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Gabriela López Noria

Banco de México

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Effects of Trade and Technology on the Mexican Labor Market*

Gabriela López Noria†
Banco de México

Abstract: This paper assesses the effects of trade and technological change on Mexico's labor market between 1994 and 2019. The implications of the exposure of local labor markets to greater trade integration under NAFTA and to greater competition from China in the US market are analyzed, as are the consequences of the exposure of local labor markets to automation. The main results show that trade integration under NAFTA promoted employment in Mexico for all demographic groups, especially for women and the less educated. In addition, it is also found that trade integration reduced unemployment and the non-participation rate. China's competition in the US market had the opposite effects on these indicators. Finally, the analysis by sector (manufacturing and non-manufacturing) suggests that those markets susceptible to automation experienced a pattern of labor polarization.

Keywords: Trade Policy, Labor Markets, Technology Adoption, and Technology and Employment

JEL Classification: F130, F160, O330

Resumen: El documento evalúa los efectos del comercio y el cambio tecnológico sobre el mercado laboral de México entre 1994 y 2019. Se analizan las implicaciones de la exposición de los mercados laborales locales a una mayor integración comercial bajo el TLCAN y a una mayor competencia de China en el mercado estadounidense, así como las consecuencias de la exposición de estos mercados a la automatización. Los resultados principales muestran que la integración comercial bajo el TLCAN detonó el empleo en México para todos los grupos demográficos, especialmente para las mujeres y los de menor escolaridad. También se encuentra que la integración comercial redujo el desempleo y la tasa de no participación. La competencia de China en el mercado estadounidense tuvo efectos opuestos sobre estos indicadores. Finalmente, el análisis por sector (manufacturero y no manufacturero) sugiere que los mercados susceptibles a la automatización experimentaron un patrón de polarización laboral.

Palabras Clave: Política Comercial, Mercados Laborales, Adopción Tecnológica y Tecnología y Empleo

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† Dirección General de Investigación Económica. Email: glopezn@banxico.org.mx.

1 Introduction

During the last three decades, the labor market implications of both trade and technological change have been a “source of controversy” (Acemoglu and Restrepo, 2019). Some studies argue that while trade has generated “welfare gains by efficiently allocating resources” (Dix-Carneiro, 2014) and technological change has increased the “productivity of capital and labor at tasks they currently performed” (Acemoglu and Restrepo, 2019), they have also led to distributional conflicts (i.e. there have been winners and losers) (see, for example, Dix-Carneiro, 2014) and have been disruptive (Autor et al., 2015). Increasing wage inequality¹ and rising job polarization, particularly in the United States (*US*) and other developed countries, have ignited this debate (see, for example, Autor et al., 2013; Autor and Dorn, 2013; and Autor et al., 2015). As a result, a vast theoretical and empirical literature has emerged, focusing on trade and technological progress as the main explanations for these and other labor market implications.²

This paper joins the debate by investigating the effect of both trade and technology on Mexico, a typical emerging market economy. Using data on labor market aggregates for 28 Mexican metropolitan areas (*MA*s) over the 3rd quarter/1994 - 4th/2019 period, this study assesses whether trade and technology have had distinct effects in terms of magnitude and direction on employment status (i.e. employment, unemployment, and non participation rate) by demographic groups (i.e. gender, education level, and age); on employment by occupation - task content crossed with demographic groups; and on employment by sectors (i.e. manufacturing and non-manufacturing) crossed with occupation - task content. In other words, the analysis places trade and technology side by side in order to compare their effects on a wide range of adjustment margins across Mexican local labor markets.

¹According to a two factor version of the Heckscher - Ohlin (H - O) model and the Stolper Samuelson theorem, wage inequality is expected to increase as a result of trade in developed countries, where skilled labor is abundant; and to decrease in developing countries, where skilled labor is scarce. However, existing evidence has rejected this prediction: several developing countries such as Mexico, Chile, Brazil, India and China have experienced rising wage inequality as trade reforms have been implemented (Harrison et al., 2011). Consequently, other factors rather than trade have been considered to explain this labor market implication. The skill-biased technological change (SBTC) hypothesis (i.e. a change in technology that leads to an increase in the relative demand for skilled workers) is an example (Autor et al., 1998).

²See Section 2 for a discussion on this literature.

Two trade events are analyzed: on the one hand, the impact of the North American Free Trade Agreement (*NAFTA*) on Mexico's local labor markets and, on the other hand, the effect of rising Chinese import competition on these same markets. The former event is worth studying since it comprehends the largest free trade area in the world (in terms of Gross Domestic Product and population); the countries involved, including Mexico, have different sectorial specializations; and this trade agreement has created a cross border production chain (Caliendo and Parro, 2015). The latter event is important since Chinese exports to both developed and developing countries have grown substantially in the last two decades as a result of this country's transition from central planning to a market-oriented economy (Autor et al., 2013) and, as a consequence of the lower trade costs it experienced following its accession into the World Trade Organization (*WTO*) in 2001.

Which are the possible mechanisms through which trade integration under *NAFTA* and the rising Chinese import competition could have affected Mexico's local labor markets? First, under *NAFTA*, Mexico specialized in the production of goods in which it had a comparative advantage, i.e. unskilled-labor intensive goods. This resulted in the proliferation of "maquiladoras" and the relocation of manufacturing processes from Central Mexico to the North (Chiquiar, 2008; and Chiquiar et al., 2017). Therefore, it is reasonable to think that those local labor markets specializing in goods, which later on were highly exported to the *US* due to Mexico's increased market access under *NAFTA*, had been more exposed to trade integration. Regarding the effect of rising Chinese import competition, while the Mexican local labor markets might have been affected directly through an increase in imports from China, it is possible that the main channel (and the one I investigate in this paper) through which they were affected was through an increase of Chinese exports to the *US*. The reason for this is that, following *NAFTA* and the greater market access it was granted, Mexico started specializing in the production of goods in which China would eventually show a comparative advantage (Chiquiar et al., 2017). As a result, Mexico faced stronger competition in its main export market, i.e. the *US*.³ Thus, China's accession to the *WTO* and, consequently, to the international export markets, may have reduced Mexico's market share in *US* imports and,

³In addition, more than 80 percent of Mexico's exports are directed to the *US*.

hence, may have led to a decrease in labor demand.

On the technology front, the hypothesis raised in this paper is that job polarization emerges as a result of the automation/computerization of routine tasks. Borrowing from Autor and Dorn (2013), the mechanism that links the automation/computerization of routine tasks to job polarization is the following. First, technological progress takes the form of a decrease in the cost of accomplishing routine tasks (i.e. these tasks “follow precise, well-understood procedures that can be (and increasingly are) codified in computer software and performed by machines” (Autor and Dorn, 2013)) with computers. Second, as this cost decrease takes place, the *MA*s that had initially specialized in routine tasks adopt computers and, therefore, substitute for workers performing this type of tasks. Third, the losses experienced by the *MA*s in routine tasks are offset by gains in manual tasks (i.e. tasks that require physical dexterity and flexible interpersonal communication), leading to the so-called job polarization. Finally, the reason this reallocation of labor supply into manual tasks takes place is that wages for workers performing routine tasks decrease, relative to those at the bottom of the wage distribution, as a result of the technological change.

These trade and technological predictions are tested by considering a spatial framework. In this framework, the spatial unit of analysis are Mexico’s *MA*s, which proxy for local labor markets. This is appropriate only if labor mobility across *MA*s is partial or incomplete (i.e. if labor is not highly mobile across areas), otherwise *MA*s-specific labor market consequences would fully diffuse across space (Autor et al., 2015).⁴ Chiquiar (2008) provides some evidence on partial labor mobility across Mexico’s regions and cities. He shows that the domestic migration pattern following Mexico’s trade liberalization is characterized by a “northward movement of labor”, i.e. the individuals that moved to the border manufacturing regions were originally from the North or the Center but not from Mexico City. In contrast, the individuals from Mexico City that lost their jobs moved to a nearby city or remain there, but started working at the services sector. Chiquiar (2008) therefore characterizes the Mexican labor force as “neither homogeneous nor perfectly mobile across regions”. Based on this

⁴If labor mobility across *MA*s was high, trade or technology would affect workers “without its consequences being identifiable at the regional level” (Autor et al, 2013).

evidence, *MA*s are considered as local labor markets in this paper. They are also conceived as sub-economies with different initial patterns of industry specialization in order to be able to exploit regional variation in trade and technology exposure.

The empirical analysis consists on estimating by System Generalized Method of Moments (*GMM*) (which is used to control for simultaneity problems) an econometric specification that includes a measure of *NAFTA* integration, a measure of exposure to rising Chinese import competition in the *US* market, and a proxy for the computerization of routine tasks or routine employment share measure as main explanatory variables. The model also includes some demographics (i.e. the share of employment in manufacturing, the share of population with high school or more education, and the employment rate among women), as well as local labor market dummies and period dummies as additional independent variables.

The main findings are as follows. First, regarding the impact of trade on employment status by demographic groups, exposure of local labor markets to rising Chinese import competition in the *US* market reduces employment for all demographic groups (especially women, the less educated, and younger workers). These negative employment effects are found to be absorbed, to a large extent, by the non participation rate, rather than by unemployment. Exposure of local labor markets to *NAFTA* integration has the opposite impact: it increases employment for all demographic groups, especially women, the most educated, and younger workers; while it reduces the non participation rate for these same demographic groups. No statistically significant impact is found on unemployment.

Second, regarding the impact of trade on employment by occupation - task content, exposure of local labor markets to rising Chinese import competition in the *US* market reduces employment in both abstract and routine-task-intensive occupations for all demographic groups (with no impact on manual-task-intensive occupations), while exposure to *NAFTA* integration increases it for these same occupation - task groups (with no impact as well on manual-task-intensive occupations). In both cases, the routine-task-intensive occupations are found to experience the largest effect and, within this occupation category, women and the less educated are the most affected. For the age group, exposure to *NAFTA* integration has a larger impact on older workers; while exposure to rising Chinese competition, on younger workers.

manual-task-intensive occupations are not affected in any of the two cases.

The routine employment share measure or technology exposure measure does not have a statistically significant effect in any of these two empirical exercises.

Finally, regarding employment in the manufacturing and non-manufacturing sectors, rising Chinese import competition in the *US* market reduces overall employment both in the manufacturing and non-manufacturing sectors, while exposure to *NAFTA* integration leads to employment gains. The breakdown of these results by occupation task content reveals trade exposure has affected both abstract and routine-task-intensive occupations. While most point estimates on the impact of technology exposure are not statistically significant, the following pattern can be observed: there is a shift of employment from routine-task-intensive occupations into manual-task-intensive occupations, which is consistent with computerization of routine tasks leading to job polarization.

I also investigate the relative contribution of each independent variable to the different labor market outcomes examined in this paper. The results show that the main driver of the labor market outcomes is trade and not technological progress. Within trade, exposure to *NAFTA* integration contributes the most to these labor market aggregates, followed by exposure to Chinese import competition in the *US* market.

This paper distinguishes from the Mexican literature on the trade/technology - labor market aggregates link in the following ways. First, it simultaneously investigates both the effect of trade and technology on labor market aggregates, and not just the impact of one or the other as it has been the case up until now (e.g. Mendez, 2015; Chiquiar et al., 2017; and Cebberos et al., 2020). In addition, the estimated empirical specification includes both a measure of exposure to rising Chinese import competition in the *US* market and a measure of *NAFTA* integration in order to assess which is more important in understanding labor market outcomes. The existing literature on Mexico typically only considers one trade exposure measure, but not both of them (except for Chiquiar et al., 2017). Furthermore, this paper examines several adjustment margins including employment status (i.e. employment, unemployment, and non participation rate) by demographic groups; employment by occupation task content crossed with demographic groups; and employment by sectors crossed with occupation - task con-

tent. The existing literature has analyzed fewer margins and has particularly missed on investigating the task content of employment as in this paper. Finally, a novel dataset has been created that merges employment data from the National Institute of Statistics and Geography in Mexico with commercial data from the *US* International Trade Commission and Banco de México, resulting in a balance panel data covering 28 metropolitan areas throughout the 3rd quarter/1994 - 4th quarter/2019 period. Furthermore, this first dataset on Mexico has been matched with data on occupations and their corresponding tasks requirements employed for the *US* case by both Autor and Dorn (2013) and Autor et al. (2015) using the National Classification of Occupations (*Clasificación Nacional de Ocupaciones (CNO)* in Spanish), the Mexican Classification of Occupations (*Clasificación Mexicana de Ocupaciones (CMO)* in Spanish), and the National System of Classification of Occupations (*Sistema Nacional de Clasificación de Ocupaciones (SINCO)* in Spanish). Hence, the final dataset has consumed several men-hours, but it constitutes a very important input for this paper that can be used in the future to perform more empirical analysis.

