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# THE IMPACT OF TRADE ON INCOME INEQUALITY IN MEXICO

# EL IMPACTO DEL COMERCIO EN LA DESIGUALDAD DE INGRESOS EN MÉXICO

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*Resumen:*

La desigualdad de ingresos sigue siendo una preocupación importante en México, a pesar de una ligera disminución en su medición en las últimas décadas. Este artículo analiza el impacto de los cambios en los patrones comerciales derivados del Tratado de Libre Comercio de América del Norte (TLCAN) sobre la desigualdad de ingresos en México durante los últimos 20 años. Mediante una descomposición en desigualdad intrasectorial e intersectorial, el estudio revela que la contribución de esta última ha aumentado en un contexto caracterizado por una disminución general de la desigualdad de ingresos. El comercio explica aproximadamente el 14.5% del cambio total en la desigualdad de ingresos entre sectores, representando la contribución más significativa entre los factores identificados en este estudio.

*Abstract:*

Income inequality remains a significant concern in Mexico, despite a slight decrease in its measure in recent decades. This paper investigates the impact of changes in trade patterns resulting from the North American Free Trade Agreement (NAFTA) on income inequality in Mexico over the past 20 years. Through a decomposition into within- and between-sector inequality, this paper reveals that the contribution of the latter has increased in an environment characterized by decreasing overall income inequality. Trade accounts for approximately 14.5% of the total change in between-sector income inequality, representing the most substantial contribution among the factors identified in this study.

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## 1. Introduction

Latin America stands out as one of the continents with the most skewed levels of income distribution globally. Income inequality persists as a substantial barrier to development, drawing significant attention and policy discourse (ECLAC, 2018). While Mexico does not exhibit the most extreme income inequality in Latin America, its distribution remains notably unequal when compared on a global scale (Ranaldi and Milanovic, 2022). Over the past four decades, Mexico's income inequality trajectory has witnessed an initial surge, particularly during the 1980s, followed by a decline since the early 2000s.

The principal catalyst driving a radical transformation in the Mexican economy throughout this period has been trade, notably underscored by the implementation of the North American Free Trade Agreement (NAFTA) in 1994. Between 1994 and 2022, exports surged at an annual rate of 8.4% (United Nations, 2024), outpacing overall economic growth, which averaged 2.0% annually during the same time frame (ECLAC, 2024). This economic shift had a profound impact, albeit unevenly distributed across sectors and regions, with the automotive industry serving as a prominent example. Through robust integration with its NAFTA partners, Mexico transformed into a significant player in the automotive sector, although the benefits were concentrated in specific regions, leading to an increasingly divergent economic landscape (Padilla-Perez and Villarreal, 2017).

Despite the anticipated benefits of NAFTA, such as stimulating economic growth and fostering convergence, the outcome is not in line with these expectations. Economic theory suggested that free trade between a less affluent country, like Mexico, and wealthier economies, such as the United States (US) and Canada, should result in conditional convergence in living standards. However, empirical evidence contradicts this, revealing a widening divergence between the three economies since 1994. In that year, Mexican GDP per capita stood at 21.5% of US GDP per capita, decreasing further to 18.7% by 2017. Similarly, the Mexican-Canadian GDP per capita ratio dwindled from 22.2% in 1994 to 19.4% in 2017 (World Bank, 2019). In terms of purchasing power parity, the divergence becomes even more pronounced, with Mexican GDP per capita declining from 36.6% of US GDP per capita in 1994 to 32.0% in 2017, and from 45.0% to 39.4% when compared to Canadian GDP per capita over the same period (World Bank, 2019).

While it is evident that NAFTA has not significantly mitigated inequality across countries, the impact of the trade agreement on inequality within Mexico is not as clear. This study seeks to shed light on whether Mexican inequality has been influenced by the agreement and, consequently, by international trade, or if its effect has been largely neutral. Utilizing two distinct methodologies and an individual-level dataset spanning from 1994 to 2014, this paper identifies an escalation in income inequality between sectors over the NAFTA era.

