Three Essays in Labor and Regional Economics

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by

Juan David Duran Vanegas

Supervised by

Martina Kirchberger

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Declaration

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Juan David Duran Vanegas

Summary

This dissertation consists of three chapters. Chapter 1 uses the 1994 North American Free Trade Agreement (NAFTA) and granular data on Mexican municipalities to study the local effects of trade liberalization on college wage premiums, housing costs, and urban amenities between 1990 and 2010. I measure local exposure to international trade by constructing a market access database of each municipality's lowest-cost route to the closest US truck port. I find that municipalities facing larger trade exposure experienced: (1) declines in local wage differences between college and non-college graduates, both in nominal and real terms; (2) smaller increases in local urban amenities. I interpret these results under the notion of spatial equilibrium in which non-monetary urban amenities compensate for gaps in real wages across cities.

Chapter 2 analyzes the effects of the COVID-19 pandemic on labor market outcomes for men and women in Mexico. Using a large longitudinal dataset and an event-study design, I find that the labor market effects of the pandemic differed by gender and changed considerably over time. While men temporarily suffered from a higher probability of unemployment, women experienced greater and more persistent declines in labor force participation. By exploring the heterogeneity of the effects across sub-samples, I show that these disparities in the recovery of labor participation are mainly driven by increased childcare needs and are linked to women being over-represented in informal and part-time jobs.

Chapter 3 investigates how gender gaps vary across space and time using census microdata for Mexico during 1990-2010. I document that female-to-male gaps in working hours increased on average for all municipality sizes, but this increase was disproportionately greater in smaller compared to larger municipalities. This novel empirical pattern also coincides with a more rapid increase in the share of services in smaller locations that initially specialized in producing goods (primary activities and manufacturing). Motivated by these stylized facts, I quantify the impact of industry-specific labor demand shocks on local gender gaps in working hours and explore the heterogeneity of the effects across municipality sizes. I find that labor demand shocks in the goods industry only affect female relative work hours in small municipalities. My results suggest that the interaction between industry specialization across locations, industry differences in female labor intensities, and the rise of the service economy boosted female employment in smaller cities.

To the family I left in Colombia,
and the one I made in Dublin.

To understand something is to understand its topography,
to know how to chart it [...] *Time does not give one much leeway:*
it thrusts us forward from behind, blows us through the narrow funnel
of the present into the future. But space is broad, teeming
with possibilities, positions, intersections, passages, detours,
U-turns, dead ends, one-way streets.
Too many possibilities, indeed.

SUSAN SOTANG, 1981

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Introduction

This dissertation consists of three independent chapters. All chapters are related to labor economics and use location-level microdata to study the effects of different aggregate shocks in the context of the Mexican economy. Throughout the thesis, I examine the unequal effects of the North American Free Trade Agreement (NAFTA) in 1994, the COVID-19 pandemic in 2019, and the secular rise of the service economy between 1990-2010, along dimensions such as educational attainment, gender, and labor informality.

Chapter 1 uses the 1994 North American Free Trade Agreement (NAFTA) and granular data on Mexican municipalities to study the local effects of trade liberalization on wage differences between college and non-college graduates (i.e. college wage premiums), housing costs, and urban amenities between 1990 and 2010. I observe that while there has been increased attention to the effects of trade liberalization on local rather than aggregate labor markets, there is little evidence on how local economies are affected in terms of costs and quality of living. To guide my identification strategy, I use a spatial equilibrium model of location decisions with tradable sectors and transport costs to predict the effect of trade liberalization on local wages, rents, and endogenous amenities. In the model, trade openness reduces local skill premiums due to the relative factor abundance of low-skilled workers, thus inducing inter-city migration flows and endogenous responses in housing costs and urban amenities. Overall, the model predicts that regions with higher trade exposure will experience declines in local skill premiums, high-skill local labor shares, and urban amenities after trade liberalization.

I empirically test the model's predictions by exploiting the regional variation in the exposure to international trade given by the access of each municipality to the US market through the highway network. I find that municipalities with greater exposure to trade liberalization experienced significant declines in local high-skill labor shares, college wage premiums, and urban amenities compared to other locations. Hence, higher housing costs and lower urban amenities partially offset gains from trade liberalization in nominal wages for low-skill workers. I interpret the empirical results under the notion of spatial equilibrium in which non-monetary urban amenities compensate for changes in real wages across cities.

Chapter 2 seeks to contribute to the emerging literature on the labor market impacts of COVID-19 in middle-income economies by investigating the early unequal gender effects of the pandemic in Mexico. I argue that the high levels of informality that characterize the Mexican labor market and that are common to many low and middle-income economies might interact with the gender dimension leading to unequal effects of the pandemic. Using a large longitudinal dataset and an event-study design, I provide a detailed picture of the early labor market effects of the pandemic by examining the impacts on labor force participation, unemployment, work hours, and earnings through 2020, when Mexico went through a national lockdown during the first of three COVID-19 epidemic waves that have occurred up to December 2021. I find that the labor market effects of the pandemic differed by gender and changed considerably over time. On the one hand, women were more likely to leave the labor force than men, an impact that only materialized two months after the onset of the pandemic and increased over time. On the other hand, men experienced a larger probability of unemployment, an effect that was temporary and emerged right after the national lockdown. By exploring the heterogeneity of the effects across job characteristics and childcare responsibilities, I show that the differential effect of the pandemic on female labor participation is associated with increased childcare needs and women being over-represented in informal and part-time jobs.

Chapter 3 studies how gender gaps vary across local labor markets and the role of the economy's structural transformation towards services in explaining these spatial patterns. I document that although female-to-male gaps in working hours and service shares increased for all municipality sizes, these changes were disproportionately greater in smaller compared to larger municipalities. To rationalize the mechanism at play, I propose a simple theoretical model in which regional specialization patterns map into heterogeneous gender gaps across locations due to the gender-specific comparative advantages that differ across sectors.

The model's main theoretical prediction is that local productivity shocks' effect on female-to-male labor gaps decreases with city size. I test this prediction empirically using shift-share instruments for labor demand and a threshold estimation strategy that allows the estimated effects to vary with the initial population size. I find that labor demand shocks in the goods industry only significantly affect female relative working hours in small municipalities. My results suggest that the interaction between industry specialization across regions, industry differences in female labor intensities, and the rise of the service economy boosted female employment in smaller cities.

The main contribution of this thesis is to show how the effects of large economic shocks vary significantly across locations and population groups. First, chapters 1 and 3 focus on local rather than national-level effects. The emphasis on local effects is motivated by the fact that, although most economies are characterized by significant spatial heterogeneity in economic outcomes, most economic literature has historically focused on the sources of economic disparities across countries (Moretti, 2011). Second, chapters 2 and 3 highlight how the interaction between gender, sectoral labor composition, and labor informality is crucial when understanding the gender-differentiated effects of aggregate shocks. The findings illustrate how gender-neutral shocks such as structural transformation or the COVID-19 pandemic lead to gender-biased labor market effects due to this segregation across sectors and job types.

Chapter 1
Spatial Equilibrium and the Regional Effects of Trade Liberalization

1.1 Introduction

The widespread increase in international trade openness observed during the second half of the twentieth century has led to increasing interest and debate regarding the effects of globalization on overall welfare and income inequality. For developing economies, abundant in unskilled labor, the standard economic theory predicts wage gains for low-skill workers when opening to trade with more advanced economies. When bringing this theoretical prediction to the data, the literature has increasingly focused on variation in the exposure to trade liberalization across regions within a given country (Goldberg and Pavcnik, 2007) to identify the impacts of trade liberalization on wage inequality (Chiquiar, 2008; Hakobyan and McLaren, 2016), poverty (Topalova, 2010), and earnings and employment (Dauth et al., 2014; Dix-Carneiro and Kovak, 2017; Kovak, 2013; Autor and Dorn, 2013; Michaels, 2008).

This increased attention to the effects of trade liberalization on local rather than aggregate labor markets calls into question how local economies are affected in terms of costs and quality of living. In a simple spatial model of cities, workers' utility depends not only on nominal wages but also on the cost of housing and local amenities (Roback, 1982). While there is increasing evidence of the effects of trade liberalization on local labor markets, very little is known about the response of local rents and urban amenities, which are important parts of the picture when determining the welfare impacts of globalization.

This chapter aims to fill this gap in the literature by using the 1994 North American Free Trade Agreement (NAFTA) and granular data on Mexican municipalities to study the local effects of trade liberalization on nominal and real wage premiums for college graduates and urban amenities during the 1990-2010 period. Mexico offers a particularly suitable context for studying the local effects of trade liberalization. On the one hand, NAFTA created the largest free trade area after the European Union (Kose et al., 2004). On the other hand, Mexico has an interesting urban structure with an urban population of nearly 100 million and 54 large urban agglomerations.

The central contribution of this chapter is to study the regional effects of trade liberalization from a perspective in which trade opening generates local labor demand shocks, thus affecting workers' sorting by skill across locations due to migration and triggering cities' endogenous responses in terms of local rents and urban amenities. In that regard, given its focus on the Mexican experience with NAFTA, the chapter contributes to an emerging literature on the effects of labor demand shocks on local economies in the developing world (Chauvin, 2017).

A second contribution of the chapter lies in that I assemble a rich dataset with location-specific information on population, wages, industry structure, migration flows, rents, and a set of urban amenities, including the presence and quality of schools, public service provision, air quality, and crime, covering more than 400 Mexican municipalities between 1990 and 2010. In particular, the chapter adds to a recent literature measuring urban amenities across the space in developing economies (Gollin et al., 2021; Chauvin et al., 2017) and provides one of the first causal estimates of the response of urban amenities to changes in the composition of local residents.

From a theoretical standpoint, I adopt a standard spatial equilibrium framework and allow firms to export tradable goods with transport costs to a single foreign market. The model's structure is close to those of Moretti (2013) and Diamond (2016) but studies the effect of shocks to local industry prices induced by trade liberalization rather than local productivity shocks. Workers differ in skill and have heterogenous idiosyncratic preferences for locations. Local amenities respond to the composition of the location's residents by skill, while rental markets differ in their response to migration flows due to region-specific housing supply elasticities. Trade liberalization affects local wage gaps between high and low-skilled workers in this setting due to the relative factor abundance (i.e. the Stolper-Samuelson) effect. Changes in regional wage gaps also imply general equilibrium effects since they affect workers' location decisions and cities' responses in terms of housing costs and urban amenities (Moretti, 2013; Diamond, 2016).

Overall, the model predicts that regions with higher trade exposure experience declines in local skill premiums, high-skill local labor shares, and urban amenities after trade liberalization. To measure the spatial differences in the exposure to liberalization, I follow an increasing literature on market access (Maurer and Rauch, 2019; Donaldson, 2018; Donaldson and Hornbeck, 2016; Faber, 2014; Redding and Sturm, 2008) and construct a new dataset of each Mexican municipality's least-cost route to the closest port of entry to the US. These routes reflect the difficulty of transporting goods given the transport network density across the space. In my baseline measure, I exploit the fact that transport by truck concentrated nearly 70 percent of Mexican exports to the US between 1993-2010 and use the least-cost path between each municipality's centroid and the the closest US truck port given the Mexican highway network in 1990.

With market access as my proxy for international trade exposure in hand, I test the reduced-form predictions of the model to the data. I find that municipalities with greater exposure to trade liberalization experienced a significant reduction in local high-skill labor shares and greater declines in college wage premiums compared to other locations. In line with the literature on the effects of local labor demand shocks and skill sorting, I find that college premiums decreased more in nominal terms than in real terms once wages are deflated with municipality-specific average rents. Furthermore, I find that municipalities facing larger exposure experienced smaller increases in urban amenities, an effect driven by lower school quality, higher air pollution, and increased crime rates. These results are robust to a wide variety of checks accounting for alternative drivers such as pre-NAFTA changes in import tariffs and privatization, as well as alternative measurements of exposure to international liberalization and a different definition of spatial boundaries.

My findings provide empirical support to the model's predictions and are consistent with the notion of spatial equilibrium in which non-monetary urban amenities compensate for changes in real wages across cities (Gollin et al., 2021; Chauvin et al., 2017; Roback, 1982). In that line, my findings suggest that higher housing costs and lower urban amenities partially offset gains in nominal wages for low-skill workers in more exposed municipalities due to labor mobility and changes in skill sorting across locations. Therefore, utility gains from trade liberalization for low-skill workers were smaller than the gains in nominal wages. The findings on skill premiums are consistent with the Stolper-Samuelson theorem that predicts increased relative remuneration to the relatively abundant factor in the Heckscher-Ohlin model. Hence, these results go in line with those of Chiquiar (2008), who finds that the effect of NAFTA on skill premiums is consistent with the Stolper-Samuelson prediction for regions closer to the US border. Moreover, the negative regional impact of trade liberalization on endogenous urban amenities resonates with Diamond (2016) and Carlino and Saiz (2019), who highlight the role of skill shares as determinants of local consumption amenities.

The chapter relates to a growing literature on the regional effects of trade liberalization (Dix-Carneiro et al., 2018; Dix-Carneiro and Kovak, 2015; Autor et al., 2013; Kovak, 2013; Topalova, 2010; Michaels, 2008). While this literature has traditionally considered effects on regional wage premiums, employment, and poverty, my results suggest that the responses of local rents and amenities are relevant to determining the effects on broader welfare gaps among high and low-skilled workers. My setting is particularly close to Chiquiar (2008) and Hanson (2003a), who study the effects of NAFTA on skill premiums in Mexico, taking into account the heterogeneous impacts by broad regions according to their proximity to the US border. This chapter differs in that I measure trade exposure more precisely using the existing highway network at baseline and expand the analysis to consider the effects on costs and quality of living.

The chapter also relates to a growing body of literature on location decisions and local economic outcomes in a spatial equilibrium framework (Chauvin, 2017; Diamond, 2016; Moretti, 2013; Notowidigdo, 2011; Katz and Murphy, 1992). Most related to this chapter are recent studies on the role of internal geography and trade costs on the spatial distribution of economic activity (Allen and Arkolakis, 2013), wage inequality (Farrokhi and Jinkins, 2019), and regional specialization (Coşar and Fajgelbaum, 2016).[1] Work by Fan (2019) is particularly close to my approach since it quantifies the distributional impacts of international trade in China using a spatial equilibrium model with international trade

[1] In this sense, the chapter also connects to a broader literature on the effects of market access and trade integration on economic activity (Maurer and Rauch, 2019; Donaldson and Hornbeck, 2016; Faber, 2014; Redding and Sturm, 2008).

costs. In this chapter, I adopt a more empirical approach by testing the model's predictions rather than using structural estimation. This methodology allows me to study the effects on a broader range of outcomes, thus overcoming limitations given by the availability of data and exogenous sources of variation to estimate multiple parameters simultaneously. Moreover, following Diamond (2016), I explicitly measure endogenous amenities instead of backing them out as residuals and keeping them constant, thus relating to a growing literature on the endogenous reaction of urban amenities to the composition of local residents (Bayer et al., 2007; Handbury, 2021).

This chapter is organized as follows. Section 1.2 presents a brief description of the trade agreement and its overall implications for the Mexican economy. Section 1.3 presents the theoretical model. Section 1.4 describes the data sources and documents some descriptive facts. Section 1.5 presents the identification strategy and discusses the estimation results. Section 1.6 concludes.

1.2 Context

Mexico engaged in a policy of unilateral trade liberalization by joining the General Agreement on Tariffs and Trade (GATT) in 1986. Trade reforms considerably lowered the average tariff rates and the number of products subject to quotas. These trade policies were part of a broader package of structural reforms that involved the liberalization of financial and exchange rate markets. Despite this drastic reduction in trade barriers, total trade as a share of GDP remained below 40 percent for the rest of the 1980s decade (Figure A2.1).

NAFTA negotiations started in 1991 and moved forward quickly as Canada, Mexico, and the US have had previous bilateral trade discussions since 1985. The agreement came into effect in June of 1994 and created the largest free trade area after the European Union (Kose et al., 2004). Mexico eliminated many tariffs on US products and agreed to remove other tariff and non-tariff barriers to trade over a period of fifteen years. As a result, between 1993 and 2001, the average tariff rate in Mexico fell from 12 percent to 1.3 percent, while the US tariff on Mexican exports decreased from 4 percent to 2.5 percent (Figure A2.3).

The trade agreement implied a drastic change in Mexican balance trade (Figure A2.1).

According to the US Census Bureau data, Mexican exports to the US expanded 4.5 times from \$30.1 billion in 1990 to \$135.9 billion in 2000. As a result, Mexico's trade balance with the US went from a deficit of USD 1.3 billion in 1994 to a surplus of USD 24.6 billion in 2000. Trade composition between the US and Mexico also changed markedly after NAFTA. UN Comtrade data shows that Mexican exports to the US changed from petroleum and related products to electrical and non-electric machinery, transport equipment, and clothing after 1994. Imports from the US, mainly consisting of machinery, transport equipment, chemicals, and cereals before NAFTA, further concentrated on electrical machinery with substantial increases in clothing and textile yarns. These product patterns suggest a rise in intra-industry trade of auto parts and textiles after the agreement (Burfisher et al., 2001).

NAFTA was enacted in the context of a financial crisis in Mexico (the Mexican peso or Tequila crisis) that followed the currency's devaluation due to pressure on the current account. While inflation soared to 35 percent and real GDP plunged 6.3 percent in 1995, the economy swiftly recovered amidst fiscal and monetary reforms implemented under external financial support from the International Monetary Fund and the US (Edwards, 1997). As indicated by Kose et al. (2004), the fact that trade reforms started in the mid-1980s with unilateral liberalization and that the economy went into a financial crisis after adopting the agreement pose difficulties when isolating the effects of NAFTA on the Mexican economy.

Rather than studying the aggregated effects of NAFTA, this chapter focuses on the local effects of the agreement. Regional disparities in the effects of NAFTA have been highlighted by different studies (Baylis et al., 2012; Chiquiar, 2008; Airola and Juhn, 2005; Hanson, 2003b). Chiquiar (2008), for instance, finds that more exposed regions exhibited an increase in overall wages and a decrease in the skill premium relative to other regions. Baylis et al. (2012) show that NAFTA caused wealthy regions closer to the US border to grow faster and reduced the agglomeration economies of locations in more densely populated areas in the center of the country. In a similar line, Chiquiar (2005) finds NAFTA induced a process of regional divergence in which northern regions closer to the US border reaped most of the benefits from trade. The distribution of exports to the US across states is informative about this regional variation in the benefits of NAFTA and the comparative advantage of northern regions to capitalize on the reduced trade barriers.

While the information on trade at the state level was not available before 2007, it is worth noting that by 2010 the six states located on the border with the US represented 54.8 percent of the total Mexican exports (Figure A1.2).

1.3 The Model

In this section, I present a simple model of location decisions that shares most of the features of the canonic setting of Roback (1982) extended with heterogeneous labor by skill and limited elasticity of local labor supply by Moretti (2013) and endogenous amenity supply by Diamond (2016). I allow for two sectors with different skill intensities and firms to trade with a single foreign market to incorporate the Heckscher-Ohlin mechanism of trade liberalization (Burstein and Vogel, 2017). Since the main goal of the model is to rationalize the mechanisms and develop testable predictions, it abstracts from more complex spatial equilibrium and regional models of international trade that incorporate features such as monopolistic competition through production varieties, interregional trade, and non-tradable sectors (Fan, 2019; Farrokhi and Jinkins, 2019; Coşar and Fajgelbaum, 2016; Arkolakis et al., 2012). As a result, the model's structure is closer to those of Moretti (2013) and Diamond (2016) but studies the effect of shocks to local industry prices induced by trade liberalization rather than local productivity shocks.

1.3.1 Setting

The economy has J regions indexed by j, and it is endowed with a fixed number of high-skill (N_H) and low-skill workers (N_L). Workers choose a region to live in and are perfectly mobile across regions. Each worker provides one unit of labor that is inelastically supplied. In each region j, there are two industries $k \in \{h, l\}$ with many firms that produce tradable goods using high-skill and low-skill labor as inputs in perfectly competitive markets. Regions are connected to an international transport network that allows firms to export goods with iceberg costs, such that $\tau_j > 1$ units have to be shipped from region j for one unit to arrive at the international market.

1.3.2 Consumption Preferences and Labor Supply

Each worker i with skill s obtains utility from the consumption of a bundle of local tradable goods C_j and housing Q_j, and local amenities a_j. Preferences have a Cobb-

Douglas form on the consumption of housing and local goods and are represented by the following function:

$$U_{ij}^{s} = \left(\frac{C_j}{\alpha}\right)^{\alpha} \left(\frac{Q_j}{1-\alpha}\right)^{1-\alpha} a_j z_{ij}, \tag{1.1}$$

where $\alpha \in [0,1]$ is the share of expenditure on the tradable good and z_{ij} is a location preference shock. The bundle C_j is defined as an aggregation of the local tradable goods of each industry (h,l) produced in the region j using a constant elasticity of substitution $\sigma > 0$:

$$C_j = \left[(C_{hj})^{\frac{\sigma-1}{\sigma}} + (C_{lj})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}. \tag{1.2}$$

The location preference shock of worker i living in location j is assumed to be drawn from an independent Frechét distribution:

$$F(z_{ij}) = e^{-E_j^{-\epsilon}}, \tag{1.3}$$

where E_j is the mean utility of living in the region j and ϵ is a shape parameter that governs the dispersion of the idiosyncratic component z_{ij}. Each worker earns a wage W_j^s and maximizes her utility facing the following budget constraint:

$$W_j^s = P_j C_j + R_j Q_j, \tag{1.4}$$

where P_j is the CES price index of the consumption bundle of local tradable goods C_j and R_j is the rental price in each region j. Taking the location as given, the solution of the utility maximization problem implies that the indirect utility of worker i living in the region j can be expressed as:

$$v_{ij}^{s} = \frac{W_j^s}{P_j^{\alpha} R_j^{1-\alpha}} a_j z_{ij}. \tag{1.5}$$

The consumption maximization problem also provides the housing demand of worker i:

$$Q_{ij} = (1-\alpha)\,\frac{W_j^s}{R_j}. \tag{1.6}$$

Each worker then decides the region j that offers the maximum utility. As the indirect utility is a monotonic function of the location preference shock z_{ij}, the properties of the Frechét distribution imply that the probability that a worker i of skill type s chooses to reside in the location j compared to all other locations $-j$ is:

$$\pi_{jk} = \left(\frac{W_j^s/P_j^{\alpha}R_j^{1-\alpha}a_j}{W_k^s/P_k^{\alpha}R_k^{1-\alpha}a_k}\right)^{\epsilon}. \tag{1.7}$$

Adding the probability across regions, the population of workers of skill type s residing in location j is:

$$N_{sj} = \sum_{i\in\mathcal{S}} \frac{\left(W_j^s/P_j^{\alpha}R_j^{1-\alpha}a_j\right)^{\epsilon}}{\sum\limits_{j=1}^{J}\left(W_k^s/P_{-j}^{\alpha}R_{-j}^{1-\alpha}a_{-j}\right)^{\epsilon}}, \tag{1.8}$$

where $\mathcal{S}$ is the set of workers of skill type s.

1.3.3 Production and Labor Demand

The production of tradable goods in each industry $k = \{h, l\}$ occurs in perfectly competitive markets by combining low-skilled (L_{kj}) and high-skilled (H_{kj}) labor under constant returns to scale. Industry h can be interpreted as a modern sector, while industry l can be interpreted as a traditional sector. The production technology follows a Cobb-Douglas form:

$$Y_{kj} = A_{kj}\left(L_{kj}\right)^{\beta_k}\left(H_{kj}\right)^{1-\beta_k}, \tag{1.9}$$

where A_{kj} is the local productivity of industry k in region j and $\beta_k \in (0,1)$. In the following, it is also assumed that the production of the modern sector is relatively intensive in high-skilled labor, so that $\beta_l > \beta_h$.

Firms take the prices of final goods (P_k), factor prices (W_j), export shipping costs (τ_j), and local productivities (A_{kj}) as given. Profit maximization implies that the local skill premium in location j, π_k, can be expressed as:

$$\pi_j \equiv \frac{W_j^H}{W_j^L} = \frac{\beta_k}{1-\beta_k}\frac{H_j}{L_j}. \tag{1.10}$$

Profit optimization also implies that prices must equal marginal costs in each industry k:

$$p_{kj} = \bar{p}_{kj}\tau_j, \tag{1.11}$$

where $\bar{p}_{kj} \equiv {(W^H)^{\alpha_k}(W^L)^{1-\alpha_k}}/{A_{kj}}$ is the unit cost of production in sector k and region j.

1.3.4 Housing Rental Market

Housing is supplied competitively by absentee landowners at a price R_j following a reduced-form housing supply function:

$$M_j = M_j^0 \left(R_j\right)^{\kappa_j}, \tag{1.12}$$

where M_j is the supply of housing in region j, M_j^0 is a location-specific exogenous constant that captures the differences in land availability, and $\kappa_j \geq 0$ is a parameter that captures the elasticity of the housing supply given by exogenous geographic and regulatory constraints. The larger the parameter κ_j, the larger the response of housing costs to the housing supply and, as a result, the lower the elasticity of housing supply.

Using Eq. 1.6 to aggregate the housing demand across all workers of skill type s ($i \in \mathcal{S}$) in region j allows for pinning down the rental price R_j:

$$R_j = \left[\frac{(1-\alpha)\left(N_j^H W_j^H + N_j^L W_j^L\right)}{M_j^0}\right]^{\frac{1}{\kappa_j+1}}. \tag{1.13}$$

1.3.5 Amenities Supply

Residents of location j have access to a set of amenities a_j that capture local features that make places attractive to live in. As in Lee and Lin (2018), it is assumed that the vector of amenities is a combination of a component of persistent natural amenities (a_j^0) and a component that is endogenous to the residents' composition (B_j). Hence, B_j is intended to capture features related to school quality, retail stores, environmental quality, and public infrastructure, among others. Following Diamond (2016), the provision of the endogenous component B_j is assumed to be a function of the ratio of high-skill to low-skill residents in region j:

$$a_j = a_j^0 B_j = a_j^0 \left(\frac{N_j^H}{N_l^H} \right)^{\gamma}, \tag{1.14}$$

where γ is a parameter that captures the elasticity of amenity supply to the high-skill to low-skill workers ratio. This structure in the supply of amenities builds on the notion that urban amenities react to residents' income directly (Lee and Lin, 2018; Guerrieri et al., 2013). Empirically, I observe amenities related to school presence and quality, air quality, public service provision, and crime. In that sense, the overall endogenous amenity component can be understood as a composite bundle that also incorporates the provision of local goods, as modeled explicitly by Fajgelbaum et al. (2015).

1.3.6 Equilibrium

Given the parameters of the model $\{\alpha, \epsilon, \beta_h, \beta_l, \sigma, \gamma\}$ and the vectors of exogenous variables $\{R_j, A_j, d_j, \kappa_j, M_j^0, a_j^0\}$, the spatial equilibrium is defined as a menu of wages, populations, rents, and endogenous amenities $\{W_j^h, W_j^l, N_j^h, N_j^l, R_j, a_j\}$ that satisfy the clearing conditions in the labor market (Eq. 1.8 and Eq. 1.10), the rental market (Eq. 1.13), and the endogenous amenity supply (Eq. 1.14).

1.3.7 Effects of Trade Liberalization

Assume the economy opens up to trade with a skill-abundant country with identical production technologies and consumer tastes. Trade liberalization increases the relative price of the traditional sector, thus increasing the marginal product and wages in that sector. Since the traditional sector is intensive in low-skill labor, trade liberalization decreases local skill premiums (the Stolper-Samuelson effect). This effect varies by location through the heterogeneity in trade costs as stated by Eq. (1.11). As a consequence, the model predicts declining nominal skill premiums in locations with higher market access.

Changes in wages induce migration flows that differ by skill. In particular, higher wages for low-skill workers induce a migration flow in location j, thus reducing the high-skill labor share in that location (Eq. 1.8). In turn, the reduced high-skill share implies a reduced supply of urban amenities as indicated by Eq. (1.14).

Effects on population and wages determine the impact on local rents that is mediated by the elasticity of housing supply (Eq. 1.12). Net migration flows of low-skill workers are set to increase total population in more exposed locations in response to higher wages, thus leading to higher local rents in these municipalities. As a result, real skill premiums (i.e., the wage gap in rent-deflated nominal wages) are set to decrease less than nominal skill premiums. Overall, the model predicts that regions with higher trade exposure experience declines in local skill premiums, high-skill local labor shares, and urban amenities after trade liberalization. In the following sections, I describe the data and methods I use to test these predictions empirically.

1.4 Data

As observed by Gollin et al. (2021), comparisons of real wages and urban amenities across locations are challenging due to the lack of high-quality disaggregated data. This chapter uses a rich dataset of wages, housing rents, urban amenities, and exposure to international trade at the municipality level that I have assembled for Mexico for the 1990-2010 period. Observation units in my baseline sample are municipalities, defined at the lowest level of administrative division, with more than 10 thousand inhabitants in 1990.[2] The resulting dataset covers 446 municipalities, representing 63.4 percent of the total Mexican population in 1990. The following subsections describe the dataset's sources, metrics, and descriptive facts.

[2] I test the robustness of my findings to defining spatial units using metropolitan areas defined by the National Institute of Statistics and Geography (INEGI) to aggregate municipalities that are economically integrated and include all municipality sizes.

1.4.1 Wages, Rents, and Urban Amenities

My main outcomes on wage differences, college graduate shares, and migration rates come from 10 percent samples of the 1990, 2000, and 2010 Population and Housing Census prepared by the National Institute of Statistics and Geography (INEGI). Using census data on individual workers, I compute skill premiums and high-skill labor shares at the municipality level. I restrict the sample to workers between 16 and 65 years old who work at least 5 hours per week.[3] In line with the literature on the geographic sorting of workers by skill (Diamond, 2016; Moretti, 2013, 2011; Notowidigdo, 2011), high-skill workers are defined as individuals who have obtained a college or postgraduate degree. Following the literature on wage structure and inequality (Baum-Snow et al., 2018; Autor and Dorn, 2013), I compute the skill premium in each municipality as the difference in average hourly wages adjusted from a Mincerian regression that controls for gender, age, and year effects. To measure internal migration flows, I use the population share of workers residing in a different municipality than the one reported in the previous census year. While NAFTA could have affected international migration decisions, I focus on the effects on internal migration across municipalities following the approach of most models on location decisions and skill sorting. Local college shares should nevertheless capture potential disproportionate changes in international migration rates for certain skill types. In the robustness analysis, I test for local international migration rates as an alternative explanation of my results.

In order to measure municipality-specific housing costs, I use anonymized microdata from the National Household Income and Expenditure Surveys (GEIH) from 1994 to 2016 at the household level. These surveys are nationally representative and are carried out every two years. Nevertheless, the geographic coverage of the survey is considerably lower than the census, which constraints my sample of municipalities. In the Appendix A1.7, I also show that my main results on labor outcomes and amenities hold when using the full sample of municipalities without this restriction on the availability of rents.

I measure housing costs as the municipality average of each household's estimated re-

[3] A relevant question is whether the census covers informal workers. While the 1990 census does not include information on registries to social security, the share of workers declaring positive labor earnings without health insurance in 2010 is 37.7%, which matches the informality rate of 37.4% for wage earners estimated with different data sources by Alcaraz et al. (2015). Comparing job tenure as a proxy of labor informality, the share of employed workers is similar between 1990 and 2010 (between 51% and 44.8%).

ported rent. In order to control for potential changes and quality improvements of the dwellings, I adjust reported rents by regressing them against a vector of physical characteristics that include floor, ceiling, and wall materials, number of rooms, and the availability of electricity, sewage, and piped water. All regressions are weighted using survey household weights. Using rents to proxy for the cost of living across municipalities is motivated by the high share of housing in the total expenditure of households and a long tradition in the literature of urban economics. Nevertheless, one concern is that changes in non-housing prices might go in a different direction, thus altering my findings on real college wage premiums. In the Appendix A1.6, I construct an index capturing other expenditure components included in the GEIH survey and show that my findings on real wage differences are robust to this alternative deflator.

In order to measure local urban amenities, I use a set of indicators from the INEGI States and Municipalities Database (1990-2010) that include teachers and schools per 1,000 students, public service provision (share of dwellings with access to electricity, piped water, and sewage), and violent crime (as measured by intentional homicides per 1,000 inhabitants) at the municipality level. Additionally, I use satellite estimates of ambient nitrogen dioxide (NO_2) pollution between 1996-2010 coming from Geddes et al. (2016) and concentration of particular matter with a diameter below 2.5 ($PM_{2.5}$) micrometers between 1998-2010 coming from van Donkelaar et al. (2021) to proxy for air quality. Finally, to reduce the dimensionality of the empirical analysis, I follow Diamond (2016) and use principal component analysis (PCA) to combine these eight different measurements into a single index.

Compared to the approach of Diamond (2016), I also measure school, violent crime, and air quality amenities. I do not observe other components included in her analysis related to retail (apparel stores, eating and drinking places, and movie theaters), transportation (public buses and average daily traffic), and job quality (parents per capita and employment). Hence, my metrics are more related to the local government's ability to provide public goods and less connected to the presence of leisure and consumption amenities. In this regard, it is worth highlighting the role of local governments in determining school and public service outcomes. Education in Mexico is mainly provided by public schools that represent an average share of 89% in primary and secondary school enrollment. Local funding shares in education expenditure vary considerably across states. According to the

Secretariat of Public Education, state shares in education expenditure ranged from 2.4 to 49.6% in 2010. INEGI's data on local public finances also suggests that the expenditure shares in public investment also varied considerably across states, ranging between 5 to 47% during 1990-2010.