The paper proceeds as follows. Section 2 surveys the literature on the effect of trade and technology on several countries' labor market aggregates. Section 3 presents the data, the empirical specification, and results. Section 4 analyzes the relative contribution of the main explanatory variables to the different labor market outcomes examined. Section 5 presents the conclusions.

2 Literature Review

This paper is related to several strands of the empirical literature on the impact of trade and technological progress on labor markets. In what follows I briefly discussed each of them.

2.1. The Impact of Trade on Labor Markets

An empirical regularity that has prompted the emergence of research on the effects of trade on labor markets is the declining trend in *US* manufacturing employment, which according to Autor et al. (2014) started in the 1980s, increased in the 1990s, and accelerated in the 2000s.

Several studies have argued that the rising Chinese import competition faced by the *US* may have been the main contributing factor to this declining trend. For example, for the 1992-2007 period Autor et al. (2014) find that greater exposure to Chinese import competition reduced total earnings via a reduction in within year earnings (i.e. lower earnings per hour and less hours worked); induced a decline in manufacturing employment, which was offset by having a new job in a different industry, but at relatively lower wages; and increased the number of years receiving Social Security benefits. Similarly, using data for the 1991-2011 period, Acemoglu et al. (2016) also show that higher import competition from China reduced domestic manufacturing employment, but production employment declined more than non-production employment.⁵ The evidence provided by these studies is corroborated by Pierce and Schott (2016), who show that granting permanent normal trade relations (*PNTR*) to China by the *US* Congress in 2000, and becoming effective once China became a *WTO* member, had a negative effect on *US* manufacturing employment.⁶

Following the argument that opening an economy to international trade might have distributional effects in a country and, hence, winners and losers, some studies have focused on analyzing the impact of *NAFTA* on its member countries. Caliendo and Parro (2015) build on Eaton and Kortum (2002) to develop a multi-country and multi-sector Ricardian model and, therefore, analyze the welfare effects of tariff reductions under this trade agreement in Mexico, the *US*, and Canada. The results show that while Mexico experienced welfare gains, the *US* and Canada had welfare losses. However, real wages increased in all three country members, being Mexico the most benefited country. Hakobyan and McLaren (2016) examine the impact of *NAFTA* on *US* workers' incomes and find that blue collar workers in highly affected industries (i.e. industries highly protected against Mexican imports or with a rising share of Mexican imports) and localities experienced lower wage growth than workers in other industries.

Within this strand of literature, some studies have exploited regional variation in import

⁵Due to China's comparative advantage in labor intensive sectors, *US* lower-skilled labor was more sensitive to trade than high-skilled labor

⁶Before 2000, *US* imports from China were subject to small normal trade relations tariffs that required to be renewed every year.

exposure, stemming from differing initial patterns of industry specialization. For example, Autor et al. (2013) study the impact of rising Chinese import competition on *US* local labor markets over the 1990-2007 period, using the growth of Chinese exports to other high income countries in order to instrument for *US* imports growth from China. Their results show that rising Chinese import competition led to a decline in manufacturing and non-manufacturing employment which was offset by an increase in unemployment and in the labor force non participation. Non-manufacturing wages also decreased, but not manufacturing wages.⁷ As a result of these changes in labor market outcomes, transfer payments, through different state and federal programs, also experienced an increase. Following Autor et al. (2013), Mendez (2015) investigates the effect of rising Chinese import competition on Mexican local labor markets over the 1990-2010 period, using the growth of Chinese exports to other middle-income countries in order to instrument for Mexican imports from China. The author mainly finds that manufacturing employment fell as a response to rising Chinese import competition and that more exposed regions were the ones that experienced the largest effect. Working age population at a municipality level also fell, but this impact was larger in non-border states. Regarding wages, the author does not find a statistically significant effect. Chiquiar et al. (2017) analyze the effect of both, *NAFTA's* implementation and China's entry into the *WTO* on Mexico's local labor markets. The authors estimate two specifications. First, using data on the 1993-2000 period, the authors regress labor market outcomes (i.e. employment, unemployment, and wage indicators) on a measure of exposure to *NAFTA* integration and on demographic controls. Second, using data on the 2000-2008 period, they estimate the same specification except that in this case they instead use a measure of exposure to Chinese competition in the *US* market.⁸ In order to control for simultaneity problems, they use an instrumental variables strategy to estimate both specifications. In the first one, they use the

⁷The authors suggest that this may have happened due to the fact that the most productive workers “retained their jobs in manufacturing, thus biasing the estimates against finding a reduction in manufacturing wages”. Another possibility offered by the authors is that rising Chinese import competition could have led manufacturing plants to accelerate their adoption of new technologies, as well as to increase innovations, resulting in higher productivity and, therefore, higher wages.

⁸The authors distinguish between those *MA*s located in border states and those located in non-border states, since the former are more exposed to the rising Chinese import competition as a result to the similarity in their production patterns.

sector-weighted average reduction in tariffs to *US* imports from Mexico as an instrument; whereas in the second one, the growth of Chinese exports to eight developed countries. The main findings show that *NAFTA* had a positive effect on employment (they found a negative effect on skilled worker employment levels except for manufacturing) and wages, while a negative effect on unemployment. These effects were mainly observed at border states. As regards the effect of rising Chinese import competition, the authors find a positive effect on unemployment and on skilled manufacturing workers in non-border states; while a negative effect on unskilled manufacturing labor employed at the border, and on wages.

2.2 The Effect of Technological Change on Labor Markets

A decelerating trend in labor demand, particularly in the *US*, over the last three decades, has also induced researchers to investigate its causes. According to the empirical evidence, automation and robots adoption are partly responsible, since labor displacement effects,⁹ owed to these technological changes, have not been fully counterbalanced by reinstatement effects (i.e. creation of new tasks). See, for example, Autor and Salomons (2018) for the case of 18 Organization for Economic Cooperation and Development (*OECD*) countries over the 1970-2008 period; Acemoglu and Restrepo (2018) and Acemoglu and Restrepo (2019) for the case of the *US* over the 1993-2014 period and the 1947-2017 period, respectively; Acemoglu et al. (2020) for the case of France over the 2010-2015 period; and Cebreros et al. (2020) for the case of Mexico over the 2016-2017 period.

In the same vein, a rise in the demand for skilled workers (and highly educated workers) across *OECD* countries over the last three decades, together with a rise in the skill premium, have led researchers to suggest that technological change, rather than trade, has been the main driving force behind that trend (Michaels et al., 2014). The skill-biased technological change hypothesis has been proposed to explain this shift in favor of skilled labor. However, a different hypothesis or factor has been required to explain job polarization, defined as an increase in the demand for skilled workers (and low skilled workers), at the expense of middle skilled workers. This is a more recent phenomenon, but some explanations have

⁹Labor displacement occurs when capital takes over tasks previously performed by labor and, hence, reduces labor's share in aggregate value.

already been presented in order to understand it: the routine-biased technological change (*RBTC*) (i.e. a technological change biased towards replacing labor in routine tasks (Goos et al., 2014); the task-based theory (which suggests that information and communication technologies (*ICT*) increase the demand for more educated people, reduce the demand for middle educated people, and has no clear effect on the least educated (Michaels et al., 2014); and the adoption of computers as a result of their declining price. Goos et al. (2014) provide some evidence on the *RBTC* by estimating demand equations for a sample of 16 European countries over the 1993-2010 period. Their main findings show that there is a shift away from routine and offshorable occupations leading to job polarization within industries. The authors also present a decomposition of occupational employment shares into within-industry and between-industry components, and find that both *RBTC* and offshoring have reduced the demand for middling relative to high-skilled and low-skilled occupations. Using data on 11 developed countries over the 1980- 2004 period, Michaels et al. (2014) find that *ICT* indeed benefit high skilled occupations, while they harm middle skilled occupations. Autor and Dorn (2013) show that *US* commuting zones with a greater initial routine employment share adopted computers as a result of their falling price and, hence, the number of routine intensive occupations experienced a decline.

2.3 The Impact of Both Trade and Technological Change on Labor Markets

While the previous strands of literature have provided evidence on the distributional conflicts trade and technological progress have caused by their own, very few studies have considered analyzing them together. Whether their effects overlap, and, hence, they must be treated co-jointly (Autor et al., 2015) or not is still a matter that needs further investigation. Dauth et al. (2018) analyze the impact of robot adoption, investment on *ICT*, and rising international trade with China and Eastern Europe (measured as net exports vis a vis China and 21 Eastern European countries) on the German labor market over the 1994-2014 period. The authors first show that robot adoption and *ICT* are not statistically significant, although net exports do have a positive and statistically effect on local employment. By separately analyzing the manufacturing and non-manufacturing (i.e. services) sectors, the authors then

find that rising robot exposure reduces manufacturing employment, while it increases non-manufacturing employment, having as a result an overall negative but small impact on total employment. Similarly, Autor et al. (2015) study the impact of exposure to rising Chinese import competition and technology on employment, unemployment, and labor force participation for a sample of 722 *US* commuting (*CZ*), over the 1980-2007 period. Following the literature on the task content of employment, the authors use data on job tasks by occupation to measure the extent to which *CZ* have specialized in routine job activities (Autor et al., 2015). The reason for this is that routine job activities are “highly predictive of computer adoption” (Autor and Dorn, 2013) and can, therefore, be used to proxy for technology. In addition, the authors exploit cross-industry and cross-*CZ* variation in the exposure to import competition from China (Autor et al., 2015) to identify trade shocks. Their main results show that rising Chinese import competition has a negative and a statistically significant effect on *US* employment across all occupations groups in manufacturing, while technology leads to occupation polarization both in the manufacturing and non-manufacturing sectors.

While the literature reviewed on Mexico has just focused on analyzing the trade effect on labor aggregates, this paper goes one step further and also investigates the task content of employment. This is important since this additional analysis has enabled me to measure the extent to which each local labor market has specialized in routine job tasks and, therefore, to obtain a technology exposure measure as in Autor and Dorn (2013) and Autor et al. (2015).¹⁰ Thus, this paper examines both the impact of trade and that of technology on Mexico’s local labor markets.

3 Empirical Analysis

This Section first describes the variables of interest (i.e. labor market aggregates and measures of technology and trade exposure), and then presents the empirical specification and the results.

¹⁰See Section 3.3 for more details on the derivation of the technology exposure measure.

3.1 Variables of Interest: Labor Market Aggregates

The data on the Mexican labor market come from two household surveys, conducted on a quarterly basis by the National Institute of Statistics and Geography (*INEGI* in Spanish): the National Survey of Urban Employment (*ENEU* in Spanish) and the National Survey of Occupation and Employment (*ENOE* in Spanish). In this paper, *ENEU* covers the 3rd quarter/1994 - 4th quarter/2004 period,¹¹ while *ENOE* covers the 1st quarter/2005 - 4th quarter/2019 period, so both surveys are merged following Alcaraz et al. (2013) in order to analyze a longer period of time (from 3rd quarter/1994 to 4th quarter/2019) than previous studies.¹²

ENEU differs from *ENOE* in that the former only comprehends data on urban areas; while the latter, data on both, rural and urban areas. Hence, by merging them, rural areas are eliminated, as well as the *MAs* that are not present in both Surveys. Thus, the final number of *MAs* considered in the empirical analysis is 28.¹³ In this paper, *MAs* became the spatial unit of analysis and, therefore, used to approximate for local labor markets, as in Autor et al. (2015).

ENEU and *ENOE* are rich in the sense that they provide information on housing characteristics, on household characteristics, on socio-demographic characteristics (i.e. civil status, gender, age, education, place of birth, etc.), and on occupation and employment (i.e. type of job, occupation, industry affiliation, income, hours worked per week, informal sector, etc.) of those of 12 years of age or more. However, this paper focuses on potential wage earners and only individuals between 15 and 65 years of age are considered in the empirical analysis.¹⁴

The Surveys' data on socio-demographic characteristics and on occupation and employ-

¹¹*INEGI* conducted *ENEU* from 1st quarter/1983 to 4th quarter/2004, but it was until the 3rd quarter/1994 that housing became the sampling unit, as well as the observation unit, and that the Survey's questionnaire became more precise (some questions were eliminated and others were added).