Upon gauging the contribution of various factors–such as trade patterns, fluctuations in capital intensity, educational attainment, and Foreign Direct Investment (FDI)–to this rise in between-sector income inequality, this study determines that trade has exerted the most substantial impact. Trade contributes approximately 14.5% to the total change in between-sector income inequality. Moreover, this finding remains robust even when controlling for significant sources of sectoral heterogeneity, such as differential exposure to Chinese competition, increasing automation, and shifts in import tariffs. This finding thus establishes a direct link between NAFTA and an increase in income inequality within Mexico, delineating winners and losers at both the individual and sector levels. Consequently, this study underscores the importance of additional redistributive measures to compensate those who did not benefit from the upsurge in trade. This paper is structured as follows. Section 2 provides an overview of the ongoing debate surrounding inequality and trade, accompanied by contextual insights into both aspects in the Mexican context. Section 3 delineates the methodology employed in this study. The subsequent sections present the data (section 4), the results of the multi-step analysis (section 5), and a discussion of potential additional mechanisms (section 6). Section 7 concludes.

## 2. Research on income inequality and trade

Examining the intricate relationship between income inequality and trade has proven to be a complex undertaking, evident in the divergent outcomes arising from both theoretical predictions and empirical investigations. Despite a rich body of literature spanning disciplines from economics to political science, there is no consensus on the direction of this relationship. Theoretically, critics of economic openness draw upon the Stolper-Samuelson theorem and the Factor Price Equalization hypothesis, which mutually reinforce each other.[1]

[1] The Stolper-Samuelson theorem predicts that free trade benefits a country's relatively abundant factors of production while potentially harming its scarce

Applied to a developed economy, this framework predicts increased vulnerability for and adverse effects on unskilled workers, juxtaposed with contemporaneous positive outcomes for their skilled counterparts, ultimately resulting in heightened within-country inequality. On the flip side, proponents of economic openness argue that a more nuanced modeling approach is necessary to fully grasp these intricate dynamics, asserting that the aforementioned concepts are overly restrictive, as they are founded on assumptions seldom applicable in the real world. Notably, these models fail to account for numerous positive externalities of globalization, including technological advancements and economies of scale.

### 2.1 *Measuring inequality: The Gini coefficient*

The absence of a consensus on the relationship between trade and income inequality can be attributed, in part, to the inherent challenges in defining and measuring the latter. An additional complication arises from the frequent conflation of income inequality with wealth inequality, introducing significant issues since, typically, global levels of wealth inequality surpass those of income inequality. Even when income inequality is accurately conceptualized, additional complexities persist due to the absence of a singular measurement approach.

Conventionally, the Gini coefficient serves as the standard metric for quantifying income inequality. This coefficient is defined as:

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} x_i - x_j}{2n \sum_{i=1}^{n} x_i} \tag{1}$$

where $i, j \in N$ represent two individuals in a population and $x_i$ the income of a given individual $i$. $G = 0$ implies equal shares of income, whereas $G = 1$ indicates all income is in the hands of a single individual.

Gaining insights into the trends of income inequality using the Gini indicator is a nuanced endeavor, beset with challenges. First, results heavily depend on the underlying data used in their computation. Notably, variations arise depending on whether income is narrowly defined, encompassing solely wages, or more comprehensively incorporating all forms of non-wage income. Compounding these issues is the prevalent under-counting of high-income households. Castillo (2015) estimates that, in Mexico's case, accounting

ones. The Factor Price Equalization hypothesis asserts that global trade will equalize relative prices of factors of production.

for these factors would raise the estimated Gini coefficient by approximately 50%, from 0.45 to 0.68. Second, a crucial distinction lies in whether inequality is assessed before or after government transfers, the latter generally serving to alleviate the level of inequality. For instance, Castillo (2015) demonstrates that excluding government transfers could raise the Gini coefficient to 0.73. Third, not all countries consistently collect data at the national level. In some instances, only urban income inequality is measured, yielding lower estimates compared to comprehensive data covering the entire economy. In the case of Mexico, urban income inequality and rural income inequality behave very differently. Figure A.1 illustrates not only a substantial difference in the levels of income inequality between rural and urban areas but also a noteworthy divergence in the trends over time.[2]

This paper proposes alternative methods to explore various facets of income inequality, employing analytical frameworks that integrate information from detailed micro-level data to more aggregated country-level statistics. Using a diverse range of information and techniques allows for comprehensively dissecting and analyzing the link between economic openness and income inequality, offering a broader perspective than solely relying on the Gini coefficient.