Table 1.1 reports summary statistics for the main outcomes. On average, college employment shares across municipalities increased from 9% to 15.7% between 1990-2010. Wage differences between college and non-college workers, captured by the nominal wage premium, decreased from 4.8% in 1990 to 3.2% in 2010, although there was a strong increase to 6.5% in 2000. This increase in the college premium at the national level between 1990-2000 appears puzzling against the predictions of the standard trade theory, as Mexico had already started its process of trade liberalization during the 1980s and NAFTA was enacted in the mid-1990s. Nevertheless, as noted by Chiquiar (2008) and Robertson (2004), increased trade integration occurred with NAFTA, and year-level data suggests that the college premium started decreasing after NAFTA was enacted.

Table 1.1 also reports that average migration rates are higher for college graduates (5.3% on average) than for non-college graduates (3.5% on average). Moreover, on average, all urban amenities (except homicide rates) improved across municipalities implying more teachers and schools per 1,000 students, higher access to tap water, sewage connection, electricity, and lower concentration of nitrogen dioxide and particular matter.

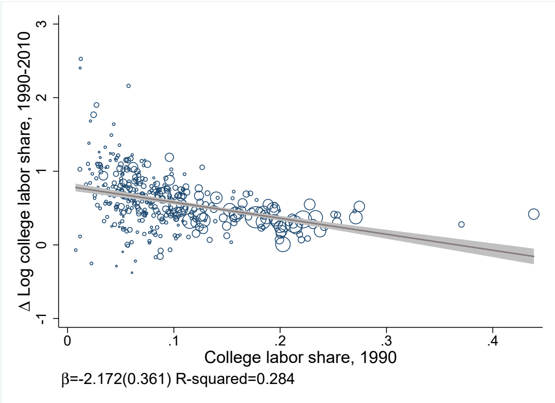
A crucial question is how the skill sorting and wage differences changed over time across municipalities. Panel A of Figure 1.1 shows that the change in the employment share of college graduates between 1990 and 2010 is negatively related to the initial college share in 1990. Panel B and C show the lack of spatial convergence in wages by plotting the log hourly wage in 1990 against 2010 for college graduates and non-college graduates, respectively. The slope of the regression line is 0.26(0.05) for college graduates and 0.64(0.07) for non-college graduates, which implies that spatial differences increased more for non-college graduates. These stylized facts suggest that the overall reduction in the college wage gap across municipalities was accompanied by decreased skill sorting of college graduates and larger spatial differences in non-college wages. These patterns also suggest that the main driver of the resorting of workers across locations is potentially related to a shock to low-skill wages.

Table 1.1: Summary Statistics.

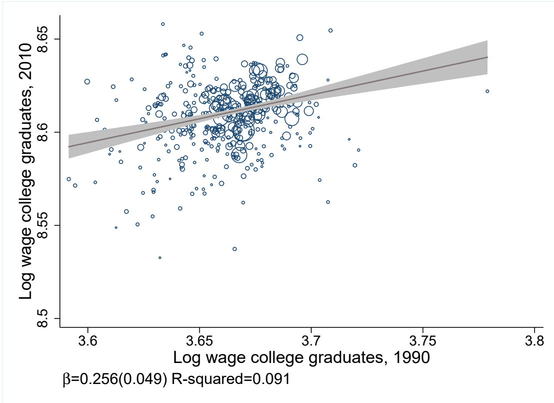
	1990	2000	2010
College employment share (%)	0.090	0.138	0.157
	(0.059)	(0.066)	(0.086)
Log non-college wage	2.255	3.815	4.655
	(0.335)	(0.307)	(0.272)
Log college wage	2.985	4.764	5.523
	(0.324)	(0.388)	(0.356)
Nominal college premium (%)	0.048	0.065	0.032
	(0.031)	(0.030)	(0.024)
Log average rent	5.308	5.802	5.792
	(0.335)	(0.346)	(0.325)
Non-college migration rate (%)	.	0.037	0.031
	(.)	(0.039)	(0.028)
College migration rate (%)	.	0.055	0.049
	(.)	(0.053)	(0.045)
Teacher-to-student ratio*	4.091	4.620	4.957
	(0.618)	(0.728)	(0.788)
School-to-student ratio*	0.787	0.941	0.930
	(0.417)	(0.637)	(0.575)
Dwellings with electricity (%)	0.841	0.921	0.960
	(0.155)	(0.089)	(0.049)
Dwellings with piped water (%)	0.749	0.799	0.887
	(0.190)	(0.161)	(0.128)
Dwellings with sewage connection (%)	0.528	0.699	0.862
	(0.242)	(0.227)	(0.145)
Particular matter	30.759	11.318	11.318
	(16.930)	(5.004)	(5.004)
Nitrogen dioxide	0.938	0.793	0.763
	(1.734)	(1.426)	(1.273)

Notes: Mean outcomes across municipalities by census year. Standard deviations in parentheses. *Measurements per 1000 students.

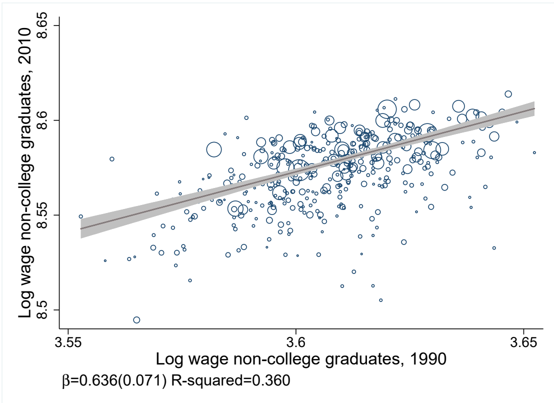
Figure 1.1: Changes in Skill Sorting and Wages across Municipalities.



Panel A.



Panel B.



Panel C.

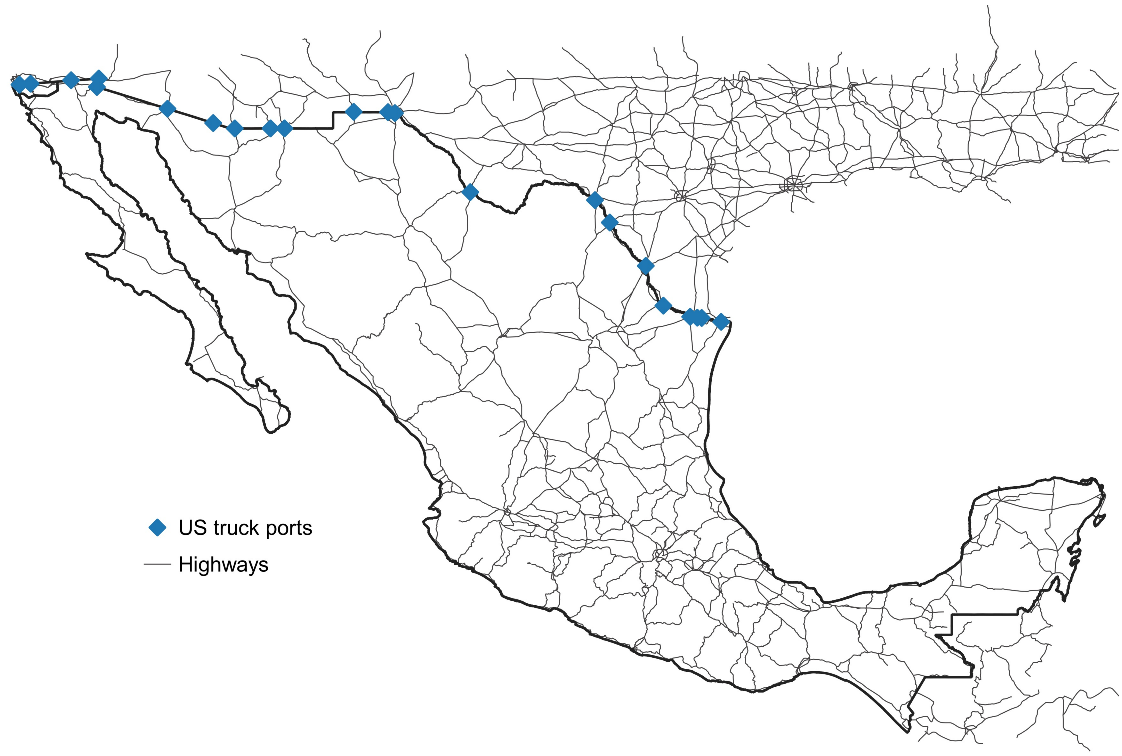
Notes: Panel A plots the share of college graduates in 1990 against the log change of college graduates between 1990-2010. Panels B and C plot the log hourly wage in 1990 against 2010 for college and non-college graduates, respectively. There are 446 municipalities. The size of the bubbles is proportional to the total population in 1990. Lines are OLS fit regressions weighted by log population in 1990.

1.4.2 Market Access

Following recent work on the economics of internal geography (Farrokhi and Jinkins, 2019; Allen and Arkolakis, 2013; Donaldson, 2018; Donaldson and Hornbeck, 2016), I use maps of transport networks to build measurements of market access as the least-cost paths between each Mexican municipality and the US. More specifically, I compute least-cost routes using Dijkstra's algorithm in R to find the shortest path between nodes in a two-dimensional network. My baseline measurement is based on transport by truck due to the fact that this transport mode concentrated 67 percent of total Mexican exports to the US on average (Figure A1.4). In the robustness analysis, I make my measurement more flexible by including transport by rail and vessel.

Least-cost paths computation requires three inputs: source nodes, destination nodes, and the cost surface. Source nodes in the algorithm are centroids of each Mexican municipality, while destination nodes are given by the coordinates of the 22 ports that received loaded truck containers from Mexico in 1996, according to the Border Crossing Database of the US Bureau of Transport Statistics (BTS). To create the cost surface, I use rasterized data of the Mexican highway network of Mexico in 1990 from the Commission for Environmental Cooperation's North American Environmental Atlas and assign a lower cost to the pixels with higher highway density. Figure 1.2 plots the raster of the road network and the ports' location as vector points. As Farrokhi and Jinkins (2019) and Allen and Arkolakis (2013), I take the transport network as fixed in order to capture the initial exposure to international trade.[4]

Figure 1.2: Highway Network and US Truck Ports.

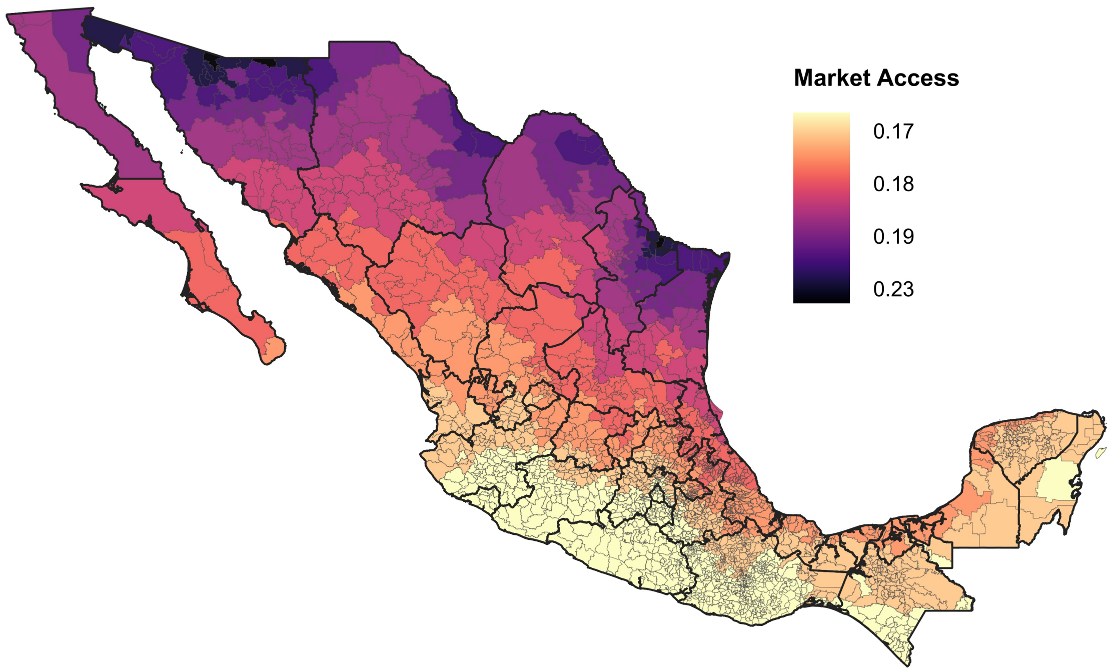


Notes: The map plots the Mexican highway network in 1990 from the North American Environmental Atlas. Blue vector points denote the location of the US ports that received loaded truck containers from Mexico in 1996, according to the Border Crossing Database of the US BTS.

[4]Appendix A1.5 contains details on the construction of the market access measure.

Departing from each destination node, the algorithm computes the tentative cost to all unvisited surrounding pixels at each point of the route and assigns the smaller one until a destination node is visited. In the empirical analysis, I use the inverse of the least-cost route of each municipality to the closes US truck port in logs as the baseline measurement for market access. Figure 1.3 presents this international market access measurement. While municipalities located in the north tend to have better market access to the US market, there exists variation due to the road density and the relative position of the ports on the border. The municipality with the shortest least-cost path is Sáric, state of Sonora, which is only 24 kilometers away from the Sasabe Port in Arizona; the municipality with the largest least-cost route is Cozumel, state of Quintana Roo on the Yucatán Peninsula, which is 3,155 kilometers away from the Port of Brownsville in Texas. The average least-cost route to the closest US truck port is 1,423 kilometers.

Figure 1.3: Market Access to Closest US Truck Port by Municipality.



Notes: The map plots the inverse of the log distance between each municipality's centroid and the closest US port depicted in Figure 1.2. Distances are computed using Dijkstra's algorithm with a cost surface given by the rasterized highway density given Mexico's highway network in 1990. Thick black lines depict state borders. Thin gray lines depict municipality borders.

1.5 Identification and Estimation Results

1.5.1 Empirical Strategy

To identify the effect of trade liberalization on local labor and urban outcomes, I use the following specification:

$$\Delta \log y_j^{t,t+1} = \delta \log TE_j^t + \Gamma \mathbf{X}_j^t + \mu_{state} + \epsilon_j^{t,t+1}, \tag{1.15}$$

where $\Delta y_j^{t,t+1}$ is the change in the local outcome of interest (college graduate shares, skill premiums, urban amenities) between period t and $t+1$ in municipality j, TE_j is a measure of trade exposure at baseline, X_j^t is a vector of controls for initial characteristics, and μ_{state} are state-fixed effects.

The specification in Eq. 1.15 compares the change in local equilibrium outcomes among municipalities (Dix-Carneiro and Kovak, 2017; Goldberg and Pavcnik, 2007). The coefficient of interest is δ, and I estimate it using within-state variation in market access as my measurement of trade liberalization exposure. For my baseline estimates, I set t =1990 and $t+1$ =2010. All regressions are weighted by log population in 1990, and standard errors are clustered at the municipality level.

The identifying assumption to consistently estimate δ in Eq. 1.15 is that errors must not be correlated to my measurements of trade exposure conditional on the vector of controls $Cov\left(\epsilon_j^{t,t+k}, TE_j^t | \mathbf{X}_j^t\right) = 0$. This assumption would be violated if there are variables not captured by the vector of controls ($\mathbf{X}_j^t$), correlated with market access (TE_j^t), and driving the local outcomes. One such concern is the nonrandom placement of highways that can be correlated to unobservable determinants of my outcomes. To address this concern, I consider a wide range of base-year controls, including urbanization rates, college graduate shares, elevation, and distance to the closest coastline. My identification strategy also benefits from the fact that the basic structure of the Mexican road network was established between 1970-1975, and road construction remained practically stagnant between 1978-1993 (Rangel, 2015), which reduces the likelihood of my market access measurements to capture outcome pre-trends before the adoption of NAFTA. Nonetheless, in Appendix 1.5.3 of this section, I show that my results are robust to different potential confounders such as pre-NAFTA trends in local US tariff declines (Kovak, 2013) or changes in government employment that proxy for variation in privatization across municipalities.

1.5.2 Estimation Results

This subsection presents the estimation results of the coefficient of trade exposure. Even when I also present estimation results with no controls, my preferred specifications include controls and state-fixed effects.

I start by presenting the estimation results for the effects on local labor markets. According to the model's predictions, more exposed municipalities should experience stronger declines in college graduate shares and college wage premiums. All the estimates in Table 1.2 for the coefficient of market access are negative and statistically significant at the 5% level, implying that municipalities facing larger exposure to international trade experienced proportional declines in college graduate shares and college premiums. According to the estimates in column (2), a one percent increase in market access leads to 1.36 percent average decline (or a smaller increase) in the share of college graduates. Columns (3) and (4) show the estimation results when the outcome of interest is the change in log college wage premium. I find that college wage premiums decreased significantly more in locations that faced larger trade exposure. Local college premiums in nominal wages decreased 0.1 percent for a one percent increase in market access. Since college premiums are defined as the wage difference between college and non-college graduates, declines imply relative wage gains for non-college graduates. These estimated effects on local wage differences are in line with the findings of Chiquiar (2008), who uses distance to the US border and share of maquiladora employment to show that more exposed Mexican regions experienced significant decreases in skill premiums compared to other regions. These estimated effects of trade liberalization on local labor markets are economically large. Moving from the minimum to the maximum trade exposure across municipalities implies a decrease in the college share of 27.1%, one-third of the mean growth observed during 1990-2010. Similarly, going from the lowest to the highest trade exposure at baseline implies a 2.42 percentage point decline in college wage premiums, 1.5 times the mean observed decrease from 1990 to 2010.

I then turn to the effects on college wage premiums in rent-deflated wages. Columns (5) and (6) of Table 1.2 show that when nominal wages are deflated with municipality-specific rent indices, the effect of the exposure to trade liberalization on college premiums slightly decreases to -0.09 percent for a one percent increase in trade exposure. This result goes in line with the theoretical model's predictions and indicates that average rents partially offset the increase in nominal wages for non-college graduates. In the model, higher rents occur due to additional population caused by the net inflow of workers responding to changes in wage differences across locations.[5] More broadly, the difference between the effects on nominal and real wage gaps is in line with Moretti (2013) in that higher housing costs erode the benefits of local shocks to wages.

Table 1.2: Effects of Trade Liberalization on Local Labor Market Outcomes.

	Δ Log college labor share		Δ Log college premium		Δ Log college premium - rent deflated	
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.613**	-1.364***	-0.121***	-0.101**	-0.108***	-0.094**
	(0.2822)	(0.4494)	(0.0238)	(0.0475)	(0.0203)	(0.0447)
Obs.	446	446	446	446	446	446
R-squared	0.011	0.431	0.064	0.388	0.056	0.363
Controls	No	Yes	No	Yes	No	Yes

Notes: Results of the coefficient estimates for local market access by road. Changes are measured between 1990 and 2010. Skill premiums are computed as the difference between average residualized wages of high-skill and low-skill workers for each municipality. Real skill premiums are computed after deflating nominal residualized wages with municipality-specific rent indices. All specifications are weighted by 1990 population andinclude a constant term. Controls include the intial share of graduate workers, urbanization rates, distance to the closest coastline, and elevation. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

I next examine the effects of trade liberalization on migration flows. In the model, non-college graduates migrate to more exposed locations due to increased wages reflected in lower college premiums. Columns (1) to (4) of Table 1.3 show that municipalities with greater exposure to trade liberalization experienced greater migration inflows of non-college graduates between 1990 and 2000. A one percent increase in market exposure leads to a 0.24 percent average proportional increase in the migration rate of non-college

[5] Table A1.5 in the Appendix shows that, in line with this mechanism, the estimated effects on the population are positive and statistically significant.

graduates. Interestingly, the estimates are not statistically significant for college graduates' migration flows. Hence, and in line with the theoretical prediction, the evidence suggests that trade liberalization induced net inflows of low-skill workers to more exposed locations, which is consistent with my previous finding of decreased college graduate shares in more exposed municipalities.

Finally, I look at the effects of trade liberalization on local urban amenities. Consistent with the theoretical predictions, the last two columns of Table 1.3 show that municipalities facing greater exposure to trade liberalization also experienced statistically significant proportional declines in the overall amenity index. Given that most individual amenities improved on average across municipalities, I read these estimates as a smaller increase in overall amenities in more exposed municipalities. Table A1.4 in the Appendix presents the estimation results for each amenity separately and shows that municipalities facing larger exposure to trade liberalization experienced declines in school presence and quality, increased concentration of particular matter, and increased crime rates.

Table 1.3: Effects of Trade Liberalization on Migration Flows and Amenities.

	Log college graduates migration rate, 2000		Log noncollege graduates migration rate, 2000		Δ Log overall amenity index	
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.015	0.090	0.134	0.237***	-0.548***	-0.366***
	(0.0676)	(0.0702)	(0.0845)	(0.0806)	(0.1177)	(0.1180)
Obs.	446	446	446	446	446	446
R-squared	0.000	0.113	0.018	0.215	0.087	0.332
Controls	No	Yes	No	Yes	No	Yes

Notes: Results of the coefficient estimates for local market access by road. Changes are measured between 1990 and 2010. Overall amenity index calculated as the first principal component of school quality, air quality, and public service access indices. All specifications are weighted by 1990 population and include a constant term. Controls include the intial share of graduate workers, urbanization rates, distance to the closest coastline, and elevation.* p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

Overall, I find that the differential exposure to trade liberalization caused decreased skill wage premiums as predicted by the Heckscher-Ohlin mechanism in standard international models. More exposed locations also experienced greater inflows of low-skill workers, a result that is consistent with a skill-biased trade shock that altered relative prices across tradable and non-tradable sectors in a low-skill abundant economy. Finally, my results also show that the response of local housing rents and urban amenities compensated for the changes in nominal wage gaps. This finding is consistent with the notion of spatial equilibrium in which real wage gaps across locations are compensated through non-monetary amenities.

1.5.3 Robustness

I conduct different robustness tests for my main results presented above. The main concern with the identification is that the estimates may be driven by confounders that are not captured in my vector of controls. In the Appendix A1.8, I consider a potential confounder given by pre-liberalization differential trends that might have risen with Mexico joining the GATT in the 1980s. Accordingly, I include pre-liberalization local tariff declines measured US tariff changes between 1989 and 1992 across industries interacted with the initial industry composition of labor across municipalities (Dix-Carneiro and Kovak, 2017; Kovak, 2013). Details on the construction of these local tariff declines are presented in Appendix A1.5. Next, I consider two alternative mechanisms driving the changes in skill sorting across municipalities. First, I control for changes in the share of government employment to account for the privatization process that accompanied the liberalization reforms in the 1990s and could have affected the location decisions of skilled workers in that sector. Second, I control for the change in population shares residing in the US to test whether my results are mainly explained by NAFTA affecting international migration decisions (Majlesi and Narciso, 2018).[6] Additionally, in order to further minimize the chance that my market access measure is picking unobserved pre-trends across municipalities, I interact market access with local tariff reductions between 1993 and 2001. By interacting tariff declines with international market access, I can consider each municipality's relative advantage in terms of location and market specialization. Estimation results in Table A1.6 and Table A1.7 show that my findings remain quantitatively unchanged when including each of these additional controls.

A further concern is that my market access measurement only considers transportation by truck. While transport by truck concentrated 70 percent of Mexican exports to the

[6] Organized crime and changes in the regional presence of drug cartels can also be a potential mechanism driving the results. While I consider crime as an endogenous local amenity, my findings are also robust to using intentional homicides or police intervention per municipality as controls.

US in 1994, exports through rail and vessel were not negligible, representing 15 and 12 percent of the total. Considering different transport methods in the market access analysis is challenging given the different freight that varies with the exported product, its volume, and the use of intermodal shipments. I partially address this concern by computing an alternative market access measurement that selects the lowest-cost distance between the three transport modes. In all cases, as in my baseline measurement, the source nodes are the centroids of each municipality. For the potential destination nodes, I use the coordinates of the US ports of entry that received loaded rail containers from Mexico in 1996, according to the BTS, and the location of all maritime ports with a medium or large harbor size coming from the 2019 World Port Index. I then compute the least-cost path for each transport mode separately using rasterized data of the highway, railway, and shipping routes. As these figures reflect the shortest distance for each separate mode, I then add estimates of fixed and multiplied distances with variable costs estimated by Farrokhi and Jinkins (2019) for the US in order to compare the three alternatives. Finally, I use the lowest cost-distance transport mode and path for each municipality.[7] Moreover, I also consider an alternative least-cost path by road using the highway network in 1972 from the Bureau of Business Research at the University of Texas at Austin and re-compute each municipality's access to the closest US truck port in order to test for the presence of anticipation effects or specific pre-trends that took place before the adoption of the agreement. Table A1.8 and Table A1.9 show that the estimated effects obtained when using the alternative market access measurements are slightly smaller in magnitude but have the expected direction and are statistically significant.

I also evaluate the sensitivity of the results to consider alternative samples. More specifically, I test whether the results hold for a particular sample of municipalities by including all municipality sizes and using the full sample of municipalities available for each one of my data sources. Since the definition of the spatial units using administrative boundaries might not properly reflect the existence of larger labor markets, I also aggregate municipalities using the Metropolitan Zones defined by INEGI, which reduces my number of observations to 340 spatial units. Table A1.10 and Table A1.11 confirm that my findings are robust to these alternative sample definitions.

An additional concern relates to the use of PCA to aggregate the invidiual measurements

[7] Appendix A1.5 provides more details on how I built these alternative market access measurements.

of local amenities. While I provide estimates on the estimated effect on each individual amenity, I also consider the effects on the second principal for robustness. Estimation results in Table A1.12 are smaller in magnitude but remain negative and statistically significant. Finally, in Tables A1.13 and A1.14 I show that the results are robust to using Conley standard errors instead of clustered standard errors.

1.5.4 Heterogeneity

I also explore the timing of the effects by considering the impacts during the first ten census years, 1990-2000, and the following ten-year period 2000-2010. Table 1.4 shows that the labor market effects of trade liberalization are statistically significant for both periods, although they decrease in magnitude in 2000-2010 compared to 1990-2000. These results resonate with the findings of Dix-Carneiro and Kovak (2015), who find evidence for persistent regional effects of trade liberalization. Nevertheless, their estimated labor market effects are increasing in magnitude while the estimates in this chapter decrease with time. When considering the effects on migration flows and amenities, Table 1.5 shows that the effects on migration and local amenities occurred during the first decade. While the coefficient of college graduates' migration rates is only significant at the ten percent level, it is worth noting that it is negative during 2000-2010, thus suggesting an outflow of workers that can also explain a further decrease in the share of college graduates. A potential explanation for most of the effects arising in 1990-2000 and the lack of increasing effects is the increased international competition in low-skill-intensive industries coming from China joining the World Trade Organization (WTO) in 2001, which likely reverted the initial effects of NAFTA.

Table 1.4: EFFECTS OF TRADE LIBERALIZATION ON LOCAL LABOR MARKET OUTCOMES - TIME HETEROGENEITY.

	Δ Log high-skill share		Δ Log skill premium		Δ Log skill premium - rent deflated	
	Panel A: *1990-2000*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.412	-1.030**	-0.059***	-0.168***	-0.060***	-0.172***
	(0.2694)	(0.5005)	(0.0194)	(0.0485)	(0.0175)	(0.0463)
Obs.	464	464	464	464	464	464
R-squared	0.004	0.474	0.017	0.276	0.018	0.277
Controls	No	Yes	No	Yes	No	Yes
	Panel B: *2010-2000*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.116	-0.574**	-0.065***	-0.040*	-0.050***	-0.026
	(0.2680)	(0.2773)	(0.0200)	(0.0210)	(0.0179)	(0.0188)
Obs.	530	530	530	530	530	530
R-squared	0.000	0.097	0.022	0.057	0.015	0.052
Controls	No	Yes	No	Yes	No	Yes

Notes: The table presents the results of Table 1.3 by splitting the sample into two periods: 1990-2000 and 2000-2010. All specifications are weighted by 1990 population andi nclude a constant term. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

Table 1.5: Effects of Trade Liberalization on Migration Flows and Amenities - Time Heterogeneity.

	Log high-skill migration rate, 2000		Log low-skill migration rate, 2000		Δ Log overall amenity index	
	Panel A: *1990-2000*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.014	0.099	0.136	0.239***	-0.288***	-0.170**
	(0.0686)	(0.0713)	(0.0859)	(0.0821)	(0.0750)	(0.0789)
Obs.	464	464	464	464	464	464
R-squared	0.000	0.099	0.019	0.198	0.068	0.343
Controls	No	Yes	No	Yes	No	Yes
	Panel B: *2010-2000*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.164**	-0.010	-0.027	0.084*	-0.061	-0.020
	(0.0670)	(0.0694)	(0.0485)	(0.0485)	(0.0700)	(0.0757)
Obs.	530	530	530	530	530	530
R-squared	0.018	0.121	0.001	0.109	0.003	0.148
Controls	No	Yes	No	Yes	No	Yes

Notes: The table presents the results of Table 1.3 by splitting the sample into two periods: 1990-2000 and 2000-2010. All specifications are weighted by 1990 population andi nclude a constant term. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

1.6 Conclusion

This chapter studies the impact of trade liberalization on local economies in the context of Mexico during the 1990-2010 period. I use a spatial equilibrium model of location decisions with tradable sectors and transport costs to predict the effect of trade liberalization on local wages, rents, and endogenous amenities. In this setting, trade liberalization reduces local skill premiums due to the relative factor abundance (Stolper-Samuelson) effect, generating migration inflows of low-skill workers and endogenous responses in housing costs and urban amenities. The impact of trade liberalization on inequality between high and low-skill workers is given not only by changes in nominal wages but also by changes in real wages adjusted by the quality of life in each location.

I empirically test the predictions of the theoretical model by exploiting the regional variation in the exposure to trade openness before the adoption of NAFTA in 1994. To measure exposure to trade liberalization, I build measurements of each municipality's market access using a lowest-cost route to the closest US truck port given the highway network in 1990.

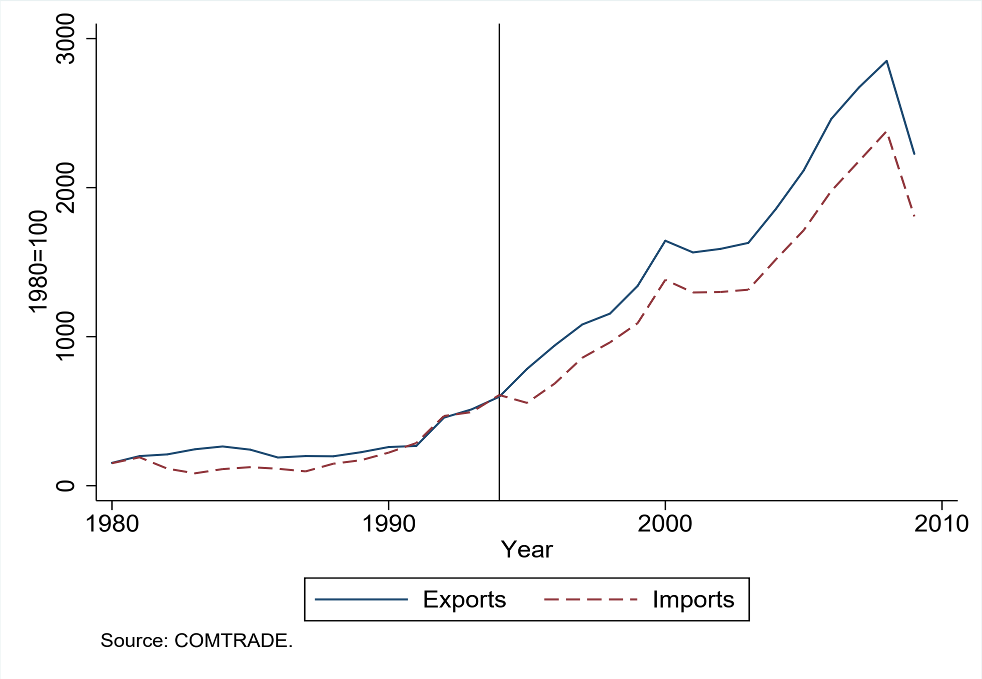
I find that, compared to other locations, municipalities with greater exposure to trade liberalization experienced significant increases in relative wages and migration inflows of non-college (low-skill) workers between 1990 and 2010. Nominal wage gains for non-college graduates in locations facing higher exposure to trade liberalization were lower in real terms once deflated with housing costs and were also accompanied by smaller increases in local urban amenities. As a result, I conclude that trade liberalization caused gains in nominal wages for low-skill workers, but these gains were partially offset by higher cost of living and lower non-monetary amenities.

My results have two main implications. First, from a methodological perspective, the empirical findings stress the importance of re-examing inequality effects by considering the uneven distribution of workers across locations and the local changes in prices and amenities. While the literature on the effects of trade liberalization has focused on local economies, it has typically paid less attention to the broader general equilibrium effects given by the endogenous reaction in the cost of living and the quality of life that fundamentally characterize these locations (Moretti, 2011). Second, from a policy perspective, spatial heterogeneity is important when designing policy responses to counteract the adverse effects. In particular, my findings point towards the importance of considering house affordability, urban planning, and public goods provision when designing trade reforms.