¹²The analysis in this paper only covers until 4th quarter/2019. The reason for this is that due to the current global pandemic *INEGI* replaced *ENOE* for *ETOE* (i.e. a survey conducted by phone) on the 2nd quarter of 2020 and so the results that were traditionally published are not comparable with those from this survey conducted by phone.

¹³The final sample is comprised by the following *MAs*: Ciudad de México, Guadalajara, Monterrey, Puebla, León, San Luis Potosí, Mérida, Chihuahua, Tampico, Veracruz, Acapulco, Aguascalientes, Morelia, Toluca, Saltillo, Villahermosa, Tuxtla Gutiérrez, Tijuana, Culiacán, Hermosillo, Durango, Tepic, Campeche, Cuernavaca, Oaxaca, Zacatecas, Colima y Querétaro. Torreón, Ciudad Juárez, Coatzacoalcos, Tlaxcala, and La Paz are eliminated.

¹⁴The Mexican Federal Labor Law establishes that the legal age to start working is 15 years.

ment are used to obtain the labor market aggregates that will become the dependent variable in the empirical specification, i.e. the employment to population ratio, the unemployment to population ratio, or the non participation ratio. On average, the data used in this paper cover 87 percent of the Mexican total employment. As in Autor et al. (2015), the dependent variable is the decadal change in each of these ratios. Therefore, for the 3rd quarter/1994 - 4th quarter/1999 (which is not a complete decade), I follow Autor et al. (2015) and "rescale the dependent variable(s) to represent a decadal change" by multiplying it(them) by 10/6.

The data on socio-demographic characteristics and on occupation and employment are also used to derive start of period demographics that will be used as explanatory variables in the empirical specification. These demographics are the share of employment in manufacturing, the share of population with high school education or more, and the employment rate among women.

3.2 Variable of Interest: Measures of Trade Exposure

As mentioned in the Introduction, Mexico's *MA*s in this paper are used to approximate local labor markets. A reason for doing this is that it permits to avoid the degrees of freedom problem that emerges when estimating the impact of trade on labor markets using national data (Autor et al., 2013). When doing so, "one needs to map many industry-specific shocks into a small number of aggregate outcomes. For national labor markets at annual frequencies, one is left with few observations and many confounding factors" (Autor et al., 2013; and Autor et al., 2015). Instead, the degrees of freedom problem is addressed in this paper by using data on Mexico's *MA*s.

In addition, this local labor markets approach is adequate to identify the labor market implications of trade as long as: 1) *MA*s exhibit different initial patterns of industry specialization and, 2) differences in unemployment and the non participation rate, at the *MA*s level, induced by labor market frictions, persist over time (Autor et al., 2015).

In addition, the local labor markets approach permits to consider Autor et al. (2013) trade model with monopolistic competition as the theoretical motivation for the empirical analysis performed in this paper. This model shows how trade shocks, such as the rising

Chinese import competition, can affect labor market aggregates at a regional level in the *US*. Each region in the model is considered as a small open economy that produces both traded and non traded goods.¹⁵ In the traded goods sector, firms are monopolistically competitive and, therefore, differentiate their products.¹⁶ A trade shock, such as an increase in China’s productivity as a result of its transition from central planning to a market economy or a fall in its trade costs due to its accession into the *WTO*, affects region’s *i* labor market by increasing import competition in the markets where that particular region sells its output;¹⁷ or by shifting upwards China’s demand for goods. In order to derive the equation that shows how a Chinese trade shock impacts *US* labor market aggregates, Autor et al. (2013) assume trade imbalance¹⁸ and focus on just one channel through which trade with China affects region *i*, i.e. “greater import competition in the *US* market”.¹⁹ The author justify their decision by mentioning “*US* imports from China vastly exceed *US* exports to China”. Thus, the authors derive an expression for the change in employment in the traded goods sector in region *i* that depends on “the growth in *US* imports from China mandated by growth in China’s export supply capability ($M_{C,j,U}\hat{A}_{C,j}$), scaled by region *i*’s labor force $L_{T,i}$, and weighted by the share of region *i* in *US* employment in industry *j*, ($\frac{L_{i,j}}{L_{U,j}}$,” (Autor et al., 2013). This expression is the following:

$$\hat{L}_{T,i} = -\tilde{\alpha} \sum_j \frac{L_{i,j}}{L_{U,j}} \frac{M_{C,j,U}\hat{A}_{C,j}}{L_{T,i}} \quad (1)$$

Based on Autor et al.’s (2013) trade model with monopolistic competition and result (i.e. equation (1)), I therefore use similar expressions to analyze both the effect of the exposure to rising Chinese import competition and to *NAFTA* integration on Mexican local labor markets.

I exploit the variation in the degree of exposure of Mexican local labor markets (i.e. *MAs*) to the increase in *US* imports from China and, the variation in the degree of exposure of these

¹⁵The non-traded good could be leisure

¹⁶It is this assumption on the firms’ market structure that permits to assume that “trade has a gravity structure” and, therefore, to “map changes in trade quantities into labor market outcomes” (Autor et al., 2013).

¹⁷This channel is captured by China’s capability to export in each industry *j* ($\hat{A}_{C,j}$).

¹⁸Under balanced trade, a reduction in the labor demand due to greater import competition would be offset by an increase in the labor demand due to greater export production.

¹⁹The authors do not focus on *US* exports to China or on the competition *US* regions face in foreign markets.

same local labor markets to the increase in market access due to *NAFTA* in order to identify both trade shocks.

Regarding the effect of the rising Chinese import competition, I assume that, while the Mexican local labor markets might have been affected directly through an increase in imports from China, it is possible that the main channel (and the one I investigate in this paper) through which they were affected was through an increase of Chinese exports to the *US*. The reason for this is that, following *NAFTA* and the greater market access it was granted, Mexico started specializing in the production of goods in which China would eventually show a comparative advantage (Chiquiar et al., 2017). As a result, Mexico faced stronger competition in its main export market, i.e. the *US*. Thus, China's accession to the *WTO* and, consequently, to the international export markets, may have reduced Mexico's market share in *US* imports and, hence, may have led to a decrease in labor demand.

By considering this particular channel through which trade with China could have affected Mexico's local labor markets, I then proceed to calculate an index per worker of *MA*'s *i* exposure to the increase in *US* imports from China as follows:

$$\Delta IPW_{i,t}^{US} = \sum_j \frac{L_{i,j,t}}{L_{j,t}} \frac{\Delta M_{j,t}^{ChUS}}{L_{i,t}} \quad (2)$$

where $\Delta M_{j,t}^{ChUS}$ is the change in *US* imports from China of goods produced in industry *j* between the start and end of period; $L_{i,j,t}$ is the start of period number of workers in industry *j* at *MA* *i*; $L_{j,t}$ is start of period total number of workers in industry *j*; and $L_{i,t}$ is start of period total number of workers in *MA* *i*. As in Chiquiar et al. (2017), the intuition behind this *IPW* measure is the following: if *Y* percent of industry's *j* employment is located in *MA* *i* at the start of the period, then *Y* percent of the increase in *US* imports from China of goods produced by industry *j* will be allocated to *MA* *i*. If this criterion is followed for each and every industry and then summed up over all industries, the result is the labor market exposure of *MA* *i* to rising Chinese import competition in the *US*. This implies that if *MA* *i*'s employment is concentrated in industries that produce goods in which China has a comparative advantage and, therefore, has increased substantially its exports to the *US*, then

MA i will be more exposed to Chinese competition.

Similarly, under *NAFTA*, it is reasonable to think that those local labor markets specializing in the production of goods in which Mexico had a comparative advantage, i.e. unskilled-labor intensive goods, and that later on were highly exported to the *US* due to Mexico's increased market access under this free trade agreement had been more exposed to trade integration.

By considering this particular mechanism through which trade under *NAFTA* could have affected Mexico's local labor markets, I then proceed to calculate a measure of local labor market openness per worker (*OPW*) or local labor market exposure to increased market access due to *NAFTA* as:

$$\Delta OPW_{i,t}^{US} = \sum_j \frac{L_{i,j,t}}{L_{j,t}} \frac{\Delta X_{j,t}^{MxUS}}{L_{i,t}} \quad (3)$$

where, $\Delta X_{j,t}^{MxUS}$ is the increase in Mexican exports to the *US* of goods produced in industry *j*; and the rest of the variables are the same as in Equation (2). Intuitively, equation (3) implies that if *MA i*'s employment is concentrated in industries producing goods largely exported to the *US*, then *MA i* will be more exposed to trade integration due to *NAFTA*.

The data used to build the *IPW* and *OPW* measures come from three sources. First, employment data come from *ENEU* and *ENOE* and is arranged according to the North American Industry Classification System (*NAICS*) industry codes. Second, data on Mexican exports to the *US* come from Banco de México, who follows the guidelines of *SNIEG* (*Sistema Nacional de Información Estadística y Geográfica* in Spanish), while data on *US* imports from China come from the United States International Trade Commission. Trade data is arranged according to Harmonized Tariff Schedule (*HTS*) codes. Both, employment and trade data are obtained at 6 digits level. Pierce and Schott (2012) is followed in order to create a bridge between *NAICS* codes and *HTS* codes and, therefore, to link domestic economic activity data with trade data.

3.3 Variable of Interest: Measure of Technology Exposure

In order to justify the inclusion of a technology exposure measure in the estimated specifi-

cation and, therefore, to test if job polarization emerges as a result of the computerization of routine tasks, I first recall Autor and Dorn's (2013) general equilibrium model where technological progress substitutes for workers performing routine job tasks.

Under this framework, technological progress takes the form of a decrease in the cost of accomplishing routine tasks with computers. As this decrease takes place, computers are adopted and workers performing routine tasks (i.e. "precise, well-understood procedures that can be (and increasingly are) codified in computer software and performed by machines" (Autor and Dorn, 2013)) substituted for. As in Acemoglu and Autor (2011), intermediate tasks, such as routine tasks, are generally performed by workers located in the middle of the skill distribution. This technological change complements abstract tasks (i.e. "creative, problem solving and coordination tasks") performed by high skilled workers, but does not substitute for nor complement manual tasks performed by low skilled workers. Regarding medium skilled workers, the emergence of this technological change leads to a decline in their wages and, hence, to a reallocation of their labor supply into manual tasks. Overall, the model implies that if the "elasticity of substitution in production" (Autor and Dorn, 2013) between computers' adoption and routine labor is higher than the "elasticity of substitution in consumption between goods and services" (Autor and Dorn, 2013), then the technological change causes wages for workers performing routine tasks to decrease relative to wages for workers performing manual tasks. This result leads medium skilled workers to reallocate their labor supply from the goods into the services sector and, since high skilled workers remain producing goods, employment polarization emerges.

Autor and Dorn's (2013) predictions are tested by extending this model to a spatial equilibrium framework. Key to this spatial equilibrium framework is the fact that each local labor market has a different degree of industrial specialization in routine job tasks ("due to initial differences in comparative advantage at the regional level" (Autor et al., 2015)).

Based on Autor and Dorn (2013) and Autor et al. (2015), I match data on occupations with their corresponding data on job tasks requirements in order to measure the extent to which each Mexican local labor market has specialized in routine job tasks.

In doing so, I use the National Classification of Occupations (*Clasificación Nacional de*

Ocupaciones (CNO) in Spanish), the Mexican Classification of Occupations (*Clasificación Mexicana de Ocupaciones (CMO)* in Spanish), and the National System of Classification of Occupations (*Sistema Nacional de Clasificación de Ocupaciones (SINCO)* in Spanish) to first match *US* data on occupations and their corresponding task requirements employed by both Autor and Dorn (2013) and Autor et al. (2015) with Mexican data on occupations and tasks coming from *ENEU* and *ENOE*. *SINCO* is used as a bridge between the *US* and the Mexican data since it reflects Mexico's occupational structure and it is comparable with other international systems of classification of occupations.

The matching described enables me to first calculate a routine task intensity (*RTI*) measure for each occupation k as follows:

$$RTI_k = \ln(T_{k,1980}^R - T_{k,1980}^M - T_{k,1980}^A) \quad (4)$$

where T_k^R , T_k^M , and T_k^A are, respectively, the routine, manual, and abstract task content of each occupation k in 1980.^{20,21}

I then identify those occupations that are in the top-third of the employment-weighted distribution of the *RTI* measure as in Autor and Dorn (2013) and Autor et al. (2015), and classify them as routine-task-intensive.

