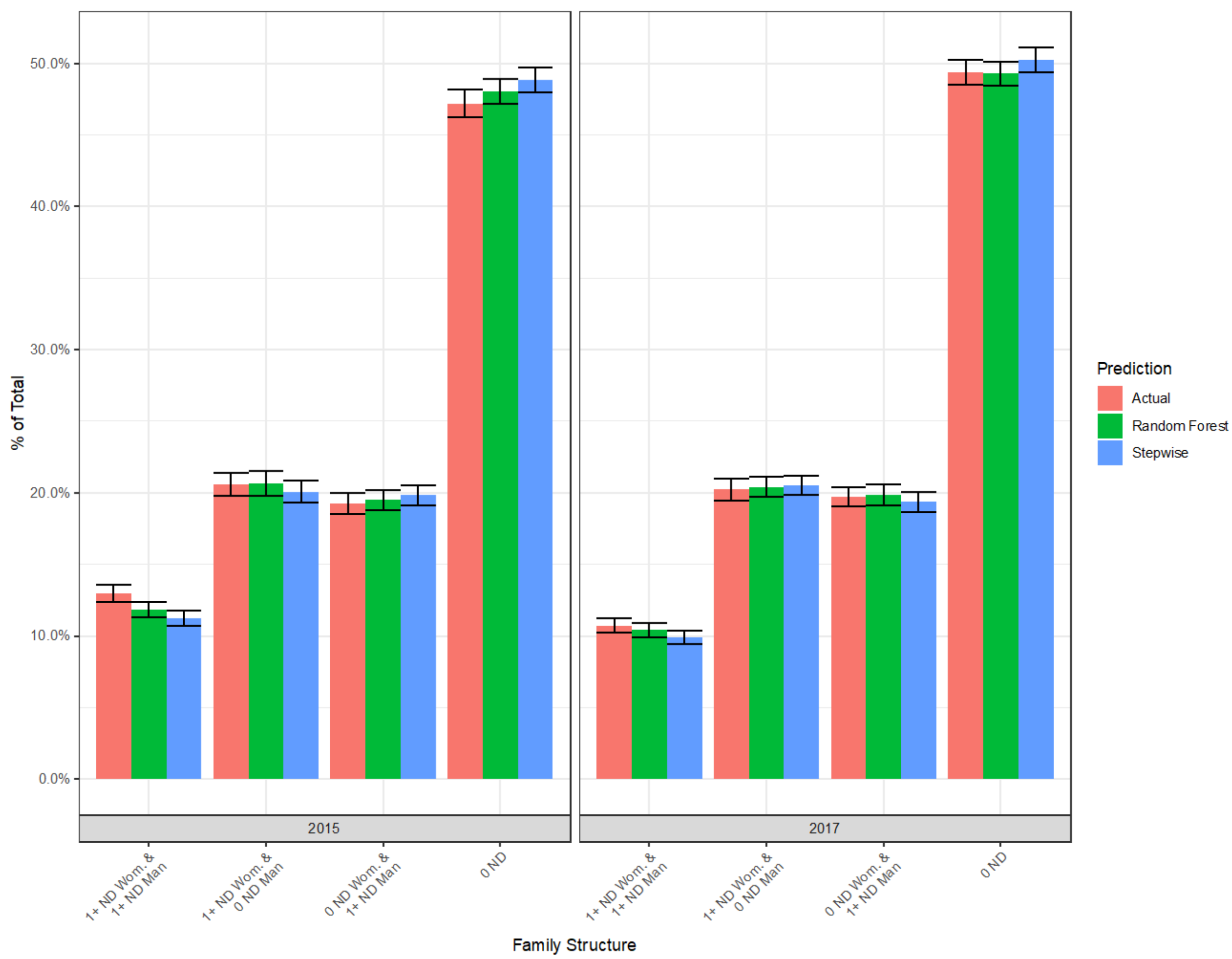

Figure B-21: Comparison between the actual distribution of dependents' family types and the predicted distributions in the testing data. For illustrative purposes, the testing data has been divided by year.

Table B-25: Goodness-of-fit tests comparing the actual distribution of dependents to that of predicted dependents in the 2015 subset of the testing data. Survey weights were included in the calculations.

Prediction	Goodnes of Fit Test	Coef.	F-value	P-value
Random Forest	Paerson's Chi-squared	8.4281	1.1650	0.3206
	Log likelihood ratio	8.6388	1.1941	0.3098
Stepwise	Paerson's Chi-squared	22.8009	3.2996	0.0205
	Log likelihood ratio	23.5306	3.4052	0.0178

Table B-26: Goodness-of-fit tests comparing the actual distribution of dependents to that of predicted dependents in the 2017 subset of the testing data. Survey weights were included in the calculations.