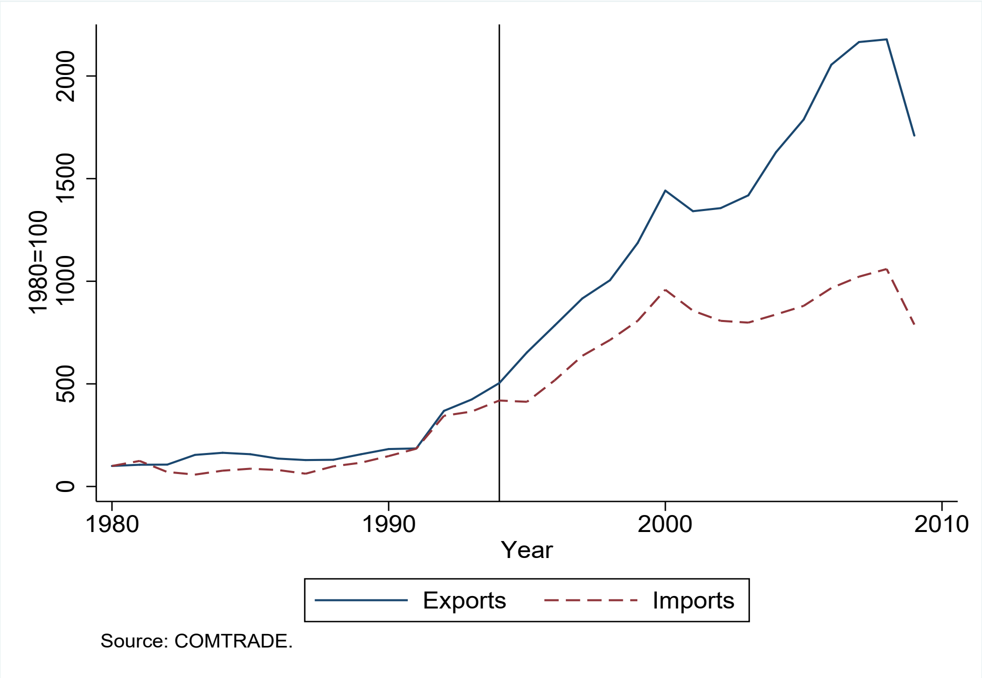
Appendix Chapter 1

A1.1 Figures

Figure A1.1: International Trade in Mexico.

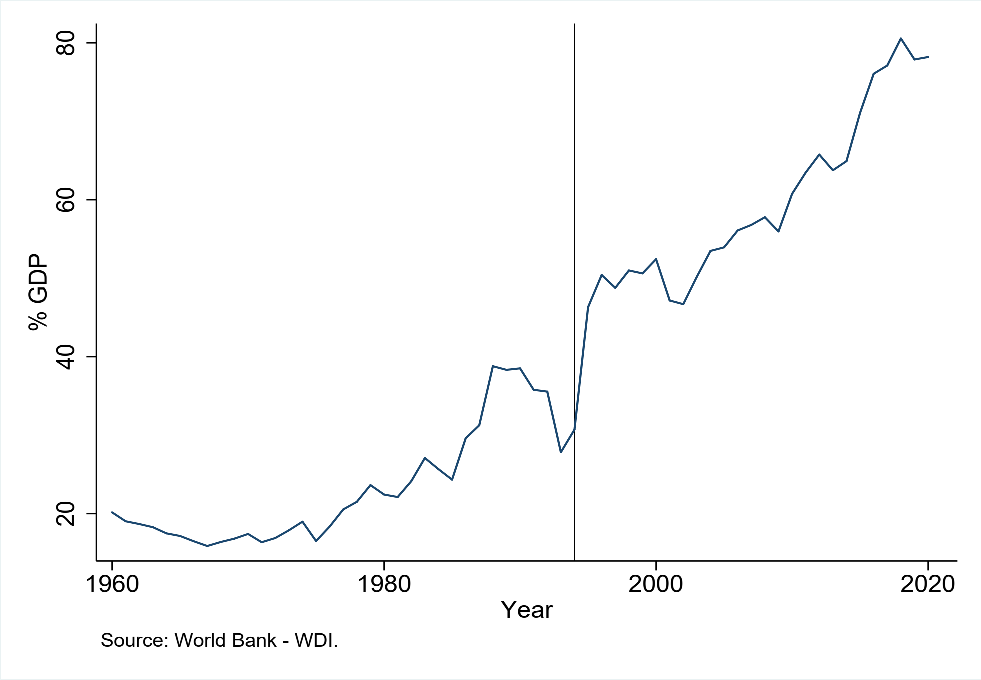


Panel A: Mexican Trade with the US.



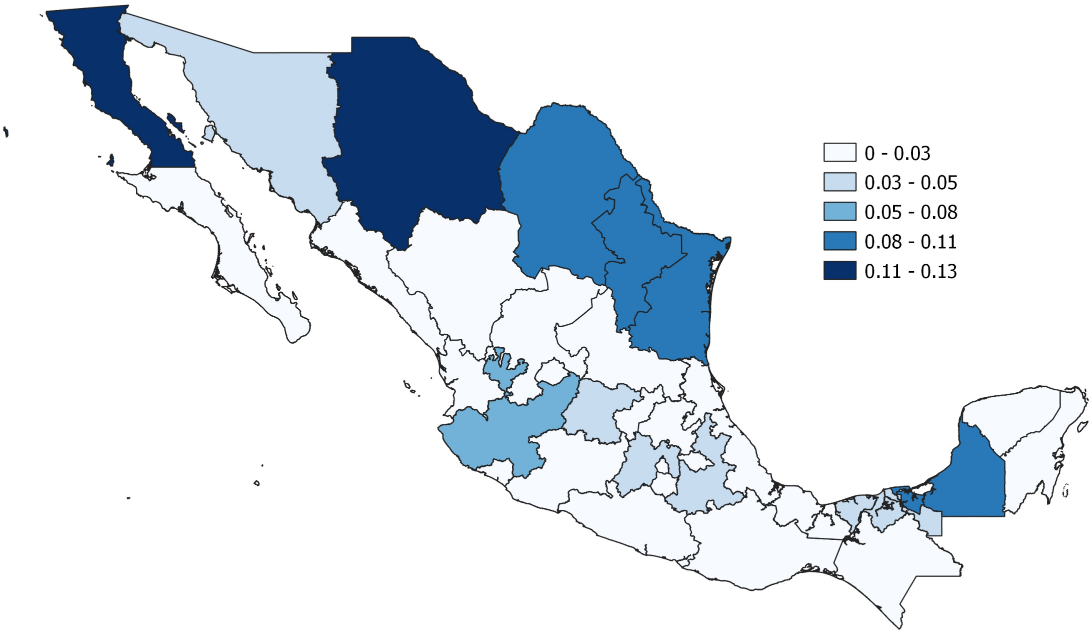
Panel B: Mexican Trade with the World.

Figure A1.1: *(continued)* International Trade in Mexico.



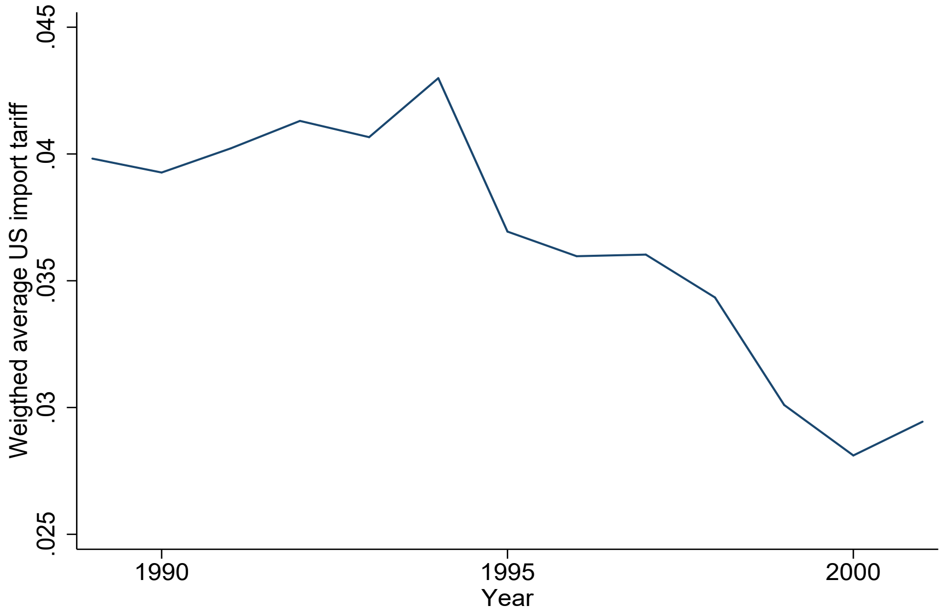
Panel C: Mexican Trade - GDP Share.

Figure A1.2: Share of Total Exported Value by State, 2010.



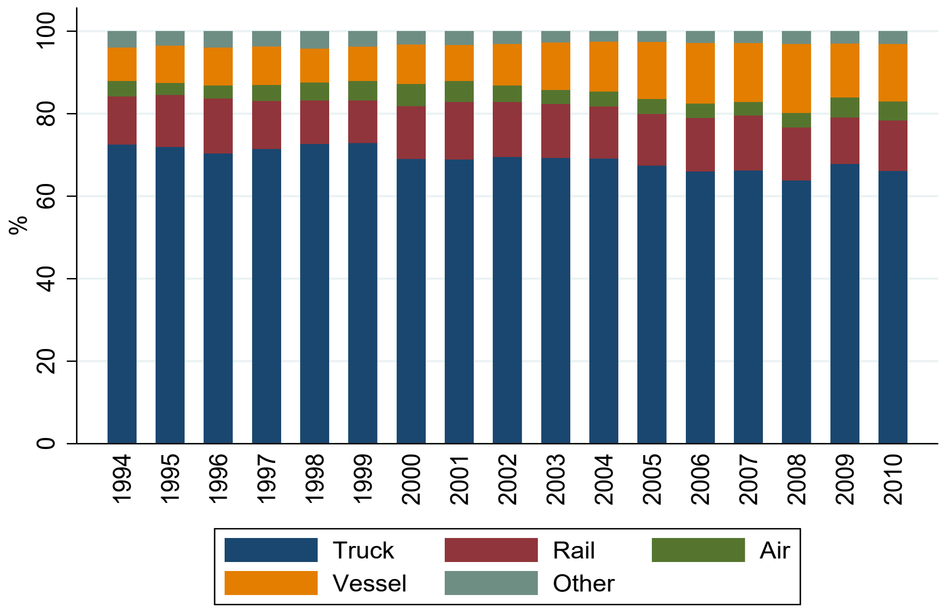
Source: INEGI.

Figure A1.3: US Tariff on Mexican Imports.



Source: Feenstra et al. (2002).

Figure A1.4: Mexico-US Trade by Transportation Mode.



Source: US Bureau of Transport Statistics.

A1.2 Data

Table A1.1: DATA SOURCES.

Variable	Description	Database	Source
Workers	Individuals aged 16-65 years old who report positive labor incomes.	Population and Housing Census 10% Samples (1990, 2000, 2010)	INEGI
High-skill shares	Workers who have obtained a college or postgraduate degree over total number of workers		
Wages	Monthly labor income divided by worked hours. The sample excludes top and bottom percentiles. Wages are residualized using a Mincer regression controlling for gender and quadratic age.		
Migration flows	Share of workers residing in a different municipality in the previous census year.		
Access to piped water	Housing units with access to piped water as a share of total occupied housing units.		
Access to sewage connection	Housing units with sewage connection as a share of total occupied housing units.		
Average rents	Municipality average of monthly rent are residualized using a hedonic regression of physical characteristics, including floor materials and the number of rooms.	National Household Income and Expenditure Surveys - ENIGH (1992 to 2016)	INEGI
Teacher-to-student ratio	Number of teachers in middle and basic education per 1,000 students.	Municipalities Database (SIMBAD)	INAFED
School-to-student ratio	Number of schools in middle and basic education oer 1,000 students.		
Homicide rates	Number of intentional homicides per 1,000 inhabitants.		
Air quality	Average concentration of ambient nitrogen dioxide (NO_2) pollution and particular matter $PM_{2.5}$.	Global NO_2 and $PM_{2.5}$ Grids from NASA (1996-2010)	Geddes et al. (2016) van Donkelaar et al. (2021)
Elevation	Terrain elevation at 90 m spatial resolution.	NASA global DTM (Digital Terrain Model)	NASA.
US tariff rates	Mean US import tariffs by product between 1993 and 2001.	US tariff schedule 1989-2001	Feenstra et al. (2002).

A1.3 Overall Amenity Index

In this subsection, I provide details on the construction of the overall amenity index. The methodology follows Diamond (2016) and uses principal component analysis (PCA) to combine seven measurements into a single index. On each census year, I extract the first principal component after performing PCA on the log indices of teachers per 1,000 students, schools per 1,000 students, the share of dwellings with access to electricity, piped water, sewage connection, the concentration of particular matter ($PM_{2.5}$), the concentration or nitrogen dioxide (NO_2), and the homicide rates per 1,000 inhabitants.

Table A1.2 presents the scores of each individual amenity in the overall index. The PCA assigns positive loadings to urban amenities related to school quality and public service provision and negative loadings to disamenities related to higher air pollution. On average, the first principal component concentrates 41% of the total explained variance.

Table A1.2: First Principal Component Scores for Amenity Indices.

	1990	2000	2010
Log teachers per 1.000 students	0.517	0.530	0.311
Log schools per 1.000 students	0.251	0.275	0.042
Log share of dwellings with access to electricity	0.137	0.242	0.394
Log share of dwellings with access to piped water	0.186	0.308	0.325
Log share of dwellings with sewage connection	0.142	0.288	0.483
Log concentration of particular matter ($PM_{2.5}$)	-0.644	-0.536	-0.492
Log concentration or nitrogen dioxide (NO_2)	0.418	-0.300	-0.183
Log homicide rates	-0.086	-0.339	-0.334
Variance explained PC1	0.415	0.404	0.404

Notes: The table reports the scores of each amenity measurement in the first principal component.

A1.4 Local Tariff Decline

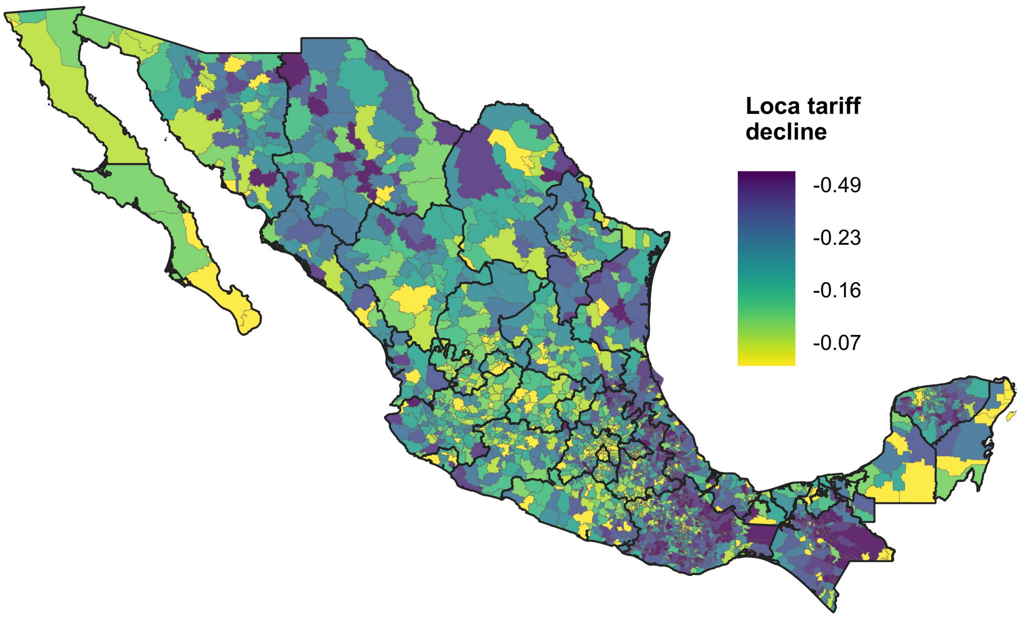
I complement my market access measurements with local tariff decline indices that consider how US tariff declines affected locations differently according to their initial employment composition by industry. Following Kovak (2013), I compute local tariff declines as the interaction between the cross-industry variation in tariff cuts and the cross-regional variation in industry labor shares. More formally, the tariff reduction in municipality j is defined as:

$$TR_j = s_{ij,t} \sum_i \cdot \Delta \tau_i, \tag{1.16}$$

where $s_{j,t}$ is the share of municipality j on national employment in initial time t, Δ is a time operator difference, and τ_i is the US tariff rate on Mexican imports in industry i. I use data on US tariffs from Feenstra et al. (2002) using 4-digit Harmonized Tariff System (HS) codes and link them to Mexican Classification of Activities and Products 4-digit codes.

Figure A1.5 shows the high spatial variation of local tariff declines between 1993 and 2000.

Figure A1.5: Tariff Decline by Municipality.



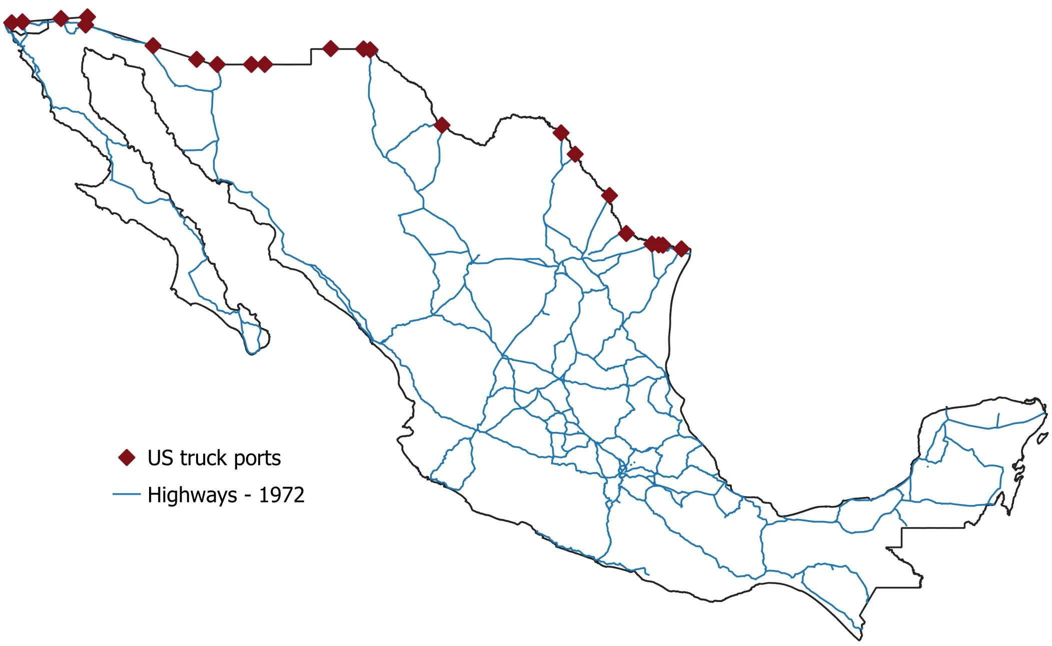
Notes: The map plots the average US tariff decline per municipality computed following Eq. 1.16. Data on US tariffs comes from Feenstra et al. (2002). Thick black lines depict state borders. Thin gray lines depict municipality borders.

A1.5 Market Access Measurements

This subsection details the construction of two alternative measurements of international market access. I use R to compute the least-cost distances between each municipality centroid and the closest US trade port for both measures. In both cases, I rasterize vector data on transport networks, normalize the raster values to 1, and use the inverse of the mean density as a cost function. The transport network is taken as fixed to measure the initial trade exposure before the liberalization policy. The difference between both measures is the cost surface given by the route density across the space.

The first and baseline measure of international market access uses the Mexican highway network of Mexico in 1990 from the Environmental Systems Research Institute. Alternatively, I use the 1972 highway network from the Bureau of Business Research, University of Texas at Austin (Figure A1.6). The potential destination nodes are given by the coordinates of the 22 ports that received loaded truck containers from Mexico in 1996, according to the Border Crossing Database of the US Bureau of Transport Statistics (BTS).

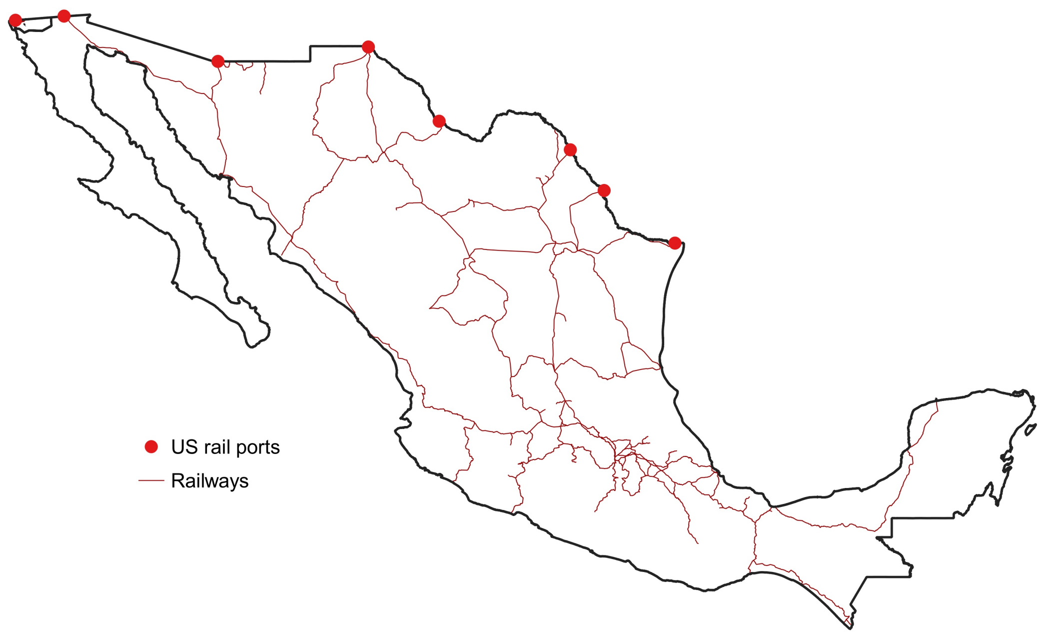
Figure A1.6: 1972 Road Network and US Truck Ports.



Notes: The map plots the Mexican highway network in 1972 from the Bureau of Business Research, University of Texas at Austin. Red vector points denote the location of the US ports that received loaded truck containers from Mexico in 1996, according to the Border Crossing Database of the US Bureau of Transport Statistics (BTS).

As an alternative measure, I compute the minimum cost-distances when comparing road, railway, and vessel transport networks. The international market access is then computed as the normalized cost-distance multiplied by the variable cost and added to the fixed costs as estimated by Farrokhi and Jinkins (2019). In the case of rails, I use the rasterized image of the railway network prepared by INEGI and the coordinates of ports that received loaded rail containers from Mexico in 1996, according to the Border Crossing Database of the US Bureau of Transport Statistics (BTS). Figure A1.7 plots the location of the rail ports and the raster of the railway network density.

Figure A1.7: US Rail Ports and Railway Network Density.

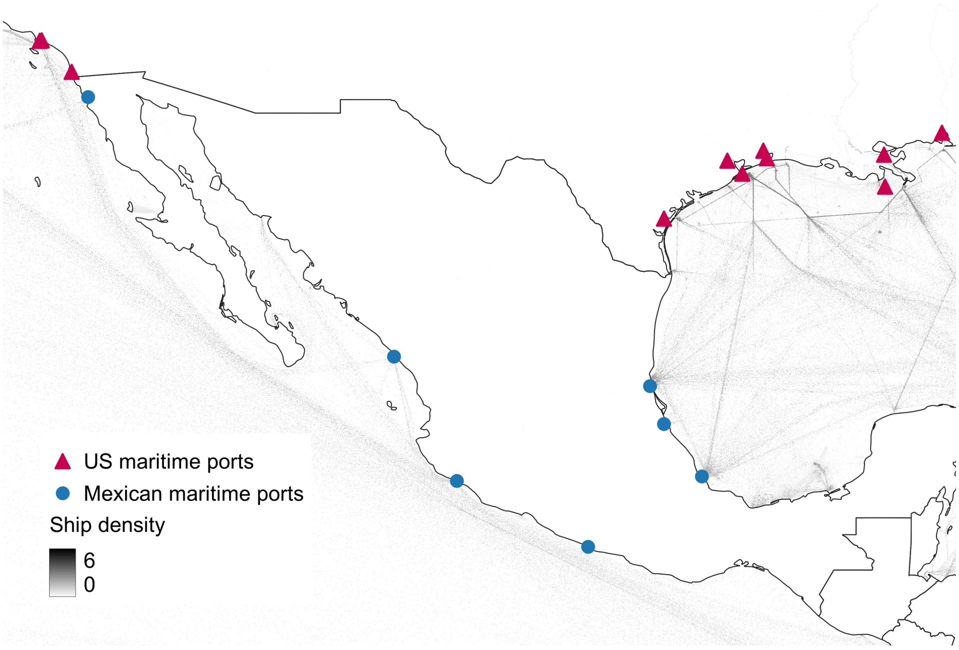


Notes: The map plots the Mexican railway network prepared by INEGI. Red vector points denote the location of the US ports that received loaded rail containers from Mexico in 1996, according to the Border Crossing Database of the US Bureau of Transport Statistics (BTS).

In the case of vessels, I use the location of all maritime ports with a medium or large harbor size coming from the 2019 World Port Index prepared and published by the National Geospatial-Intelligence Agency. For the cost surface, I use rasterized data of the ArcGIS Global Shipping Routes (2004) shapefile from the Global Map of Human Impacts to Marine Ecosystems prepared by the National Center for Ecological Analysis and Synthesis (NCEAS). Figure A1.8 plots the location of the maritime ports and the raster of the ship routes density.

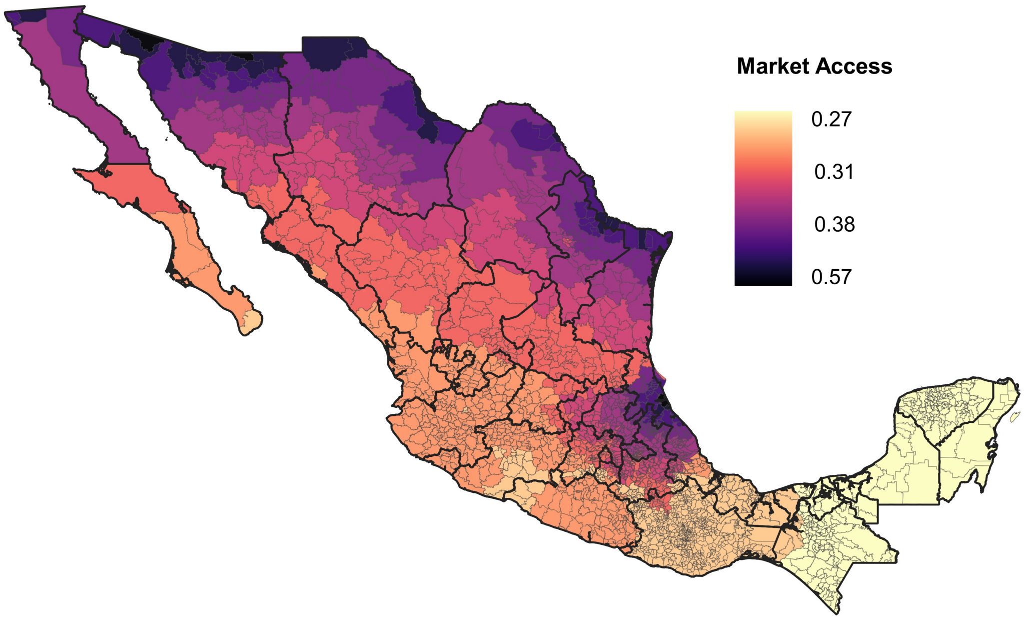
Figure A1.9 plots the alternative measure of international market access. As in my baseline measure, municipalities close to the US border have higher market access than the center or south locations. Nevertheless, this measure also captures higher access given by the ports of Tuxpan and Veracruz, located in the east of the country and with good access to the US ports located in Texas and Louisiana.

Figure A1.8: Maritime Ports and Ship Routes Density.



Notes: The map plots the rasterized spatial data of the ship routes' density. Blue circle vector points denote the location of Mexican maritime ports, while red triangle vector points denote the location of US maritime ports. Ports' locations come from the World Port Index (2019), while shipping routes come from the Global Map of Human Impacts to Marine Ecosystems (2004).

Figure A1.9: Cost-Distance to the US by Municipality.



Notes: The map plots the inverse of the shortest cost-distance path between each municipality's centroid and the closes US port, taking into account road, rail, and vessel transport modes. Distances are computed using Dijkstra's algorithm with a cost surface given by the rasterized images of the road networks. Thick black lines depict state borders. Thin gray lines depict municipality borders.

A1.6 Price Deflators

In this subsection, I complement my measurement of rents by creating an index of local prices. As I do not have detailed disaggregated data on quantities and prices for individual goods, I use a more aggregated approach and build a Consumer Price Index using household out-of-pocket expenditures from the GEIH survey (Moulton, 1996). More specifically, I use cross-municipality average expenditure shares on food, clothing, health, transport, education, personal expenses, and housing (including rent and maintenance) in 1992 as a baseline consumption basket. I then compute a weighted average change in expenditure shares across decades using the shares of the initial consumption basket as weights to create municipality-specific price indices. Table A1.3 presents the initial expenditure shares and the average shares across decades.

This approach has the advantage of including a wider range of non-housing expenditures into the price deflators. Nevertheless, it has different limitations (Moulton, 1996). First, it might capture substitution effects in the expenditure of households that do not necessarily reflect pure price changes. Second, it does not correct for changes in the quality of the goods. Addressing this potential measurement error requires more detailed data on generic goods in the consumption basket that are only available for food items in the GEIH survey. Although imperfect, this alternative measure provides additional evidence on housing and non-housing price movements across locations.

Table A1.3: Household Share Expenditures and Price Indices.

	Expenditure Shares			
	1992	1990	2000	2010
Housing	0.219	0.220	0.319	0.309
Food	0.399	0.394	0.663	0.799
Clothing	0.055	0.053	0.036	0.033
Health	0.018	0.017	0.018	0.014
Transport	0.102	0.109	0.189	0.221
Education	0.070	0.074	0.084	0.062
Personal	0.067	0.065	0.095	0.104
PCI	-	1.001	1.733	1.856

*Notes:*The table presents the average expenditure shares across municipalities for each component of total household expenditure per year. Shares in 1992 are taken as fixed in an initial consumption basket. Municipality averages are computed using household survey weights.

A1.7 Estimation Results

Table A1.4: Effects of Trade Liberalization on Urban Amenities.

	Δ Teacher/ student	Δ School/ student	Δ Electricity access	Δ Piped water
	(1)	(2)	(3)	(4)
Market access	-0.509***	-1.065***	0.113	-0.187
	(0.1536)	(0.2837)	(0.1091)	(0.1874)
Obs.	446	446	446	446
R-squared	0.199	0.236	0.353	0.375
Controls	Yes	Yes	Yes	Yes
	Δ Sewage access	$\Delta PM_{2.5}$	ΔNO_2	Δ Homicide rate
	(1)	(2)	(3)	(4)
Market access	0.416*	2.845***	0.595	1.792***
	(0.2358)	(0.3461)	(0.3997)	(0.6701)
Obs.	446	446	446	446
R-squared	0.631	0.363	0.132	0.240
Controls	Yes	Yes	Yes	Yes

Notes: Results of the coefficient estimates for local market access by road. Changes are measured between 1990 and 2010. Overall amenity index calculated as the first principal component of school quality, air quality, and public service access indices. All specifications are weighted by 1990 population and include a constant term. Controls include the intial share of graduate workers, urbanization rates, distance to the closest coastline, and elevation.* p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

Table A1.5: Effects of Trade Liberalization on Population and Wages.

	Δ Log population		Δ Log college wages		Δ Log noncollege wages	
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	0.940**	1.810***	0.024	-0.027	0.150***	0.081**
	(0.4633)	(0.6134)	(0.0192)	(0.0425)	(0.0216)	(0.0386)
Obs.	446	446	446	446	446	446
R-squared	0.026	0.208	0.004	0.232	0.216	0.502
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Results of the coefficient estimates for local market access by road. Changes are measured between 1990 and 2010. All specifications are weighted by 1990 population and include a constant term. Controls include the intial share of graduate workers, urbanization rates, distance to the closest coastline, and elevation.* p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

A1.8 Robustness Tests

Table A1.6: Effects of Trade Liberalization on Local Labor Market Outcomes - Alternative Mechanisms.

	Δ Log college labor share		Δ Log college premium		Δ Log college premium - rent deflated	
	Panel A: *Local tariff decline pre-trends*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.613**	-1.366***	-0.121***	-0.094**	-0.108***	-0.087**
	(0.2822)	(0.4756)	(0.0238)	(0.0461)	(0.0203)	(0.0434)
Obs.	446	446	446	446	446	446
R-squared	0.011	0.412	0.064	0.429	0.056	0.409
Controls	No	Yes	No	Yes	No	Yes
	Panel B: *Local change in government employment*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.613**	-1.340***	-0.121***	-0.101**	-0.108***	-0.094**
	(0.2822)	(0.4779)	(0.0238)	(0.0468)	(0.0203)	(0.0444)
Obs.	446	446	446	446	446	446
R-squared	0.011	0.418	0.064	0.390	0.056	0.364
Controls	No	Yes	No	Yes	No	Yes
	Panel C: *Local change in international migration*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.613**	-1.192**	-0.121***	-0.111**	-0.108***	-0.104**
	(0.2822)	(0.4818)	(0.0238)	(0.0476)	(0.0203)	(0.0451)
Obs.	446	446	446	446	446	446
R-squared	0.011	0.416	0.064	0.391	0.056	0.366
Controls	No	Yes	No	Yes	No	Yes
	Panel D: *Interactions wiht local tariff decline*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.015	0.081	0.134	0.233***	-0.548***	-0.341***
	(0.0676)	(0.0827)	(0.0845)	(0.0878)	(0.1177)	(0.1223)
Obs.	446	446	446	446	446	446
R-squared	0.000	0.051	0.018	0.160	0.087	0.350
Controls	No	Yes	No	Yes	No	Yes

Notes: Robustness check for results presented in Table 1.2. All specifications are weighted by 1990 population,include a constant term , and further control for local US tariff declines between 1989 and 1993, and changes in government employment between 1990 and 2010. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

Table A1.7: Effects of Trade Liberalization on Migration Flows and Amenities - Alternative Mechanisms.