Using this information, I finally calculate for each *MA* i a routine employment share measure (*RSH*) as follows:

$$RSH_{i,t} = [\sum_{k=1}^K L_{i,k,t} \times 1(RTI_k > RTI^{P66})] \times (\sum_{k=1}^K L_{i,k,t})^{-1} \quad (5)$$

where $L_{i,k,t}$ is employment in occupation k in *MA* i , at time t ; and $1(\cdot)$ is a function that takes the value of one if the occupation is routine-intensive. The *RSH* measure is the per-

²⁰The *RTI* measure is calculated for 1980 since computers' prices in the world suddenly declined after this year, which led labor markets to adopt computers and, therefore, to reduce employment in routing task-intensive occupations (Autor et al., 2015).

²¹Given the lack of historical data for the case of Mexico, the tasks content in each occupation used for the construction of the *RTI* index is taken from Autor and Dorn (2013) and Autor et al. (2015) for the *US* case in 1980. I assume the tasks content in each occupation is the same in the *US* and in Mexico. Thus, the base year of the *RTI* constructed for Mexico is also 1980.

centage of employment in *MA i* at the start of a decade that falls in routine task-intensive occupations (Autor et al., 2015) and it represents the technology exposure measure considered in this analysis.

3.4 Empirical Specification

Following Autor et al. (2015), this study stacks three sets of first differences (i.e. 3rd quarter/1994 - 4th quarter/1999, 1st quarter/2000 - 4th quarter/2009, and 1st quarter/2010 - 4th quarter/2019) to investigate the impact of trade and technology exposure on employment status (i.e. employment to population ratio, unemployment to population ratio, and non participation rate) by demographic groups; on occupational categories that differ in their intensity of abstract, routine, and manual task content, also by demographic groups; and on employment by sector and occupation.

The estimated model is the following:

$$\Delta Y_{i,k,t} = \beta_0 + \beta_1 \Delta IPW_{i,t}^{US} + \beta_2 \Delta OPW_{i,t}^{US} + \beta_3 RSH_{i,t} + \beta_4 X_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t} \quad (6)$$

where:^{22,23}

$\Delta Y_{i,k,t}$ stands for the decadal change in the employment to population ratio (or unemployment to population ratio or non participation rate) in *MA i*, in occupation *k*, during decade *t*;

$\Delta IPW_{i,t}^{US}$ is the decadal change in import exposure per worker measure in *MA i*, during decade *t* (i.e. measure of exposure of *MA i*, during decade *t* to Chinese competition in the *US* market);

$\Delta OPW_{i,t}^{US}$ is the decadal change in the openness per worker measure in *MA i*, during

²²It is a standard approach in the literature described in Section 2 to relate (decadal) changes in labor market outcomes to (decadal) changes in exposure to trade and/or technological change, i.e. the only way to capture a change in the dependent variable is with a change in the explanatory variables. In this paper, I study, among other things, if a change in exposure to international trade generates a change in labor market outcomes.

²³The decadal changes are considered as follows: 1) for each of the three periods considered in this paper, I subtracted $Y_{i,final} - Y_{i,initial}$. 2) I stacked the three subtractions obtained and attached them to each *MA i*. The same occurs with the trade explanatory variables.

decade t (i.e. measure of exposure of MA i , during decade t to *NAFTA* integration);

$RSH_{i,t}$ is the start of decade routine employment share in MA i (i.e. measure of technology exposure);

$X_{i,t}$ stands for start of period demographics in MA i such as the share of employment in manufacturing; share of population with high school education or more, and employment rate among women;

δ_i stands for MA fixed effects;

γ_t stands for time period effects; and

$\varepsilon_{i,t}$, for the specification error term.

Equation (6) might present simultaneity problems due to factors related to the trade and technology exposure measures considered in the analysis:

1) According to Autor and Dorn (2013), if $RSH_{i,t_0} = RSH_i^* + v_{i,t_0}$, where RSH_i^* is a "long run quasi-fixed component of industrial structure" that determines MA 's routine occupation share and v_{i,t_0} , a time-varying factor such as a cyclical shock to the demand for a MA 's manufacturing product, then v_{i,t_0} could induce a positive correlation between the start of period routine employment share (RSH_{i,t_0}) and the decadal change in the labor market aggregate under analysis, not caused by RSH_i^* , that could bias the *OLS* estimate of Equation (6).

2) Shocks to *US* product demand could affect *US* imports from China and, therefore, generate a positive correlation between *US* imports from China and the labor market aggregate under analysis (e.g. employment), thus biasing *OLS* estimates of Equation (6) (Chiquiar et al., 2017; and Mendez, 2015).

3) Similarly, a supply shock to Mexican exports to the *US* could generate a positive correlation between these exports and Mexico's labor market aggregate under analysis (e.g. employment), thus biasing *OLS* estimates of Equation (6) (Chiquiar et al., 2017).²⁴

Hence, equation (6) is estimated by *System GMM* (in a static form) in order to control for simultaneity problems and to restore consistency of the parameters' estimates.^{25,26} I use

²⁴Some examples of this particular shock could be an unexpected increase in the oil price or the discovery of new oil wells in Mexico which increases the production base.

²⁵In addition, *System GMM* estimator is used since it "turns out to be efficient within the class of instrumental variable estimators" (p. 115, Nucci and Pozzolo, 2010).

²⁶Since *System GMM* combines equations in first differences with equations in levels, the instruments for

STATA's xtabond2 command written by Roodman (2009) to implement this econometric technique.

Together with the results, I present the Hansen test of over-identifying restrictions, which is a test for the exogeneity of the set of instruments included; and the Arellano-Bond tests for first and second order autocorrelation in the level residuals. Robust standard errors (clustered by *MA*) to account for general forms of heteroskedasticity and serial correlation in the error term are also registered with the results.

Table (1) in the Annex presents some summary statistics on the dependent and independent variables used in the empirical analysis, while Table (2) in the Annex as well shows some examples of occupations that differ in primary task content. Figures (1), (2), and (3) in Annex A show the evolution of employment status (i.e. employment to population ratio, unemployment to population ratio and not in labor force to population ratio) by demographic groups throughout the three time periods considered.²⁷

Figure 1 presents the employment to population ratio by demographic groups. Throughout the decades, the employment ratio of men has decreased, while the ratio for women has increased, which helps to explain the marginal bump in the overall employment to population ratio. It is worth noting the existing substantial difference in the ratio employed between genders. A narrower gap between employment ratios is observed across age, where the share of older workers on their population has increased, meanwhile the share of younger workers have decreased. Furthermore, as should be expected, the share of high-skilled workers is higher relative to the low-skilled workers. The share for low-skilled has remained relatively stable over time, but the share for high-skilled workers has slightly increased. Finally, the bottom right graph allows us to observe the compositional structure of employment, where manual intensive tasks occupations prevail followed by abstract and routine intensive tasks occupations. The share of workers in routine intensive task occupations has remained stable, while the share of abstract and manual intensive task occupations has somewhat increased.

the first type of equations are the lagged levels of the endogenous regressors (first lag), while the instruments for the second type of equations are the first differences of these same independent variables.

²⁷The labor market outcome (i.e. employment, unemployment, or population not in labor force) in each demographic group is divided by the total population in that particular demographic group.

Figure 2 shows the unemployment to population ratio by demographic group. In this case, the unemployment ratio of men remains stable in the first two time periods considered and increases in the last decade, while that of women increases gradually across time. As regards age, the unemployment ratio of young and old individuals has increased gradually across time, but that of young individuals has increased at a faster rate. Finally, the unemployment ratio of individuals with high school education or more has increased substantially throughout the decades, while that of individuals with less than high school education remains stable in the first two time periods considered, and then increases in the last one.

Figure 3 shows the not in labor force to population ratio by demographic group. It is worth noting that, in this case, women's non participation rate decreases substantially throughout the periods considered, while that of men remains stable in the first two periods and then increases. Regarding age, the non participation rate has remain stable across time for both young and old individuals. Finally, as regards education, the non participation rate of individuals with high school education or more has decreased across time as should be expected, while that of individuals with less than high school education has remain stable.

3.4 Results

This Section presents the findings of the empirical analysis.

3.4.1 Trade and Technology Effects on Employment Status by Demographic Groups

First, Equation (6) is estimated by *System GMM* in order to analyze the impact of trade and technology exposure on employment status by demographic groups (i.e. gender, level of education, and age). Table 1 show these results.

Regarding $\Delta IPW_{i,t}^{US}$ or exposure of *MA i*, during decade *t*, to Chinese import competition in the *US* market, the results show that it has a negative and a statistically significant effect on employment for all demographic groups (while a positive and a statistically significant impact on unemployment and the population not in the labor force, also for all demographic groups). However, a closer look at the findings reveals that the negative employment effects of the exposure to rising Chinese import competition in the *US* market were larger for women, the less educated, and younger workers. For example, in the case of the age group, a 1,000

dollars increase in per-worker import competition exposure over a 10 year period reduces employment for younger workers by 0.013 percentage points, while employment for older workers by 0.008 percentage points. In addition, it can be observed that the negative employment effects just described were mainly absorbed by an increase in the non participation rate rather than by an increase in unemployment.

As regards $\Delta OPW_{i,t}^{US}$ or exposure of *MA i*, during decade *t*, to *NAFTA* integration, the findings show that it has a positive and statistically significant effect on employment for all demographic groups, while a negative and a statistically significant effect on the non participation rate, also for all demographic groups. The effect on unemployment is positive for all demographic groups, but statistically not significant, except for the 40 years or more group. A closer look at the results show that exposure to *NAFTA* integration had a larger positive employment effect on women, the most educated, and younger workers, while a larger negative effect on the non participation rate of these same demographic groups. Again, in the case of the age group (the younger workers group is the one that experienced the strongest effect), a 1,000 dollars increase in-per worker exposure to *NAFTA* integration over a 10 year period increases employment for younger workers by 0.026 percentage points, while employment for older workers by 0.021 percentage points.

Overall, the results on trade show that while exposure to *NAFTA* integration created employment and reduced the non participation rate (while it has no effect on unemployment), exposure to Chinese import competition in the *US* market had the opposite effect: it negatively affected employment and increased unemployment and the non participation rate. As described in Section 2.1, these findings are most similar to those of Chiquiar et al. (2017), who also investigates the effect of exposure to *NAFTA* integration and to rising Chinese import competition on Mexico's local labor markets.

The findings on the routine employment share variable or technology exposure measure are not statistical significant.

These first estimates highlight that trade and technology exposure are not a single force having an impact on Mexico's local labor markets, but rather two distinct effects.

The results on trade are similar to those of Autor et al. (2015) in the sense that exposure

to rising Chinese import competition reduced employment in the *US*, while it increased unemployment and the non participation rate. Regarding the effect of the technology exposure measure, Autor et al. (2015) reveal that it had a negative and a statistically significant effect on employment for certain demographic groups (e.g. women, college workers, and old workers), while a positive and a statistically significant effect on the non participation rate of these same demographic groups, with no effect on unemployment. While this paper shows the computerization of routine tasks has no statistically significant effects on the labor market outcomes being analyzed, the results are similar to those found by Autor et al. (2015) in terms of the direction of the impact.