Prediction	Goodnes of Fit Test	Coef.	F-value	P-value
Random Forest	Paerson's Chi-squared	0.7559	0.1302	0.9401
	Log likelihood ratio	0.7606	0.1310	0.9396
Stepwise	Paerson's Chi-squared	5.7222	0.9940	0.3938
	Log likelihood ratio	5.8217	1.0113	0.3859

APPENDIX C

MATHEMATICAL APPENDIX TO CHAPTER 3

C.1 Labor supply model for women residing with dependents under gendered expectations

C.1.1. First and second order conditions

In this model, women maximize the following utility function:

$$U_w = u(X,L) + \beta A(N) - \gamma S(N) \tag{A-1}$$

subject to:

$$X = \hat{Y} + \frac{w}{(1+t(j))}(T - L - Z) \tag{A-2}$$

Thus, the Lagrangian equation is:

$$\mathcal{L}_w = u(X,L) + \beta A(N) - \gamma S(N) + \lambda(\hat{Y} + \frac{w}{(1+t(j))}(T - L - Z) - X) \tag{A-3}$$

First order conditions:

$$\frac{\partial \mathcal{L}}{\partial X} = u'_X - \lambda = 0 \tag{A-4}$$

$$\frac{\partial \mathcal{L}}{\partial L} = u'_L - \frac{\lambda w}{(1+t(j))} = 0 \tag{A-5}$$

$$\frac{\partial \mathcal{L}}{\partial Z} = \beta A'_N - \gamma S'_N - \frac{\lambda w}{(1+t(j))} = 0 \tag{A-6}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = \hat{Y} + \frac{w}{(1+t(j))}(T - L - Z) - X = 0 \tag{A-7}$$

The bordered Hessian for the second order conditions would look like this:

$$H = \begin{vmatrix} 0 & 1 & \frac{w}{(1+t(j))} & \frac{w}{(1+t(j))} \\ 1 & u''_{XX} & u''_{XL} & 0 \\ \frac{w}{(1+t(j))} & u''_{LX} & u''_{LL} & 0 \\ \frac{w}{(1+t(j))} & 0 & 0 & \beta A''_{NN} - \gamma S''_{NN} \end{vmatrix} \qquad \text{(A-8)}$$

To find a local maximum, the second order conditions have to satisfy:

$$-det|H_3| \quad < \quad 0$$

$$\textit{and} \qquad \text{(A-9)}$$

$$-det|H_4| \quad > \quad 0$$

Solving for H_3 and H_4, we find:

$$\begin{aligned} det|H_3| &= \frac{1}{1+t(j)}\left(b - \frac{aw}{1+t(j)}\right) && > 0 \\ & and && \text{(A-10)} \\ det|H_4| &= \left(\frac{\beta A''_{NN} - \gamma S''_{NN}}{1+t(j)}\right)\left(b - \frac{wa}{(1+t(j))}\right) - \frac{w}{(1+t(j))^2}\left(au''_{LL} - bu''_{LX}\right) && < 0 \end{aligned}$$

with

$$\begin{aligned} a &= wu''_{XX} - (1+t(j))u''_{LX} && < 0, \\ b &= wu''_{XL} - (1+t(j))u''_{LL} && > 0 \qquad \text{(A-11)} \end{aligned}$$

If $u''_{XX}u''_{LL} = u''XLu''LX \Rightarrow au''_{LL} - bu''_{LX}$= 0. Therefore, if this common assumption is satisfied, second order conditions are always satisfied.

C.1.2. Job density effects on female caregivers' labor supply

From equations 4, 5, 6, and 7 we get the following system of equations:

$$\begin{aligned} wu'_X - (1+t(j))u'_L &= 0 \\ u'_L - (\beta A'_N - \gamma S'_N) &= 0 \\ \hat{Y} + \pi + \frac{w}{(1+t(j))}(T - L - Z) - X &= 0 \end{aligned}$$

(A-12)

To capture job density effects we differentiate 12 considering

dj > 0:

$$\begin{aligned} dX(a) + dL(b) - dj(t'_j u'_L) &= 0 \\ dX(u''_{LX}) + dL(u''_{LL}) - dZ(\beta A''_{NN} - \gamma S''_{NN}) &= 0 \\ dX + dL(\frac{w}{(1+t(j))}) + dZ(\frac{w}{(1+t(j))}) - dj(\frac{t'_j w}{(1+t(j))^2}(T-L-Z)) &= 0 \end{aligned} \quad \text{(A-13)}$$

In matrix form, this can be converted to:

$$\begin{vmatrix} a & b & 0 \\ u''_{LX} & u''_{LL} & -(\beta A''_{NN} - \gamma S''_{NN}) \\ 1 & \frac{w}{(1+t(j))} & \frac{w}{(1+t(j))} \end{vmatrix} \begin{vmatrix} dX/dj \\ dL/dj \\ dZ/dj \end{vmatrix} = \begin{vmatrix} t'_j u'_L \\ 0 \\ \Theta \end{vmatrix} \quad \text{(A- 14)}$$

With Θ = $\frac{t'_j w}{(1+t(j))^2}(T-L-Z) <$ 0 and (*T* − *L* − *Z*)

.