	Log college graduates migration rate, 2000		Log noncollege graduates migration rate, 2000		Δ Log overall amenity index	
	Panel A: *Local tariff decline pre-trends*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.015	0.079	0.134	0.225***	-0.548***	-0.375***
	(0.0676)	(0.0825)	(0.0845)	(0.0863)	(0.1177)	(0.1155)
Obs.	446	446	446	446	446	446
R-squared	0.000	0.052	0.018	0.152	0.087	0.323
Controls	No	Yes	No	Yes	No	Yes
	Panel B: *Local change in government employment*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.015	0.083	0.134	0.233***	-0.548***	-0.374***
	(0.0676)	(0.0869)	(0.0845)	(0.0886)	(0.1177)	(0.1181)
Obs.	446	446	446	446	446	446
R-squared	0.000	0.050	0.018	0.153	0.087	0.323
Controls	No	Yes	No	Yes	No	Yes
	Panel C: *Local change in international migration*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.015	0.081	0.134	0.233***	-0.548***	-0.341***
	(0.0676)	(0.0827)	(0.0845)	(0.0878)	(0.1177)	(0.1223)
Obs.	446	446	446	446	446	446
R-squared	0.000	0.051	0.018	0.160	0.087	0.350
Controls	No	Yes	No	Yes	No	Yes
	Panel D: *Interactions wiht local tariff decline*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.015	0.072	0.134	0.221**	-0.548***	-0.377***
	(0.0676)	(0.0819)	(0.0845)	(0.0864)	(0.1177)	(0.1173)
Obs.	446	446	446	446	446	446
R-squared	0.000	0.047	0.018	0.149	0.087	0.322
Controls	No	Yes	No	Yes	No	Yes

Notes: Robustness check for results presented in Table 1.3. All specifications are weighted by 1990 population, include a constant term , and further control for local US tariff declines between 1989 and 1993, and changes in government employment between 1990 and 2010. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

Table A1.8: Effects of Trade Liberalization on Local Labor Market Outcomes - Alternative Market Access Measurements.

	Δ Log college labor share		Δ Log college premium		Δ Log college premium - rent deflated	
	Panel A: *Alternative transport modes*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access × Tariff reduction	-0.099***	-0.037**	-0.007***	-0.004**	-0.005***	-0.003**
	(0.0170)	(0.0167)	(0.0017)	(0.0018)	(0.0015)	(0.0016)
Obs.	446	446	446	446	446	446
R-squared	0.091	0.303	0.063	0.186	0.044	0.166
Controls	No	Yes	No	Yes	No	Yes
	Panel C: *Road network in 1972*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.425***	-0.724***	-0.062***	-0.049***	-0.053***	-0.041***
	(0.1073)	(0.1278)	(0.0097)	(0.0161)	(0.0086)	(0.0139)
Obs.	446	446	446	446	446	446
R-squared	0.023	0.436	0.073	0.341	0.058	0.317
Controls	No	Yes	No	Yes	No	Yes

Notes: Robustness check for results presented in Table 1.2 using alternative market access measurements. All specifications are weighted by 1990 population and include a constant term and controls. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

Table A1.9: Effects of Trade Liberalization on Migration Flows and Amenities - Alternative Market Access Measurements.

	Log college graduates migration rate, 2000		Log noncollege graduates migration rate, 2000		Δ Log overall amenity index	
	Panel A: *Alternative transport modes*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access × Tariff reduction	0.017***	0.018***	0.025***	0.026***	-0.009	0.003
	(0.0034)	(0.0034)	(0.0035)	(0.0042)	(0.0084)	(0.0089)
Obs.	446	446	446	446	446	446
R-squared	0.074	0.094	0.207	0.250	0.007	0.292
Controls	No	Yes	No	Yes	No	Yes
	Panel C: *Road network in 1972*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	0.009	0.050**	0.108***	0.166***	-0.299***	-0.283***
	(0.0271)	(0.0245)	(0.0349)	(0.0314)	(0.0562)	(0.0805)
Obs.	446	446	446	446	446	446
R-squared	0.000	0.114	0.052	0.237	0.113	0.320
Controls	No	Yes	No	Yes	No	Yes

Notes: Robustness check for results presented in Table 1.3 using alternative market access measurements. All specifications are weighted by 1990 population and include a constant term and controls. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

Table A1.10: Effects of Trade Liberalization on Local Labor Market Outcomes - Alternative Samples.

	Δ Log college labor share		Δ Log college premium		Δ Log college premium - rent deflated	
	Panel A: *All municipality sizes*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.625**	-1.390***	-0.122***	-0.105**	-0.109***	-0.098**
	(0.2813)	(0.4715)	(0.0238)	(0.0472)	(0.0203)	(0.0447)
Obs.	466	466	466	466	466	466
R-squared	0.011	0.406	0.063	0.374	0.055	0.349
Controls	No	Yes	No	Yes	No	Yes
	Panel B: *Metropolitan zones*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-1.145***	-0.466	-0.170***	-0.098***	-0.143***	-0.072**
	(0.2774)	(0.5037)	(0.0271)	(0.0368)	(0.0239)	(0.0339)
Obs.	340	340	340	340	340	340
R-squared	0.046	0.405	0.109	0.448	0.083	0.419
Controls	No	Yes	No	Yes	No	Yes
	Panel C: *Full municipality sample*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-1.084***	-1.108***	-0.161***	-0.110***	-0.109***	-0.098**
	(0.2799)	(0.4244)	(0.0241)	(0.0415)	(0.0203)	(0.0447)
Obs.	1,919	1,919	1,919	1,919	466	466
R-squared	0.014	0.320	0.032	0.234	0.055	0.349
Controls	No	Yes	No	Yes	No	Yes

Notes: Robustness check for results presented in Table 1.2 by using alternative municipality samples. All specifications are weighted by 1990 population and include a constant term and controls. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Clustered standard errors at the municipality level in parentheses.

Table A1.11: Effects of Trade Liberalization on Migration Flows and Amenities - Alternative Samples.

	Log college graduates migration rate, 2000		Log noncollege graduates migration rate, 2000		Δ Log overall amenity index	
	Panel A: *All municipality sizes*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.010	0.002	0.184**	0.219***	-0.451***	-0.264***
	(0.0477)	(0.0542)	(0.0846)	(0.0802)	(0.0813)	(0.0900)
Obs.	466	466	466	466	466	466
R-squared	0.000	0.028	0.062	0.166	0.082	0.385
Controls	No	Yes	No	Yes	No	Yes
	Panel B: *Metropolitan zones*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	0.068	0.030	0.321***	0.275***	-0.322***	-0.230**
	(0.0492)	(0.0554)	(0.0901)	(0.0755)	(0.0882)	(0.0975)
Obs.	340	340	340	340	340	340
R-squared	0.009	0.053	0.200	0.321	0.048	0.280
Controls	No	Yes	No	Yes	No	Yes
	Panel C: *Full municipality sample*					
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	0.043	0.026	0.186**	0.184***	-0.458***	-0.296***
	(0.0395)	(0.0433)	(0.0737)	(0.0680)	(0.0655)	(0.0745)
Obs.	1,919	1,919	1,919	1,919	1,919	1,919
R-squared	0.002	0.054	0.063	0.191	0.042	0.199
Controls	No	Yes	No	Yes	No	Yes

Notes: Robustness check for results presented in Table 1.3 by using alternative municipality samples. All specifications are weighted by 1990 population and include a constant term and controls. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

Table A1.12: Effects of Trade Liberalization on Urban Amenities - Second Principal Component.

	Δ Log overall amenity index	
	(1)	(2)
Market access	-1.316***	-0.870***
	(0.2810)	(0.2034)
Obs.	446	446
R-squared	0.158	0.437
Controls	No	Yes

Notes: Robustness check for results presented in Table 1.3. All specifications are weighted by 1990 population and include a constant term. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

Table A1.13: Effects of Trade Liberalization on Local Labor Market Outcomes - Conley standard errors.

	Δ Log college labor share		Δ Log college premium		Δ Log college premium - rent deflated	
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.613	-1.355***	-0.121***	-0.101**	-0.108***	-0.094**
	(0.3935)	(0.4671)	(0.0321)	(0.0432)	(0.0259)	(0.0406)
Obs.	446	446	446	446	446	446
R-squared	0.011	0.411	0.064	0.388	0.056	0.363
Controls	No	Yes	No	Yes	No	Yes

Notes: Robustness check for results presented in Table 1.2 using the spatial correction proposed by Conley (1999) with a threshold of 30 kilometers. All specifications are weighted by 1990 population and include a constant term and controls. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

Table A1.14: Effects of Trade Liberalization on Migration Flows and Amenities - Conley standard errors.

	Log college graduates migration rate, 2000		Log non-college graduates migration rate, 2000		Δ Log overall amenity index	
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.010	0.002	0.185	0.220**	-0.548***	-0.377***
	(0.0637)	(0.0619)	(0.1130)	(0.0916)	(0.1178)	(0.1213)
Obs.	446	446	446	446	446	446
R-squared	0.000	0.028	0.062	0.166	0.087	0.322
Controls	No	Yes	No	Yes	No	Yes

Notes: Robustness check for results presented in Table 1.3 using the spatial correction proposed by Conley (1999) with a threshold of 30 kilometers. All specifications are weighted by 1990 population and include a constant term and controls. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

Table A1.15: Effects of Trade Liberalization on College Premiums - Alternative Price Deflators.

	Δ Log college premium		Δ Log college premium - rent deflated		Δ Log college premium - PCI deflated	
	(1)	(2)	(3)	(4)	(5)	(6)
Market access	-0.121***	-0.101**	-0.108***	-0.094**	-0.084***	-0.055**
	(0.0238)	(0.0471)	(0.0203)	(0.0446)	(0.0234)	(0.0246)
Obs.	446	446	446	446	384	384
R-squared	0.064	0.388	0.056	0.363	0.032	0.236
Controls	No	Yes	No	Yes	No	Yes

Notes: Robustness check for results presented in Table 1.2 using the spatial correction proposed by Conley (1999) with a threshold of 30 kilometers. All specifications are weighted by 1990 population and include a constant term and controls. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

Chapter 2
Gender Gaps in the Labor Market Effects of COVID-19: Evidence from Mexico

2.1 Introduction

The COVID-19 pandemic has affected labor markets worldwide in an unprecedented way. The restrictions on economic activity imposed during the pandemic have highlighted previously neglected differences among occupations and sectors, such as the possibility of working from home or the degree of frequent interactions with customers, providers, and coworkers (Dingel and Neiman, 2020). Moreover, the pandemic resulted in the closure of schools and daycare centers, thus affecting the volumes of home production and childcare (Sevilla and Smith, 2020; Del Boca et al., 2020; Huebener et al., 2021).

Since the hardest hit sectors, such as hospitality and services, tend to use female labor more intensively and women are the primary providers of childcare, the COVID-19 economic downturn was expected to have disproportionate effects on female labor outcomes (Alon et al., 2020). Consequently, the emerging but growing literature on the labor market effects of COVID-19 restrictions has devoted attention to the unequal impacts on men and women in developed economies (Adams-Prassl et al., 2020; Montenovo et al., 2020; Angelucci et al., 2020; Casarico and Lattanzio, 2020; Petrongolo and Ronchi, 2020; Dang and Viet Nguyen, 2021; Fairlie et al., 2021; Kalenkoski and Pabilonia, 2022). However, there is limited evidence of gender differences in the impacts of the pandemic on low and middle-income economies (Hoehn-Velasco et al., 2022; Viollaz et al., 2022; Cueva et al., 2021; García-Rojas et al., 2020; Nieves et al., 2020), where the effects are likely to differ due to several factors. First, the high levels of labor informality that characterize these economies imply greater vulnerability due to the lack of access to social protection schemes. Second, and likely related to the high share of the informal economy, the ability to work from home is low in developing economies as documented by Gottlieb et al. (2021), thus increasing the exposure to contagion and job loss. Third, segmentation by labor informality has an important gender dimension as informal employment is more prevalent among women than men in Latin America, sub-Saharan Africa, and South Asia (OECD and ILO, 2019).

This chapter seeks to fill the gap in the literature on the labor market impacts of COVID-19 in middle-income economies by investigating the early unequal gender effects of the pandemic in Mexico. The Mexican context is particularly interesting to study for three main reasons. First, the country was strongly hit by the pandemic, with 1.4 million cases in 2020, ranking 12^{th} worldwide, and implemented relatively strict lockdown measures. Second, the Mexican labor market exhibits feature characteristics for labor markets in middle and low-income economies: i) nearly 56% of the Mexican workforce is informal, and ii) only 25% of jobs can be performed from home (Dingel and Neiman, 2020). Third, there is rich longitudinal information on labor market outcomes that allows following the same individuals before and after the onset of the restrictions and checking for the presence of pre-trends in labor outcomes.

The central contribution of this chapter is to investigate the effects of the pandemic on a wide range of labor outcomes that account for the impacts on labor supply decisions and employment at extensive and intensive margins. To explain these effects, I also study the role of gender segregation across childcare responsibilities, labor informality, and part-time work. Therefore, the chapter deals with a comprehensive range of outcomes and channels explaining the gender-unequal effects of the COVID-19 crisis in the context of a middle-income economy.

I provide a detailed picture of the early labor market effects of the pandemic by examining the impacts on labor force participation, unemployment, work hours, and earnings through 2020, when Mexico went through a national lockdown during the first of three COVID-19 epidemic waves that have occurred up to December 2021. Using longitudinal data from the Mexican National Survey of Occupation and Employment (ENOE) and an event-study design, I compare the changes in labor market outcomes after the pandemic's onset with pre-pandemic periods. I find evidence for contrasting differential effects in unemployment and labor force participation among men and women. On the one hand, the probability of unemployment increased more for men immediately after the start of the pandemic. However, this gender gap in the unemployment effect narrowed by the last quarter of 2020. On the other hand, although the initial decrease in labor participation was similar for men and women, the slower recovery of female labor participation produced a gender differential that only materialized after June 2020 and progressively widened. Hence, the most pronounced gender gap in the effects of the COVID-19 pandemic on the Mexican labor market was a greater decrease in labor market participation for women than for men. These persistent unequal effects on labor force participation are particularly relevant since re-entering the labor force after a dropout may imply significant penalties regarding position and earnings (Kleven et al., 2019; Angrist and Evans, 1998). Moreover, potential long-term reductions in female labor force participation would mean a reversal of the recent narrowing of the gender gap in Mexico, implying economic and social opportunity losses (Lim and Zabek, 2021; Lopez-Acevedo et al., 2020).

To further explore heterogeneous effects among sub-samples, I estimate the impacts across different pre-pandemic labor features and childcare responsibilities. My results indicate that the largest decrease in female labor participation occurred among those workers with informal and part-time jobs. Moreover, the gender gap in the effect on labor force participation is only significant for individuals with children of school-going age. Hence, I conclude that women were more likely to leave the labor force due to a double penalty given by a disproportionate increase in childcare responsibilities (the *COVID-motherhood penalty*) (Fairlie et al., 2021) and a higher likelihood of having more flexible jobs.

This chapter contributes to an emerging literature on the unequal gender effects of the COVID-19 shock on labor outcomes that has focused on high-income economies (Dang and Viet Nguyen, 2021; Albanesi and Kim, 2021; Petrongolo and Ronchi, 2020; Fairlie et al., 2021; Farré et al., 2021; Blundell et al., 2020; Casarico and Lattanzio, 2020; Angelucci et al., 2020; Adams-Prassl et al., 2020; Montenovo et al., 2020; Alon et al., 2020). In general, these studies find mixed evidence on gender gaps in job loss probability and highlight the importance of occupation and industry fixed effects in accounting for the gaps. Most of the studies examine job loss by restricting the samples to individuals that became unemployed after the onset of the pandemic and exploring the role of different controls in explaining the unemployment differences among demographic groups (Adams-Prassl et al., 2020; Casarico and Lattanzio, 2020; Montenovo et al., 2020; Dang and Viet Nguyen, 2021).

The chapter relates to a set of studies using difference-in-difference and event study strategies to estimate gender gaps in COVID-19 labor effects (Couch et al., 2020; Fairlie et al., 2021; Angelucci et al., 2020). This approach allows assessing for differential pre-trends in labor outcomes (Goodman-Bacon and Marcus, 2020). Using this approach and Current Population Survey (CPS) data for the US, Angelucci et al. (2020) find that job loss was 6 to 7.5 percentage points higher for women, while Fairlie et al. (2021) finds that male-to-female gaps in employment rates and hours worked widened after the pandemic for women with school-age children but not for those with younger children.

Most related to this chapter is work by Hoehn-Velasco et al. (2022) and Viollaz et al. (2022), who also use the ENOE survey for Mexico and difference-in-difference estimates to examine the unequal labor market effects of the pandemic across different dimensions. Hoehn-Velasco et al. (2022) study the unequal gender effects on employment, work hours, informality, and earnings at the household level and show that the COVID-19 pandemic led to persistent employment losses for female-headed households. Viollaz et al. (2022) use individual longitudinal data for Brazil, Chile, Dominican Republic, and Mexico to study the impacts of the pandemic on labor force participation and employment and look into the heterogeneous effects by job type and childcare responsibilities. In the case of Mexico, they find that women were not disproportionately affected by the pandemic, and little evidence for heterogeneous effects for women with school-age children.

My approach differs in several ways. First, compared to Viollaz et al. (2022) and similar to Hoehn-Velasco et al. (2022), I exploit the phone surveys conducted between April and June 2020, thus capturing the immediate effects of the restrictions on economic activity, and incorporate individual fixed effects to address for the role of potential time-invariant unobservables as innate ability driving the effects. Second, compared to Hoehn-Velasco et al. (2022), I use this approach to study the heterogeneity of the gender differential effects across childcare responsibilities and job characteristics. As a result, my main result of Mexican women being more affected in terms of labor force participation due to increased childcare work and over-representation in more flexible jobs is new in the literature.

The rest of the chapter is organized as follows. Section 2.2 describes the context. Section 2.3 presents the data. Section 2.4 discusses the empirical strategy. Section 2.5 presents the results. Section 2.6 concludes.

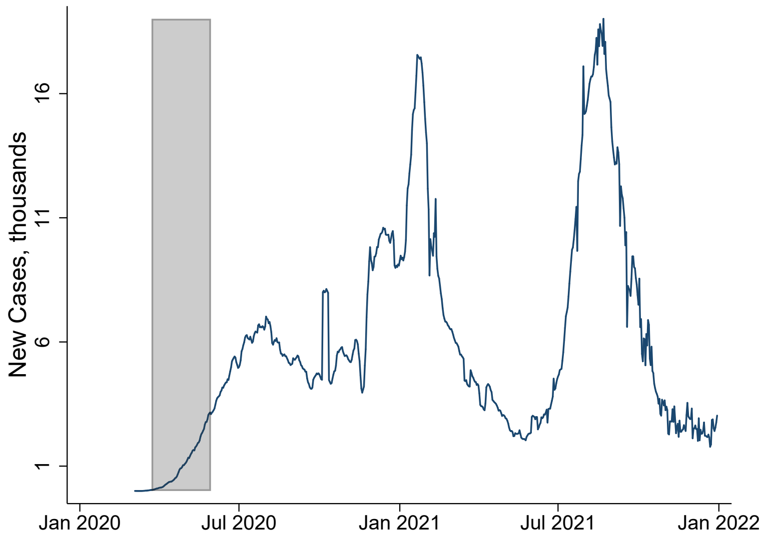
2.2 Context

The first COVID-19 epidemic wave ended in November 2020 and was followed by two stronger waves in 2021-2022. Following the first reported case of COVID-19 in Mexico on February 2, 2020, the number of new and deaths quickly escalated and reached their first peaks by the end of July 2020 (Figure 2.1). By the end of 2020, the cumulative number of cases increased to 1.44 million, the 12^{th} largest in the world and the fourth largest in Latin America after Brazil, Colombia, and Argentina. Death rates were also high, with 936 confirmed deaths per one million inhabitants, ranking 16^{th} worldwide.

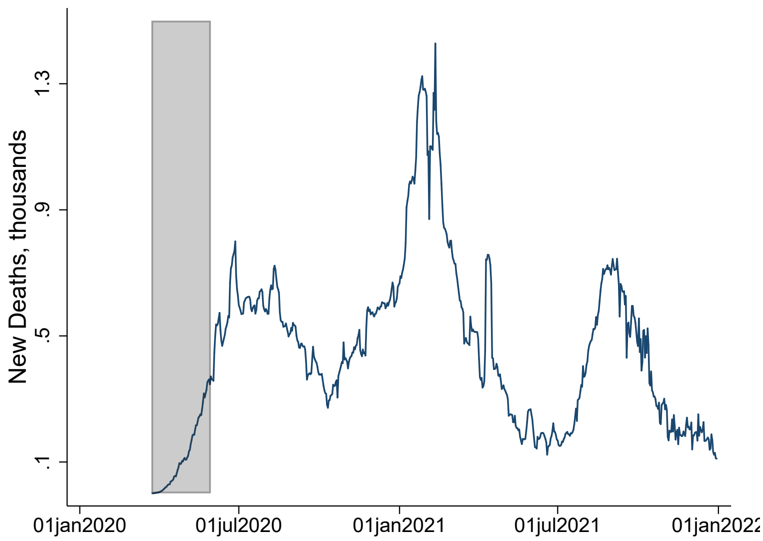
The pandemic caused severe effects on the economy. Real GDP declined 8.2 percent annually in 2020, the largest contraction since 1932 and one of the strongest in the region after Peru (11 percent) and Argentina (8.2 percent). According to the Mexican National Institute of Statistics and Geography (INEGI), nearly 12 million jobs were lost during the start of the pandemic. In Figure 2.3, I observe that job loss was up to 6 times larger in 2020 compared to 2018-2019 averages.

Authorities' policy response in terms of economic assistance and relief was limited. As noted by Ahmed Hannan et al. (2020), Mexico's fiscal response to the pandemic was modest compared to its peers: additional expenditures amounted to 0.2 percent of GDP in health spending and 0.5 percent of GDP to support households and firms compared to the average response of 3.1 and 2 percent of GDP in emerging economies (Figure 2.2). Authorities announced one million loans of MXN 25 thousand each (1,164 USD in 2020) to support small and medium-sized enterprises, with total spending of MXN 3 billion. Unemployment insurance was also provided to workers holding a mortgage with the Housing Institute, with total spending of MXN 7.3 billion.

Figure 2.1: New COVID-19 Cases and Deaths in Mexico.



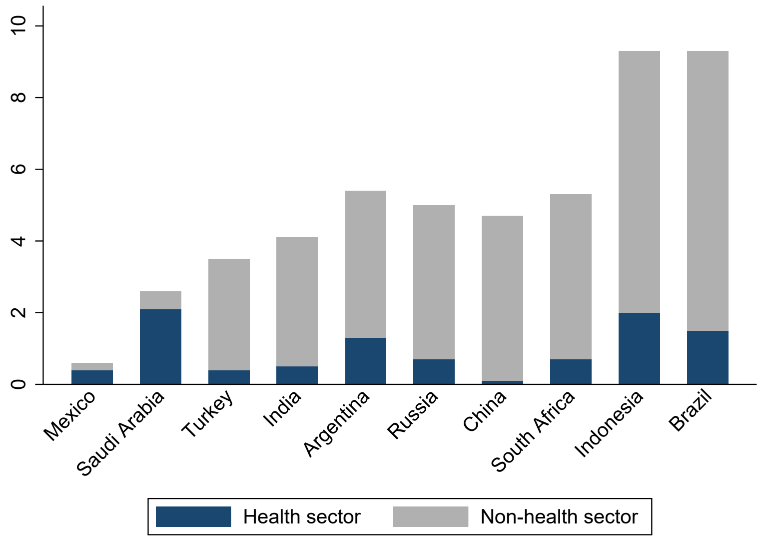
Panel A. New Cases (smoothed)



Panel B. New Deaths (smoothed)

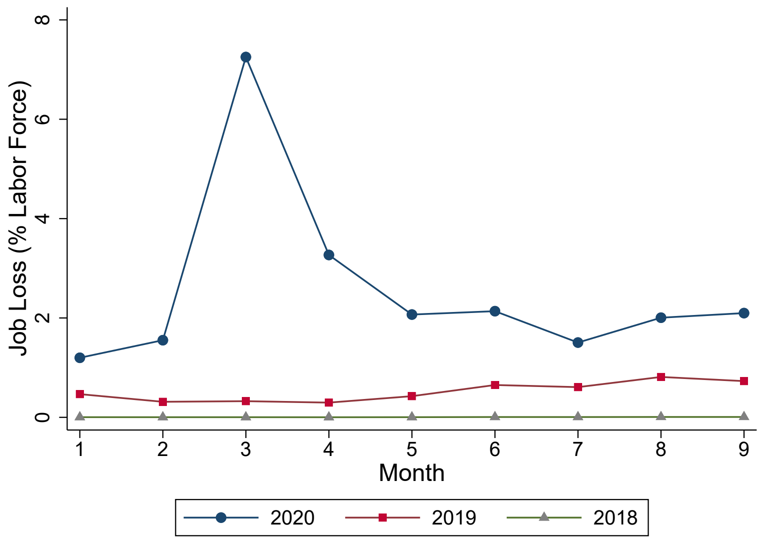
Notes: The figures plot the 7-day rolling average of the number of new COVID-19 cases and related dates from the Johns Hopkins University CSSE COVID-19 Data. Shaded areas denote national lockdown.

Figure 2.2: Response to the COVID-19 Crisis in 2020 (GDP %) - Selected Emerging Economies.



Notes: The figure plots the discretionary fiscal response in additional spending and forgone revenue in selected emerging economies from the IMF Fiscal Policy Responses to COVID-19.

Figure 2.3: Job Loss Incidence.

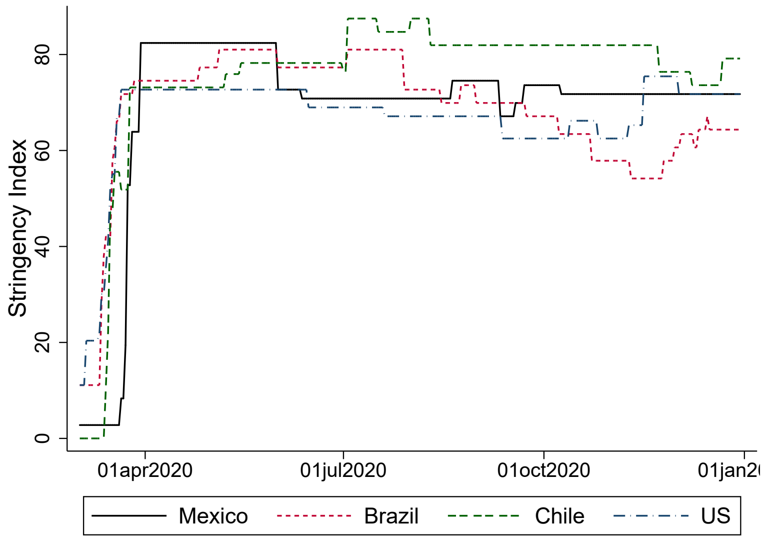


Notes: The figure plots the total number of individuals reporting employment loss per month as a proportion of the working force (adults aged between 16 and 65) across years. Figures are obtained using the retrospective labor market module of the National Survey on Occupation and Employment (ENOE).

In terms of public health policy responses, Mexican authorities implemented a national lockdown under the National Campaign of Healthy Distancing from March 23 to May

30, 2020. This policy included the closure of non-essential activities[1] and was followed by a state-level alarm system that imposed measures according to using a risk-based approach. Regarding the strictness of these restrictions, Figure 2.4 plots the stringency index computed by Hale et al. (2021), which is a composite measure based on nine response indicators, including school closures, workplace closures, and travel bans. Higher values of the index imply stricter restrictions. The figure shows that Mexico's restrictions implemented between March and May 2020 were more strict compared to other economies in Latin America and the US.

Figure 2.4: STRINGENCY INDEX SELECTED COUNTRIES.



Notes: The figure plots the stringency index computed by Hale et al. (2021). The index is a composite measure based on nine response indicators, including school closures, workplace closures, and travel bans. Values from 0 to 100 (100 = strictest). Data comes from the Oxford COVID-19 Government Response Tracker.

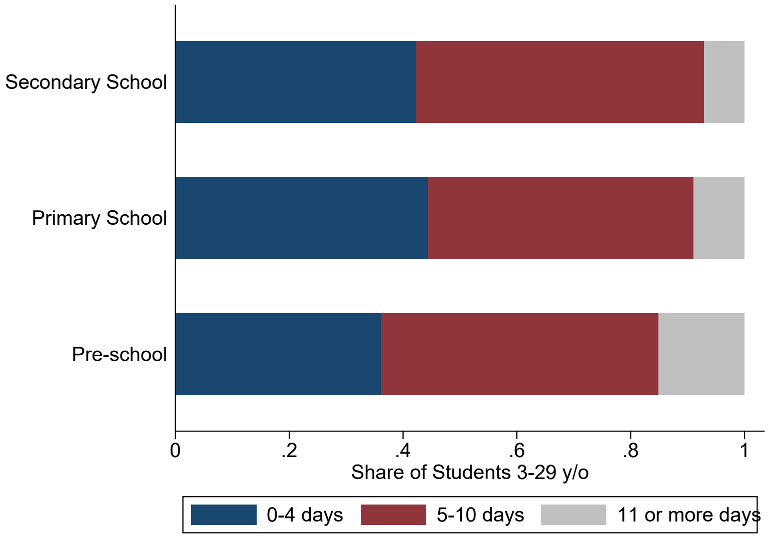
The national lockdown also implied the closure of schools and daycare centers that only began to reopen by the mid of 2021. Public policy focused on educational television programs and distribution of textbooks during this period under the program *Aprende en Casa* given the low share of students with access to digital resources.[2] School closures persisted during 2021-22 when, according to the Mexican National Institute of Statistics

[1] According to the health emergency decree, the essential business included hospitals, pharmacies, health services, finance, telecommunications, hotels, restaurants, supermarkets, retail shops, transport, and gas distribution.

[2] According to INEGI, 72% of the population between 3 and 29 years old enrolled in school had internet access in 2021-22.

and Geography (INEGI), 36.1% of the population between 3 and 29 years old reported taking classes through distance learning while 35.6% were using hybrid models. For students attending hybrid or in-person classes in 2021-22, only up to 45% attended schools more than 11 days per month (Figure 2.5).

Figure 2.5: In-person School Attendance by Number of Days per Month in 2021-2022.



Notes: The figure plots the share of students aged 3-29 in public schools attending in-person classes by the numbers of days per month according to the National Survey on Access and Permanence in Education (ENAPE).

2.3 Data

The primary data source of this chapter is the National Survey on Occupation and Employment (ENOE), a nationally representative survey with a rotating panel structure in which one-fifth of the sample is replaced every three months after five interviews. Due to COVID-19 restrictions, ENOE information collection was suspended after the first quarter of 2020 and temporarily replaced by telephone surveys (the Telephone Survey of Occupation and Employment - ETOE) that provided monthly information between April and June 2020. While both surveys are nationally representative and use a probability-sampling design, the telephone surveys were conducted using a sub-sample of housing units in ENOE's first quarter of 2020. As a result, the sample size decreases from around 126,000 households in ENOE to about 14,000 households.

This chapter uses a longitudinal data set that matches individual data from the telephone survey waves collected in April, May, and June 2020 with previous quarterly rounds of the traditional ENOE survey. Additionally, I match subsequent waves of the ENOE to explore the persistence of the effects during the last two quarters of 2020. This approach allows me to evaluate the short-term effects of the lockdown and check for pre-trends in labor market outcomes. The sample contains all individuals between 16 and 65 who participated in the April 2020 survey. Since the survey is a rotating panel and I follow the same individuals over time, this criterion restricts the studied period from 2019Q2 to 2020Q4. I define observations collected in May 2020 and onwards as post-treatment and set 2020Q1 as my baseline and reference period. Since lockdown restrictions began in March 2020, I omit the observations collected during this month. After tracing individuals during previous and subsequent waves, the resulting subsample includes 11,512 individuals observed for an average of five periods. For the heterogeneity analysis, I use labor and family characteristics in the fourth quarter of 2019 as the baseline. Labor informality is defined following INEGI and includes individuals employed in economic units that are not legally registered as businesses or workers who are not covered by social security benefits.

By using the ETOE sample, I differ from Viollaz et al. (2022), who use the traditional ENOE sample and drop the second quarter of 2020 due to the change in samples. As Hoehn-Velasco et al. (2022), I include the ETOE phone survey to explore the immediate effects of the pandemic as long as it is nationally representative. A concern with this approach is the potential bias that might arise when using a subsample of surveys conducted by phone. In my setting, individuals who managed to keep their job or spent more time doing housework may be less likely to answer. Table 2.1 shows the mean differences between the ENOE sample from the last quarter of 2019 and the sub-sample from the same quarter of individuals who were contacted by phone in May 2020. While the difference in the means is statistically significant for most characteristics, the differences in magnitude are considerably small. Still, this feature of the data must be considered when considering the external validity of my results.[3]

[3]It is worth noting that, although the phone survey is a 10% subsample of the original survey, the number of individuals in this sample is larger compared to other studies using longitudinal data for Latin America and other developing (and even developed) economies (Adams-Prassl et al., 2020; Angelucci et al., 2020; Petrongolo and Ronchi, 2020; Cueva et al., 2021).