### 2.2 *Trade liberalization and trade agreements*

Over recent decades, global international trade has undergone extensive liberalization. The World Trade Organization (WTO) and its predecessor have spearheaded significant reductions in both international tariffs and Non-Tariff Barriers (NTBs). Simultaneously, various international trade agreements, both bilateral and multilateral, have played a pivotal role, with NAFTA being among the most prominent.[3] While NAFTA's impact on the signatory countries remains a topic of debate, early investigations by Burfisher *et al.* (2001) suggest that Mexico has reaped substantial benefits, whereas the US has seen more marginal gains. Romalis (2007) reports only modest changes in the welfare of the NAFTA member states but finds substantial effects

[2] The Mexican Gini coefficient increased from 49.0 in 1984 to 51.7 in 2000, before decreasing to 48.2 in 2014 (World Bank, 2019).

[3] The effective applied tariffs for Mexican imports with a Most-Favored Nation (MFN) status, for manufactured goods, ores, and metals, decreased from 13.3% in 1991 to 1.9% in 2014. In the US, the same rate decreased from 5.9% in 1989 to 3.1% in 2015 (UNCTAD, 2017).

on trade volume. Drawing upon a Ricardian model that incorporates sector linkages, trade in intermediate goods, and sector heterogeneity in production, Caliendo and Parro (2014) find that NAFTA has increased intra-bloc trade by 118% for Mexico and 41% for the US, delivering welfare gains of 1.31% and 0.08% to Mexico and the US, respectively.

However, despite these positive findings, there is no clear sign of convergence in economic growth between Mexico and the US over the NAFTA era. The GDP gap between the two countries has widened, with Mexican GDP per capita decreasing from 21.5% of the US level in 1994 to 18.7% by 2017 (World Bank, 2019). Padilla-Perez and Villarreal (2017) attribute this productivity gap to workers transitioning from high- to low-productivity sectors, while López and Rebolledo (2016) suggest that labor and capital misallocation, coupled with a robust informal labor market and a relatively weak private sector, are contributing factors.

Trade agreements often have significant distributional consequences, challenging the assumption that losers will be adequately compensated by winners. Moreover, Helpman *et al.* (2017) show that trade can affect wage inequality within groups, with companies more engaged in trade experiencing an increase in wage inequality among their workforce. In the Mexican context, Markusen and Zahniser (1999) propose that NAFTA may not increase wages for unskilled Mexican labor, implying a persistence in the skilled-unskilled wage differential. Echoing this prediction, Hanson (2003) argues that NAFTA has increased inequality through geographical disparities and an upsurge in the skill premium. Meanwhile, capturing regional variation in exposure to international markets, Chiquiar (2008) finds that regions with stronger trade links with the US experienced a larger decline in the skill premium, though this effect is not enough to compensate for the increase in overall wage disparity generated by rising geographical disparities from trade. ECLAC (2016) and Dussel-Peters (2018) confirm a widening territorial gap, with northern regions benefiting more from trade. Conversely, Esquivel and Cruces (2011) contend that NAFTA has had little impact on income inequality, attributing recent declines to better-targeted social programs and an overall increase in education levels.

Several interpretations have been proposed to explain the evolution of income inequality in Mexico. The increase during the 1980s and 1990s could be linked to the growing payoff of higher education. Indeed, Cragg and Epelbaum (1996) find the economy to have become more skill-intensive, especially for the trade sector. In particular, foreign direct investments were found to be a significant driver of increases in the skilled labor wage share during the 1980s (Feenstra and Hanson, 1997). From the late 1990s onward, factors contributing to the reduction in inequality include a lower birth rate, increased labor participation, and diminishing wage inequality among salaried workers.[4] Other factors include a narrowing gap between qualified and unqualified workers and an increase in government-mandated transfers. Kahhat (2010) emphasizes that significant investments in human capital contributed to higher wages, reducing overall income inequality.

### 2.3 *This paper*

The evidence on the impact of NAFTA on economic growth in Mexico is limited and suggests that its effects have not been evenly distributed across sectors. For example, the contribution of the automobile sector to total exports increased from 20.9% to 30.3% between 1994 and 2016, while other sectors have not benefited equally from an increase in integration with Mexico's northern neighbors.