Table 1: Effect of Trade and Technology Exposure on Employment Status by Demographic Group (3/1994 - 4/2019)

Dependent Variable: ΔY , Decadal change in the employment to population ratio, unemployment to population ratio, or non participation rate							
Independent Variables:	Estimation by System GMM						
	All	Men	Women	Less than High School	High School or More	Less than 40 years	40 Years or More
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Status: Employed</i>							
ΔOPW	0.01923* (0.00946)	0.02208** (0.0097)	0.02552* (0.01267)	0.02221*** (0.00696)	0.02498** (0.01144)	0.02588*** (0.00726)	0.02133** (0.00948)
ΔIPW	-0.00980** (0.0039)	-0.01081** (0.00455)	-0.01164** (0.00448)	-0.01144*** (0.00272)	-0.01108*** (0.00338)	-0.01323*** (0.00257)	-0.00799*** (0.00281)
RSH: Share of employed in routine occupations	-0.34762 (0.37199)	-0.86805 (0.91249)	-1.02875 (1.72764)	-0.66074 (1.05666)	-0.02394 (1.30139)	-1.01206 (0.99377)	0.54163 (1.38144)
AR(1) p-value:	0.491	0.332	0.417	0.312	0.373	0.322	0.686
AR(2) p-value:	0.114	0.307	0.187	0.142	0.0404	0.0623	0.129
Hansen test of overid. restrictions p-value:	0.490	0.240	0.378	0.433	0.293	0.281	0.353
<i>Status: Unemployed</i>							
ΔOPW	-0.00129 (0.00135)	-0.00202 (0.00294)	-0.0008 (0.00183)	-0.00058 (0.0023)	-0.00022 (0.00128)	-0.00015 (0.00233)	-0.00395*** (0.00117)
ΔIPW	0.00138* (0.00075)	0.00230* (0.00123)	0.00109* (0.00059)	0.00154** (0.00074)	0.00137*** (0.00041)	0.00139* (0.00076)	0.00227*** (0.00038)
RSH: Share of employed in routine occupations	0.24240 (0.2502)	-0.0509 (0.52932)	0.13255 (0.34596)	-0.16893 (0.47571)	0.27086 (0.36958)	-0.18081 (0.417)	0.24705 (0.19479)
AR(1) p-value:	0.358	0.369	0.453	0.478	0.347	0.625	0.131
AR(2) p-value:	0.346	0.852	0.826	0.997	0.0870	0.410	0.165
Hansen test of overid. restrictions p-value:	0.279	0.330	0.148	0.475	0.631	0.625	0.128
<i>Status: Not in Labor Force</i>							
ΔOPW	-0.02211** (0.00971)	-0.01949* (0.00951)	-0.02658* (0.01454)	-0.02211*** (0.00777)	-0.02499** (0.01209)	-0.02689*** (0.00748)	-0.01964** (0.00937)
ΔIPW	0.00925*** (0.00286)	0.00803** (0.00343)	0.01100** (0.00505)	0.00959*** (0.00291)	0.0098*** (0.00346)	0.01195*** (0.00269)	0.00606** (0.00276)
RSH: Share of employed in routine occupations	0.26663 (0.5982)	-0.25731 (1.44211)	1.17270 (1.96171)	1.24521 (1.17179)	0.32845 (1.58944)	1.60280 (1.15481)	-0.00387 (1.26668)
AR(1) p-value:	0.648	0.414	0.459	0.202	0.644	0.194	0.933
AR(2) p-value:	0.120	0.650	0.252	0.147	0.179	0.0788	0.202
Hansen test of overid. restrictions p-value:	0.374	0.132	0.334	0.503	0.383	0.363	0.326

All estimations have 84 observations. N : 28 metropolitan areas x 3 decades = 84 observations

All estimations include additional controls, metropolitan areas fixed effects (which disappear with the first difference), and period fixed effects.

Additional controls stand for the start of period of the following variables: share of employment in manufacturing; share of population with high-school education or more; and employment rate among women.

Robust standard errors in parentheses, clustered by metropolitan areas.

*** p<0.01, ** p<0.05, * p<0.1

3.4.2 Trade and Technology Effects on Employment by Occupation-Task Groups

Equation (6) is now estimated by *System GMM* to investigate the effect of trade and technology exposure on employment by occupation - task content (i.e. abstract, routine or manual) crossed with demographic groups. Table 2 shows these results.

$\Delta IPW_{i,t}^{US}$ or exposure of *MA i*, during decade *t*, to Chinese import competition in the *US* market has a negative and a statistically significant impact on employment in abstract (with the largest effect found in men, the most educated, and older workers) and routine-task-intensive occupations (with the largest effect found in women, the less educated, and younger workers), but not in manual-task-intensive occupations. However, the largest employment effect is found on the routine-task-intensive occupations. For example, a 1000 dollars increase in per-worker import competition exposure over a 10 year period reduces employment for younger workers in routine task-intensive occupations by 0.009 percentage points, while employment for older workers in this same type of occupations by 0.005 percentage points.

$\Delta OPW_{i,t}^{US}$ or exposure of *MA i*, during decade *t*, to *NAFTA* integration increased employment in abstract (with the largest effect found in the most educated and older workers) and routine-task-intensive occupations (with the largest effect found in women, the less educated, and older workers), but had no effect on the manual-task-intensive occupations. Again, the largest impact is found on employment in routine-task-intensive occupations. For example, a 1000 dollars rise in-per worker exposure to *NAFTA* integration over a 10 year period increases employment for women in routine task-intensive occupations by 0.014 percentage points, while employment for men in this same type of occupations by 0.006 percentage points.

Regarding the routine employment share variable or technology exposure measure, the results are not statistically significant.

Overall, the findings described are in line with Autor et al. (2015) since both, exposure to rising Chinese import competition and to *NAFTA* integration had their largest employment effects on the routine-task-intensive occupations and, within this category, on women and the less educated. In the case of Mexico, this might be associated to the following factors: 1) under *NAFTA*, maquiladoras proliferated and it is well known that mostly women work there,

and 2) given the nature of routine tasks, which “follow precise, well-understood procedures that can be (and increasingly are) codified in computer software and performed by machines” (Autor and Dorn, 2013), it is reasonable to think that they are mainly performed by low skilled or less educated workers.

Another similarity with Autor et al. (2015) is that exposure to rising Chinese import competition has negative effects throughout the task distribution, while the technology exposure measure does not. Exposure to *NAFTA* integration affects as well all the task distribution but we cannot contrast this result with Autor et al. (2015).

Table 2: Effect of Trade and Technology Exposure on Employment by Occupation - Task Group (3/1994 - 4/2019)

Dependent Variable: ΔY , Decadal change in the employment to population ratio in indicated occupation-task group							
Independent Variables:	Estimation by System GMM						
	All	Men	Women	Less than High School	High School or More	Less than 40 years	40 Years or More
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Occupation - Primary task : Abstract</i>							
ΔOPW	0.00770** (0.00329)	0.00466 (0.00731)	0.00783* (0.00414)	0.00521** (0.00234)	0.00965* (0.00533)	0.00669** (0.00305)	0.01090*** (0.00333)
ΔIPW	-0.00487*** (0.00108)	-0.00501** (0.00227)	-0.00389** (0.0016)	-0.00235*** (0.00077)	-0.00781*** (0.00178)	-0.00419*** (0.00095)	-0.00617*** (0.00112)
RSH: Share of employed in routine occupations	-0.22028 (0.50688)	0.35089 (0.79052)	-0.69011 (0.89781)	-0.17737 (0.25496)	0.17275 (0.6416)	-0.16254 (0.38407)	-0.16328 (0.62144)
AR(1) p-value:	0.418	0.913	0.249	0.0685	0.687	0.945	0.859
AR(2) p-value:	0.770	0.845	0.511	0.804	0.157	0.906	0.949
Hansen test of overid. restrictions p-value:	0.231	0.162	0.469	0.440	0.183	0.244	0.129
<i>Occupation - Primary task : Routine</i>							
ΔOPW	0.01178* (0.00583)	0.00610 (0.00704)	0.01369** (0.00556)	0.01285*** (0.00396)	0.00862 (0.00517)	0.00983 (0.00586)	0.01367*** (0.004)
ΔIPW	-0.00755** (0.00359)	-0.00542** (0.0025)	-0.00798** (0.00365)	-0.00756*** (0.00206)	-0.00459** (0.00166)	-0.00913*** (0.00222)	-0.0052*** (0.00113)
RSH: Share of employed in routine occupations	-0.14718 (1.12748)	0.31661 (0.90863)	0.02160 (1.49466)	-0.43842 (0.72874)	0.29993 (1.08574)	0.35847 (1.13894)	-0.08356 (0.72059)
AR(1) p-value:	0.999	0.301	0.865	0.515	0.839	0.245	0.808
AR(2) p-value:	0.816	0.322	0.965	0.777	0.559	0.440	0.851
Hansen test of overid. restrictions p-value:	0.421	0.745	0.475	0.447	0.606	0.384	0.451
<i>Occupation - Primary task : Manual</i>							
ΔOPW	0.00476 (0.00545)	0.00390 (0.00782)	0.00480 (0.00691)	0.00529 (0.00732)	0.00858 (0.00688)	0.00879 (0.0062)	0.00304 (0.0049)
ΔIPW	0.00053 (0.00315)	0.00182 (0.00301)	-0.00139 (0.00395)	-0.00045 (0.00277)	-0.00016 (0.00185)	-0.00177 (0.00233)	0.00119 (0.00181)
RSH: Share of employed in routine occupations	-0.12001 (1.04683)	0.88177 (1.34141)	-0.19724 (0.68784)	-0.88408 (0.94625)	-0.25212 (0.79616)	-0.80866 (0.78734)	0.37446 (0.5103)
AR(1) p-value:	0.861	0.602	0.802	0.426	0.974	0.381	0.876
AR(2) p-value:	0.971	0.873	0.423	0.958	0.324	0.705	0.741
Hansen test of overid. restrictions p-value:	0.204	0.131	0.384	0.132	0.643	0.408	0.138

All estimations have 84 observations. N : 28 metropolitan areas x 3 decades = 84 observations

All estimations include additional controls, metropolitan areas fixed effects (which disappear with the first difference), and period fixed effects.

Additional controls stand for the start of period of the following variables: share of employment in manufacturing; share of population with high-school education or more; and employment rate among women.

Robust standard errors in parentheses, clustered by metropolitan areas.

*** p<0.01, ** p<0.05, * p<0.1

3.4.3 Trade and Technology Effects on Employment in the Manufacturing and Non-Manufacturing Sectors

This third exercise explores the effect of trade and technology exposure on employment in the manufacturing and non-manufacturing sectors crossed with abstract, routine, and manual-task-intensive occupations. Tables 3 presents the results.

First, $\Delta IPW_{i,t}^{US}$ or exposure of *MA i*, during decade *t*, to Chinese import competition in the *US* market has a negative and a statistically significant effect on both manufacturing and non-manufacturing overall employment. A 1000 dollars increase in per-worker import competition exposure over a 10 year period reduces overall employment by 0.0052 percentage points in the manufacturing sector and by 0.0109 percentage points in the non-manufacturing sector. The breakdown of these findings by occupation task content suggests the following. In the manufacturing sector, rising Chinese import competition in the *US* market reduced employment both in abstract and routine-task-intensive occupations, while it increased employment in manual-task-intensive occupations. While the effects on the routine and manual-task-intensive occupations are not statistically significant, it can be seen that the model is predicting countervailing effects across task intensive occupations. On the other hand, in the non-manufacturing sector, rising Chinese import competition in the *US* market reduced employment in the three types of occupations (though only the effect on manual-task-intensive occupations is not statistically significant). Overall, the results suggest that rising Chinese import competition in the *US* market adversely affected employment both in the manufacturing and non-manufacturing sectors and, within those sectors, routine as well as abstract task intensive occupations.

Autor et al. (2015) show that the Chinese import competition measure has a negative and a statistically significant effect on abstract and routine-task-intensive occupations in the manufacturing sector and on routine and manual-task-intensive occupations in the non-manufacturing sector.

Regarding $\Delta OPW_{i,t}^{US}$ or exposure of *MA i*, during decade *t*, to *NAFTA* integration, the model predicts overall employment gains both in the manufacturing and non-manufacturing sectors. For example, a 1000 dollars rise in per-worker exposure to *NAFTA* integration over a

10 year period increases overall employment by 0.0114 percentage points in the manufacturing sector and by 0.01998 percentage points in the non-manufacturing sector. The breakdown of these results by occupation task content shows a positive employment effect in the three types of occupations both in the manufacturing (only statistically significant in abstract task intensive occupations) and non-manufacturing sectors (statistically significant in abstract and routine-task-intensive occupations). This effect is not considered in Autor et al. (2015), so I cannot contrast the results.

Finally, the routine employment share variable or technology exposure measure has a positive and a statistically significant effect on overall manufacturing employment, while a negative but not statistically significant effect on overall non-manufacturing employment. In the manufacturing sector, it can be observed that there is a shift of employment from routine to manual-task-intensive occupations, as seen by comparing column (3) to column (4) of Table 3, though only the effect on manual-task-intensive occupations is statistically significant. In the case of the non-manufacturing sector, a similar finding is observed: employment losses in routine-task-intensive occupations are offset with gains in manual-task-intensive occupations, though non of these results are statistically significant in this latter case. While the majority of the point estimates regarding the technology exposure measure are not statistically significant, the pattern of results seems to be consistent with computerization of routine tasks leading to job polarization, i.e. gains in manual-task-intensive occupations relative to employment in routine-task-intensive occupations.