Following the same steps, it can be shown that men's optimization problem can be written as[101]:

$$\begin{vmatrix} a & b & 0 \\ u''_{LX} & u''_{LL} & -\beta A''_{NN} \\ 1 & \frac{w}{(1+t(j))} & \frac{w}{(1+t(j))} \end{vmatrix} \begin{vmatrix} dX/dj \\ dL/dj \\ dZ/dj \end{vmatrix} = \begin{vmatrix} t'_j u'_L \\ 0 \\ \Theta \end{vmatrix} \quad \text{(A-15)}$$

C.1.2.1. Job density effects on total consumption

[101] Men's determinant would be exactly the same to women's with γ=0

Using Cramer's rule, we know that:

$$\frac{dX}{dj} = \frac{det|M_X^j|}{det|M|} = \frac{\begin{vmatrix} t_j' u_L' & b & 0 \\ 0 & u_{LL}'' & -(\beta A_{NN}'' - \gamma S_{NN}'') \\ \Theta & \frac{w}{(1+t(j))} & \frac{w}{(1+t(j))} \end{vmatrix}}{\begin{vmatrix} a & b & 0 \\ u_{LX}'' & u_{LL}'' & -(\beta A_{NN}'' - \gamma S_{NN}'') \\ 1 & \frac{w}{(1+t(j))} & \frac{w}{(1+t(j))} \end{vmatrix}} \tag{A-16}$$

With

$$det|M| = \frac{(\beta A_{NN}'' - \gamma S_{NN}'')(aw - b(1+t(j))) + w(au_{LL}'' - bu_{LX}'')}{(1+t(j))}{}_1 \tag{A-17}$$

Since $au''_{LL} - bu''_{LX} = 0$, we know that $det|M| > 0$

For $det|M_X^j|$, we can arrive at the following formulation:

$$det|M_X^j| = (\beta A_{NN}'' - \gamma S_{NN}'')(\frac{t_j' u_L' w}{(1+t(j))} - b\Theta) + \frac{t_j' u_L' w u_{LL}''}{(1+t(j))} > 0^2 \tag{A-18}$$

[102]This means that $dX/dj > 0$ when we don't consider altruism and social penalty effects, and job density effects on consumption decrease with higher values of β or γ. Since $\gamma = 0$ for men, men increment their consumption more at similar levels of job density than women do.

C.1.2.2. Job density effects on leisure time

[102] The sign of will depend on the value of Θ.

Here, we assume that substitution effects are higher than income effects.

$$\frac{dL}{dj} = \frac{det|M_L^j|}{det|M|} \quad \text{(A-19)}$$

$$det|M_L^j| = det\begin{vmatrix} a & t_j' u_L' & 0 \\ u_{LX}'' & 0 & -(\beta A_{NN}'' - \gamma S_{NN}'') \\ 1 & \Theta & \frac{w}{(1+t(j))} \end{vmatrix} \quad \text{(A-20)}$$

Which gives:

$$det|M_L^j| = (\beta A_{NN}'' - \gamma S_{NN}'')(a\Theta + t_j' u_L') - \frac{t_j' u_L' u_{LX}'' w}{1+t(j)} > 0 \quad \text{(A-21)}$$

Notice that in the absence of a social penalty and altruism effects, *dL/dj* > 0. However, as these effects grow larger (increments in β or γ), job density effects on leisure time become smaller (*det*|*M*| becomes larger and *det*|M_L^j| is reduced).

C.1.2.3. Job density effects on domestic caring time

$$\frac{dZ}{dj} = \frac{det|M_Z^j|}{det|M|} \quad \text{(A-22)}$$

$$det|M_Z^j| = det\begin{vmatrix} a & b & t_j' u_L' \\ u_{LX}'' & u_{LL}'' & 0 \\ 1 & \frac{w}{(1+t(j))} & \Theta \end{vmatrix} \quad \text{(A-23)}$$

Which gives:

$$det|M_Z^j| = \Theta(au_{LL}'' - bu_{LX}'') + t_j' u_L' (\frac{u_{LX}'' w}{(1+t(j))} - u_{LL}'') = t_j' u_L' (\frac{u_{LX}'' w}{(1+t(j))} - u_{LL}'') \quad \text{(A-24)}$$

This means that:

$$0 \ \frac{dZ}{dj} < \quad \text{(A-25)}$$

q.e.d.

C.1.2.4. Job density effects over labor supply

Since *dX/dj* is positive, and no other source of income is changed, *dLS/dj* > 0. The functional form of *dLS/dj* > 0 can be calculated from out temporal restriction:

$$T = (1 + t(j))LS + L + Z \tag{A-26}$$

If we differentiate with *dj* > 0, we get:

$$0 = (1+t(j))\frac{dLS}{dj} + t'_j LS + \frac{dL}{dj} + \frac{dZ}{dj} \tag{A-27}$$

If we replace and rearrange 27, we get:

$$\frac{dLS}{dj} = -\frac{(\beta A''_{NN} - \gamma S''_{NN})(a\Theta + t'_j u'_L) + t' u'_L u''_{LL}}{(\beta A''_{NN} - \gamma S''_{NN})(aw - b(1+t(j)))} - \frac{t'_j LS}{(1+t(j))} > 0 \tag{A-28}$$

Labor supply is more inelastic on job density for women facing social penalties than for men.