Table 2.1: Sample Mean Difference Tests

Variable	(1) 2019Q4 ENOE Sample	(2) 2019Q4 Sub-sample	T-test Difference (1)-(2)
Female	0.524	0.524	-0.000
	(0.001)	(0.000)	
Age	37.414	37.811	-0.397***
	(0.027)	(0.117)	
College degree	0.405	0.405	-0.000
	(0.001)	(0.000)	
Living as couple	0.576	0.561	0.015***
	(0.001)	(0.004)	
Children 0-5	0.284	0.248	0.036***
	(0.001)	(0.004)	
Children 6-12	0.309	0.293	0.016***
	(0.001)	(0.004)	
Informal	0.321	0.306	0.015***
	(0.001)	(0.004)	
Working from home	0.218	0.232	-0.014***
	(0.001)	(0.003)	
Temporary	0.045	0.062	-0.016***
	(0.000)	(0.002)	
Self-employed	0.121	0.112	0.009***
	(0.001)	(0.003)	
Log Weekly Working Hours	3.660	3.642	0.018***
	(0.001)	(0.004)	
Log Monthly earnings	5.617	5.692	-0.075***
	(0.001)	(0.005)	
Observations	261,139	13,782	

Notes: The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical levels. Samples are restricted to individuals between 18-65 years old.

Table 2.2 reports descriptive statistics on employment characteristics at baseline in the first quarter of 2020. Mean outcomes reveal different gender gaps in the Mexican labor market. Women have lower labor participation rates (51 percent compared to 80 percent for men) and a higher share of part-time contracts (26 percent compared to 19 percent for men). Average monthly earnings and weekly work hours are also about 22 percent lower for women than men. The table also reports differences in gender distribution across sectors. The share of employment in services is higher for women, while the share of employment in primary activities (agriculture, construction, and mining) is higher for men.

Table 2.2: Summary Statistics at Baseline - Labor Characteristics.

	Men	Women	All
Labor participation (%)	0.803	0.515	0.651
	(0.009)	(0.011)	(0.008)
Unemployment (%)	0.055	0.056	0.056
	(0.005)	(0.004)	(0.003)
Informal (%)	0.434	0.430	0.432
	(0.010)	(0.008)	(0.006)
Part-time (%)	0.187	0.258	0.224
	(0.008)	(0.007)	(0.005)
Self-employed (%)	0.171	0.168	0.169
	(0.008)	(0.006)	(0.005)
Weekly work hours	36.625	29.831	33.049
	(0.491)	(0.385)	(0.313)
Monthly earnings (USD)	271.629	212.129	240.309
	(8.002)	(4.491)	(4.491)
Share employed - primary sector (%)	0.237	0.027	0.150
	(0.011)	(0.005)	(0.007)
Share employed - manufacturing (%)	0.139	0.146	0.142
	(0.009)	(0.011)	(0.007)
Share employed - services (%)	0.624	0.827	0.709
	(0.013)	(0.012)	(0.009)
Obs.	1,902	2,114	4,016

Notes: The table displays descriptive statistics for the sample during the first quarter of 2020 (excluding March) using survey weights. Standard deviations in parentheses. The primary sector includes agriculture, construction, and mining.

Table 2.3 presents summary statistics on socioeconomic characteristics. On average, the share of college graduates is lower for women. The presence of children in the household is higher for women than for men, both for children aged between 0 and 5 and school-age children aged between 6 and 15. The table also reports that the chance of being a single household head is higher for women than men. Another interesting socioeconomic dimension relates to time use. Using information available in the 2019Q4 survey, on average, women spent 22.2 hours per week on unpaid care to children and older people, while men only spent 13.2 hours per week. Similarly, the average weekly time devoted to household chores was 20.4 hours for women and only 6.8 hours for men [4]. Hence, as noted

[4]Although focusing on 2021 and 2022, the ENAPE survey also provides an idea of the distribution of parents' involvement in educational activities at home by gender. For students in preschool and primary

by Alon et al. (2020), gender differences in the distribution of employment across sectors and housework responsibilities at baseline are set to place a disproportionate burden of the pandemic on women due to the large impact on services and increased childcare needs.

Table 2.3: Summary Statistics at Baseline - Socioeconomic Characteristics.

	Men	Women
Age	37.800	38.209
	(13.587)	13.892
College degree (%)	0.486	0.428
	(0.012)	(0.011)
Household head	0.544	0.201
	(0.011)	(0.009)
Living as a couple	0.566	0.565
	(0.011)	(0.011)
Children presence, 0-5 y/o	0.213	0.281
	(0.009)	(0.010)
and household head	0.123	0.057
	(0.008)	0.005
and household head and single	0.005	0.033
	(0.002)	(0.004)
Children presence, 6-15 y/o	0.323	0.352
	(0.011)	(0.010)
and household head	0.167	0.073
	(0.009)	(0.006)
and household head and single	0.004	0.041
	(0.001)	(0.004)
Time devoted to unpaid care (hours)*	13.174	22.211
	(0.119)	(0.084)
Time devoted to household chores (hours)*	6.855	20.379
	(0.031)	(0.036)
Obs.	1,902	2,114

Notes: The table displays descriptive statistics for the sample during the first quarter of 2020 (excluding March) using survey weights. Standard deviations in parentheses. *Data for 2019Q4.

school, mothers were involved for 82% to 92% of students, while parents were involved for around 20% of students.

2.4 Empirical Strategy

My baseline event-study specification to estimate the effect of the COVID-19 pandemic is:

$$Y_{it} = \alpha_i + \sum_{t=1,t\neq 4}^{9} \beta_t D_t + u_{it}, \tag{2.1}$$

where Y_{it} is a labor outcome of individual i in period t, α_i are individual fixed effects, and D_t is a vector of dummy variables for each period. t ranges from the second quarter of 2019 to the fourth quarter of 2020 ($t = 1, 2, ..., 9$). β_t parameters are estimated using the first quarter of 2020 as a reference period ($t = 4$). My vector of outcomes Y_{it} includes an indicator variable for labor participation and unemployment, the log of weekly work hours, and the log of monthly earnings. Throughout the chapter, I present unemployment results with and without conditioning on labor participation. While the interpretation of the effect of unemployment conditioning on participation is closer to the usual measurement of unemployment rates (unemployed as a share of the labor force), analyzing the effect without conditioning on labor participation is useful to assess the potential selection of workers given by discouraged or added worker effects.

I estimate differential effects by gender using the following specification:

$$Y_{it} = \alpha_i + \sum_{t\neq 4}^{9} \left(\beta_t D_t + \gamma_t D_t \cdot I_i^f\right) + \epsilon_{it}, \tag{2.2}$$

where I_i^f is a gender dummy variable equal to 1 for female individuals. I estimate all specifications using linear estimators, individual weights, and clustered standard errors at the municipality level.

The identifying assumption for estimates of coefficients β to recover the causal effect of the pandemic is that counterfactual outcomes would have remained unchanged in the absence of the shock. Additionally, I require the lack of differential trends between men and women in the absence of the pandemic for estimates of coefficients γ to recover the differential effects. These assumptions are plausible since the national lockdown was an unprecedented shock to economic activity. Nonetheless, I also evaluate this assumption more directly by analyzing the estimates of pre-treatment periods ($t = 1, 2, 3$).

2.5 Results

This section presents the estimation results of the event-study specifications. I start by presenting baseline estimates of the overall effects of the pandemic before turning to the gender unequal effects. In all cases, I use the first quarter of 2020 as the reference period.[5] In the case of the heterogeneity analysis, I report the reduced-form coefficients of a post-COVID binary variable that activates between April and December 2020 to simplify the analysis and include the full-interaction estimates for each outcome variable and sub-sample in Appendix A2.3.

2.5.1 Overall Effects

Figure 2.6 plots the estimates of average effects for the binary variables of labor participation and unemployment. Estimates of pre-COVID periods are not statistically significant at the 5 percent level, except for the estimates of labor participation that are insignificant at the 10 percent level, which validates the assumption of parallel pre-trends in labor outcomes.

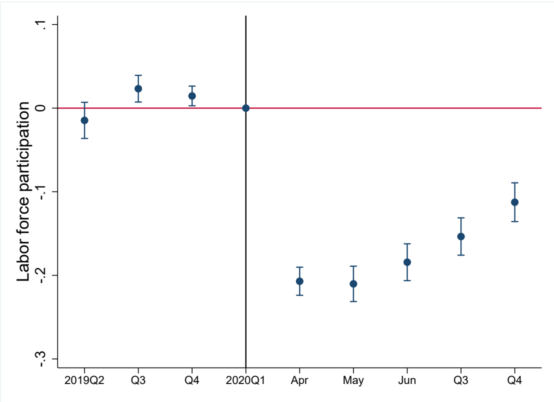
Panels A shows that the probability of participation in the labor market decreased by 21-22 percentage points immediately after the pandemic's start in April 2020. These effects progressively decreased to 12-14 percentage points but remained statistically significant at the end of 2020. Panels B and C plot the estimates of unemployment effects. Without conditioning on participation (i.e., when the reference category includes employed and non-active individuals), the probability of unemployment increased by 1-3 percentage points, and the effects are only significant after June 2020. When restricting the sample to individuals participating in the labor force in Panel C, the effects arise in April 2020 and increase in magnitude to 4-6 percentage points. These estimates align with official statistics on labor participation and unemployment released by INEGI. On the one hand, the national participation rate decreased from 59.8% in March 2020 to 47.2% in April 2020 and progressively recovered to 56.5% at the end of the year. On the other hand, the national unemployment rate increased from 3.66% in March 2020 to 5.11% in April

[5]Appendix A2.2 presents the estimates using equal timing (quarters) between survey waves.

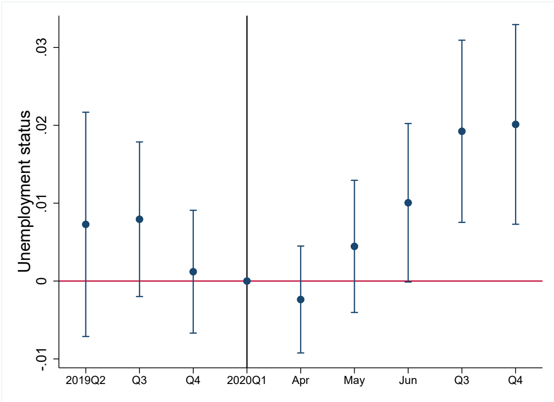
2020, peaking at 6.88% in August. Historically, while the impact of the shock in terms of unemployment was milder compared to the Great Recession in 2009 or the Peso Crisis in 1995, the decrease in labor participation has been unprecedented over past decades.

Lastly, Panels D and E present the effects on the intensive labor margin. Work hours and earnings declined by 21 and 17 percentage points, respectively, immediately after the onset of the restrictions. These effects decreased in magnitude to about 6-8 percentage points in subsequent periods and were no longer statistically significant by the end of the year.

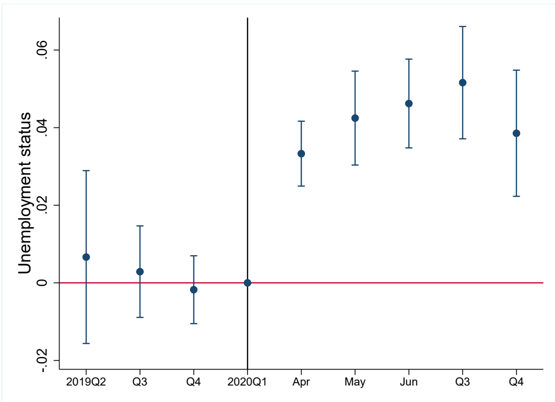
Figure 2.6: Event Study Baseline Estimates.



Panel A: Labor Force Participation.

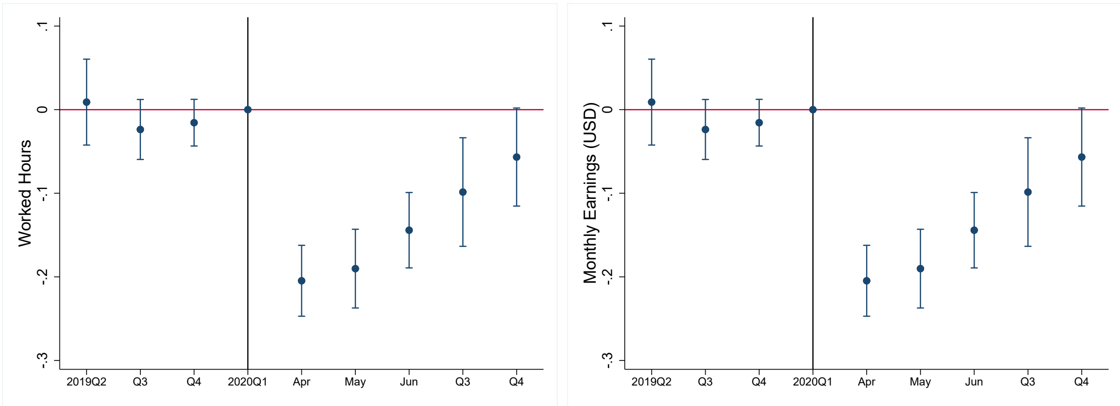


Panel B: Unemployment.



Panel C: Unemployment - conditional on participation.

Figure 2.6: *Continued.*



Panel D: Log Work hours. Panel E: Log Monthly Earnings.

Notes: The figure plots estimated coefficients of the event-study regressions. Vertical lines denote 95 percent confidence intervals. The sample period runs from the second quarter of 2019 to the fourth quarter of 2020. The reference period is the first quarter of 2020. All specifications are weighted using ENOE sample weights in 2020Q1 and include respondent fixed effects and a constant term. Standard errors are clustered at the municipality level.

2.5.2 Gender Effects

I next proceed to assess the existence of gender gaps in the labor market effects of the pandemic. Table 2.4 reports the estimates for differential effects for women. Estimates in column (1) indicate that, while there was no gender differential in labor force participation during the first two months after the start of the restrictions, women were more likely to leave the workforce after June 2020. More specifically, the probability of labor participation decreased 7-16 percentage points for men and 15-21 percentage points for women. When examining the timing of the effects for men and women subsamples separately, results indicate that the gender gap in the effect of the pandemic on labor participation occurs due to the slower recovery of female labor participation relative to male participation (Appendix Figure A2.1).

I also find evidence for gender unequal effects on the probability of unemployment in columns (2) and (3). Conditioning on participation, women experienced between 2.7-3.9 percentage points lower incidence of unemployment compared to men between April and September 2020. Nevertheless, this gender differential in unemployment narrowed and was no longer statistically significant by the fourth quarter of 2020. Hence, these results show that women who did not leave the labor force experienced a lower probability of unemployment only in the short term.

Table 2.4: Gender Gaps in COVID-19 Effects.

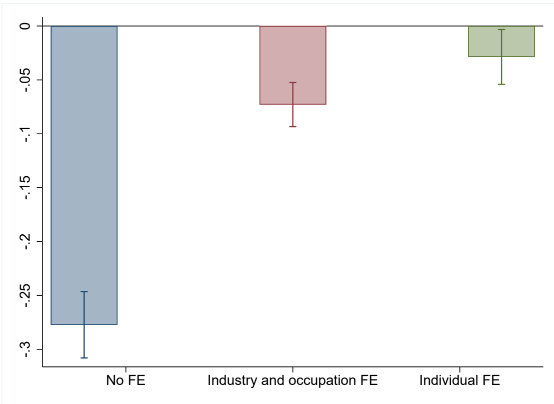
	Participation	Unemployment	Unemployment (cond. on part.)	Worked Hours	Earnings
	(1)	(2)	(3)	(4)	(5)
Apr 2020	-0.204***	0.007	0.044***	-0.229***	-0.229***
	(0.0108)	(0.0053)	(0.0060)	(0.0246)	(0.0246)
May 2020	-0.207***	0.016**	0.054***	-0.210***	-0.210***
	(0.0174)	(0.0069)	(0.0079)	(0.0260)	(0.0260)
June 2020	-0.162***	0.022**	0.057***	-0.147***	-0.147***
	(0.0141)	(0.0084)	(0.0074)	(0.0261)	(0.0261)
2020 Q3	-0.119***	0.044***	0.066***	-0.122***	-0.122***
	(0.0174)	(0.0117)	(0.0108)	(0.0422)	(0.0422)
2020 Q4	-0.071***	0.037***	0.043***	-0.043	-0.043
	(0.0150)	(0.0123)	(0.0112)	(0.0376)	(0.0376)
Female×Apr 2020	-0.007	-0.019***	-0.027***	0.063*	0.063*
	(0.0169)	(0.0061)	(0.0083)	(0.0337)	(0.0337)
Female×May 2020	-0.006	-0.022***	-0.028***	0.049	0.049
	(0.0187)	(0.0071)	(0.0073)	(0.0360)	(0.0360)
Female×June 2020	-0.043***	-0.023***	-0.027***	0.008	0.008
	(0.0130)	(0.0080)	(0.0086)	(0.0441)	(0.0441)
Female×2020 Q3	-0.067***	-0.047***	-0.039**	0.062	0.062
	(0.0218)	(0.0135)	(0.0157)	(0.0489)	(0.0489)
Female×2020 Q4	-0.078***	-0.032**	-0.009	-0.041	-0.041
	(0.0217)	(0.0130)	(0.0129)	(0.0608)	(0.0608)
Obs.	65,511	65,511	41,407	29,787	29,787
R-squared	0.118	0.003	0.018	0.039	0.039

Notes: Dependent variable: binary variable for unemployment. All specifications are weighted and include respondent fixed effects, and a constant term. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

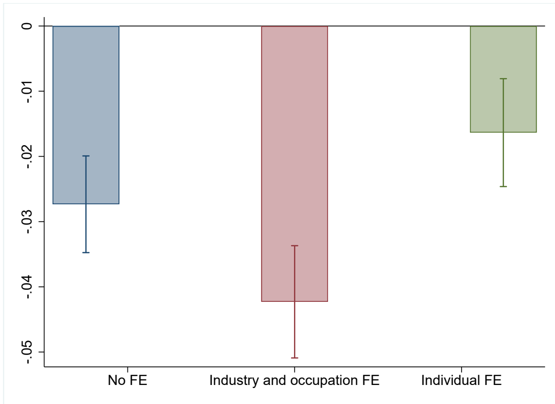
Finally, columns (4) and (5) of Table 2.4 present the estimation results for unequal gender effects at the intensive margin. The estimates suggest no statistically significant gender unequal effects on work hours and earnings. Although these results may imply that most of the differences in the effects of the pandemic between men and women occurred at the extensive margin, positive selection effects also intervene when the sample is restricted to individuals who managed to keep their job after the pandemic.

It is important to recall that all gender effects are estimated using individual fixed effects that absorb time-invariant socioeconomic and job characteristics. An interesting question is how important individual features are in explaining the raw gender differentials in the labor market effects of the pandemic. Figure 2.7 seeks to address this question by estimating the reduced-form coefficient of a post-COVID binary variable (April to Dec 2020) and its interaction with a dummy variable that activates for women without fixed effects, and progressively adding industry and occupation fixed effects and individual fixed effects.

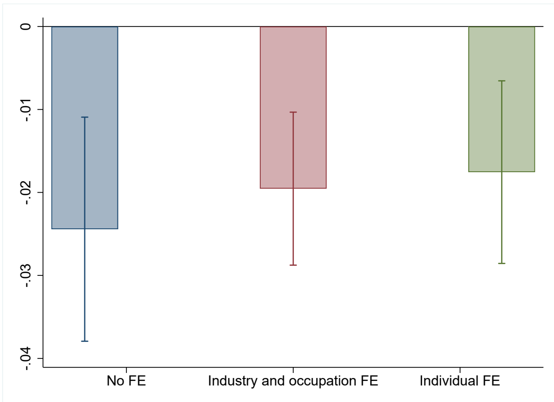
Figure 2.7: Gender Effects in COVID-19 Effects - The Role of Fixed Effects.



Panel A: Labor Force Participation.



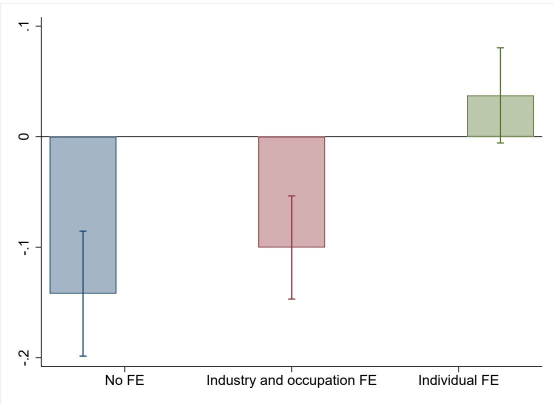
Panel B: Unemployment.



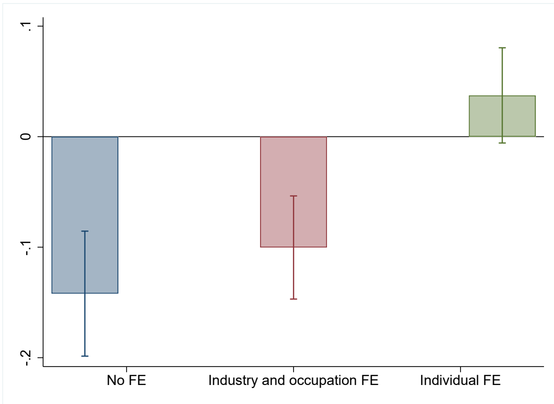
Panel C: Unemployment - conditional on participation.

Two important patterns emerge from these results. First, the raw gender gaps in the decrease of labor participation, work hours, and earnings are dramatically large. Namely, the decline in labor force participation was 26 percentage points larger for women than men (Panel A), while the decrease in work hours and earnings was about 13 percentage points for women (Panels D and E). This raw effect on labor participation is reflected in the official statistic of female labor force participation, which decreased sharply from 45 to 41 percent between 2019 and 2020. Regarding unemployment estimates, the lower increase in unemployment for women obtained before is also observed when estimating the effects without individual fixed effects (Panels B and C). Second, the results suggest that industry and occupation fixed effects account for most of the raw gender gap in the effects on labor force participation. Conversely, these characteristics are less important when explaining the effects on unemployment. In the case of labor market participation, the gender differential effect decreases from 26 to 2.9 percentage points when controlling for the sorting across sectors and occupations. Regarding intensive margins in work hours and earnings, negative differentials for women are fully explained by individual characteristics aside from sorting across industries and occupations.

Figure 2.7: *Continued.*



Panel D: Log Work hours.



Panel E: Log Monthly Earnings.

Notes: The figure plots estimated coefficients of the interaction between a post-COVID dummy activated between April and December 2020 and a female dummy. Blue bars add no fixed effects; red bars include industry and occupation fixed effects; green bars include respondent fixed effects.

In summary, I find contrasting gender gaps in the labor market effects of the pandemic with very different dynamics. On the one hand, women were more likely to leave the labor force than men, an impact that only materialized two months after the onset of the pandemic and increased over time. On the other hand, men experienced a larger probability of unemployment, an effect that was temporary and emerged right after the national lockdown.

2.5.3 Heterogeneity across Job Characteristics and Childcare

To further investigate the mechanism behind the differential effects by gender, I first analyze selected sub-samples and report the reduced-form coefficients of a post-COVID binary variable (April to Dec 2020) and its interaction with a dummy variable for women. Since I found evidence of gender differential effects at the extensive margin, I restrict the analysis to the effects on labor participation and unemployment.

I begin by exploring the heterogeneity of the effects given baseline labor formality and part-time status. While it is clear that women are overrepresented in informal and part-time jobs, the effect of the pandemic in these subsamples can go in both directions. On the one hand, this kind of job has higher flexibility than full-time and formal jobs, which can help to adjust the burden of the shock (Leyva and Urrutia, 2020) and reduce the likelihood of inactivity and job loss. On the other hand, the fact that low-skilled jobs that cannot be performed from home tend to be disproportionately concentrated in the informal sector (Hatayama et al., 2020) along with the lower opportunity cost of transitioning to non-participation compared to formal jobs may imply a higher probability of becoming unemployed and leaving the labor force. Hence, the direction of the gender effect is ultimately an empirical question. Table 2.5 presents the estimated coefficients and reports the value of the chi-square statistic of the Wald test for the difference of the coefficients (informal vs. formal and part-time vs. full-time). Panel A shows that the gender differential effect on labor participation is driven by women in the informal sector, for which the associated effect is significantly different from women in the formal sector. Moreover, there exists a 14 percentage point additional decrease in the labor force participation for women in part-time jobs, which is significantly different from women in other positions.

Panel B of Table 2.5 presents the estimates for gender differential effects on the probability of unemployment conditional on labor participation. The differential effect for women is only statistically significant for women in formal and full-time jobs, although the coefficients are not statistically different compared to those for informal and part-time women. These findings could result from a positive selection of women who kept their jobs during the economic downturn: as women were more likely to move to inactivity than men, women with a better labor market position could have been less likely to lose their jobs relative to men.

Table 2.5: Heterogeneity in Gender Differential Effects - Job Characteristics.

	All	Formal	Informal	Non Part-time	Part-time
	Panel A. *Dependent variable: labor force participation*				
	(1)	(2)	(3)	(4)	(5)
Post-COVID	-0.187***	-0.140***	-0.294***	-0.187***	-0.371***
	(0.0098)	(0.0096)	(0.0177)	(0.0115)	(0.0281)
Post-COVID × Female	-0.029**	-0.031	-0.206***	-0.074***	-0.140***
	(0.0129)	(0.0203)	(0.0225)	(0.0192)	(0.0358)
Obs.	65,511	25,792	20,577	35,652	10,717
R-squared	0.112	0.098	0.286	0.142	0.333
χ stat	-	-	6.00	-	8.69
χ p-value	-	-	0.01	-	0.00
	Panel B. *Dependent variable: unemployment status (conditional on participation)*				
	(1)	(2)	(3)	(4)	(5)
Post-COVID	0.047***	0.037***	0.065***	0.051***	0.060***
	(0.0048)	(0.0048)	(0.0088)	(0.0051)	(0.0120)
Post-COVID × Female	-0.018***	-0.022***	-0.021*	-0.026***	-0.023*
	(0.0056)	(0.0056)	(0.0124)	(0.0062)	(0.0140)
Obs.	41,407	23,906	16,374	31,939	8,341
R-squared	0.016	0.023	0.042	0.033	0.035
χ stat	-	-	0.00	-	0.99
χ p-value	-	-	0.97	-	0.32

Notes: Dependent variable: binary variable for labor participation, employment, and unemployment. All specifications are weighted and include respondent fixed effects, and a constant term. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses. The hypothesis tests are Wald chi-square tests of the hypotheses: $H_0 : \beta_{formal} - \beta_{informal} = 0$ and $H_0 : \beta_{full-time} - \beta_{part-time} = 0$ on the lincom effects for women.

I next explore the heterogeneity of the effects regarding childcare responsibilities in Table 2.6. The coefficients of the gender differential effects for women living in households with the presence of young children (aged between 0 and 5 years old) and school-age children (aged between 6 and 15 years old) are not statistically different compared to the subsample of individuals living in the household with no children under 15 years old. Nevertheless, columns (2) to (4) of Panel A show that the gender gap in the effect on labor force participation is only statistically significant for women with school-aged children. This finding call attention to the crucial role of childcare availability as a contributor to female labor participation in Mexico (Lopez-Acevedo et al., 2020) and the role of increased childcare responsibilities in explaining larger labor force exits for women after the pandemic (Lim and Zabek, 2021). The fact that women with this kind of childcare responsibilities were more likely to leave the labor market might also explain why women in this subsample had a lower probability of becoming unemployed, as shown in Panel B.

Table 2.6: Heterogeneity in Gender Differential Effects - Childcare Responsibilities.

	All	No children under 15 y/o	Children 0-5	Children 6-15
	Panel A. *Dependent variable: labor force participation*			
	(1)	(2)	(3)	(4)
Post-COVID	-0.187***	-0.194***	-0.166***	-0.169***
	(0.0098)	(0.0118)	(0.0155)	(0.0163)
Post-COVID × Female	-0.029**	-0.021	-0.039*	-0.042**
	(0.0129)	(0.0172)	(0.0215)	(0.0171)
Obs.	65,511	37,453	15,807	18,815
R-squared	0.112	0.114	0.104	0.106
χ stat	-	-	0.03	0.06
χ p-value	-	-	0.86	0.81
	Panel B. *Dependent variable: unemployment status (conditional on participation)*			
	(1)	(2)	(3)	(4)
Post-COVID	0.047***	0.044***	0.038***	0.057***
	(0.0048)	(0.0070)	(0.0086)	(0.0089)
Post-COVID × Female	-0.018***	-0.013	-0.017	-0.025**
	(0.0056)	(0.0084)	(0.0111)	(0.0110)
Obs.	41,407	23,436	10,034	12,144
R-squared	0.016	0.015	0.011	0.024
χ stat	-	-	0.02	0.07
χ p-value	-	-	0.90	0.79

Notes: Dependent variable: binary variable for labor participation, employment, and unemployment. All specifications are weighted and include respondent fixed effects, and a constant term. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses. The hypothesis tests are Wald chi-square tests of the hypotheses: $H_0 : \beta_{children0-5} - \beta_{nochildren} = 0$ and $H_0 : \beta_{children5-15} - \beta_{nochildren} = 0$ on the lincom effects for women.

Overall, the mechanism behind the unequal gender effects of the pandemic on labor participation appears to come from two sources. First, women are over-represented in informal and part-time jobs, where the associated opportunity cost of transitioning from employment to non-participation is lower. Second, the increased childcare needs resulting from the closure of schools and childcare facilities implied a disproportionate burden on women.

These two explanations are closely related as women have a greater demand for labor flexibility, given their predominant role in home production. This mechanism, which has been studied as a relevant force in explaining earnings penalties for women in the labor market (Bertrand, 2018; Mas and Pallais, 2017), also seems to have a crucial role in explaining the unequal labor effects of the pandemic among men and women.

2.5.4 Robustness Test

Measuring labor market outcomes in times of COVID-19 represents the main concern when estimating the effects since conventional definitions of employed and unemployed individuals could have been altered by the restrictions on economic activity (Coibion et al., 2020). First, the standard employment definition includes individuals who did not work due to a temporal suspension of their duties. Hence, I redefine employed individuals as those working at least one hour over the last week. Second, it is likely that newly unemployed individuals were not actively looking for a job given the abnormal conditions of the labor market, thus being classified as out of the labor force. Hence, I redefine unemployed individuals by including those who did not look for a job but were willing to work.

Table A2.5 in the Appendix presents the results for the adjusted labor outcomes. The main difference with my main results is that women had a larger and statistically significant probability of being unemployed between April and June 2020, as shown in columns (2) and (3). Moreover, the gender gap in the probability of labor participation is no longer statistically significant except for the last quarter of 2020 (column 1). This change in the estimated effects suggests that the gender gap in labor participation was mainly driven by women becoming discouraged workers who were available but stopped looking for jobs when the pandemic hit.

Appendix Tables A2.6 to A2.7 present the heterogeneity results across job characteristics and childcare responsibilities for these adjusted outcomes. The larger increase in the probability of unemployment for women is statistically significant among informal and part-time workers, as was the case for my main results on labor participation. Similarly, the larger increase in the probability of unemployment for women occurs among individuals with the presence of school-going-age children in the household. Hence, the effects captured in terms of labor participation are now reflected in unemployment.

2.6 Concluding Remarks

This chapter uses Mexican longitudinal data to study the early unequal effects of COVID-19 on labor outcomes among men and women. Mexican authorities implemented a national lockdown between March 23 to May 30, 2020, that included restrictions on non-essential activities and the closure of schools. Using an event-study design, I find that although men suffered larger losses in unemployment, women were more likely to exit the labor market after the pandemic. The estimates indicate that while the unequal effect on unemployment was immediate and diluted by the end of 2020, the unequal effect on female labor participation only materialized after June 2020 and widened during the following periods.

By exploring heterogeneity in the effects across different sub-samples, I find that the additional decrease in labor participation for women occurred among those individuals with informal and part-time jobs. Moreover, the gender gap in the effect on labor force participation was only significant for individuals with school-aged children.

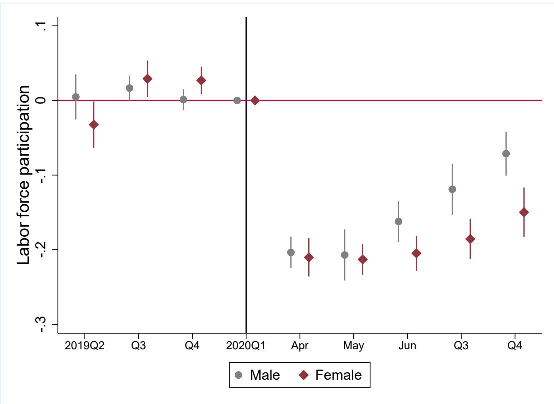
Overall, the empirical evidence suggests that the differential effect of the pandemic on female labor participation is attributable to the increased childcare needs that created a motherhood penalty for women as primary providers of childcare (Fairlie et al., 2021; Collins et al., 2021). Moreover, these adjustments mainly occurred among those with more flexible work arrangements, which also links with women being over-represented in the informal and part-time workforce (OECD and ILO, 2019).