Autor et al. (2015) find similar results regarding the technology exposure measure. Both in the manufacturing and non-manufacturing sectors, employment losses in routine-task-intensive occupations are offset with gains in abstract and manual-task-intensive occupations, though only the estimated coefficient of routine-task-intensive occupations in the non-manufacturing sectors is statistically significant. While the majority of their estimates are as well not statistically significant, they conclude there is a pattern of job polarization in the *US* case.

Overall, the results suggest the following. 1) Rising Chinese import competition in the *US* market has a negative and a statistically significant effect on overall employment both in

the manufacturing and non-manufacturing sectors; while exposure to *NAFTA* integration, a positive and a statistically significant effect in both sectors as well. 2) The breakdown of these first results by occupation task content reveals trade exposure has not only affected routine, but also abstract task intensive occupations. 3) Regarding the technology exposure measure, while most point estimates are not statistically significant, they seem to be consistent with computerization of routine tasks leading to job polarization, i.e. gains in manual-task-intensive occupations relative to employment in routine-task-intensive occupations.

The fact that the technology exposure measure does not have a statistically significant effect (in general) on employment by demographic groups, on employment by occupation-task groups crossed with demographic groups, and on employment by sectors crossed with abstract, routine, and manual-task-intensive occupations might be surprising given the recent advances in technology. For the *US* case, Autor et al. (2015) suggest that the employment effects might have been present before but not during the sample period considered in their paper. The authors test for this hypothesis and find that this is the case. This prediction cannot be tested in this paper since detailed data on labor market aggregates is not available pre-1994 for Mexico.

Regarding the specifications tests presented in Tables 1 to 3, the null hypotheses in the Hansen test and the Arellano Bond tests are not rejected as expected.²⁸

²⁸Equation (6) is not a dynamic model so the null hypothesis in the Arellano Bond test for first order serial correlation (establishes there is no serial correlation) should not be rejected for a correct specification and it is not rejected.

Table 3: Effect of Trade and Technology Exposure on Employment in the Manufacturing and Non-Manufacturing Sectors by Type of Occupation (3/1994 - 4/2019)

Independent Variables:	Dependent Variable: ΔY , Decadal change in the employment to population ratio in indicated sector - occupation							
	Estimation by System GMM							
	Manufacturing Sector		Non-Manufacturing Sector		Manufacturing Sector		Non-Manufacturing Sector	
All	Abstract	Routine	Manual	All	Abstract	Routine	Manual	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
ΔOPW	0.01144*** (0.00271)	0.00235*** (0.00081)	0.01322 (0.01541)	0.00100 (0.00274)	0.01998** (0.00806)	0.0077*** (0.00329)	0.01178* (0.00583)	0.01073 (0.01055)
ΔIPW	-0.0052*** (0.00129)	-0.00079* (0.00044)	-0.00479 (0.00375)	0.00090 (0.0013)	-0.01086*** (0.00246)	-0.00487*** (0.00108)	-0.00755*** (0.00359)	-0.00187 (0.00441)
RSH: Share of sectorial employed in routine occupations	0.10223** (0.04054)	-0.01584 (0.02065)	-0.00651 (0.12024)	0.12103* (0.06065)	-0.26415 (0.41208)	-0.22028 (0.50688)	-0.14718 (1.12748)	0.03991 (0.46884)
AR(1) p-value:	0.123	0.199	0.344	0.200	0.340	0.418	0.999	0.624
AR(2) p-value:	0.228	0.637	0.389	0.487	0.151	0.770	0.816	0.658
Hansen test of overid. restrictions p-value:	0.0951	0.403	0.602	0.273	0.406	0.231	0.421	0.461

All estimations have 84 observations. N : 28 metropolitan areas x 3 decades = 84 observations
 All estimations include additional controls, metropolitan areas fixed effects (which disappear with the first difference), and period fixed effects.
Additional controls stand for the start of period of the following variables: share of employment in manufacturing; share of population with high-school education or more; and employment rate among women.
 Robust standard errors in parentheses, clustered by metropolitan areas.
 *** p < 0.01, ** p < 0.05, * p < 0.1

4 Relative Contribution to Local Labor Market Outcomes

In this Section, the relative contribution of the main explanatory variables (i.e. trade and technological exposure measures) to the different labor market outcomes analyzed in this paper is investigated by calculating standard beta coefficients. The formula used to calculate them is the following:

$$\beta_{coefficient} = \frac{\hat{\beta}_x * \sigma_x}{\sigma_y} \quad (7)$$

where $\hat{\beta}_x$ stands for the estimated coefficient of the independent variable, σ_x stands for the regressor's standard deviation, and σ_y , for the labor market outcomes' standard deviation.

Tables 4, 5, and 6 present the beta coefficients that correspond to the estimated coefficients in Tables 1, 2, and 3.

Regarding Table 4, the main results show that $\Delta OPW_{i,t}^{US}$ or exposure of *MA* *i*, during decade *t*, to *NAFTA* integration is the explanatory variable that contributes the most to the decadal change in employment to population ratio and the decadal change in the non participation rate, followed by ΔIPW or exposure to rising Chinese import competition in the *US* market. In addition, ΔIPW is the only variable that contributes to the decadal change in unemployment to population ratio, while the technology exposure measure (i.e. *RSH*) does not have a statistically significant effect in any of the three labor market aggregates under study.

Table 5 presents a similar story. $\Delta OPW_{i,t}^{US}$ is the variable that contributes the most to employment in abstract and routine-task-intensive occupations, followed by ΔIPW . As in the previous Table, *RSH* does not have a statistically significant effect in any of the three occupation - task groups assessed.

Finally, Table 6 shows that $\Delta OPW_{i,t}^{US}$ is the variable that contributes the most to employment in the manufacturing (particularly in abstract task intensive occupations) and non-manufacturing (particularly in abstract and routine-task-intensive occupations) sectors, followed by ΔIPW . In this case, *RSH* does have a statistically significant impact on overall employment, but its contribution is the smallest.

Therefore, I conclude that the driver of the local labor market aggregates under analysis in this paper is trade and not technological change. $\Delta OPW_{i,t}^{US}$ is the trade exposure measure that contributes the most to labor market aggregates, followed by ΔIPW .

Table 4: Effect of Trade and Technology Exposure on Employment Status by Demographic Group (3/1994 - 4/2019) : Beta Coefficients

Dependent Variable: ΔY , Decadal change in the employment to population ratio, unemployment to population ratio, or non participation rate							
Independent Variables:	Estimation by System GMM						-Beta Coefficients
	All	Men	Women	Less than High School	High School or More	Less than 40 years	40 Years or More
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Status: Employed</i>							
ΔOPW	0.90982* (0.44758)	0.82042** (0.36042)	0.99171* (0.49236)	0.9364*** (0.29344)	1.08948** (0.49894)	1.0413*** (0.29211)	0.94669** (0.42075)
ΔIPW	-0.70931** (0.28228)	-0.61446** (0.25863)	-0.69197** (0.26633)	-0.73786*** (0.17543)	-0.73926*** (0.22552)	-0.81434*** (0.15819)	-0.5425*** (0.19079)
RSH: Share of employed in routine occupations	-0.77157 (0.82566)	-1.51313 (1.59059)	-1.87547 (3.14957)	-1.30689 (2.08999)	-0.04898 (2.66274)	-1.91036 (1.87584)	1.12777 (2.87637)
AR(1) p-value:	0.491	0.332	0.417	0.312	0.373	0.322	0.686
AR(2) p-value:	0.114	0.307	0.187	0.142	0.0404	0.0623	0.129
Hansen test of overid. restrictions p-value:	0.490	0.240	0.378	0.433	0.293	0.281	0.353
<i>Status: Unemployed</i>							
ΔOPW	-0.10251 (0.10728)	-0.13053 (0.18998)	-0.07541 (0.17249)	-0.0454 (0.18004)	-0.01639 (0.09536)	-0.00981 (0.15246)	-0.47046*** (0.13935)
ΔIPW	0.16776* (0.09117)	0.22736* (0.12159)	0.15717* (0.08508)	0.18441** (0.08861)	0.15614*** (0.04673)	0.13914* (0.07608)	0.4136*** (0.06924)
RSH: Share of employed in routine occupations	0.90365 (0.93273)	-0.15431 (1.60465)	0.58613 (1.52985)	-0.62033 (1.74688)	0.94669 (1.29174)	-0.55504 (1.28007)	1.38038 (1.0884)
AR(1) p-value:	0.358	0.369	0.453	0.478	0.347	0.625	0.131
AR(2) p-value:	0.346	0.852	0.826	0.997	0.0870	0.410	0.165
Hansen test of overid. restrictions p-value:	0.279	0.330	0.148	0.475	0.631	0.625	0.128
<i>Status: Not in Labor Force</i>							
ΔOPW	-1.18008** (0.51825)	-1.11281* (0.54299)	-0.95076* (0.52009)	-1.01929*** (0.3582)	-1.05563** (0.51071)	-1.28602*** (0.35773)	-0.90486** (0.4317)
ΔIPW	0.75526*** (0.23352)	0.70138** (0.29959)	0.60193** (0.27634)	0.67633*** (0.20523)	0.63329*** (0.22359)	0.8743*** (0.19681)	0.42712** (0.19453)
RSH: Share of employed in routine occupations	0.66762 (1.49785)	-0.68922 (3.8628)	1.96788 (3.29192)	2.69307 (2.53427)	0.65089 (3.14981)	3.59611 (2.59099)	-0.00836 (2.73781)
AR(1) p-value:	0.648	0.414	0.459	0.202	0.644	0.194	0.933
AR(2) p-value:	0.120	0.650	0.252	0.147	0.179	0.0788	0.202
Hansen test of overid. restrictions p-value:	0.374	0.132	0.334	0.503	0.383	0.363	0.326

All estimations have 84 observations. N : 28 metropolitan areas x 3 decades = 84 observations

All estimations include additional controls, metropolitan areas fixed effects (which disappear with the first difference), and period fixed effects.

Additional controls stand for the start of period of the following variables: share of employment in manufacturing; share of population with high-school education or more; and employment rate among women.

Robust standard errors in parentheses, clustered by metropolitan areas.

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Effect of Trade and Technology Exposure on Employment by Occupation -Task Group (3/1994 - 4/2019) : Beta Coefficients

Dependent Variable: ΔY , Decadal change in the employment to population ratio in indicated occupation-task group							
Independent Variables:	Estimation by System GMM						
	All	Men	Women	Less than High School	High School or More	Less than 40 years	40 Years or More
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Occupation - Primary task : Abstract</i>							
ΔOPW	0.68802** (0.29397)	0.32183 (0.50484)	0.75881* (0.40121)	0.61247** (0.27508)	0.5062* (0.27959)	0.47274** (0.21553)	0.5906*** (0.18043)
ΔIPW	-0.66569*** (0.14763)	-0.52931** (0.23983)	-0.57671** (0.23721)	-0.42262*** (0.13848)	-0.62673*** (0.14284)	-0.45295*** (0.1027)	-0.51143*** (0.09284)
RSH: Share of employed in routine occupations	-0.92339 (2.12475)	1.13686 (2.56123)	-3.13754 (4.08182)	-0.97819 (1.40608)	0.42511 (1.5789)	-0.53885 (1.27322)	-0.41504 (1.57966)
AR(1) p-value:	0.418	0.913	0.249	0.0685	0.687	0.945	0.859
AR(2) p-value:	0.770	0.845	0.511	0.804	0.157	0.906	0.949
Hansen test of overid. restrictions p-value:	0.231	0.162	0.469	0.440	0.183	0.244	0.129
<i>Occupation - Primary task : Routine</i>							
ΔOPW	0.75431* (0.37331)	0.27861 (0.32154)	0.95999** (0.38989)	0.67225*** (0.20717)	0.76458 (0.45857)	0.53412 (0.31841)	1.10728*** (0.324)
ΔIPW	-0.73958** (0.35167)	-0.3787** (0.17468)	-0.85605** (0.39155)	-0.60504*** (0.16486)	-0.62282** (0.22525)	-0.75891*** (0.18453)	-0.64435*** (0.14002)
RSH: Share of employed in routine occupations	-0.44214 (3.38696)	0.6784 (1.9469)	0.07105 (4.91701)	-1.07601 (1.78853)	1.24803 (4.5179)	0.91378 (2.90325)	-0.31752 (2.73824)
AR(1) p-value:	0.999	0.301	0.865	0.515	0.839	0.245	0.808
AR(2) p-value:	0.816	0.322	0.965	0.777	0.559	0.440	0.851
Hansen test of overid. restrictions p-value:	0.421	0.745	0.475	0.447	0.606	0.384	0.451
<i>Occupation - Primary task : Manual</i>							
ΔOPW	0.31009 (0.35504)	0.16535 (0.33154)	0.31243 (0.44977)	0.27228 (0.37677)	0.50891 (0.40807)	0.542 (0.3823)	0.16639 (0.2682)
ΔIPW	0.05282 (0.31392)	0.11804 (0.19522)	-0.13841 (0.39332)	-0.03543 (0.21811)	-0.01452 (0.16786)	-0.16696 (0.21978)	0.09964 (0.15156)
RSH: Share of employed in routine occupations	-0.36676 (3.19926)	1.75383 (2.66803)	-0.60229 (2.10036)	-2.13476 (2.28488)	-0.70155 (2.21537)	-2.33922 (2.27754)	0.96154 (1.31034)
AR(1) p-value:	0.861	0.602	0.802	0.426	0.974	0.381	0.876
AR(2) p-value:	0.971	0.873	0.423	0.958	0.324	0.705	0.741
Hansen test of overid. restrictions p-value:	0.204	0.131	0.384	0.132	0.643	0.408	0.138

All estimations have 84 observations. N : 28 metropolitan areas x 3 decades = 84 observations

All estimations include additional controls, metropolitan areas fixed effects (which disappear with the first difference), and period fixed effects.