How would the varied impact across sectors translate into changes in relative input prices? The general equilibrium literature offers a few explanations. Traditional Stolper-Samuelson reasoning posits that international trade raises demand for unskilled labor in developing countries, lowering wage inequality by narrowing the gap between the returns of skilled and unskilled labor inputs. In particular, the expansion in Mexico's automobile sector would bid up wages in other less skill-dominated sectors through labor mobility and market clearing, reducing the wage disparity between different skill labor types. However, this view is challenged by Feenstra and Hanson (1996), who argue that outsourcing from developed countries to developing countries is, in fact, biased towards skill-intensive production, raising the demand for skilled labor in developing countries and hence wage inequality. In the context of this paper, the automobile sector could be considered as a less skill-intensive sector in the US, but as a highly skill-intensive sector by Mexican standards. Therefore, US foreign direct investment in Mexico would raise wage inequality in both Mexico and the US. This claim is supported by Zhu and Trefler (2005), who observe a strong positive correlation between wage inequality and shifts in export shares towards more skill-intensive goods, using a panel dataset of 20 developing and newly industrialized countries.

[4] Esquivel *et al.* (2010) attribute about 50% of the overall reduction in wage inequality to the decrease in inequality among salaried workers.

This paper seeks to reconcile these divergent interpretations by employing two methodologies. First, total income inequality is broken down into within-group and between-group inequality at the sectoral, educational, and regional levels. Second, the analysis considers total inequality between sectors, decomposing trends into various contributing factors. This approach helps quantify the importance of trade in Mexico and provides insights into the factors influencing changes in income inequality. The varied impact across sectors and regions highlights the complexity of the relationship between trade and inequality, emphasizing the need for a nuanced analysis that considers multiple factors simultaneously.

## 3. Methodology

### 3.1 *Decomposing overall inequality: Between and within groups*

Building on the work of Akerman *et al.* (2013) and Helpman *et al.* (2017), the initial step in the analysis involves decomposing overall inequality into two components: inequality levels between sectors and those within sectors. Total inequality is defined as follows:

$$I_t = \frac{1}{N_t} \sum_i (w_{i,t} - \bar{w}_t)^2 \tag{2}$$

where, for each point in time $t$,$w_t$, $\bar{w}_t$ are the log of an individual's wage and the average wage, respectively. Each individual is denoted by $i$, and the total population is denoted by $N$, with $i \in N$.

This measure of income inequality primarily assesses the variation in wages, distinguishing itself from more commonly used metrics like the Gini coefficient. Unlike the Gini coefficient, which has a theoretical distribution bound between 0 and 1, this inequality measure lacks a clearly defined maximum. It continues to increase as the sole income earner raises their absolute income while retaining a 100% share. This measure could be broken down as:

$$I_t = \frac{1}{N_t} \sum_i (w_{i,t} - \bar{w}_t)^2 = \frac{1}{N_t} \sum_g \sum_{i \in g} (w_{i,t} - \bar{w}_{g,t})^2 + \frac{1}{N_t} \sum_g N_{g,t} (\bar{w}_{g,t} - \bar{w}_t)^2 \tag{3}$$

where $g$ represents an arbitrary group of interest. The two terms on the right-hand side of equation(3) measure within-group inequality and between-group inequality, respectively. This means that it is possible to look at different decompositions of the available data to observe how total inequality develops over time, and to analyze this in relation to trends in inequality both within and across groups.

The within-group component of inequality can be written as:

$$I_{within,t} = \frac{1}{N_t} \sum_g \sum_{i \in g} \left(w_{i,t} - \bar{w}_{g,t}\right)^2 = \sum_g S_{g,t} V_{g,t} \tag{4}$$

where $s_g$ is the total share of the population that is in group $g$, and $v_g$ is the variation of income in that specific group, defined as $V_g = \frac{1}{N_{g,t}} \sum\limits_{i \in g} \left(w_{i,t} - \bar{w}_{g,t}\right)^2$. The change of the within-component side of inequality could then be defined as:

$$\Delta I_{within} = \sum_g S_{g,t+1} V_{g,t+1} - \sum_g S_{g,t} V_{g,t} \tag{5}$$