My findings point toward the crucial role of childcare availability as a contributor to female labor participation. In particular, the results indicate that designing policies to provide childcare support is an important measure to counteract the gender-unequal effects of the pandemic on labor participation and avoid the labor penalties related to long spells of non-participation. Childcare allowance has been utilized in high-income economies such as Austria, Canada, France, and Norway. However, to date, they have not been included in the policy response to the pandemic in Latin America (ISSA, 2021). Finally, policymakers should also consider the effects of government recovery plans, which have typically focused on sectors intensive in male labor like construction and infrastructure and may thus exacerbate the unequal gender effects of the pandemic (García-Rojas et al., 2020).

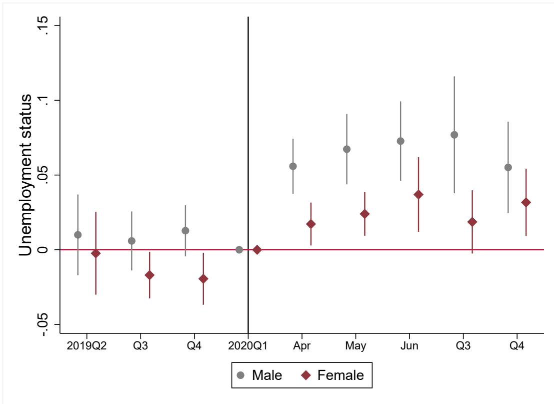
Appendix Chapter 2

A2.1 Event Study Estimates for Men and Women

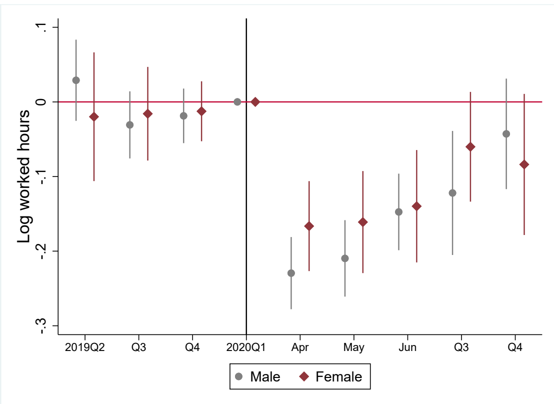
Figure A2.1: Event Study Estimates by Gender.



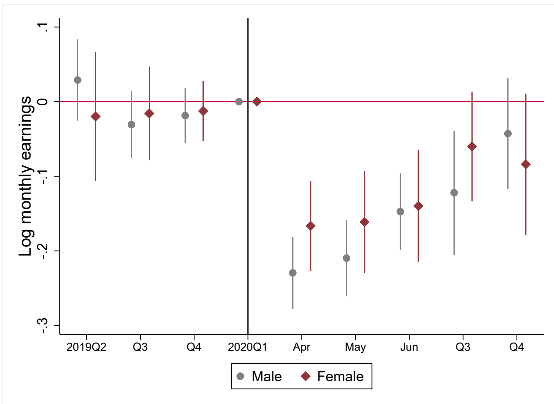
Panel A: Labor Force Participation.



Panel B: Unemployment - conditional on participation.



Panel C: Log work hours.

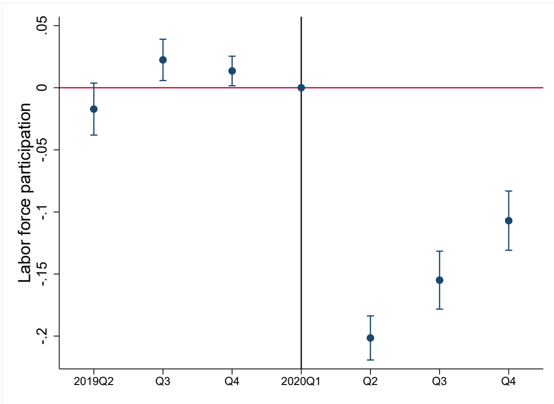


Panel D: Log monthly earnings.

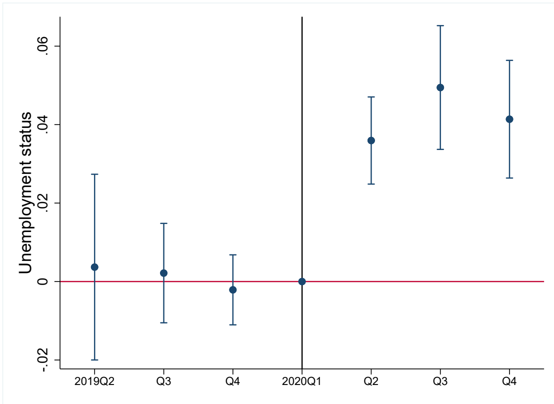
Notes: The figure plots estimated coefficients of the event-study regressions for men and women. Vertical lines denote 95 percent confidence intervals. The sample period covers the first quarter of 2019 to the fourth quarter of 2020. The reference period is the first quarter of 2020. All specifications are weighted using ENOE sample weights in 2020Q1 and include respondent fixed effects, and a constant term. Standard errors are clustered at the municipality level.

A2.2 Event Study Estimates - Equal Timing

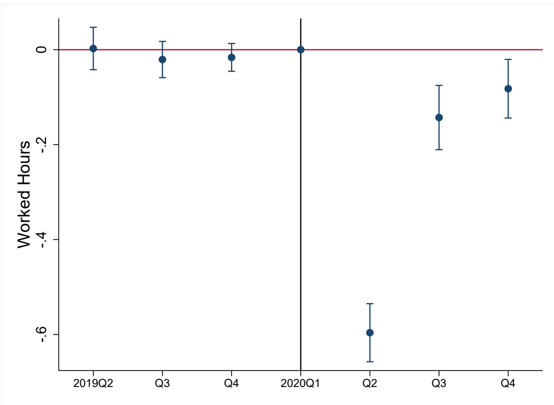
Figure A2.2: Event Study Estimates - Equal Timing.



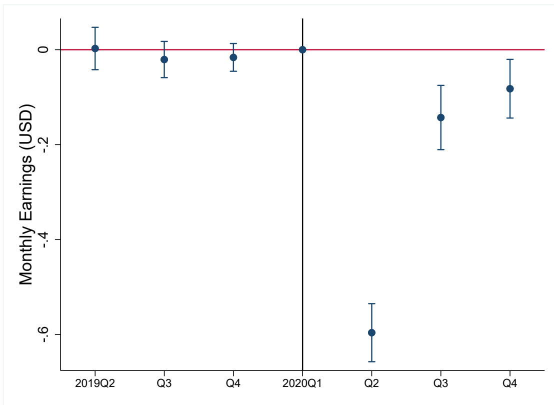
Panel A: Labor Force Participation.



Panel B: Unemployment - conditional on participation.



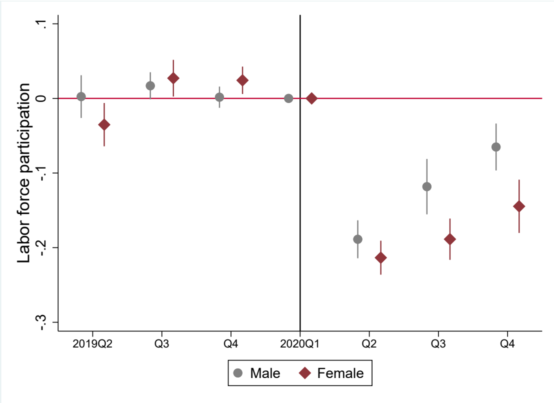
Panel C: Log Work hours.



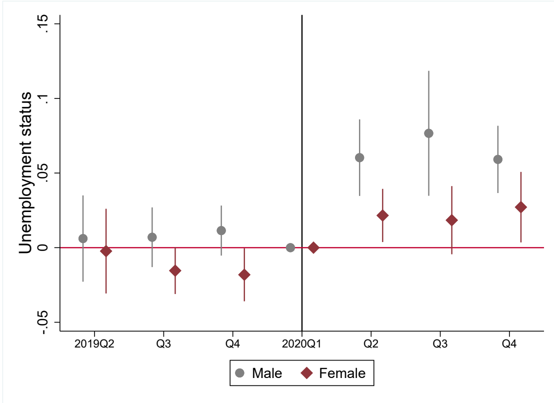
Panel D: Log Monthly Earnings.

Notes: The figure plots estimated coefficients of the event-study regressions using equal timing (quarters) between survey waves. Observations in 2020Q2 are computed as average outcomes for each individual. Vertical lines denote 95 percent confidence intervals. The sample period runs from the second quarter of 2019 to the fourth quarter of 2020. The reference period is the first quarter of 2020. All specifications are weighted using ENOE sample weights in 2020Q1 and include respondent fixed effects and a constant term. Standard errors are clustered at the municipality level.

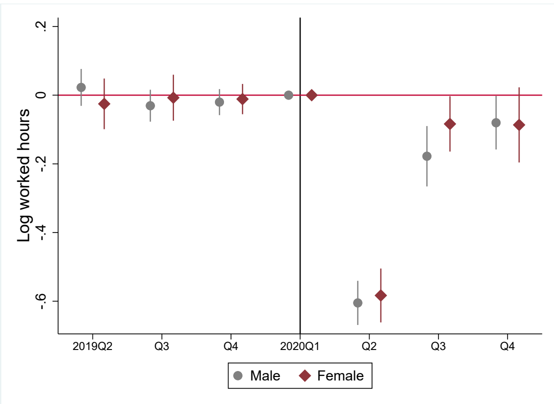
Figure A2.3: Event Study Estimates by Gender - Equal Timing.



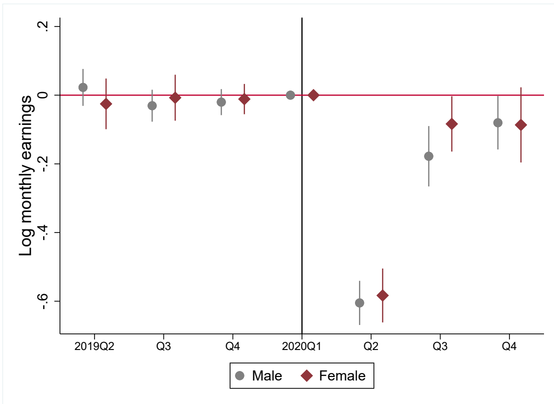
Panel A: Labor Force Participation.



Panel B: Unemployment - conditional on participation.



Panel C: Log work hours.



Panel D: Log monthly earnings.

Notes: The figure plots estimated coefficients of the event-study regressions for men and women using equal timing (quarters) between survey waves. Observations in 2020Q2 are computed as average outcomes for each individual. Vertical lines denote 95 percent confidence intervals. The sample period covers the first quarter of 2019 to the fourth quarter of 2020. The reference period is the first quarter of 2020. All specifications are weighted using ENOE sample weights in 2020Q1 and include respondent fixed effects, and a constant term. Standard errors are clustered at the municipality level.

Table A2.1: Gender Gaps in COVID-19 Effects - Equal Timing.

	Participation	Unemployment	Unemployment (conditional on part.)	Worked Hours	Earnings
	(1)	(2)	(3)	(4)	(5)
2020 Q2	-0.189***	0.016**	0.046***	-0.605***	-0.605***
	(0.0129)	(0.0065)	(0.0071)	(0.0327)	(0.0327)
2020 Q3	-0.118***	0.046***	0.063***	-0.178***	-0.178***
	(0.0189)	(0.0125)	(0.0118)	(0.0447)	(0.0447)
2020 Q4	-0.065***	0.042***	0.049***	-0.080**	-0.080**
	(0.0160)	(0.0111)	(0.0098)	(0.0396)	(0.0396)
Female × 2020 Q2	-0.025	-0.023***	-0.025***	0.022	0.022
	(0.0165)	(0.0061)	(0.0075)	(0.0356)	(0.0356)
Female × 2020 Q3	-0.070***	-0.047***	-0.038**	0.094*	0.094*
	(0.0233)	(0.0143)	(0.0173)	(0.0551)	(0.0551)
Female × 2020 Q4	-0.079***	-0.037***	-0.019	-0.006	-0.006
	(0.0244)	(0.0118)	(0.0124)	(0.0700)	(0.0700)
Obs.	47,747	47,747	31,683	24,724	24,724
R-squared	0.116	0.004	0.015	0.246	0.246

Notes: Dependent variable: binary variable for unemployment. using equal timing (quarters) between survey waves. Observations in 2020Q2 are computed as average outcomes for each individual. All specifications are weighted and include respondent fixed effects, and a constant term. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

A2.3 Heterogeneity Analysis

Table A2.2: Heterogeneity in Gender Effects - Labor Participation.

	Formal	Informal	Full-time	Part-time	No children under 12 y/o	Children 0-5	Children 6-12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Apr 2020	-0.150***	-0.343***	-0.211***	-0.405***	-0.219***	-0.159***	-0.177***
	(0.0118)	(0.0197)	(0.0144)	(0.0335)	(0.0146)	(0.0182)	(0.0174)
May 2020	-0.170***	-0.342***	-0.221***	-0.421***	-0.218***	-0.175***	-0.193***
	(0.0174)	(0.0290)	(0.0196)	(0.0360)	(0.0196)	(0.0252)	(0.0273)
June 2020	-0.143***	-0.258***	-0.173***	-0.326***	-0.178***	-0.129***	-0.135***
	(0.0138)	(0.0239)	(0.0133)	(0.0385)	(0.0165)	(0.0195)	(0.0209)
2020 Q3	-0.115***	-0.195***	-0.124***	-0.318***	-0.095***	-0.159***	-0.169***
	(0.0195)	(0.0280)	(0.0177)	(0.0441)	(0.0193)	(0.0405)	(0.0366)
2020 Q4	-0.122***	-0.098***	-0.094***	-0.172***	-0.104***	-0.055**	-0.027
	(0.0250)	(0.0170)	(0.0177)	(0.0377)	(0.0212)	(0.0247)	(0.0256)
Female × Apr 2020	-0.024	-0.192***	-0.074***	-0.117***	0.012	-0.053**	-0.039*
	(0.0287)	(0.0310)	(0.0249)	(0.0418)	(0.0232)	(0.0204)	(0.0232)
Female × May 2020	-0.019	-0.188***	-0.058**	-0.132***	0.018	-0.045	-0.022
	(0.0251)	(0.0267)	(0.0236)	(0.0452)	(0.0237)	(0.0328)	(0.0234)
Female × June 2020	-0.052**	-0.253***	-0.113***	-0.187***	-0.017	-0.074***	-0.076***
	(0.0231)	(0.0297)	(0.0167)	(0.0460)	(0.0192)	(0.0283)	(0.0197)
Female × 2020 Q3	-0.038	-0.300***	-0.142***	-0.160**	-0.070**	-0.048	-0.045
	(0.0356)	(0.0448)	(0.0332)	(0.0706)	(0.0275)	(0.0410)	(0.0406)
Female × 2020 Q4	-0.024	-0.284***	-0.077***	-0.299***	-0.023	-0.134***	-0.123***
	(0.0385)	(0.0432)	(0.0290)	(0.0634)	(0.0278)	(0.0332)	(0.0401)
Obs.	25,792	20,577	35,652	10,717	37,453	15,807	18,815

Notes: All specifications are weighted using ENOE sample weights in 2020Q1 and include respondent fixed effects, and a constant term. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Clustered standard errors at the municipality level in parentheses.

Table A2.3: Heterogeneity in Gender Effects - Unemployment.

	Formal	Informal	Full-time	Part-time	No children under 15 y/o	Children 0-5	Children 6-12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Apr 2020	0.021***	0.042***	0.029***	0.039***	-0.001	0.022**	0.026***
	(0.0038)	(0.0084)	(0.0050)	(0.0105)	(0.0072)	(0.0087)	(0.0099)
May 2020	0.034***	0.038***	0.036***	0.033***	0.006	0.017*	0.045***
	(0.0067)	(0.0087)	(0.0059)	(0.0097)	(0.0087)	(0.0099)	(0.0122)
June 2020	0.036***	0.049***	0.045***	0.029**	0.008	0.037***	0.045***
	(0.0058)	(0.0104)	(0.0071)	(0.0122)	(0.0110)	(0.0123)	(0.0125)
2020 Q3	0.049***	0.059***	0.056***	0.033**	0.050***	0.024**	0.046**
	(0.0140)	(0.0164)	(0.0127)	(0.0136)	(0.0165)	(0.0118)	(0.0195)
2020 Q4	0.037***	0.042***	0.037***	0.047**	0.037**	0.027***	0.042*
	(0.0133)	(0.0148)	(0.0111)	(0.0222)	(0.0164)	(0.0101)	(0.0222)
Female × Apr 2020	-0.013***	-0.027***	-0.016**	-0.031***	-0.009	-0.033***	-0.035***
	(0.0047)	(0.0101)	(0.0070)	(0.0111)	(0.0083)	(0.0106)	(0.0123)
Female × May 2020	-0.020***	-0.020*	-0.020***	-0.018*	-0.010	-0.018	-0.050***
	(0.0078)	(0.0110)	(0.0067)	(0.0095)	(0.0082)	(0.0113)	(0.0162)
Female × June 2020	-0.023***	-0.025**	-0.026***	-0.010	-0.002	-0.038***	-0.056***
	(0.0074)	(0.0125)	(0.0079)	(0.0147)	(0.0112)	(0.0124)	(0.0140)
Female × 2020 Q3	-0.038***	-0.034	-0.039**	-0.015	-0.059***	-0.023	-0.045**
	(0.0144)	(0.0216)	(0.0158)	(0.0162)	(0.0180)	(0.0145)	(0.0224)
Female × 2020 Q4	-0.023*	-0.008	-0.010	-0.029	-0.027	-0.026*	-0.043*
	(0.0131)	(0.0195)	(0.0135)	(0.0253)	(0.0168)	(0.0135)	(0.0236)
Obs.	25,792	20,577	35,652	10,717	37,453	15,807	18,815

Notes: All specifications are weighted using ENOE sample weights in 2020Q1 and include respondent fixed effects, and a constant term. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

Table A2.4: Heterogeneity in Gender Effects - Unemployment (Conditional on Participation).

	Formal	Informal	Full-time	Part-time	No children under 15 y/o	Children 0-5	Children 6-12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Apr 2020	0.029***	0.070***	0.043***	0.068***	0.040***	0.040***	0.059***
	(0.0041)	(0.0122)	(0.0060)	(0.0179)	(0.0078)	(0.0110)	(0.0147)
May 2020	0.046***	0.063***	0.054***	0.059***	0.051***	0.037***	0.070***
	(0.0075)	(0.0124)	(0.0071)	(0.0158)	(0.0100)	(0.0123)	(0.0148)
June 2020	0.043***	0.075***	0.058***	0.053***	0.051***	0.052***	0.068***
	(0.0062)	(0.0137)	(0.0079)	(0.0161)	(0.0094)	(0.0147)	(0.0163)
2020 Q3	0.057***	0.078***	0.069***	0.044**	0.073***	0.029	0.084***
	(0.0146)	(0.0201)	(0.0136)	(0.0193)	(0.0183)	(0.0180)	(0.0256)
2020 Q4	0.042***	0.047***	0.040***	0.067**	0.051***	0.032***	0.035**
	(0.0154)	(0.0161)	(0.0123)	(0.0278)	(0.0162)	(0.0114)	(0.0171)
Female × Apr 2020	-0.016***	-0.033*	-0.019**	-0.045**	-0.023**	-0.027**	-0.029
	(0.0057)	(0.0167)	(0.0093)	(0.0191)	(0.0107)	(0.0128)	(0.0183)
Female × May 2020	-0.026***	-0.022	-0.027***	-0.018	-0.032***	-0.005	-0.026
	(0.0088)	(0.0177)	(0.0084)	(0.0163)	(0.0095)	(0.0150)	(0.0173)
Female × June 2020	-0.024***	-0.022	-0.028***	-0.009	-0.014	-0.024	-0.044**
	(0.0083)	(0.0200)	(0.0102)	(0.0219)	(0.0125)	(0.0179)	(0.0184)
Female × 2020 Q3	-0.039**	-0.027	-0.040**	-0.003	-0.060***	-0.001	-0.034
	(0.0152)	(0.0328)	(0.0183)	(0.0240)	(0.0232)	(0.0217)	(0.0350)
Female × 2020 Q4	-0.025*	0.006	-0.007	-0.032	-0.016	0.006	-0.004
	(0.0152)	(0.0268)	(0.0158)	(0.0333)	(0.0175)	(0.0216)	(0.0206)
Obs.	23,906	16,374	31,939	8,341	23,436	10,034	12,144

Notes: All specifications are weighted using ENOE sample weights in 2020Q1 and include respondent fixed effects, and a constant term. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

A2.4 Robustness

Table A2.5: Gender Gaps in COVID-19 Effects - Alternative measurements.

	Participation	Unemployment	Unemployment (cond. on part.)	Worked Hours	Earnings
	(1)	(2)	(3)	(4)	(5)
Apr 2020	-0.174***	0.172***	0.241***	-0.229***	-0.229***
	(0.0106)	(0.0129)	(0.0138)	(0.0246)	(0.0246)
May 2020	-0.158***	0.162***	0.214***	-0.210***	-0.210***
	(0.0178)	(0.0125)	(0.0137)	(0.0260)	(0.0260)
June 2020	-0.126***	0.102***	0.136***	-0.147***	-0.147***
	(0.0141)	(0.0107)	(0.0124)	(0.0261)	(0.0261)
2020 Q3	-0.091***	0.105***	0.124***	-0.122***	-0.122***
	(0.0164)	(0.0218)	(0.0219)	(0.0422)	(0.0422)
2020 Q4	-0.033**	0.067***	0.071***	-0.043	-0.043
	(0.0148)	(0.0195)	(0.0201)	(0.0376)	(0.0376)
Female×Apr 2020	0.007	0.049***	0.081***	0.063*	0.063*
	(0.0172)	(0.0186)	(0.0214)	(0.0337)	(0.0337)
Female×May 2020	0.014	0.039**	0.059***	0.049	0.049
	(0.0192)	(0.0171)	(0.0178)	(0.0360)	(0.0360)
Female×June 2020	-0.016	0.050***	0.079***	0.008	0.008
	(0.0158)	(0.0181)	(0.0186)	(0.0441)	(0.0441)
Female×2020 Q3	-0.034	0.000	0.020	0.062	0.062
	(0.0235)	(0.0319)	(0.0323)	(0.0489)	(0.0489)
Female×2020 Q4	-0.067***	0.025	0.033	-0.041	-0.041
	(0.0217)	(0.0322)	(0.0331)	(0.0608)	(0.0608)
Obs.	65,511	49,318	45,422	29,787	29,787
R-squared	0.062	0.080	0.144	0.039	0.039

Notes: Dependent variable: binary variable for unemployment. All specifications are weighted and include respondent fixed effects, and a constant term. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses.

Table A2.6: Heterogeneity in Gender Differential Effects - Job Characteristics, Alternative Measurement.

	All	Formal	Informal	Non Part-time	Part-time
	Panel A. *Dependent variable: labor force participation*				
	(1)	(2)	(3)	(4)	(5)
Post-COVID	-0.152***	-0.104***	-0.254***	-0.152***	-0.309***
	(0.0093)	(0.0078)	(0.0174)	(0.0100)	(0.0246)
Post-COVID × Female	-0.006	-0.026	-0.153***	-0.049***	-0.117***
	(0.0116)	(0.0177)	(0.0201)	(0.0157)	(0.0310)
Obs.	65,511	25,792	20,577	35,652	10,717
R-squared	0.057	0.069	0.219	0.105	0.250
χ stat	-	-	8.15	-	6.60
χ p-value	-	-	0.00	-	0.01
	Panel B. *Dependent variable: unemployment status (conditional on participation)*				
	(1)	(2)	(3)	(4)	(5)
Post-COVID	0.189***	0.230***	0.159***	0.196***	0.250***
	(0.0095)	(0.0125)	(0.0128)	(0.0115)	(0.0244)
Post-COVID × Female	0.085***	0.024	0.131***	0.043**	0.112***
	(0.0136)	(0.0214)	(0.0239)	(0.0192)	(0.0300)
Obs.	45,422	24,287	17,087	32,653	8,721
R-squared	0.125	0.137	0.164	0.126	0.236
χ stat	-	-	1.96	-	3.62
χ p-value	-	-	0.16	-	0.06

Notes: Dependent variable: binary variable for labor participation, employment, and unemployment. All specifications are weighted and include respondent fixed effects, and a constant term. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses. The hypothesis tests are Wald chi-square tests of the hypotheses: $\beta_{children0-5} - \beta_{nochildren} = 0$ and : $\beta_{children5-15} - \beta_{nochildren} = 0$ for the lincom effects for women.

Table A2.7: HETEROGENEITY IN GENDER DIFFERENTIAL EFFECTS - CHILDCARE RESPONSIBILITIES, ALTERNATIVE MEASUREMENTS.

	All	No children under 15 y/o	Children 0-5	Children 5-15
	Panel A. *Dependent variable: labor force participation*			
	(1)	(2)	(3)	(4)
Post-COVID	-0.152***	-0.158***	-0.134***	-0.139***
	(0.0093)	(0.0102)	(0.0156)	(0.0141)
Post-COVID × Female	-0.006	-0.006	-0.007	-0.016
	(0.0116)	(0.0159)	(0.0204)	(0.0181)
Obs.	65,511	37,453	15,807	18,815
R-squared	0.057	0.061	0.047	0.052
χ stat	-	-	0.00	0.01
χ p-value	-	-	1.00	0.91
	Panel B. *Dependent variable: unemployment status (conditional on participation)*			
	(1)	(2)	(3)	(4)
Post-COVID	0.189***	0.186***	0.181***	0.195***
	(0.0095)	(0.0123)	(0.0188)	(0.0150)
Post-COVID × Female	0.085***	0.088***	0.091***	0.055**
	(0.0136)	(0.0200)	(0.0253)	(0.0241)
Obs.	45,422	25,834	10,910	13,252
R-squared	0.125	0.123	0.119	0.118
χ stat	-	-	0.00	0.21
χ p-value	-	-	0.98	0.65

Notes: Dependent variable: binary variable for labor participation, employment, and unemployment. All specifications are weighted and include respondent fixed effects, and a constant term. * p<0.1, ** p<0.05, *** p<0.01. Clustered standard errors at the municipality level in parentheses. The hypothesis tests are Wald chi-square tests of the hypotheses: : $\beta_{children0-5} - \beta_{nochildren} = 0$ and : $\beta_{children5-15} - \beta_{nochildren} = 0$ for the lincom effects for women.

Chapter 3
Regional Industry Transformation, Labor Demand, and Local Gender Gaps

3.1 Introduction

One of the most remarkable developments in the labor market during the last decades in many economies is the substantial increase in the participation of women. A growing literature has highlighted the role of the sectoral recomposition of the economy towards services in explaining the increase in the relative demand for female labor (Ngai and Petrongolo, 2017; Olivetti and Petrongolo, 2014; Ghani and Kharas, 2010). According to this mechanism, the comparative advantage of women in producing services, which are more intensive in communication and interpersonal skills, turns the rise of service labor shares into a gender-biased force that reduces gender gaps in work hours and wages (Borghans et al., 2014; Rendall, 2017).

Although there is increasing evidence on the role of labor demand and sectoral structure in explaining the increase in female labor at the aggregate level (Ngai and Petrongolo, 2017; Olivetti and Petrongolo, 2014; Petrongolo and Ronchi, 2020), little is known about the effects of industry recomposition on gender gaps in local labor markets at the subnational level. This chapter aims to fill this gap in the literature by studying the role of labor demand in explaining the spatial and temporal variation in female relative work hours across Mexican municipalities between 1990 and 2010. Mexico has experienced structural changes in terms of female employment and sectoral composition over the last decades, therefore providing a useful setting to study the spatial variation in these outcomes. For instance, the rate of female participation rapidly increased by 20 percentage points to 42 percent between 1990 and 2010, a development that took almost 50 years in other high-income economies as the US, while the employment share of services rose from 58 percent to 69 percent over the same period.

A major challenge when studying the spatial heterogeneity in local labor market developments is the availability of location-level data, a restriction that is even more prevalent in low and middle-income economies. In this chapter, I rely on detailed individual data on wages, work hours, and employment by sector from the Mexican Census of Population and Housing to assemble a dataset at the administrative municipality level covering more than 900 municipalities between 1990 and 2010.

My emphasis on local labor markets is motivated by the fact that industry recomposition is an uneven spatial process (Eckert et al., 2018). I start by documenting the specialization of locations of different population sizes into different production sectors: smaller municipalities specialize in the production of goods, including primary activities, manufacturing, and construction), while larger municipalities specialize in the production of services. I then explore to what extent the aggregated trend in the rise of the service economy maps into local labor markets. Although the share of services in total work hours has increased nationally between 1990-2010, the change has been greater in smaller than larger municipalities, thus suggesting that the sectoral recomposition towards services occurred within local labor markets.

I next link these spatial patterns in industry transformation to the changes in local gender gaps in work hours across municipality population sizes and document two empirical facts. First, the ratio of female-to-male working hours increased with municipality size in each decade since 1990. Second, I document a largely unexplored pattern in the change of the female-to-male ratios across time *and* space. While there has been an overall increase in female relative work hours between 2010 and 1990, these ratios have increased disproportionately more in smaller than larger municipalities.

Overall, these empirical trends suggest that sectoral recomposition mainly took place in smaller municipalities that initially specialized in producing goods, and the corresponding increase in service shares disproportionately benefited women's working hours in these locations. To rationalize the mechanism, I propose a theoretical model with two production sectors, goods and services, and two worker types, males and females. Goods, interpreted as manufacturing and primary industries, are tradable across locations, while services are non-tradable and can only be consumed in the exact location they are produced (Cerina et al., 2019). Regions are populated by female and male workers who face no migration cost and decide to live in the region that offers the highest utility. Urban size implies productivity externalities on the production side but also higher congestion costs on the consumption side that can be interpreted as higher housing and commuting costs (Tabuchi and Thisse, 2006; Tabuchi, 1998).

In the model, the interaction between urban size externalities and tradability across sectors allows for regional specialization patterns. Additionally, because gender-specific comparative advantages differ by sector, regional specialization maps into heterogeneous gender gaps across locations. Industry specialization across regions alongside industry differences in female labor intensities leads to heterogeneous effects of sector-specific labor demand shocks on local gender gaps in working hours. In particular, I show that the effect of local productivity shocks on female-to-male labor gaps decreases with city size.

To empirically quantify to what extent differences in labor demand affected local gender gaps and how these effects varied across municipality size, I exploit the spatial variation in relative labor demand using shift-share instruments for labor demand proposed by Bartik (1991). This approach allows me to isolate changes in labor demand from changes in observed employment across sectors that also occur due to changes in labor supply. In order to explore the heterogeneity across municipality sizes, I use a threshold estimation strategy that allows the coefficients to vary across regimes identified using the initial population size (Hansen, 1999). Consistent with the theoretical mechanism, I find that labor demand shocks in the goods industry only significantly affect female relative working hours in small municipalities. Moreover, labor demand shocks in the service sector produce a higher effect on female relative working hours in smaller compared to larger municipalities. These findings are robust to the use of alternative estimators and different definitions of the spatial units, as well as the inclusion of additional controls related to labor supply factors such as fertility rates and population age structure.

This chapter contributes to different strands of the literature. First, it relates to the emerging literature on the role of labor demand in explaining contrasting gender trends in the labor market (Gottlieb et al., for; Olivetti and Petrongolo, 2014; Ngai and Petrongolo, 2017; Verdugo and Allègre, 2020; Petrongolo and Ronchi, 2020). In particular, Ngai and Petrongolo (2017) show how the rise of the service economy, driven by structural transformation and the marketization of home production, raised female relative wages and work hours in the US. Similarly, Verdugo and Allègre (2020) find that female labor force participation increased in regions more affected by the destruction of men's jobs during the Great Recession in Europe. The approach of this chapter also highlights the role of labor demand changes in a setting of segregation by gender across sectors, but it explicitly incorporates the segregation across locations of different population sizes. Investigating the spatial component of this labor demand-driven mechanism is crucial to understanding the aggregated trends in gender labor outcomes because it sheds light on the spatial sources of these patterns at the national level.

Also related to this chapter is a growing literature on the patterns of female labor provision in relation to the structural transformation of the economy. Studies in this area have focused on the historical patterns across sections of countries to show that the relationship between women's employment and economic development exhibits a U-shape (Gottlieb et al., for; Ngai and Olivetti, 2015; Tam, 2011; Goldin, 1994). While this chapter studies a shorter period of time and focuses on the upward section of the U-shape, it sheds light on the way in which this aggregated process maps into local labor markets, given the specialization of cities across sectors.

Another related strand of the literature studies the effect of labor demand shocks on local outcomes (Katz and Murphy, 1992; Notowidigdo, 2011; Moretti, 2013; Diamond, 2016). Most closely related is the work by Chauvin (2017), who studies how employment, wages, rents, and gender employment gaps respond to labor demand changes in Brazil using a setting of gender-segmented local labor markets. This chapter differs in two main aspects. First, while I also use a spatial approach, I characterize the effects of local labor demand shocks along the city-size distribution. Second, I focus on sector-specific instead of gender-specific labor demand shocks. While gender segregation across sectors is at the heart of my mechanism, I use variation in predicted changes in labor demand across sectors rather than predicted changes in employment for men and women. This approach allows me to investigate the role of industry recomposition in explaining differential gender trends in work hours across municipalities, while the approach of Chauvin (2017) suits his interest in comparing the effects of gender-specific labor demand shocks on migratory responses, population, and local prices.