Additional controls stand for the start of period of the following variables: share of employment in manufacturing; share of population with high-school education or more; and employment rate among women.

Robust standard errors in parentheses, clustered by metropolitan areas.

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Effect of Trade and Technology Exposure on Employment in the Manufacturing and Non-Manufacturing Sectors by type of Occupation (3/1994 - 4/2019) : Beta Coefficients

Independent Variables:	Dependent Variable: ΔY , Decadal change in the employment to population ratio in indicated sector - occupation							
	Estimation by System GMM							
	Manufacturing Sector		Non-Manufacturing Sector		Manufacturing Sector		Non-Manufacturing Sector	
All	Abstract	Routine	Manual	All	Abstract	Routine	Manual	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
ΔOPW	0.67682*** (0.16033)	0.61531*** (0.21114)	1.02444 (1.19415)	0.12353 (0.33848)	0.92611*** (0.37359)	0.68802** (0.29397)	0.75431* (0.37331)	0.699 (0.68727)
ΔIPW	-0.47064*** (0.11675)	-0.31541* (0.17567)	-0.56784 (0.44455)	0.17008 (0.24568)	-0.77007*** (0.17443)	-0.66569*** (0.14763)	-0.73958** (0.35167)	-0.18636 (0.43949)
RSH: Share of sectorial employed in routine occupations	0.28375** (0.11252)	-0.19391 (0.25287)	-0.02367 (0.43712)	0.70141* (0.35148)	-0.5744 (0.89608)	-0.92339 (2.12475)	-0.44214 (3.38696)	0.12198 (1.43284)
AR(1) p-value:	0.123	0.199	0.344	0.200	0.340	0.418	0.999	0.624
AR(2) p-value:	0.228	0.637	0.389	0.487	0.151	0.770	0.816	0.658
Hansen test of overid. restrictions p-value:	0.0951	0.403	0.602	0.273	0.406	0.231	0.421	0.461

All estimations have 84 observations. N: 28 metropolitan areas x 3 decades = 84 observations
 All estimations include additional controls, metropolitan areas fixed effects (which disappear with the first difference), and period fixed effects.
Additional controls stand for the start of period of the following variables: share of employment in manufacturing; share of population with high-school education or more; and employment rate among women.
 Robust standard errors in parentheses, clustered by metropolitan areas.
 *** p<0.01, ** p<0.05, * p<0.1

5 Conclusions

This paper assesses the effect of both trade and technology on Mexico *MAs'* labor market aggregates (i.e. employment status (i.e. employment, unemployment and the population not in labor force) by demographic groups; on employment by occupation - task content crossed with demographic groups; and on employment by sector crossed with occupation - task content) over the 3rd quarter/1994 - 4th quarter/2019 period. The estimated model includes as main independent variables a measure of exposure to *NAFTA* integration, a measure of exposure to Chinese import competition in the *US* market, and a routine employment share measure to control for technology exposure. The share of employment in manufacturing, the share of population with high school education or more, and the employment rate among women are also considered as additional explanatory variables. The model is estimated by *System GMM* in order to control for simultaneity problems.

Regarding the impact of trade on employment status by demographic groups, exposure of local labor markets to rising Chinese import competition in the *US* market reduces employment for all demographic groups (especially for women, the less educated, and younger workers). These negative employment effects are found to be absorbed, to a large extent, by the non participation rate, rather than by unemployment. Exposure of local labor markets to *NAFTA* integration has the opposite impact: it increases employment for all demographic groups, especially for women, the most educated, and younger workers; while it reduces the non participation rate for these same demographic groups. The effect on unemployment is not statistically significant in this case.

Turning to the impact of trade on employment by occupation - task content, exposure of local labor markets to Chinese import competition in the *US* market reduces employment in both abstract and routine-task-intensive occupations for all demographic groups (with no impact on manual-task-intensive occupations), while exposure of local labor markets to *NAFTA* integration increases it for these same occupation - task groups (with no impact as well on manual-task-intensive occupations). In both cases, the routine-task-intensive occupations are found to experience the largest trade effects and, within this category, women and the less ed-

ucated are the most affected. For the age group, exposure to *NAFTA* integration has a larger impact on older workers; while exposure to rising Chinese competition, on younger workers.

The routine employment share measure or technology exposure measure does not have a statistically significant effect in any of these two empirical exercises.

Finally, as regards employment in the manufacturing and non-manufacturing sectors, rising Chinese import competition in the *US* market reduces overall employment both in the manufacturing and non-manufacturing sectors, while exposure to *NAFTA* integration increases it. The breakdown of these results by occupation task content reveals trade exposure has not only affected routine, but also abstract task intensive occupations. While most point estimates on the impact of technology exposure are not statistically significant, the following pattern can be observed: there is a shift of employment from routine intensive occupations into manual-task-intensive occupations, which is consistent with computerization of routine tasks leading to job polarization.

I also investigate the relative contribution of each independent variable to the different labor market outcomes assessed in this paper. The results show that the main driver of the labor market outcomes is trade and not technological progress. Within trade, exposure to *NAFTA* integration contributes the most to these labor market aggregates, followed by exposure to Chinese import competition in the *US* market.

This paper improves on previous studies for Mexico in that it investigates both the effect of trade and technology on labor market aggregates simultaneously, and not just one or the other as it has been the case up until now. In addition, the estimated empirical specification included both a measure of exposure to rising Chinese import competition in the *US* market and a measure of *NAFTA* integration in order to assess which is more important in understanding labor market outcomes. The existing literature on Mexico typically only considers one trade exposure measure, but not both of them. This paper examines several adjustment aggregates including labor market outcomes by demographic groups, by occupational categories that differ in their intensity of task content, and by sector cross with occupation - task content. The existing literature on Mexico has analyzed fewer margins and has particularly missed on investigating the task content of employment as in this paper. However, there still

remain some important limitations in this paper. For example, given the lack of historical data for the case of Mexico, the tasks content in each occupation used for the construction of the *RTI* index is taken from Autor and Dorn (2013) and Autor et al. (2015) for the *US* in 1980. I assume the tasks content in each occupation is the same in the *US* and in Mexico. In addition, as mentioned in Section 3.4.3, I could not verify if the technology exposure measure had employment effects before the sample period as in Autor et al. (2015), since detailed data on labor market aggregates is not available pre-1994 for Mexico.

This study highlights, on one hand, the employment losses Mexico experienced due to its exposure to rising Chinese import competition in the *US* market; while, on the other hand, the employment gains it experienced due to *NAFTA* integration.

A possible avenue for future research could be to explore the impact of trade and technology on wages for the different adjustment margins analyzed in this paper. This could be done using the novel database created for Mexican *MA*s.

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6 Annex A

Table 1: Summary Statistics

Variables	Obs	Mean	Std. Dev.	Min.	Max.
Metropolitan Area	84	14.50	8.126	1	28
Dependent Variable					
Employment to population	84	0.0239	0.0354	-0.0561	0.140
Employment to population of male	84	-0.00985	0.0450	-0.124	0.0960
Employment to population of female	84	0.0548	0.0431	-0.0373	0.240
Employment to population with high-school education or more	84	0.0112	0.0384	-0.0688	0.102
Employment to population with less than high-school education	84	0.0179	0.0397	-0.0712	0.140
Employment to population of young	84	0.0123	0.0416	-0.0810	0.134
Employment to population of adults	84	0.0391	0.0377	-0.0294	0.144
Unemployment to population	84	-0.00151	0.0211	-0.0487	0.0444
Unemployment to population of male	84	-0.00118	0.0259	-0.0498	0.0569
Unemployment to population of female	84	-0.00182	0.0178	-0.0481	0.0356
Unemployment to population with high-school education or more	84	0.00114	0.0225	-0.0597	0.0452
Unemployment to population with less than high-school education	84	-0.00366	0.0214	-0.0491	0.0464
Unemployment to population of young	84	-0.00132	0.0256	-0.0641	0.0558
Unemployment to population of adults	84	0.000825	0.0140	-0.0280	0.0371
Non Labor Force to population	84	-0.0222	0.0314	-0.129	0.0475
Non Labor Force to population of male	84	0.0112	0.0293	-0.0913	0.0667
Non Labor Force to population of female	84	-0.0528	0.0468	-0.237	0.0529
Non Labor Force to population with high-school education or more	84	-0.0121	0.0396	-0.121	0.0990
Non Labor Force to population with less than high-school education	84	-0.0140	0.0363	-0.127	0.0645
Non Labor Force to population of young	84	-0.0108	0.0350	-0.124	0.0643
Non Labor Force to population of adults	84	-0.0399	0.0363	-0.135	0.0288
Employment to population by primary task	84	0.000964	0.0187	-0.0520	0.0470
Employment to population of male by primary task	84	-0.00378	0.0242	-0.0763	0.0529
Employment to population of female by primary task	84	0.00529	0.0173	-0.0309	0.0538
Employment to population with high-school education or more by primary task	84	-0.0251	0.0319	-0.0850	0.0437
Employment to population with less than high-school education by primary task	84	-0.0187	0.0142	-0.0730	0.00587
Employment to population of young by primary task	84	0.00865	0.0309	-0.0654	0.108
Employment to population of adults by primary task	84	-0.00210	0.0237	-0.0789	0.0449
Employment in manufacturing to population	84	0.00533	0.0283	-0.0527	0.0773
Employment in non-manufacturing to population	84	0.0182	0.0361	-0.0707	0.122
Employment in manufacturing to population by primary task	84	0.000600	0.00641	-0.0116	0.0226
Employment in non-manufacturing to population by primary task	84	0.000964	0.0187	-0.0520	0.0470
Independent Variables					
Openness per worker (Δ OPW)	84	1,326	1,673	-246.2	9,129
Index per worker (Δ IPW)	84	1,494	2,560	-713.5	18,188
Share of Employed in routine occupations (RSH)	84	0.432	0.0785	0.306	0.676
Share of Employed in manufacturing routine occupations (RSH)	84	0.637	0.0927	0.412	0.861
Share of Employed in non-manufacturing routine occupations (RSH)	84	0.432	0.0785	0.306	0.676
Employment rate of women	84	0.958	0.0207	0.903	0.992
Employment rate of men	84	0.964	0.0201	0.917	0.993
Share of population with high-school education or more	84	0.353	0.0662	0.175	0.538
Share of employment in manufacturing	84	0.165	0.0806	0.0574	0.404
Employment rate of young	84	0.657	0.0619	0.533	0.756