C.1.3. Greater public care availability and female caregivers' labor supply

To capture the effects of public care availability we differentiate 12 considering *dZ* > 0:

$$\begin{aligned} dX(a) + dL(b) &= 0 \\ dX(u''_{LX}) + dL(u''_{LL}) - dZ(\beta A''_{NN} - \gamma S''_{NN}) - d\overline{Z}\eta(\beta A''_{NN} - \gamma S''_{NN}) &= 0 \\ dX + dL(\frac{w}{(1+t(j))}) + dZ(\frac{w}{(1+t(j))}) &= 0 \end{aligned} \tag{A-29}$$

In matrix form, this can be converted to:

$$\begin{vmatrix} a & b & 0 \\ u''_{LX} & u''_{LL} & -(\beta A''_{NN} - \gamma S''_{NN}) \\ 1 & \dfrac{w}{(1+t(j))} & \dfrac{w}{(1+t(j))} \end{vmatrix} \begin{vmatrix} dX/d\overline{Z} \\ dL/d\overline{Z} \\ dZ/d\overline{Z} \end{vmatrix} = \begin{vmatrix} 0 \\ \eta(\beta A''_{NN} - \gamma S''_{NN}) \\ 0 \end{vmatrix} \tag{A-30}$$

C.1.3.1. Public care effects on total consumption

$$\frac{dX}{d\overline{Z}} = \frac{det|M_X^{\overline{Z}}|}{det|M|} \tag{A-31}$$

with

$$det|M_X^{\overline{Z}}| = det \begin{vmatrix} 0 & b & 0 \\ \eta(\beta A''_{NN} - \gamma S''_{NN}) & u''_{LL} & -(\beta A''_{NN} - \gamma S''_{NN}) \\ 0 & \dfrac{w}{(1+t(j))} & \dfrac{w}{(1+t(j))} \end{vmatrix} \tag{A-32}$$

Which gives:

$$det|M_X^{\overline{Z}}| = \frac{-bw\eta(\beta A''_{NN} - \gamma S''_{NN})}{(1+t(j))} > 0 \tag{A-33}$$

Therefore:

$$\frac{dX}{d\overline{Z}} > 0 \tag{A-34}$$

C.1.3.2. Public care effects on total leisure time

$$\frac{dL}{d\overline{Z}} = \frac{det|M_L^{\overline{Z}}|}{det|M|} \tag{A-35}$$

with

$$det|M_L^{\overline{Z}}| = det\begin{vmatrix} a & 0 & 0 \\ u''_{XL} & \eta(\beta A''_{NN} - \gamma S''_{NN}) & -(\beta A''_{NN} - \gamma S''_{NN}) \\ 1 & 0 & \dfrac{w}{(1+t(j))} \end{vmatrix} \quad \text{(A-36)}$$

Which gives:

$$det|M_L^{\overline{Z}}| = \frac{aw\eta(\beta A''_{NN} - \gamma S''_{NN})}{(1+t(j))} > 0 \quad \text{(A-37)}$$

Therefore:

$$\frac{dL}{d\overline{Z}} > 0 \quad \text{(A-38)}$$

C.1.3.3. Public care effects on total domestic caring time

$$\frac{dZ}{d\overline{Z}} = \frac{det|M_Z^{\overline{Z}}|}{det|M|} \quad \text{(A-39)}$$

with

$$det|M_Z^{\overline{Z}}| = det\begin{vmatrix} a & b & 0 \\ u''_{XL} & u''_{LL} & \eta(\beta A''_{NN} - \gamma S''_{NN}) \\ 1 & \dfrac{w}{(1+t(j))} & 0 \end{vmatrix} \quad \text{(A-40)}$$

Which gives:

$$det|M_Z^{\overline{Z}}| = \frac{-\eta(\beta A''_{NN} - \gamma S''_{NN})(aw - b(1+t(j))}{(1+t(j))} < 0 \quad \text{(41)}$$

Therefore:

$$\frac{dZ}{d\overline{Z}} < 0 \quad \text{(42)}$$

C.1.3.4. Public care effects on labor supply

If we differentiate with *dZ* > 0, we get:

$$0 = (1+t(j))\frac{dLS}{d\overline{Z}} + \frac{dL}{d\overline{Z}} + \frac{dZ}{d\overline{Z}} \tag{A-43}$$

Replacing and rearranging, we get:

$$\frac{dLS}{d\overline{Z}} = \frac{1}{1+t(j)}\left(\eta - \frac{b\eta}{aw - b(1+t(j))}\right) > 0 \tag{A-44}$$

C.1.4. Universal basic income effects over female caregivers' labor supply

To capture the effects of a universal basic income policy we differentiate 12 considering