The chapter also contributes to the growing literature on the spatial heterogeneity of local outcomes as wage premiums, labor polarization, and skill sorting across city-size (Glaeser and Resseger, 2010; Baum-Snow and Pavan, 2013; Eeckhout et al., 2014; Cerina et al., 2017, 2019; Petrongolo and Ronchi, 2020). In particular, Cerina et al. (2019) show that the contribution of women to employment polarization in the US is particularly strong in large cities where education premiums rose faster. This chapter differs as it focuses on industry composition and abstracts from labor polarization by skill.

The rest of the chapter is organized as follows. Section 3.2 presents the data. Section 3.3 establishes the empirical facts. Section 3.4 describes the mechanism using a theoretical model. Section 3.5 discusses the empirical strategy. Section 3.6 presents the results. Section 3.7 concludes.

3.2 Data

This chapter uses nationally representative samples from the Mexican Housing and Population Censuses prepared by the National Institute of Statistics and Geography (INEGI) for 1990, 2000, and 2010 as its primary data source. This anonymized dataset contains individual information on educational attainment, labor conditions, migration status, and socioeconomic characteristics. I restrict the sample to individuals aged 16 to 65 and define employed individuals as those reporting positive monthly wages. On average, each sample contains information on 1.5 million individuals.

For the analysis at the municipality level, I aggregate individual outcomes at the municipality level defined using administrative boundaries. Following the standard approach in the literature (Eeckhout et al., 2014; Baum-Snow and Ferreira, 2015; Cerina et al., 2019), I define urban size using the total population in each municipality. Because I am interested in spatial variation across urban sizes, I restrict the sample to municipalities with more than 10 thousand inhabitants in 1990, which results in 983 municipalities representing 89.56 percent of the national population in 1990. Since large integrated labor markets might differ from administrative spatial units, in the robustness analysis, I use an alternative definition by aggregating municipalities that belong to the same Metropolitan Zone (MZ) defined by INEGI based on geographical proximity, urban density, and economic integration.

Labor shares by industry are computed using two-digit industry codes. Since industry classification changed for each census year, I harmonize the Mexican Classification of Activities and Products used in 1990 with the 2017 North American Industry Classification System (NAICS) version at the two-digit level. Details on the definition of the variables and additional data sources are presented in Appendix A3.1.

3.3 Motivating Facts

This section documents three stylized facts in the data. I start by describing national trends in labor gender outcomes and industry composition and then explore the spatial heterogeneity of these outcomes across municipalities of different population sizes. While I present the overall evolution of gender gaps in labor participation rates, employment rates, and total working hours, the remaining analysis focuses on the ratio between female-to-male total working hours to capture changes at both extensive and intensive margins.

3.3.1 Overall Trends in Gender Gaps

Table 3.1 presents the national trends in gender gaps in the labor market defined as the ratio between female over male outcomes. Panel A shows that the rate of female participation increased from 14.6 percent to 27.4 percent between 1990 and 2010, while the male participation rate was stable at 74 percent. As a result, the participation gap narrowed from 19.1 percent to 48.6 percent. Employment gaps presented in Panel B followed a similar pattern; employment rates increased from 13.6 percent to 24.7 percent for women and remained around 70 percent for men. Finally, Panel C shows how the female-to-male gap in total working hours also narrowed from 35.3 percent to 49.7 percent between 1990 and 2010.

Table 3.1: National Trends in Labor Outcomes.

	1990	2000	2010	Δ 1990-2010
	Panel A: *Labor participation rates*			
Male	0.829	0.847	0.852	+0.0324
Female	0.249	0.368	0.423	+0.174
Female-to-male gap	0.300	0.435	0.496	+0.196
	Panel B: Employment rates			
Male	0.789	0.804	0.778	-0.010
Female	0.240	0.322	0.368	+0.128
Female-to-male gap	0.304	0.400	0.473	+0.169
	Panel C: *Total working hours*			
Female-to-male ratio	0.305	0.418	0.478	+0.173
	Panel D: *Industry structure*			
Goods female intensity	0.149	0.200	0.200	+0.051
Service female intensity	0.332	0.392	0.392	+0.060
Total service share	0.578	0.437	0.686	+0.108

Notes: The table presents trends in total and gender-specific labor participation rates, employment rates, and weekly work hours from 1990 to 2010. The sample is restricted to individuals aged 18 to 65 years old and municipalities with more than 15 thousand inhabitants in 1990. Gender gaps are computed as the ratio of female to male labor outcomes.

3.3.2 The Role of the Between-industry Component

An interesting question about the rise in women's labor is how this change in female employment varied across different sectors of the economy. Table 3.2 presents female intensities by industry, defined as the share of female hours in total working hours by sector, and sector shares in total working hours for each census year. On average, female intensities tend to be larger in service industries such as health care, education, accommodation, personal services, finance, and retail and lower in the agriculture, mining, and construction sectors. The last three columns of the table reveal that between 1990 and 2010, the employment composition of the economy changed from sectors with lower initial female intensities, such as agriculture or manufacturing, towards services that were already intensive in female labor, such as professional services, retail, or accommodation.

To gain a broader perspective on the change in industry shares and its relationship with the rise in female employment, Table 3.2 also adopts a common approach in the literature (Petrongolo and Ronchi, 2020; Ngai and Petrongolo, 2017; Olivetti and Petrongolo, 2014) and divides the economy into the production of goods (primary sector, manufacturing, utilities, and construction) and the production of services.[1] Two trends emerge when looking at the aggregate evolution of these two sectors. First, the share of female hours in the service sector is comparatively higher and increased more from 33.2 percent to 39.2 percent, almost doubling the change in the goods sector from 14.1 percent to 20 percent. Second, the total share of the service sector increased from 60.2 percent to 68.6 percent between 1990 and 2010.

Following Petrongolo and Ronchi (2020) and Ngai and Petrongolo (2017), I explore to what extent the expansion of the service sector accounts for the increase in the share of female hours using a shift-share decomposition. This method decomposes the total change in female hours into two components:

$$\Delta l_{ft} = \underbrace{\sum_j \alpha_{fj} \Delta l_{jt}}_{\substack{\text{Between-industry} \\ \text{component}}} + \underbrace{\sum_j \alpha_j \Delta l_{fjt}}_{\substack{\text{Within-industry} \\ \text{component}}} \tag{3.1}$$

where t denotes the year of reference, l_{ft} denotes the share of female hours in total hours, and l_{fjt} is the share of female hours in sector j, the decomposition weights are defined as $\alpha_{fj} = (l_{fjt} + l_{fjt_0})/2$ and $\alpha_j = (l_{jt} + l_{jt_0})/2$, and t_0 denotes the initial year. The first term to the right of Eq. 3.1 is the between-industry component that measures the change in sector shares in total employment given average female intensities across periods. The second term is the within-industry component that measures the change in each sector's female intensities given average sector shares in total employment.

The result of this decomposition reveals that the between-industry component accounted for roughly one-fourth (26.2 percent) of the total change in female hours, a figure that is in line with other studies on developed economies (Ngai and Petrongolo, 2017; Olivetti and Petrongolo, 2014). This exercise suggests that the industry recomposition of the economy towards the production of services was a sizable component explaining the increase in female labor over the last decades. Due to the initial gender segregation across sectors,

[1] I import this binary categorization throughout the chapter, although there might be important heterogeneity among industries in the service category. For instance, the spatial distribution of economic activity can vary according to the degree of product differentiation (Behrens, 2005). Of particular relevance in my analysis is whether different service industries are traded and can then not necessarily locate in larger municipalities. In Appendix A3.2, I further explore the spatial distribution of economic activity across municipality sizes and show that, except for education, all service industries are heavily urbanized compared to the good industries.

Table 3.2: FEMALE INTENSITIES AND SECTORAL COMPOSITION.

	Female Intensities			Sector Shares		
	1990	2010	Δ 1990-2010	1990	2010	Δ 1990-2010
			Panel A: *Goods Sector*			
Agriculture	3.09	6.65	+3.562	8.41	3.96	-4.450
Mining	10.48	8.24	-2.235	1.11	0.74	-0.370
Utilities	11.28	15.55	+4.261	0.90	0.60	-0.301
Construction	3.36	4.14	+0.776	6.80	7.94	+0.142
Manufacturing	22.30	30.44	+8.146	25.01	18.15	-6.858
Goods total	0.141	0.200	+ 0.059	0.398	0.314	-0.084
			Panel B: *Service Sector*			
Wholesale trade	16.57	21.60	+5.027	2.13	3.04	+0.867
Retail trade	32.81	41.59	+8.783	14.67	17.47	+2.794
Transport	6.15	5.94	-0.211	5.95	6.82	+0.867
Information and culture	30.56	33.28	+2.719	1.05	1.15	+0.105
Finance and insurance	37.62	46.93	+9.317	1.82	1.30	-0.516
Real estate	31.67	35.16	+3.487	0.28	0.55	+0.270
Professional and technical services	30.72	32.75	+2.023	1.99	6.76	+4.768
Educational and research	53.56	58.95	+5.388	5.75	5.58	-0.172
Health care and social assistance	59.83	65.42	+5.585	3.81	3.73	-0.086
Entertainment and arts	22.06	28.87	+6.809	0.73	0.75	+0.021
Accommodation and food	41.81	49.74	+7.925	4.45	6.13	+1.683
Personal and repair services	32.96	45.99	+13.034	9.39	8.57	-1.816
Public administration	25.03	32.88	+7.848	5.75	6.75	+1.009
Service total	0.332	0.392	+0.060	0.602	0.686	+0.084

Notes: Columns 2 to 4 present the levels and change of female intensities defined as the share of female hours in total hours per industry. Columns 5 to 7 present the levels and change of sector shares, defined as the share of each industry on total work hours.

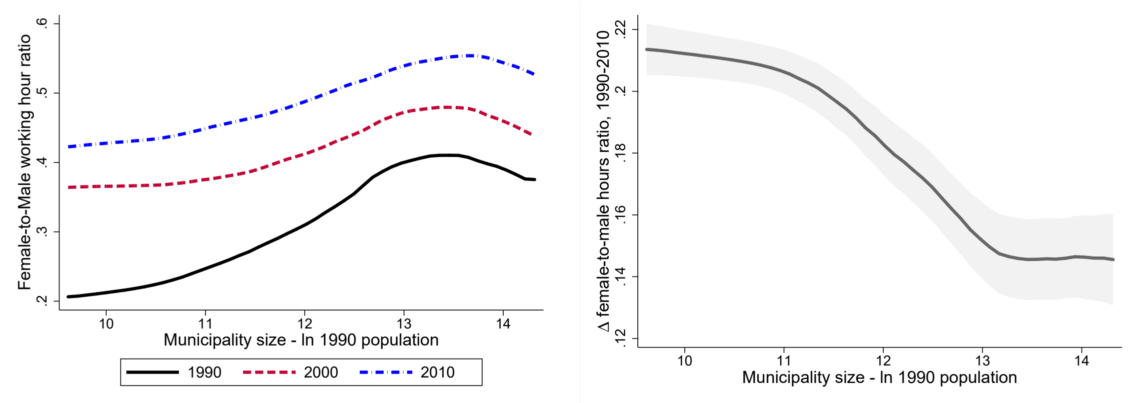
men bore the burden of deindustrialization, while women benefited from the transition to services. In the next subsections, I will examine how this aggregated trend maps into the size distribution of local labor markets.

3.3.3 Spatial Gender Gaps and Regional Industry Transformation

This subsection documents empirical trends of labor gender gaps in working hours and industry shares across municipalities of different sizes. Panel A of Figure 3.1 shows that female-to-male ratios in working hours increase with municipality size in each census decade. However, the increase in the relative female working hours between 1990 and

2010 was larger in smaller compared to bigger municipalities. Panel B of Figure 3.1 confirms this pattern by plotting the negative relationship between the change in relative working hours between 1990-2010 and the log population size in 1990.

Figure 3.1: Female-to-Male Work Hours Ratio by Municipality Size.



Panel A

Panel B

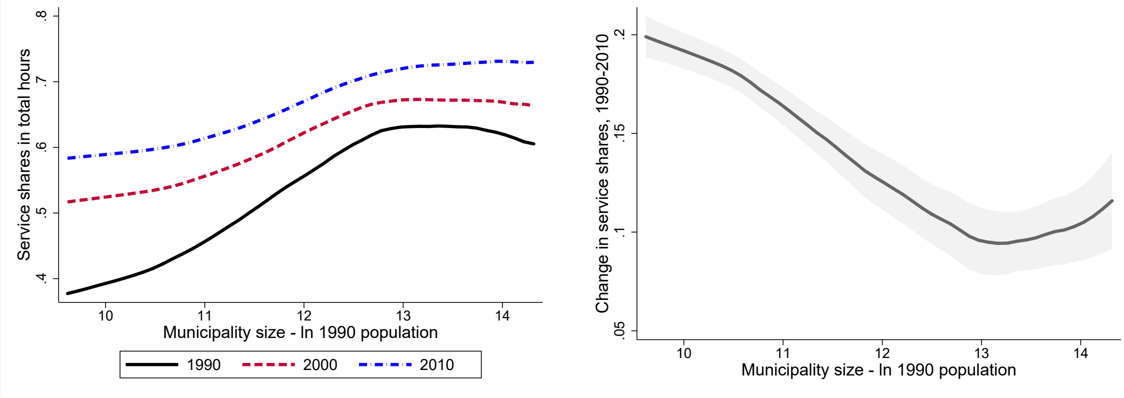
Notes: Panel A plots a local polynomial regression for the ratio of female-to-male total work hours against the log of total population per municipality in 1990. Each line corresponds to a census year. Panel B plots the smoothed change of female-to-male total working hours between 2010-1990 with the 95 percent confidence interval on the y-axis against the log of total population per municipality in 1990.

I then explore to what extent changes in the industry composition also vary across municipalities of different population sizes and whether this pattern coincides with the one in local gender gaps. Panel A of Figure 3.2 plots the service share on total working hours across municipalities ranked by the total population in 1990. Panel A shows that service shares increase with municipality size, a stylized fact consistent with different studies that document the concentration of business services and management activities in larger cities and production activities in smaller cities (Duranton and Puga, 2005; Holmes and Stevens, 2004). Panel B of Figure 3.2 shows that, while there was an overall rise in service shares between 1990 and 2010, this increase is stronger in smaller municipalities [2].

In Figure 3.3, I further disaggregate the local change in the composition of total work hours by subsectors groups. The figure reproduces the Panel B of Figure 3.2 by plotting the change in the service share on total work hours by splitting the goods sector into primary activities and manufacturing and the service sector into high-skill intensive services (finance, insurance, real estate, professional, government, and education) and low-skill

[2] Appendix A3.2 documents these key motivating facts using alternative definitions of the spatial boundaries as metropolitan areas, and alternative measures as population in neighboring municipalities and population in 2010.

Figure 3.2: Service share of total working hours by Municipality Size.

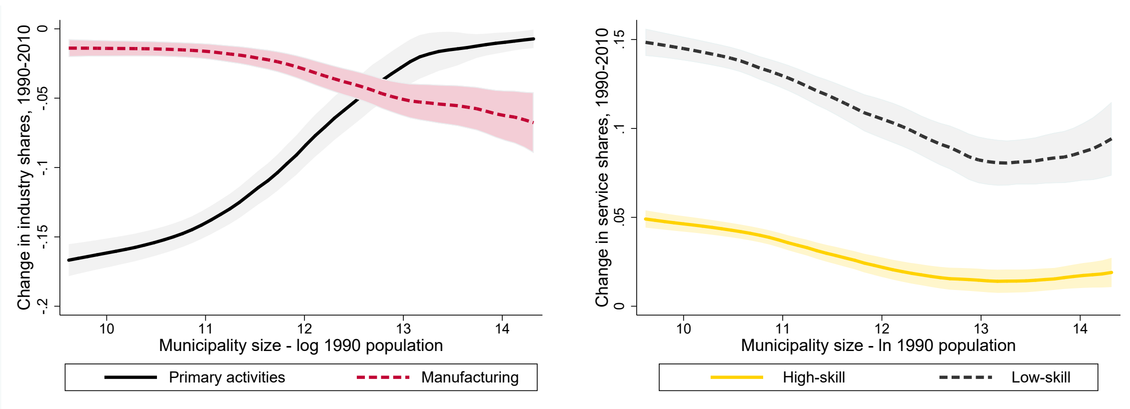


Panel A Panel B

Notes: Panel A plots a local polynomial regression for the service share on total working hours with the 95 percent confidence interval on the y-axis against the log of total population per municipality in 1990. Each line corresponds to a census year. Panel B plots the smoothed change in service shares between 1990 and 2010 with the 95 percent confidence interval on the y-axis against the log of total population per municipality in 1990.

intensive services (the rest of the service industries). The figure shows that the spatial sectoral recomposition in smaller compared to larger municipalities is mainly driven by the contraction of the primary sector on the side of goods production (Panel A) and the rise of low-skill intensive services (Panel B).

Figure 3.3: Change in Sector Shares between 1990 and 2010.



Panel A Panel B

Notes: The figure plots a local polynomial regression for the share of different subsectors on total working hours between 2010-1990 with the 95 percent confidence interval against the log of total population per municipality in 1990. Each line corresponds to a census year. Primary activities include agriculture, construction, and mining. High-skill services include finance, insurance, real estate, professional, government, and education, while low-skill services include retail, wholesale trade, personal services, accommodation, and transport.

The fact that service shares increased on average in municipalities of all sizes also suggests that the recomposition of employment across industries did not entirely result from labor shifting away from smaller municipalities. To highlight this fact, I follow Eckert et al. (2018) and decompose the decline of the goods sector into two spatial margins. Under the first margin, labor reallocates from regions specialized in producing goods towards locations specialized in producing services. Hence, the negative correlation between the change in labor shares and the initial share of goods drives the total decline of the goods sector. Alternatively, under the second margin, the decline of the goods labor share occurs locally within regional labor markets. More formally,

$$\Delta l_{gt} = \underbrace{\sum_k l_{gkt_0} \Delta l_{kt}}_{\substack{\text{Spatial reallocation} \\ \text{margin}}} + \underbrace{\sum_k l_{kt} \Delta l_{gkt}}_{\substack{\text{Regional transformation} \\ \text{margin}}} \tag{3.2}$$

where l_g is the employment share of the goods sector, l_{gkt} is the employment share of the goods sector in municipality k and time t, and l_{kt} is the employment share of municipality k. The first term to the right of Eq. 3.2 is the reallocation margin that is prevalent when total employment shares decline in regions specialized in the production of goods, while the second term captures the regional transformation margin that gains importance when industry transformation occurs *within* local labor markets.

Table 3.3 presents the result of this accounting exercise. It shows that the overall decline in the goods share is explained by the regional transformation margin. If anything, total employment shares of municipalities with high goods shares increased between 1990 and 2010. This result suggests that the rise of the service economy was a phenomenon occurring at the local level in both large and small cities.

Table 3.3: Spatial Margins in the Decline of Goods.

Total change 1990-2010	-0.108
Spatial reallocation margin	0.008
Regional transformation margin	-0.116

Notes: The table presents the results of the shift-share decomposition of the change in the employment share of the goods sector between 1990 and 2010 following Eq. 3.2. The goods sector includes the primary sector, construction, utilities, and manufacturing. The service sector is defined as the total economy, excluding the goods and national security sectors.

3.3.4 Stylized Facts Summary

The following facts summarize the key empirical patterns presented in this section:

Fact 1 (Spatial Gender Gaps): While there has been an overall increase in female-to-male ratios, this increase was greater in smaller compared to larger municipalities.

Fact 2 (Spatial Industry Recomposition): While there has been an overall increase in service shares, this increase was greater in smaller compared to larger municipalities.

Fact 3 (Regional Industry Transformation): Sectoral recomposition from goods to services occurred *within* local labor markets, rather than through the reallocation of labor *across* local labor markets.

As such, these empirical facts suggest that the recomposition of industry towards services can be an important factor explaining the greater increase of female employment in smaller municipalities.

3.4 Conceptual Framework

In this section, I present a simple spatial equilibrium model to rationalize the spatial between-industry component of differential gender trends in local labor markets. The model has two key ingredients: i) there is sector specialization across locations; ii) there are differences in gender intensities across sectors. Regional specialization is modeled by assuming urban size externalities and the production of tradables and non-tradables. In that sense, regional specialization in the model resembles the theoretical framework of Tabuchi (1998) and Tabuchi and Thisse (2006). I model the second ingredient, differential gender intensities, by assuming that women have a comparative advantage in producing services (Ngai and Petrongolo, 2017; Rendall, 2017). The interaction between differences in gender intensities across sectors and spatial specialization generates heterogeneous gender gaps across locations and leaves room to study the effects of local productivity shocks in each industry.

3.4.1 Environment

Consider an economy with a fixed number of cities J indexed by j, populated by female and male workers. There is a fixed number of workers at the national level L, while L_j denotes the population of each city. There are two market sectors in each city, producing goods (g) and services (s). Goods are interpreted as primary and manufacturing output that is perfectly tradable across cities with no transport costs, while services are non-tradable and can only be consumed in the location where they are produced. For simplicity, I assume female and male workers in the same city work in different sectors, with female workers sorting into the production of services and male workers sorting into the production of goods.

Workers are perfectly mobile across cities and make location decisions by choosing the location that offers the highest indirect utility. Each worker of gender $i = m, f$ obtains utility from the consumption of goods and services. Her or his indirect utility is thus positively affected by wages w_j^i and negatively affected by urban congestion costs b_j that increase with city size and capture commuting and rent payment costs.

3.4.2 Production

Firms in each city j and sector k use labor as their only input to produce a level of output Y_{kj}:

$$Y_{gj} = A_{gj} \left(L_j^m\right)^{\alpha_g} \tag{3.3}$$

$$Y_{sj} = A_{sj} \left(L_j^f\right)^{\alpha_s}, \tag{3.4}$$

where A_{kj} is a city-specific productivity shifter and $0 < \alpha_s, \alpha_g < 1$. Because goods are perfectly tradable across cities, the price of goods equalizes across space and is taken as a numeraire ($p_g = 1$).

Profit maximization implies that the marginal product of labor must be equal to the wages in each sector. Combining these two conditions yields:

$$\frac{L_j^f}{L_j^m} = \frac{\left(w_j^m/\alpha_g A_{gj}\right)^{\eta_g}}{\left(w_j^f/\alpha_s A_{sj} p_j^s\right)^{\eta_s}} \tag{3.5}$$

with $\eta_k = 1/(\alpha_k - 1)$. Hence, local labor gender gaps are determined by wage gaps and relative productivity across sectors.

3.4.3 Preferences

Each representative agent of gender $i = f, m$ living in city j has preferences over the consumption of goods c^i_{gj} and services c^i_{gj}, and faces the following utility maximization problem:

$$\begin{aligned} \max_{c^i_{gj}, c^i_{sj}} \quad & U^i_j(c^i_{gj}, c^i_{sj}) = \left(c^i_{gj}\right)^{\beta} \left(c^i_{sj}\right)^{1-\beta} \\ \text{s.t.} \quad & c^i_{gj} + p^s_j c^i_{sj} = w^i_j - b_j L_j, \end{aligned} \tag{3.6}$$

where p^s_j is the local price of services, b_j is the urban cost parameter, and $0 < \beta < 1$. Replacing the optimal consumption of goods and services into the utility function yields the indirect utility of agents living in city j:

$$V^i_j \left(w^i_j, b_j, p^s_j\right) = \beta^{\beta} \left(\frac{1-\beta}{p^s_j}\right)^{1-\beta} w^i_j - b_j L_j \tag{3.7}$$

Moreover, the free mobility of workers across cities implies that utility must be equalized across locations. Because of this, wages must compensate for higher urban congestions costs in larger cities:

$$w^i_j = \overline{w^i_j} \left(p^s_j\right)^{1-\beta} + b_j L_j, \tag{3.8}$$

where $\overline{w^i_j} = \overline{V^i}/\beta^{\beta} (1-\beta)^{1-\beta}$.

3.4.4 Equilibrium

Equilibrium is defined as a set of wages $\{w^M_j, w^F_j\}$, service prices $\{p^s_j\}$, and labor $\{L^M_{kj}, L^F_{kj}\}$ such that:

1. Firms optimize profits subject to the technology (Eq. 3.4) and workers maximize utility subject to the budget constraint (Eq. 3.6).

2. Utility is equalized across cities.

3. The local markets of goods, services, and labor clear.

3.4.5 Labor Gender Gaps and Labor Demand Shocks

Replacing local service prices from Eq. 3.8 into Eq. 3.5 yields:

$$\frac{L_j^f}{L_j^m} = \left[\frac{w_j^m}{\alpha_g A_{gj}}\right]^{\eta_g} \left[\frac{w_j^f}{\alpha_s A_{sj} \left(\frac{w_j^f - b_j L_j}{\overline{w}_j^f}\right)^{\frac{1}{1-\beta}}}\right]^{-\eta_g} \tag{3.9}$$

Eq. 3.9 implies that the ratio of female-to-male labor increases with city size L_j ($\frac{\partial L_j^f / L_j^m}{\partial L_j} > 0$). Because the price of services rises with city size, larger cities specialize in the production of services while firms in the goods sector sort into smaller cities with lower labor and congestion costs. Since services are relatively more intensive in female labor, industry sorting across city size maps into greater female-to-male labor ratios in larger cities, which matches the empirical trend in the data (Fact 1).

To explore the response to sectoral transformation, the theoretical literature on structural change typically assumes higher productivity growth in the goods sector, which releases labor from this sector (Ngai and Petrongolo, 2017). In this model, I adopt a similar approach and consider a positive local productivity shock in the goods sector. By abusing the notation to introduce two time periods t and $t+1$, the local productivity shock would imply $A_{gj(t+1)} = A_{gj(t)} + \Delta$, with $\Delta > 0$.[3] Because the goods industry is more productive in city j, the local ratio of female-to-male labor increases due to changes in labor demand across sectors ($\frac{\partial \left(L_j^f / L_j^m\right)}{\partial A_{gj}} > 0$). Moreover, because the labor share of the goods sector is higher in smaller than larger locations, the proportional effect of a given shock to local productivity in that sector is stronger in smaller cities. This result is summarized in the following proposition that is illustrated in Appendix A3.3 using numerical simulations.

[3] It is important to highlight that a local productivity shock is interpreted as a positive local labor demand shock that pushes wages up in most spatial equilibrium models. Because I am focusing on quantities, a positive local productivity shock implies lower local labor demand for male labor, given that labor demand curves are negatively sloped. This mechanism is then closer to the literature on structural change that assumes exogenous productivity growth in the agricultural sector (Gollin et al., 2002; Murphy et al., 1989).

PROPOSITION 1: *Under decreasing returns to scale, the effect of a negative labor demand shock in the goods sector on female relative hours decreases with city size.*

In the next section, I empirically evaluate this prediction by quantifying the effect of changes in sector-specific changes in labor demand.

3.5 Empirical Strategy

This section aims to estimate the effect of changes in local labor demand across sectors on local gender employment gaps. The ideal experiment for causal identification would randomly assign changes in labor demand in the goods and service sectors across municipalities and recover the effects on gender labor gaps with the following specification:

$$\Delta_{t,t_0}\frac{L_j^f}{L_j^m} = \theta_0 + \theta_1\Delta_{t,t_0}L_{kj} + \Theta\mathbf{X_j} + \epsilon_j, \tag{3.10}$$

where Δ_{t,t_0} denotes the change between the year t and the baseline year t_0, L_j^f/L_j^m denotes the gender gap between female and male work hours in municipality j, L_{kj} denotes industry-specific local labor demand, $\mathbf{X_j}$ includes a vector of municipality-specific controls and state fixed effects, and ϵ is an error term. My controls include the share of college graduates and average wages in 1990 to account for initial differences in skill sorting and productivity across municipalities. Moreover, because local productivity shocks trigger migration flows in the model, I also control for migration rates across decades.

As changes in labor across municipalities can occur because of supply and demand factors, I use an instrumental variable (IV) approach to isolate labor changes that are driven by relative labor demand in a given industry. Following the literature on local effects of labor demand (Verdugo and Allègre, 2020; Chauvin, 2017; Diamond, 2016; Moretti, 2013; Notowidigdo, 2011; Katz and Murphy, 1992), changes in employment are instrumented using Bartik labor demand shocks defined using nationwide relative employment growth by industry interacted with local employment share by industry. More formally, the Bartik instrument for sector k, municipality j, and year t is defined as:

$$B_{kjt} = \sum_k \Phi_{kjt_0}\left(L_{kt} - L_{kt_0}\right), \tag{3.11}$$

where Φ_{kjt_0} denotes the initial share of municipality j in national employment of sector k, and $L_{-kjt} - L_{-kjt_0}$ denotes the change in national employment in sector k between year t and the baseline year t_0. In order to avoid spatial interdependence, I use leave-one-out national employment changes to construct $L_{kt} - L_{kt_0}$ by excluding municipality j. The intuition behind the Bartik labor demand shock is that if employment in industry k grows nationally and municipality j has a large employment share in that industry, then local labor demand is predicted to increase in that municipality.

I build the instruments at the NAICS two-digit industry levels separately for goods and services, following the classification adopted in the chapter. The first stage is then:

$$\Delta_{t,t_0} L_{kj} = \omega_0 + \omega_1 \Delta_{t,t_0} B_{kjt} + \Omega \mathbf{X_j} + \varepsilon_{jt}. \tag{3.12}$$

Recent work by Goldsmith-Pinkham et al. (2020) shows that the identification comes exclusively from local industry shares in this setting. Moreover, they show that local industry shares are usually correlated with observable education and labor characteristics. Hence, the key identifying assumption of this two-stage strategy is that shocks are not correlated with the error terms *conditional on the controls*, and it is then vital to control for these local features in order to avoid biased estimates (Chauvin, 2017). Following these authors, I explore the plausibility of the assumptions by running two tests. First, I regress the initial shares on initial local characteristics to determine the existence of other potential confounders. Table A3.3 shows industry shares are strongly correlated with my vector of controls, thus reducing the likelihood of the shocks being correlated with alternative local characteristics not included as controls. Still, I present more evidence on this assumption by testing the robustness of my results to including additional controls related to female labor supply as fertility rate and age structure of the population in the robustness analysis. Second, I check for misspecification by using alternative estimators and running overidentification tests.

To explore the heterogeneity of the estimated effects across municipality sizes, one would need to interact the treatment (the labor demand shocks instruments) with indicator variables of population groups. In the context of 2SLS, estimating interaction terms would require an increasing number of instrumental variables, which typically implies including lagged explanatory variables with additional identification assumptions and pre-period datasets (Bellemare et al., 2017). As an alternative approach, I re-estimate the 2SLS model for each population tercile. Because selecting several population groups to split the sample can be arbitrary, I also use the instrumental variable threshold estimation strategy developed by Caner and Hansen (2004) that allows the coefficients to vary across regimes that are identified using the initial population size. The optimal number of thresholds is determined using information criteria. The reduced form of the threshold model has the following form:

$$\Delta_{t,t_0}\frac{L_j^f}{L_j^m} = \sum_{r=1} \psi_r \Delta_{t,t_0} L_{kj} I_r\left(\gamma_r, q_t\right) + \Psi \mathbf{X_j} + \epsilon_{jt}, \tag{3.13}$$

where r indexes the number of regimes, γ_r are the estimated ordered thresholds, q_t is the threshold variable, and $I_r\left(\gamma_r, q_j\right)$ is an indicator function for the r^{th} regime.

3.6 Estimation Results

Before considering the heterogeneity by municipality size, I discuss the estimation results for the full sample of municipalities. All regressions are estimated using 2SLS with robust standard errors clustered at the municipality level and include the vector of controls. I instrument industry-employment changes in goods and services with own-industry Bartik shocks.

3.6.1 Baseline Estimates

Table 3.4 presents the first stage estimation results. Bartik instruments are strong predictors of employment changes in each industry; F-statistics exceed ten as suggested by Stock et al. (2002) and allow me to reject the null hypothesis of weak instruments at the 1 percent significance level. According to these estimates, local employment is positively affected by labor demand shocks in each industry.

Table 3.4: First-stage Estimation Results.

Dependent variable	Δ Goods employment	Δ Services employment
	(1)	(2)
Bartik - goods	3.134***	
	(0.2178)	
Bartik - services		0.167***
		(0.0213)
R-squared	0.459	0.273
Obs.	953	953

Notes: Robust errors clustered at the municipality level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All specifications include controls and municipality fixed effects.

I next proceed to examine the effect of labor demand changes on local gender gaps in work hours in Table 3.5 where I instrument employment changes with own-industry Bartik shocks. Female-to-male gaps decrease in response to positive shocks to labor demand in the goods sector in column (2), and increase in response to positive shocks to labor demand in the service sector when instrumenting with own-industry shocks in column (4). I also present the results of the OLS regression on observed employment changes in columns (1) and (3), which underestimate the effect on local gender gaps, thus reflecting that supply factors also played an important role in explaining employment changes across sectors. The direction of the effects is consistent with the differential gender intensities across sectors, with the production services being relatively more intensive in female labor. A ten percent increase in the predicted employment of the goods sector decreases local female relative employment by 7.7-10 percentage points. In the case of services, a ten percent increase in the predicted service employment raises local female relative working hours by 18.6 percentage points. Since the average female relative hours ratio across municipalities increased by 19.28 percentage points between 1990 and 2010, the estimated effects are economically large.

Table 3.5: The Effect of Labor Demand Shocks on Working Hours Gender Gaps.