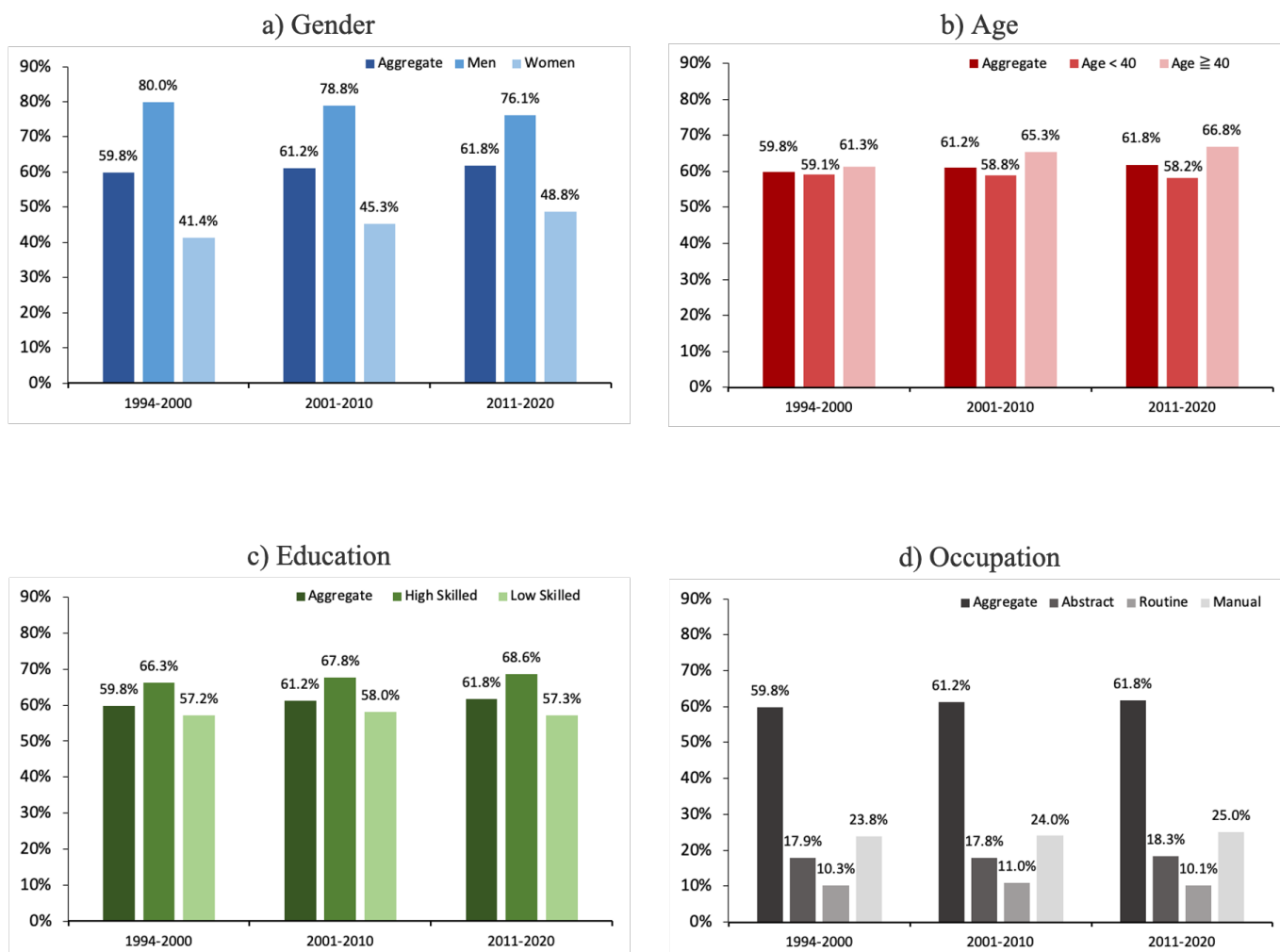
Source: From author's own calculations with data from *INEGI*.

Table 2: Examples of Occupations that Differ in their Primary Task Content

Occupation - Primary Task	Examples
Abstract	Administrators and managers in manufacturing production Instructors and trainers in trades and for work Sales, marketing and rental directors and Managers University and higher education professors
Routine	Workers installing and repairing electronic equipment Managers and workers in warehouse and warehouse control Operators of machines and installations for power generation Tinsmiths, hustlers, brass workers, copper workers
Manual	Firefighters Dancers and choreographers Athletes Police and traffic officers

Source: Constructed with data from *INEGI*.

Figure 1: Employment to Population Ratio

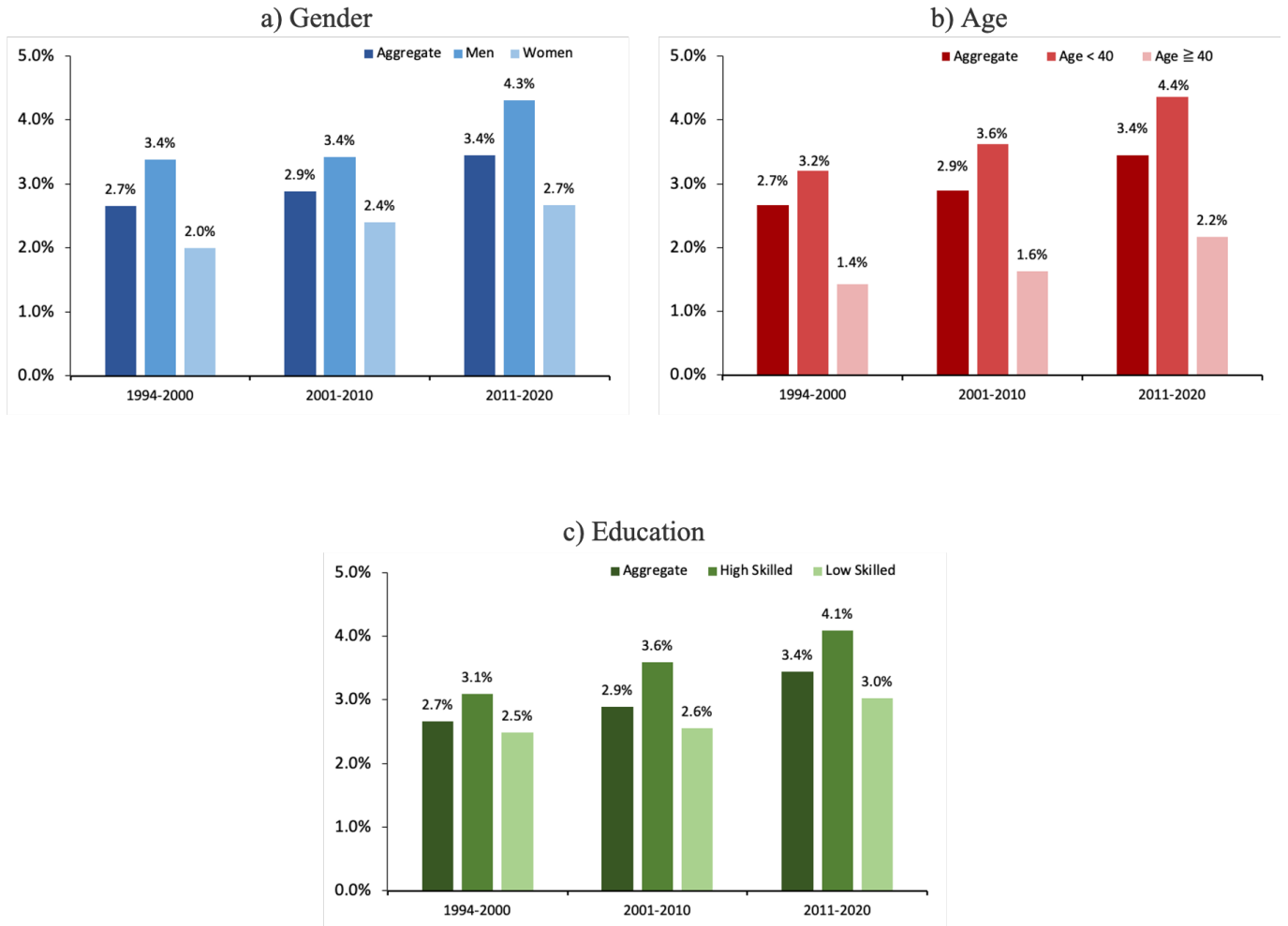


Note 1: In each Figure, the labor market outcome (i.e. employment in each demographic group) is divided by the total population in each demographic group, not by Mexico's total population. However, for the case of employment by occupation-task group, it is divided by Mexico's total population.

Note 2: It should be mention that occupation task groups do not sum to the aggregate since there were some occupations for the case of Mexico that could not be matched with those in the *US*.

Source: From author's own calculations with data from *INEGI*.

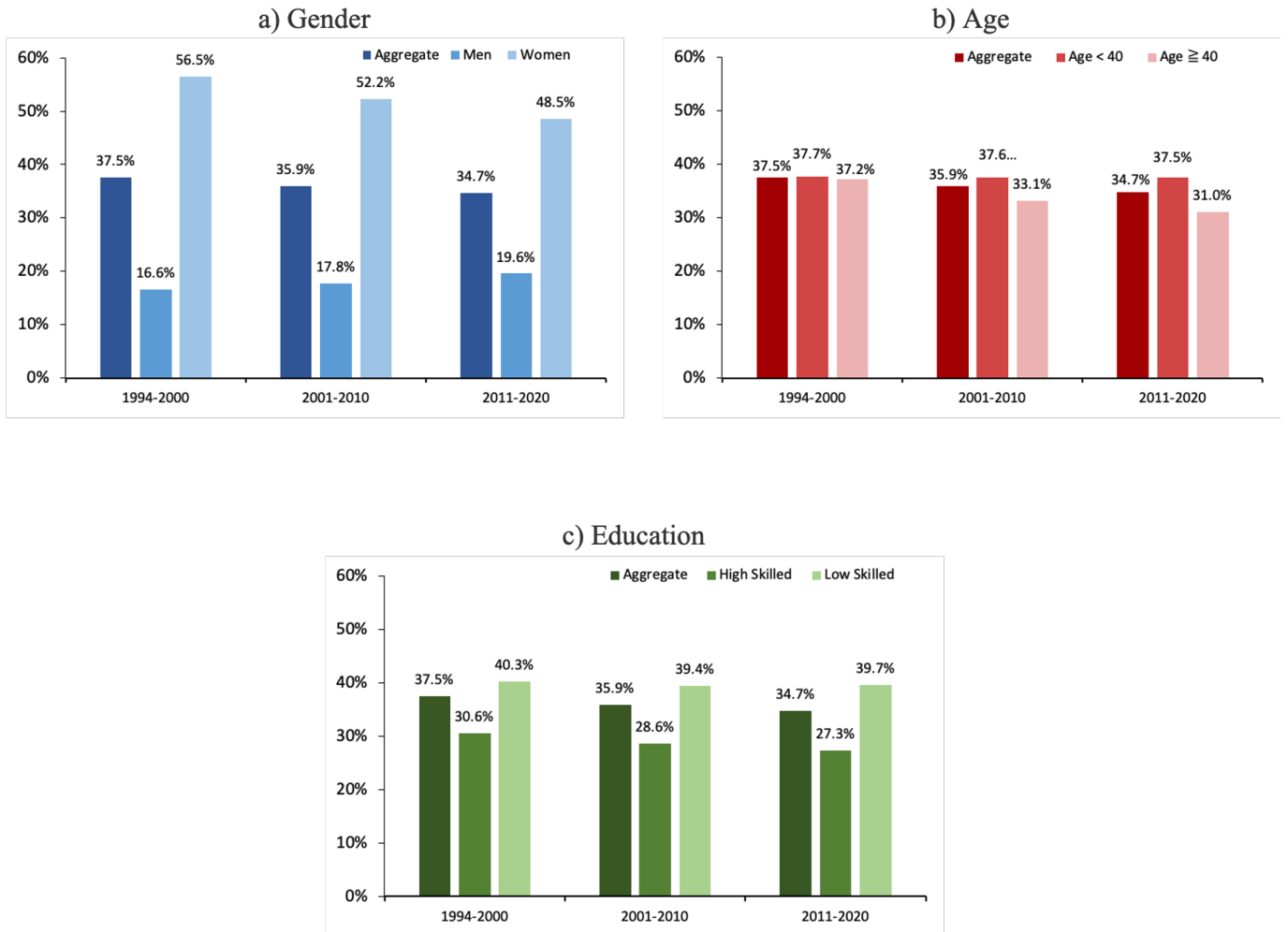
Figure 2: Unemployment to Population Ratio



Note: In each Figure, the labor market outcome (i.e. unemployment in each demographic group) is divided by the total population in each demographic group, not by Mexico's total population.

Source: From author's own calculations with data from *INEGI*.

Figure 3: Not in Labor Force to Population Ratio



Note: In each Figure, the labor market outcome (i.e. not in labor force in each demographic group) is divided by the total population in each demographic group, not by Mexico's total population.

Source: From author's own calculations with data from *INEGI*.