$d\hat{Y} > 0$:

$$\begin{aligned} dX(a) + dL(b) &= 0 \\ dX(u''_{LX}) + dL(u''_{LL}) - dZ(\beta A''_{NN} - \gamma S''_{NN}) &= 0 \\ dX + dL(\frac{w}{(1+t(j))}) + dZ(\frac{w}{(1+t(j))}) - d\hat{Y} &= 0 \end{aligned} \tag{A-45}$$

In matrix form, this can be converted to:

$$\begin{vmatrix} a & b & 0 \\ u''_{LX} & u''_{LL} & -(\beta A''_{NN} - \gamma S''_{NN}) \\ 1 & \dfrac{w}{(1+t(j))} & \dfrac{w}{(1+t(j))} \end{vmatrix} \begin{vmatrix} dX/d\hat{Y} \\ dL/d\hat{Y} \\ dZ/d\hat{Y} \end{vmatrix} = \begin{vmatrix} 0 \\ 0 \\ 1 \end{vmatrix} \tag{A-46}$$

C.1.4.1. UBI effects on total consumption

$$\frac{dX}{d\hat{Y}} = \frac{det|M_X^{\hat{Y}}|}{det|M|} \tag{A-47}$$

with

$$det|M_X^{\hat{Y}}| = det\begin{vmatrix} 0 & b & 0 \\ 0 & u''_{LL} & -(\beta A''_{NN} - \gamma S''_{NN}) \\ 1 & \dfrac{w}{(1+t(j))} & \dfrac{w}{(1+t(j))} \end{vmatrix} \tag{A-48}$$

Which gives:

$$det|M_X^{\hat{Y}}| = -b(\beta A''_{NN} - \gamma S''_{NN}) > 0 \tag{A-49}$$

Therefore:

$$\frac{dX}{d\hat{Y}} > 0 \tag{A-50}$$

C.1.4.2. UBI effects on total leisure time

$$\frac{dL}{d\hat{Y}} = \frac{det|M_L^{\hat{Y}}|}{det|M|} \tag{A-51}$$

with

$$det|M_L^{\hat{Y}}| = det\begin{vmatrix} a & 0 & 0 \\ u''_{XL} & 0 & -(\beta A''_{NN} - \gamma S''_{NN}) \\ 1 & 1 & \dfrac{w}{(1+t(j))} \end{vmatrix} \tag{A-52}$$

Which gives:

$$det|M_L^{\hat{Y}}| = a(\beta A''_{NN} - \gamma S''_{NN}) > 0 \tag{A-53}$$

Therefore:

$$\frac{dL}{d\hat{Y}} > 0 \tag{A-54}$$

C.1.4.3. *UBI effects on total domestic caring time*

$$\frac{dZ}{d\hat{Y}} = \frac{det|M_Z^{\hat{Y}}|}{det|M|} \tag{A-55}$$

with

$$det|M_Z^{\hat{Y}}| = det\begin{vmatrix} a & b & 0 \\ u''_{XL} & u''_{LL} & 0 \\ 1 & \frac{w}{(1+t(j))} & 1 \end{vmatrix} \tag{A-56}$$

Which gives:

$$det|M_Z^{\hat{Y}}| = au''_{LL} - bu''_{XL} = 0 \tag{A-57}$$

Therefore:

$$\frac{dZ}{d\hat{Y}} = 0 \tag{A-58}$$

C.1.4.4. *UBI effects on labor supply*

If we differentiate with $d\hat{Y} > 0$, we get:

$$0 = (1+t(j))\frac{dLS}{d\hat{Y}} + \frac{dL}{d\hat{Y}} + \frac{dZ}{d\hat{Y}} \tag{A-59}$$

Replacing and rearranging, we get:

$$\frac{dLS}{d\hat{Y}} = -\frac{a}{aw - b(1+t(j))} < 0 \quad \text{(A-60)}$$

C.1.5. Paying domestic caregivers' effects over female caregivers' labor supply

Now, the maximization problem is slightly different:

$$U_w = u(X,L) + \beta A(N) - \gamma S(N) \quad \text{(A-61)}$$

subject to:

$$X = \hat{Y} + Y_c Z + \frac{w}{(1+t(j))}(T - L - Z) \quad \text{(A-62)}$$

f.o.c.:

$$\begin{aligned}
\frac{\partial \mathcal{L}_{\rfloor}}{\partial X} &= u'_X &&= \lambda \\
\frac{\partial \mathcal{L}_{\rfloor}}{\partial L} &= u'_L &&= \lambda\left(\frac{w}{1+t(j)}\right) \\
\frac{\partial \mathcal{L}_{\rfloor}}{\partial Z} &= \beta A'_N - \gamma S'_N &&= \lambda\left(\frac{w - Y_c(1+t(j))}{1+t(j)}\right) \\
\frac{\partial \mathcal{L}_{\rfloor}}{\partial \lambda} &= X - \hat{Y} - Y_c Z - \frac{w}{(1+t(j))}(T - L - Z) &&= 0
\end{aligned} \quad \text{(A-63)}$$