Dependent variable	Δ Female-to-male working hours ratio			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Δ Goods employment	-0.326***	-0.773***		
	(0.0303)	(0.0644)		
Δ Services employment			0.201***	1.876***
			(0.0471)	(0.2464)
F-stat		203.722		62.298
R-squared		0.459		0.275
Obs.	953	953	953	953

Notes: Robust errors clustered at the municipality level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$. All specifications include controls and municipality fixed effects.

The aggregate results presented in this subsection imply that gender segregation across sectors renders changes in relative labor demand a gender-biased force. Hence, these findings provide evidence for the existence of the between-industry component of differential trends in the labor market proposed by Olivetti and Petrongolo (2014) and Ngai and Petrongolo (2017). In what follows, I investigate the variation of these effects in municipalities of different population sizes.

3.6.2 Heterogeneity by Municipality Size

Table 3.6 presents the estimation results by splitting the sample into two groups using the median municipality size. The first-stage F statistics imply that the instruments are strong even after splitting the samples. The effect of a labor demand shock in each sector on the change in female relative work hours is statistically significant at the one percent level for both small and large subsamples of municipalities. Morevoer, the Wald chi-square statistics allows me to reject the null hypothesis of the corresponding coefficients being the same across samples in both cases, thus providing evidence of the heterogeneity of the effects. The effect of a positive labor demand shock in the goods sector is about two-fifths larger for smaller municipalities. Similarly, the effect of a positive labor demand shock in the service sector is about three-fifths larger for the sample of smaller municipalities.

Table 3.6: The Effect of Labor Demand Shocks on Gender Gaps by Municipality Size.

Dependent variable	Δ Female-to-male working hours ratio			
	Small municipalities		Large municipalities	
	(1)	(2)	(3)	(4)
Δ Goods employment	-0.792***		-0.643***	
	(0.0844)		(0.0830)	
Δ Services employment		2.175***		1.162***
		(0.4188)		(0.1974)
F-stat	130.646	23.706	62.558	49.409
R-squared	0.499	0.293	0.428	0.331
Obs.	477	477	476	476
χ-stat	-	-	19.86***	34.50***

Notes: Robust errors clustered at the municipality level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$. All specifications include controls and municipality fixed effects.

I find similar patters across municipality sizes when estimating the threshold specification. Table 3.7 shows that, for the case of shocks in the goods sector in column (1), two estimated thresholds split the sample into three regimes. The first regime corresponds to the subsample, with the smaller municipalities sample concentrating 39.9 percent of the total sample. The second regime corresponds to 30.2 percent of the sample, while the third regime corresponds to the 32.2 percent remaining sample and contains the largest municipalities. The estimated coefficients are statistically significant at the 1 percent level in all regimes and decrease in absolute magnitude in regimes 2 and 3 compared to regime 1. In particular, compared to the first regime, female-to-male work hour ratios decrease in response to positive shocks by two-thirds in the second regime, and it is even positive, although considerably smaller in the third regime. Column (2) of Table 3.7 reports the estimation results of the threshold model for the service sector. Once again, two estimated thresholds split the sample into three regimes. All estimated coefficients are positive and statistically significant at the 1 percent level. Under the first regime, which concentrates the first 58.1 percent of the sample, the estimated effect of a positive shock in the service sector is twice as large compared to the second and third regimes.

Overall, the empirical evidence confirms that industry-specific local labor demand shocks have a differential impact on gender gaps in work hours and that these effects are heterogeneous across municipality sizes. Labor demand shocks in the service sector produce a larger and more positive effect on female relative hours in smaller municipalities. In contrast, adverse labor demand shocks in the goods sector only boost female relative hours in smaller cities.

Table 3.7: THRESHOLD REGRESSION ESTIMATES.

Dependent variable	Δ Female-to-male working hours ratio	
	(1)	(2)
Regime 1		
Δ Goods employment	-0.772***	
	(0.0679)	
Δ Services employment		0.712***
		(0.1114)
Regime 2		
Δ Goods employment	-0.448***	
	(0.0420)	
Δ Services employment		0.288***
		(0.0879)
Regime 3		
Δ Goods employment	0.091**	
	(0.0410)	
Δ Services employment		0.304***
		(0.0818)
Obs.	953	953
γ_1	10.391	10.517
γ_2	11.733	-

Notes: Robust errors clustered at the municipality level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.. All specifications include controls and municipality fixed effects.

3.6.3 Low-Skill vs. High-Skill Services

In this subsection, I explore the heterogeneity in the effects of labor demand shocks in high vs. low-skill-intensive service sectors. Table 3.8 presents the estimation results for small and large municipalities when the sample is split using the median municipality size. All first-stage regressions have sufficient explanatory power as suggested by the first-stage F statistics.

In the case of low-skill-intensive sectors, both coefficients are positive and statistically significant. The null hypothesis for the equality of the coefficients is also rejected at the 1 percent significance level. The effect of a 10 percent increase in the predicted employment of low-skill intensive services increases the female relative hours by 9.3 p.p. in smaller municipalities, an effect that is 8.5 times larger compared to the estimated coefficient for larger municipalities. In the case of high-skill-intensive sectors, the coefficient is only statistically significant for the large municipalities subsample.

Table 3.9 documents similar patterns in the estimated coefficients using the threshold regression framework to split the sample according to the initial municipality size. The evidence suggests that the positive effect of local labor demand shocks in services on female relative hours in smaller municipalities is mainly driven by low-skill intensive service activities.

Table 3.8: THE EFFECT OF LABOR DEMAND SHOCKS IN SERVICES BY MUNICIPALITY SIZE.

Dependent variable	Δ Female-to-male working hours ratio					
	Small municipalities			Large municipalities		
	(1)	(2)	(3)	(4)	(5)	(6)
Bartik shock - services	2.175^{***}			1.162^{***}		
	(0.4188)			(0.1974)		
Bartik shock - high skill services		2.590^{*}			1.322^{***}	
		(1.6888)			(0.2741)	
Bartik shock - high skill services			1.606^{***}			0.895^{***}
			(0.3330)			(0.1962)
F-stat	23.706	12.190	25.774	49.409	26.137	30.370
R-squared	0.293	0.271	0.285	0.331	0.300	0.310
Obs.	477	477	477	476	476	476
χ-stat	-	-	-	34.50^{***}	18.18^{***}	6.21^{***}

Notes: Robust errors clustered at the municipality level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All specifications include controls and municipality fixed effects.

3.6.4 Robustness

I conduct different robustness analyses in Appendix A3.2. A main concern of the identification strategy is that supply-side factors might have played an important role in explaining local changes in female employment. To account for this variation, I include a

Table 3.9: The Effect of Labor Demand Shocks in Services on Working Hours Gender Gaps - Threshold Regression.

Dependent variable	Δ Female-to-male working hours ratio		
	(1)	(2)	(3)
Regime 1			
Bartik shock - services	0.679***		
	(0.1034)		
Bartik shock - high skill services		0.546*	
		(0.4050)	
Bartik shock - high skill services			0.485***
			(0.0986)
Regime 2			
Bartik shock - services	0.393***		
	(0.0626)		
Bartik shock - high skill services		0.338***	
		(0.0645)	
Bartik shock - high skill services			0.312***
			(0.0618)
Obs.	953	953	953
γ_1	10.517	10.492	10.856

Notes: Robust errors clustered at the municipality level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All specifications include controls and municipality fixed effects.

wider variety of controls that relate to potential supply-side explanations, such as fertility rates and the population's age structure. An additional concern is that the administrative boundaries do not capture the existence of larger labor markets that are economically integrated. Consequently, I use Metropolitan Zones as my main spatial unit. Finally, I also test the robustness of the results when I re-estimate the coefficients using limited information maximum likelihood (LIML) in the IV specifications. In all cases, I am able to show that my findings remain quantitatively unchanged when considering these alternative specifications and controls.

3.7 Conclusion

This chapter uses census microdata for Mexico during 1990-2010 to analyze how gender gaps vary across time and space. I first document that female-to-male gaps in working hours increased on average for all municipality sizes, but this increase was disproportionately greater in smaller compared to larger municipalities.

I consider a labor demand explanation for the patterns in data that relies on the secular transformation in the sectoral structure of the economy from the production of goods (primary and manufacturing activities) to the production of services. I document that this aggregated trend also maps across regional labor markets by documenting that the rise in service shares has also been stronger in smaller municipalities.

To further investigate this labor-demand side explanation, I propose a theoretical model with two production sectors and heterogeneous labor by gender. In the model, the interaction between urban size externalities and tradability across sectors implies differential effects of labor demand shocks on local gender gaps across the city size distribution.

I test the theoretical implications of the model using the spatial variation in relative labor demand using shift-share instruments for labor demand for goods and service sectors and a threshold specification to explore the heterogeneity of the effects across municipalities of different sizes. Consistent with the theoretical mechanism, relative female working hours increase in response to negative shocks in the goods sector, with the effect decreasing in magnitude with municipality size. In contrast, female relative working hours increase in response to positive labor demand shocks in the service sector, with the effect increasing in magnitude with municipality size.

The results have implications for economic policy. While larger cities exhibit better amenities in terms of education and childcare, the fact that the secular trend of industry recomposition is disproportionately creating labor opportunities for women in smaller municipalities suggests that local policies to promote training and improve labor conditions in these regions are essential to narrow gender gaps in labor conditions. An important avenue for future research may explore the implications of these spatially heterogeneous effects of labor demand by sector on gender wage gaps, given the well-documented trend of bigger cities exhibiting larger wage premiums (Baum-Snow and Pavan, 2013; Moretti, 2013).

Appendix Chapter 3

A3.1 Data

Table A3.1: VARIABLES DEFINITION.

Variable	Definition	Database	Source
Labor participation rate	Population aged 18 to 65 years old as a share of total population.	Population and Housing Census 10% Samples (1990, 2000, 2010)	INEGI
Employment rate	Part and full-time employed as a share of total population.		
Gender working hours gap	Female-to-male working hours ratio.		
Share of skilled workers	Workers with a college or higher degree as a share of the total working population.		
Wages	Monthly average wages measured in 2010 pesos.		
Migration rate	Share of individuals who reported living of workers residing in a different municipality in the previous census year.		

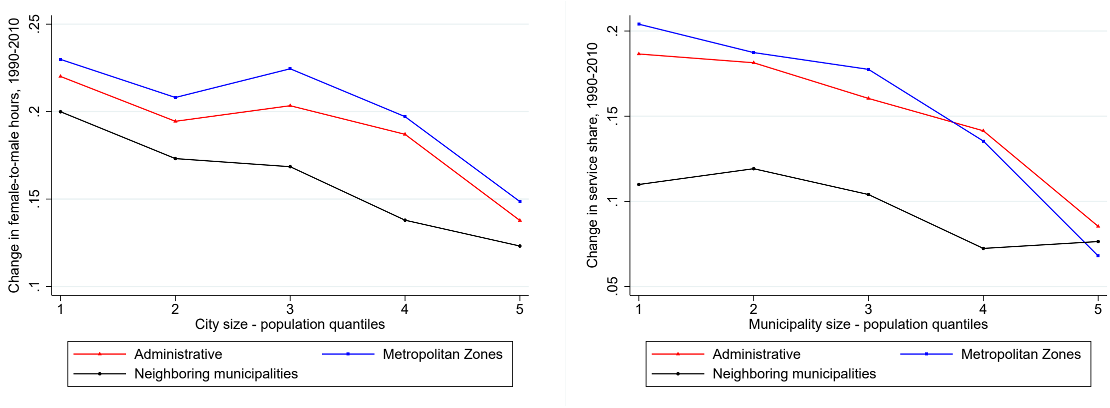
A3.2 Empirical Trends

Gender Gaps

This appendix subsection provides additional evidence on the variation in female-to-male ratios and service shares across the municipality size distribution by considering alternative definitions of the spatial units and base years. As administrative boundaries can be arbitrary, I consider two alternative definitions. First, I cluster municipalities in the same Metropolitan Zones according to INEGI definitions. Second, following Holmes and Stevens (2004), I consider the neighboring population of each municipality i defined as the total population of all municipalities within a six miles distance from i, including i itself.

Figure A3.1 plots the change in female-to-male work hours ratio (Panel A) and the change in service share (Panel B) between 1990 and 2010 across population quartiles computed using administrative boundaries (red line), metropolitan zones (blue line), and neighboring municipalities (black line) to define the spatial units. Consistent with previous findings, all series decrease with municipality size.

Figure A3.1: Change in Female and Service Shares of Total Hours by Municipality Size - Alternative Spatial Boundaries.

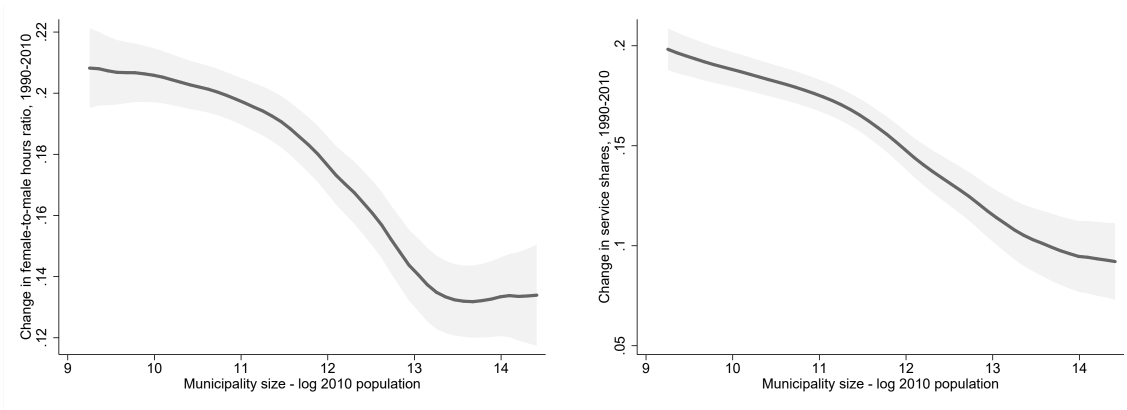


Panel A | Panel B

Notes: Both panels plot the change in female relative work hours and service shares against each population qunatiles computed using different spatial boundaries to define the geographic units. Red lines use municipalities defined using adminsitrative boundaries; blue ones use metropolitan zones defined by INEGI; black lines include the population of all municipalities within 6 miles distance.

Another concern is that the spatial patterns in the time change of female-to-male ratios and service shares are purely driven by a convergence process of population size. To address this possibility, Figure A3.2 plots the change in relative female hours and service shares between 1990-2010 against the population size in 2010 rather than the initial municipality size. I obtain similar decreasing trends in both series as the ones described in Section 3.3.

Figure A3.2: Change in Female and Service Shares of Total Hours by Municipality Size - 2010 Population Size.



Panel A Panel B

Notes: The graphs plots a local polynomial regression for the change in female-to-male total working hours (Panel A) and service shares (Panel B) between 2010-1990 with the 95 percent confidence interval on the vertical axis against the log of total population per municipality in 2010 on the horizontal axis.

Spatial Distribution of Employment

A key component of the mechanism highlighted in this chapter is the disproportional location of service industries in larger compared to smaller municipalities. While a broad categorization of economic activity into goods and services is convenient to document the stylized empirical facts and develop the theoretical model, different studies highlight that the existence of market size effects in service activities crucially depends on the degree of product differentiation (Behrens, 2005). More specifically, using data for the US and Canada, Holmes and Stevens (2004) find that weakly differentiated services such as retail, health care, and non-public services tend to be located in smaller markets, while highly differentiated services such as finance and research tend to locate in large markets.

In this appendix subsection, I closely follow the methodology of Holmes and Stevens (2004) to explore the further spatial distribution of economic activity along municipality population sizes in Mexico using a more disaggregated industry classification. To do so, I rank municipalities according to their population in 1990 and group them using their quartile ranks. For each population group q, I measure the geographic concentration of each industry j using a location ratio LR_q defined as:

$$LR_{jq} = \frac{s_{jg}}{x_q}$$

where s_{jg} denotes the share of group q on industry j national employment and x_q denotes the share of group q on total population. Values above one imply that group q is relatively specialized in industry j compared to its aggregate employment share, while values below one indicate that group q is less specialized in the industry j relative to its employment share. Then, the tendency of industry j to be located in more urban areas can be measured as the difference of the location ratio between the municipalities above the third and below the first quartile rank of population $LR_{j4} - LR_{j1}$. Table A3.2 presents the location ratio for 1990 and 2010 across population bins. Sectors are ranked according to their urbanization index in 1990.

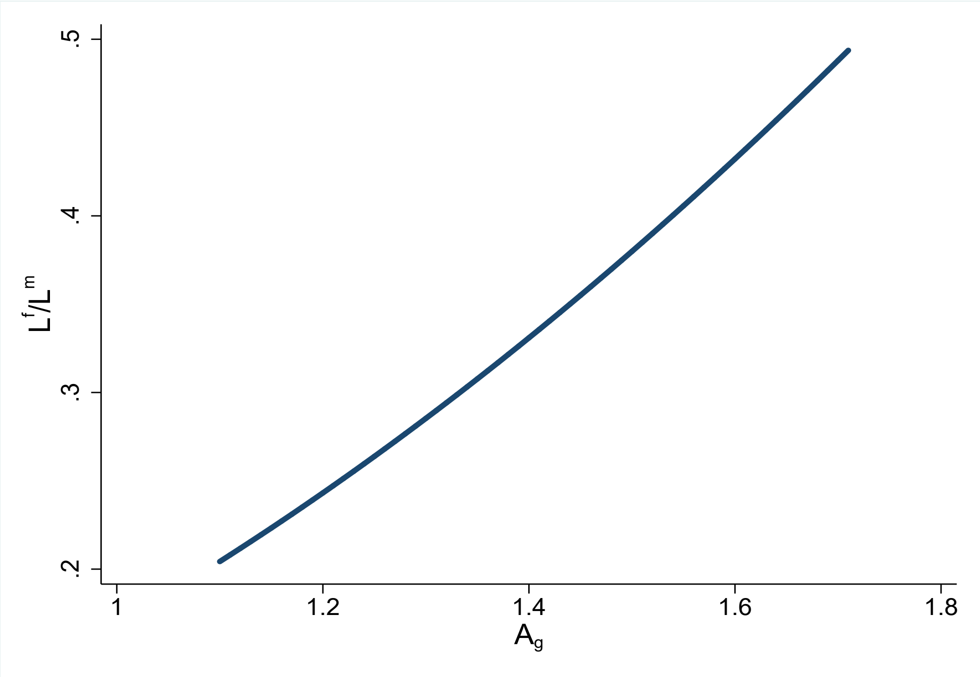
Table A3.2: Employment Distribution by Population Size.

Industry	LR_1		LR_2		LR_3		LR_4		$LR_4 - LR_1$	
	1990	2010	1990	2010	1990	2010	1990	2010	1990	2010
Real estate	0.23	0.42	0.21	0.49	0.37	0.83	1.17	1.30	0.94	0.88
Finance and banking	0.58	0.49	0.31	0.58	0.42	0.67	1.16	1.32	0.87	0.82
Professional services	0.60	0.50	0.33	0.60	0.48	0.71	1.14	1.30	0.82	0.79
Communications	0.48	0.39	0.41	0.48	0.54	0.61	1.13	1.38	0.76	0.99
Health care	0.77	0.71	0.52	0.77	0.61	0.82	1.11	1.17	0.60	0.46
Wholesale trade	0.84	0.68	0.62	0.84	0.73	0.92	1.08	1.13	0.55	0.45
Accommodation and food services	0.91	0.82	0.62	0.91	0.86	1.03	1.07	1.05	0.54	0.23
Public administration	0.99	1.00	0.65	0.99	0.67	0.88	1.09	1.04	0.49	0.04
Arts, culture and sports	0.83	0.73	0.67	0.83	0.71	0.91	1.08	1.13	0.48	0.39
Personal services	0.97	0.94	0.72	0.97	0.81	1.00	1.06	1.02	0.44	0.08
Retail trade	0.93	0.84	0.73	0.93	0.86	1.00	1.05	1.05	0.38	0.20
Transport	0.93	0.88	0.76	0.93	0.87	0.93	1.05	1.06	0.35	0.18
Manufacturing	0.90	0.95	0.80	0.90	0.89	1.09	1.04	1.01	0.27	0.06
Utilities	0.96	0.90	1.02	0.96	0.87	0.93	1.02	1.05	0.08	0.16
Construction	1.10	1.17	1.11	1.10	1.12	1.04	0.97	0.93	-0.10	-0.25
Education	1.17	1.20	1.12	1.17	1.04	1.01	0.98	0.91	-0.10	-0.29
Mining	1.26	1.60	1.48	1.26	1.22	1.07	0.90	0.79	-0.89	-0.81
Agriculture	1.93	2.19	3.40	1.93	2.60	1.30	0.50	0.43	-3.35	-1.76

The indices suggest that, except for education, all service industries have a positive urbanization index larger than 0.38. Meanwhile, all industries in the goods sector have a negative or small urbanization index. In particular, agriculture, mining, education, and construction tend to be more than proportionally located in smaller municipalities. While the fact that education activities rank among the less urbanized activities can be counterintuitive, it can be explained by the high rate of primary enrollment rate (above 98 percent since 1990) that is mainly provided by the public sector and the relatively lower rate of tertiary education enrollment (around 16 percent in 1990 and 28 percent in 2010). A contrasting case is health care services, which coverage rate reached only 66 percent in 2010 and has an important private supply component that is more prone to locate according to economies of scale.

A3.3 Theoretical Simulation

Figure A3.3: Model Generated Gender Labor Gaps vs Goods Local Productivity.



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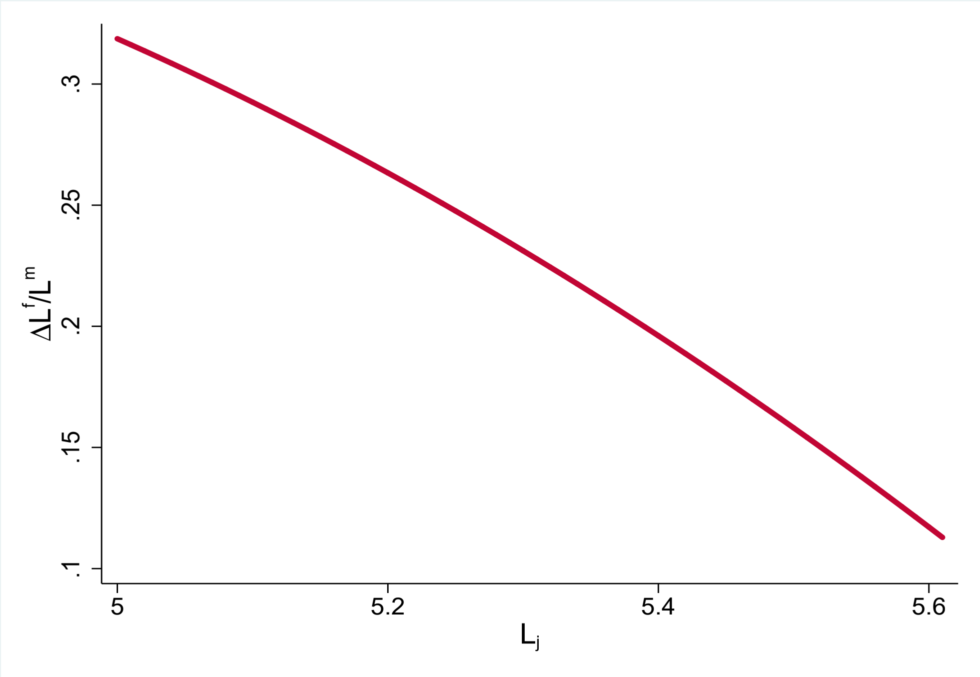
Notes: The figure plots the equilibrium female-to-male labor ratio generated by the model for different levels of local productivity in the goods (A_{gj}) sector following Eq. 3.9 and assuming $w_j^m = 5$, $w_j^f = 4$, $A_{sj} = 1.2$, $\alpha_s = 0.6$,$\alpha_g = 0.5$, $\overline{w}_j^f = 1.2$, $b_j = 0.3$, $\beta = 0.3$, and $L_j = 5$.

Figure A3.4: Model Change in Gender Labor Gaps vs City Size.



Notes: The figure plots the change in the equilibrium female-to-male labor ratio generated by the model for different city size levels in response to an increase in local productivity in the goods sector following Eq. 3.9. Parameters are set at $w_j^m = 5$, $w_j^f = 4$, $A_{sj} = 1.2$, $\alpha_s = 0.6$,$\alpha_g = 0.5$, $\overline{w}_j^f = 1.2$, $b_j = 0.3$, $\beta = 0.3$.

Table A3.3: Local Industry Shares and Baseline Characteristics.

Dependent variable	Goods shares	Service shares
	(1)	(2)
Share of college graduates	0.402***	5.754***
	(0.1106)	(1.2675)
Unemployment rates	0.530***	2.063*
	(0.1813)	(1.1593)
Average wages	0.014***	0.124***
	(0.0031)	(0.0198)
Migration rate	1.262***	9.280***
	(0.1602)	(1.1008)
Constant	-0.078***	1.317***
	(0.0116)	(0.0719)
R-squared	0.443	0.339
Obs.	953	953

Notes: Robust errors clustered at the municipality level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$. All specifications include controls and municipality fixed effects.

A3.4 Estimation Results

Table A3.4: The Effect of Labor Demand Shocks on Working Hours Gender Gaps - Alternative Estimators.

Dependent variable	Δ Female-to-male working hours ratio			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Δ Goods employment	-0.326***	-0.773***		
	(0.0303)	(0.0644)		
Δ Services employment			0.201***	1.876***
			(0.0471)	(0.2464)
F-stat		203.722		62.298
R-squared	0.275	0.459	0.459	62.298
Obs.	953	953	953	953
Bartik - goods	✓	✓		
Bartik - services			✓	✓

Notes: The table presents robust analysis for the estimation results of Table 3.5 by using limited-information maximum likelihood estimators. Robust errors clustered at the municipality level in parentheses. All specifications include state-fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3.5: The Effect of Labor Demand Shocks on Working Hours Gender Gaps - Additional Controls.

Dependent variable	Δ Female-to-male working hours ratio			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Δ Goods employment	-0.307***	-0.982***		
	(0.0327)	(0.1096)		
Δ Services employment			0.241***	1.392***
			(0.0469)	(0.1631)
F-stat		84.783		97.304
R-squared	0.321	0.477	0.477	97.304
Obs.	953	953	953	953

Notes: The table presents robust analysis for the estimation results of Table 3.5 by including additional controls. Robust errors clustered at the municipality level in parentheses. All specifications include state fixed effects. Additional controls include average fertility rates and age structure across four groups (18 to 30, 31 to 40, 41 to 50, and 50 to 65). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3.6: The Effect of Labor Demand Shocks on Working Hours Gender Gaps - Metropolitan Zones.

Dependent variable	ΔFemale-to-male working hours ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Goods employment	0.035	0.125***	0.041			
	(0.0308)	(0.0369)	(0.0302)			
Δ Services employment				0.039	0.114***	0.083***
				(0.0325)	(0.0288)	(0.0273)
Obs.	953	953	953	953	953	953
Bartik - goods	✓		✓	✓		✓
Bartik - services		✓	✓		✓	✓
F-stat	60.152	82.562	33.458	48.860	65.097	29.946
R^2	0.332	0.304	0.332	0.395	0.400	0.405

Notes: The table presents robust analysis for the estimation results of Table 3.5 by using Metropolitan Zones as spatial units. All specifications include state-fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3.7: The Effect of Labor Demand Shocks on Working Hours Gender Gaps by Population Size - Alternative Estimators.

Dependent variable	ΔFemale-to-male working hours ratio			
	Small municipalities		Large municipalities	
	(1)	(2)	(3)	(4)
Δ Goods employment	-0.792***		-0.548***	
	(0.0853)		(0.0720)	
Δ Services employment		2.198***		1.343***
		(0.4291)		(0.2768)
F-stat	129.815	23.251	69.005	30.664
R-squared	0.499	0.294	0.454	0.343
Obs.	477	477	476	476
χ-stat	-	-	6.22***	5.11***

Notes: The table presents robust analysis for the estimation results of Table 3.5 by using alternative estimators. Robust errors clustered at the municipality level in parentheses. All specifications include state fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3.8: The Effect of Labor Demand Shocks on Working Hours Gender Gaps by Population Tercile - Additional Controls.

Dependent variable	ΔFemale-to-male working hours ratio			
	Small municipalities		Large municipalities	
	(1)	(2)	(3)	(4)
Δ Goods employment	-0.634***		0.031	
	(0.1795)		(0.0281)	
Δ Services employment		0.618***		0.128***
		(0.1193)		(0.0276)
Obs.	477	477	476	476
F-stat (first stage)	28.909	44.283	70.313	65.421
R^2	0.304	0.322	0.426	0.447
χ-stat	-	15.02***	-	0.42

Notes: The table presents robust analysis for the estimation results of Table 3.5 by including additional controls. Robust errors clustered at the municipality level are in parentheses. All specifications include state-fixed effects. Additional controls include average fertility rates and age structure across four groups (18 to 30, 31 to 40, 41 to 50, and 50 to 65). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3.9: The Effect of Labor Demand Shocks on Working Hours Gender Gaps by Population Tercile - Metropolitan Zones.

Dependent variable	ΔFemale-to-male working hours ratio			
	Small municipalities		Large municipalities	
	(1)	(2)	(3)	(4)
Δ Goods employment	-0.616***		0.045	
	(0.1636)		(0.0295)	
Δ Services employment		0.734***		0.132***
		(0.1331)		(0.0295)
Obs.	477	477	476	476
F-stat (first stage)	29.574	43.254	64.124	65.022
R^2	0.253	0.317	0.382	0.428
χ-stat	-	19.86***	-	0.22

Notes: The table presents robust analysis for the estimation results of Table 3.5 by using Metropolitan Zones as spatial units. All specifications include state-fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3.10: The Effect of Labor Demand Shocks on Working Hours Gender Gaps - Threshold Regression - Alternative Estimators.

Dependent variable	ΔFemale-to-male working hours ratio						
	Regime 1		Regime 2		Regime 3	γ_1	γ_2
Δ Goods employment	-0.737***		-0.290**		0.116*	10.391	11.733
	(0.1965)		(0.1156)		(0.0654)		
Δ Services employment		0.659***		0.134***		10.517	-
		(0.1028)		(0.0292)			
Obs.	467	541	376	412	110		

Notes: The table presents robust analysis for the estimation results of Table 3.5 by using alternative estimators. Robust errors clustered at the municipality level in parentheses. All specifications include state fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3.11: THE EFFECT OF LABOR DEMAND SHOCKS ON WORKING HOURS GENDER GAPS - THRESHOLD REGRESSION - ADDITIONAL CONTROLS.

Dependent variable	ΔFemale-to-male working hours ratio						
	Regime 1		Regime 2		Regime 3	γ_1	γ_2
Δ Goods employment	-0.773***		-0.281***		0.129*	10.391	11.733
	(0.2162)		(0.1064)		(0.0696)		
Δ Services employment		0.570***		0.135***		10.517	-
		(0.0923)		(0.0283)			
Obs.	467	541	376	412	110		

Notes: The table presents robust analysis for the estimation results of Table 3.5 by including additional controls. Robust errors clustered at the municipality level are in parentheses. All specifications include state-fixed effects. Additional controls include average fertility rates and age structure across four groups (18 to 30, 31 to 40, 41 to 50, and 50 to 65). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3.12: THE EFFECT OF LABOR DEMAND SHOCKS ON WORKING HOURS GENDER GAPS - THRESHOLD REGRESSION - METROPOLITAN ZONES.

Dependent variable	ΔFemale-to-male working hours ratio						
	Regime 1		Regime 2		Regime 3	γ_1	γ_2
Δ Goods employment	-0.737***		-0.290**		0.116*	10.391	11.733
	(0.1965)		(0.1156)		(0.0654)		
Δ Services employment		0.659***		0.134***		10.517	-
		(0.1028)		(0.0292)			
Obs.	467	541	376	412	110		

Notes: The table presents robust analysis for the estimation results of Table 3.5 by including additional controls. Robust errors clustered at the municipality level are in parentheses. All specifications include state-fixed effects. Additional controls include average fertility rates and age structure across four groups (18 to 30, 31 to 40, 41 to 50, and 50 to 65). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Conclusion

This thesis examines the unequal effects of different aggregate shocks along dimensions such as educational attainment, gender, and labor informality in the context of Mexico. Each chapter employs location-level microdata to highlight the importance of three features that generate heterogeneity in the effects of aggregated labor shocks. First, the endogenous response of local prices and urban amenities that the literature on urban economics has increasingly studied is also relevant when assessing the effects of other shocks that impact local labor markets, as is the case of trade liberalization. Second, examining gender-unequal labor market effects on labor participation is particularly important given women's over-representation in part-time and informal jobs where the opportunity cost of leaving the labor force can be lower. Third, industry specialization across locations maps into spatial variation in the effects of sector-specific shocks.

Different policy recommendations can be drawn from these essays. My findings in chapter 1 imply that spatial heterogeneity across local labor makers is important when designing policy responses to counteract the adverse effects of trade liberalization. Assessing the gains and losses of this policy change should also consider housing affordability, urban planning, and public goods provision when designing trade reforms. The findings of chapter 2 point toward the crucial role of childcare availability as a contributor to female labor participation. In particular, the results indicate that designing policies to provide childcare support is an important measure to counteract the gender-unequal effects of the pandemic on labor participation and avoid the labor penalties related to long spells of non-participation. Finally, the results of chapter 3 suggest that the secular trend of industry recomposition is disproportionately creating labor opportunities for women in smaller municipalities. Hence, local policies to promote training and improve labor conditions in these regions are essential to narrow gender gaps in labor conditions.

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