From which we obtain the following system of equations:

$$\begin{aligned}
Wu'_X - (1 + t(j))u'_L &= 0 \\
U'_L(w - (1 + t(j))Y_c) - w(\beta A'_N - \gamma S'_N) &= 0 \quad \text{(A-64)} \\
X - \hat{Y} - Y_c Z - \frac{w}{(1+t(j))}(T - L - Z) &= 0
\end{aligned}$$

If we differentiate with $dY_c > 0$:

$$\begin{aligned}
dX(a) + dL(b) &= 0 \\
dX(u''_{LX}(w - (1+t(j))Y_c)) + dL(u''_{LL}(w - (1+t(j))Y_c)) - dZ(w(\beta A''_{NN} - \gamma S''_{NN})) - dY_c(u'_L(1+t(j))) &= 0 \\
dX + dL(\frac{w}{(1+t(j))}) + dZ(\frac{w}{(1+t(j))} - Y^c) - dY^c(Z) &= 0
\end{aligned}$$

(A-65)

For Cramer's rule the new denominator would be given by:

$$det|M_c| = det\begin{vmatrix} a & b & 0 \\ u''_{LX}\,(w-(1+t(j))Y_c) & u''_{LL}\,(w-(1+t(j))Y_c) & -w(\beta A''_{NN}-\gamma S''_{NN}) \\ 1 & \dfrac{w}{(1+t(j))} & \dfrac{w}{(1+t(j))}-Y^c \end{vmatrix}$$

(A-66)

If $au''_{LL} - bu''_{LX}$ = 0, it can be shown that:

$$det|M_c| = wdet|M| = w(\beta A''_{NN}-\gamma S''_{NN})\left(\frac{aw-b(1+t(j))}{(1+t(j))}\right) > 0 \qquad \text{(A-67)}$$

C.1.5.1. Paying domestic caregivers' effects on total consumption

$$\frac{dX}{dY^c} = \frac{det|M_X^{Y^c}|}{det|M|} \qquad \text{(A-68)}$$

with

$$det|M_X^{Y^c}| = det\begin{vmatrix} 0 & b & 0 \\ u'_L(1+t(j)) & u''_{LL}\left(1-\dfrac{(1+t(j))Y_c}{w}\right) & -w(\beta A''_{NN}-\gamma S''_{NN}) \\ Z & \dfrac{w}{(1+t(j))} & \dfrac{w}{(1+t(j))}-Y^c \end{vmatrix} \qquad \text{(A-69)}$$

Which gives:

$$det|M_X^{Y^c}| = -b\left(u'_L(w-(1+t(j))Y^c) + Zw(\beta A''_{NN}-\gamma S''_{NN})\right) \qquad \text{(A-70)}$$

If $Y_c > \dfrac{w}{1+t(j)}$, then:

$$\frac{dX}{dY^c} > 0 \tag{A-71}$$

Otherwise, the effect is indeterminate.

C.1.5.2. Caring Pension effects on total leisure time

$$\frac{dL}{dY^c} = \frac{det|M_L^{Y^c}|}{det|M|} \tag{A-72}$$

with

$$det|M_L^{Y^c}| = det\begin{vmatrix} a & 0 & 0 \\ u''_{LX}\,(w-(1+t(j))Y_c) & u'_L(1+t(j)) & -w(\beta A''_{NN}-\gamma S''_{NN}) \\ 1 & Z & \frac{w}{(1+t(j))}-Y^c \end{vmatrix} \tag{A-73}$$

Which gives:

$$det|M_L^{Y^c}| = a\,(u'_L(w-(1+t(j))Y^c) + Zw(\beta A''_{NN}-\gamma S''_{NN})) \tag{A-74}$$

If $Y_c > \frac{w}{1+t(j)}$, then:

$$\frac{dL}{dY^c} > 0 \tag{A-75}$$

Otherwise, the effect is indeterminate.

C.1.5.3. Caring pension effects on total domestic caring time

$$\frac{dZ}{dY^c} = \frac{det|M_Z^{Y^c}|}{det|M|} \tag{A-76}$$

with

$$det|M_Z^{Y^c}| = det\begin{vmatrix} a & b & 0 \\ u''_{XL}\,(w-(1+t(j))Y_c) & u''_{LL}\,(w-(1+t(j))Y_c) & u'_L(1+t(j)) \\ 1 & \dfrac{w}{(1+t(j))} & Z \end{vmatrix}$$ (A-77)

Which gives:

$$det|M_Z^{Y^c}| = -u'_L(a - \frac{b(1+t(j))}{w}) > 0 \qquad \text{(A-78)}$$

Therefore:

$$\frac{dZ}{dY^c} > 0 \qquad \text{(A-79)}$$

C.1.5.4. Caring pension effects on labor supply

If we differentiate with $dY^c > 0$, we get:

$$0 = (1+t(j))\frac{dLS}{dY^c} + \frac{dL}{dY^c} + \frac{dZ}{dY^c} \qquad \text{(A-80)}$$

Replacing and rearranging, we get:

$$\frac{dLS}{dY^c} = \frac{u'_L}{w(\beta A''_{NN} - \gamma S''NN} - \frac{au'_L(w-(1+t(j))Y^c)}{w(\beta A''_{NN} - \gamma S''NN(aw-b(1+t(j)))} - \frac{aZ}{aw-b(1+t(j))} < 0$$

(A-81)

If $Y_c > \dfrac{w}{1+t(j)}$, then:

$$\frac{dLS}{dY^c} < 0 \qquad \text{(A-82)}$$

C.2 Comparative parametric model

C.2.1. Base model

Women maximize the following utility function

$$U_w = X^{\alpha} L^{(1-\alpha)} + \beta Z^{\kappa} - \gamma(-Z^{\kappa}) \quad \text{(A-83)}$$

subject to:

$$X = \frac{w}{1+t(j)}(16 - L - Z) \quad \text{(A-84)}$$

The parameters of the model are given by: $\alpha = \kappa = 0.5$, $t(j) = 0.25$, $\beta = 1.2$, $\gamma = 0.45$, $w = 1.04$.

The Lagrangean would then look like this:

$$\mathrm{L}_w = X^{0.5} L^{0.5} + (\beta + \gamma) Z^{0.5} + \lambda(0.832(16 - L - Z) - X) \quad \text{(A-85)}$$

f.o.c:

$$\begin{aligned}
\frac{\partial \mathcal{L}_w}{\partial X} &= 0.5X^{-0.5}L^{0.5} &&= \lambda \\
\frac{\partial \mathcal{L}_w}{\partial L} &= 0.5X^{0.5}L^{-0.5} &&= 0.832\lambda \\
\frac{\partial \mathcal{L}_w}{\partial Z} &= 0.5(\beta+\gamma)Z^{-0.5} &&= 0.832\lambda \\
\frac{\partial \mathcal{L}_w}{\partial \lambda} &= 0.832(16 - L - Z) - X &&= 0
\end{aligned} \quad \text{(A-86)}$$

From the f.o.c., we know that:

$$\begin{aligned}
0.832L^{*} &= X^{*} \\
0.832^{0.5} &= (\beta + \gamma)Z^{*-0.5}
\end{aligned} \quad \text{(A-87)}$$

Therefore, in equilibrium:

$$Z_w^* = \frac{(\beta+\gamma)^2}{0.832} = 3.27$$
$$Z_m^* = \frac{(\beta)^2}{0.832} = 1.73 \qquad \text{(A-88)}$$

Replacing L^* and Z^* in the budget constraint we get:

$$0.832(16 - \frac{X_w^*}{0.832} - 3.27) - X_w^* = 0 \Rightarrow X_w^* = 5.3, L_w^* = 6.37, LS_w^* = 5.1$$

(A-89)

$$0.832(16 - \frac{X_m^*}{0.832} - 1.73) - X_m^* = 0 \Rightarrow X_m^* = 5.94, L_m^* = 7.14, LS_m^* = 5.71$$

C.2.1.1. Base allocation for wages = 2w

Following the same steps as above it can be shown that when wages are doubled, the optimal allocation for women is:

$$Z_w^* = 1.64 \quad ; \quad X_w^* = 11.95 \quad ; \quad L_w^* = 7.18 \quad ; LS_w^* = 5.75 \qquad \text{(A-90)}$$

And for men:

$$Z_w^* = 0.87 \quad ; \quad X_w^* = 12.59 \quad ; \quad L_w^* = 7.57 \quad ; LS_w^* = 6.04 \qquad \text{(A-91)}$$

C.2.2. Community care aides program

The program presupposes an increase in job density by 10% (a reduction in the commuting share by 0.5%) and an increase in the provision of public care to six hours. We will assume that dependents value out of household care at 0.3 times the rate they value domestic provision. The new Lagrangean would be:

$$L_w = X^{0.5}L^{0.5} + (\beta+\gamma)(Z + 0.3 * 6)^{0.5} + \lambda(0.835(16 - L - Z) - X) \qquad \text{(A-92)}$$

f.o.c:

$$
\begin{aligned}
\frac{\partial \mathcal{L}_w}{\partial X} &= 0.5X^{-0.5}L^{0.5} &&= \lambda \\
\frac{\partial \mathcal{L}_w}{\partial L} &= 0.5X^{0.5}L^{-0.5} &&= 0.835\lambda \\
\frac{\partial \mathcal{L}_w}{\partial Z} &= 0.5(\beta+\gamma)(Z+1.8)^{-0.5} &&= 0.835\lambda \\
\frac{\partial \mathcal{L}_w}{\partial \lambda} &= 0.835(16-L-Z)-X &&= 0
\end{aligned} \qquad \text{(A-93)}
$$

In equilibrium:

$$
\begin{aligned}
Z_w^* &= \frac{(\beta+\gamma)^2}{0.835} - 1.8 = 1.46 \\
Z_m^* &= \frac{(\beta)^2}{0.835} - 1.8 < 0 \Rightarrow Z_m^* = 0
\end{aligned} \qquad \text{(A-94)}
$$

Replacing L^* and Z^* in the budget constraint we get:

$$0.835(16 - \frac{X_w^*}{0.835} - 1.46) - X_w^* = 0 \Rightarrow X_w^* = 6.07, L_w^* = 7.27, LS_w^* = 5.84$$

(A-95)

$$0.835(16 - \frac{X_m^*}{0.835}) - X_m^* = 0 \Rightarrow X_m^* = 6.68, L_m^* = 8, LS_m^* = 6.42$$

C.2.2.1. CCA allocation for wages = 2w

Following the same steps as above it can be shown that when wages are doubled, the optimal allocation for women is:

Z_w^*= 0 ; $X_w^* = 13.37$; L_w^*= 8 ; $LS_w^* = 6.43$ (A-96)

And for men:

Z_w^*= 0 ; $X_w^* = 13.37$; L_w^*= 8 ; $LS_w^* = 6.43$ (A-97)

C.2.3. Universal Basic Income

The program promises an increase in autonomous income by \$CLP112,527 (in 2017). This is equivalent to 29% of the average individual expenditure. The new Lagrangean would be:

$$L_w = X^{0.5}L^{0.5} + (\beta + \gamma)Z^{0.5} + \lambda(0.29 + 0.832(16 - L - Z) - X) \qquad \text{(A-98)}$$

Replacing A-88 in the new budget constraint we obtain:

$$0.29 + 0.832(16 - \frac{X_w^*}{0.832} - 3.27) - X_w^* = 0 \Rightarrow X_w^* = 5.44, L_w^* = 6.54, LS_w^* = 4.95 \qquad \text{(A-99)}$$

$$0.29 + 0.832(16 - \frac{X_m^*}{0.832} - 1.73) - X_m^* = 0 \Rightarrow X_m^* = 6.08, L_m^* = 7.31, LS_m^* = 5.59$$

C.2.3.1. UBI allocation for wages = 2*w*

Following the same steps as above it can be shown that when wages are doubled, the optimal allocation for women is:

$$Z_w^* = 1.64 \quad ; \quad X_w^* = 12.09 \quad ; \quad L_w^* = 7.27 \quad ; LS_w^* = 5.68 \qquad \text{(A-100)}$$

And for men:

$$Z_w^* = 0.87 \quad ; \quad X_w^* = 12.73 \quad ; \quad L_w^* = 7.65 \quad ; LS_w^* = 5.98 \qquad \text{(A-101)}$$

C.2.4. Paying domestic caregivers

The program promises to pay 75% of the minimum wage to unpaid domestic workers. This is equivalent to 51% of average spending. We will assume that the maximum number of hours a person can care for is 75% of full employment maximum number of hours is full time employment (6.8 hours) The new Lagrangean would be:

$$L_w = X^{0.5}L^{0.5} + (\beta + \gamma)Z^{0.5} + \lambda(0.51Z + 0.832(16 - L - Z) - X) \qquad \text{(A-102)}$$

f.o.c:

$$\begin{aligned}
\frac{\partial \mathcal{L}_w}{\partial X} &= 0.5X^{-0.5}L^{0.5} &&= \lambda \\
\frac{\partial \mathcal{L}_w}{\partial L} &= 0.5X^{0.5}L^{-0.5} &&= 0.832\lambda \\
\frac{\partial \mathcal{L}_w}{\partial Z} &= 0.5(\beta+\gamma)Z^{-0.5} &&= 0.322\lambda \\
\frac{\partial \mathcal{L}_w}{\partial \lambda} &= 0.51Z + 0.832(16 - L - Z) - X &&= 0
\end{aligned} \qquad \text{(A-103)}$$

In equilibrium:

$$\begin{aligned}
Z_w^* &= \frac{0.832(\beta+\gamma)^2}{0.322^2} > 6 \Rightarrow Z_w^* = 6 \\
Z_m^* &= \frac{0.832(\beta)^2}{0.322^2} > 6 \Rightarrow Z_m^* = 6
\end{aligned} \qquad \text{(A-104)}$$

Replacing Z^* and L^*:

$$0.51 * 6 + 0.832(16 - \frac{X_w^*}{0.832} - 6) - X_w^* = 0 \Rightarrow X_w^* = 5.66, L_w^* = 6.84, LS_w^* = 2.56$$

(A-105)

$$0.51 * 6 + 0.832(16 - \frac{X_m^*}{0.832} - 6) - X_m^* = 0 \Rightarrow X_m^* = 5.66, L_m^* = 6.84, LS_m^* = 2.56$$

C.2.4.1. Paying domestic caregivers, allocation for wages = 2w

Following the same steps as above it can be shown that when wages are doubled, the optimal allocation for women is:

$$Z_w^* = 1.7 \quad ; \quad X_w^* = 12.33 \quad ; \quad L_w^* = 7.41 \quad ; \quad LS_w^* = 5.51 \qquad \text{(A-106)}$$

And for men:

$$Z_w^* = 0.9 \quad ; \quad X_w^* = 12.79 \quad ; \quad L_w^* = 7.69 \quad ; \quad LS_w^* = 5.93 \qquad \text{(A-107)}$$

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