and, assuming that there is no distributional change within each group over time, $V_g \equiv V_{g,t+1} = V_{g,t}$, equation (5) could be rewritten as:

$$\Delta I_{within} = \sum_g V_g \left(S_{g,t+1} - S_{g,t}\right) \tag{6}$$

Equation (6) implies that, if there is no change in income distribution within groups, the within-group component of inequality changes toward the level of inequality of the group that increases its weight. Then, if the sector that increases in importance displays a high level of inequality, the within-group component of total inequality increases, and vice versa. Keeping the shares of the different groups constant and increasing the within-group variation of one or more groups also increases the within-group component of inequality.

On the other hand, the between-group measure could be written as follows:

$$I_{between,t} = \frac{1}{N_t} \sum_g N_{g,t} (\bar{w}_{g,t} - \bar{w}_t)^2 \tag{7}$$

This shows that between-group inequality is fully independent of the within-group component, but that any shift in the group average $(\bar{w}_{g,t})$ impacts the level of inequality between groups. An increase in group average income increases between-group inequality when $(\bar{w}_{g,t} - \bar{w}_t)^2 > (\bar{w}_{g,t-1} - \bar{w}_{t-1})^2$. Furthermore, with stable within-group distributions, the increase in a group's weight leads to a rise in between-group inequality when the increasing group's average income is further away from the aggregate average compared to the decreasing group's average income.

Given that one of the central assumptions is the uneven expansion of sectors due to trade, the primary units of interest are the sectors. Therefore, the suggested decomposition will employ sectors as the identifying groups, denoted as $g$. As anecdotal evidence suggests that the returns to education have decreased in Mexico in recent years, $g$ also includes the effects over time across different education groups.[5]

### 3.2 *Principal factors of between-sector inequality*

Once the significance of between and within-group inequality has been assessed, the examination proceeds to the decomposition of inequality between sectors, unraveling its principal contributing factors. This study adopts the methodology initially introduced by Zhang and Zhang (2003), based on the decomposition method by Shorrocks (1982), to quantify the impact of FDI and economic openness on sector inequality. Departing from the conventional focus on regions, this paper directs attention to disparities between sectors. The decomposition assumes a standard Cobb-Douglas production function with constant returns to scale, yielding a logarithmic equation for the production function, as follows:

$$y = \alpha + \beta_1 k + \beta_2 e + \beta_3 v + \varepsilon \tag{8}$$

where $y$ is the log of sector-level output per hour worked, $k$ the log of sector-level capital per hour worked, $e$ the log of the skill level in a sector, $v$ the log of trade-to-output (or value-added) ratio in a sector, and $\varepsilon$ the error term.[6] The variance of the output measure $y$ can be further decomposed as follows:

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[5] It would also be interesting to analyze regional differences. However, there is not enough power in the available data to accurately compute this decomposition of inequality. Nevertheless, this paper tries to overcome this obstacle by presenting the results for inequality further decomposed into its urban and rural components.

[6] To control for the effect of FDI at the sector level, a further term in the production function is included: $\beta_4 FDI$, where FDI is the logarithm of the total flow of FDI from the world to Mexico (at constant 2008 prices and scaled

$$\sigma^2(y) = cov(y, \beta_1 k) + cov(y, \beta_2 e) + cov(y, \beta_3 v) + cov(y, \varepsilon)$$
$$= \beta_1 cov(y, k) + \beta_2 cov(y, e) + \beta_3 cov(y, v) + \sigma^2(\varepsilon) \qquad (9)$$

where $\sigma^2(\cdot)$ represents the total variance and $cov(y, \cdot)$ is the covariance of $y$ with the other variables in the equation (capital, education, trade and, when included, FDI).[7] The trade-to-output ratio, denoted as $v$, acknowledges that the openness of a sector reflects the extent to which it benefits from interactions with other markets, companies, and clients. Zhang and Zhang (2003) introduced the notion of treating the trade-to-output ratio as an explicit input to the production function, since the level of openness could affect aggregate output for given levels of other inputs. In fact, it has been widely recognized that a high level of openness leads to a better allocation of resources in terms of concepts of comparative advantages and specialization (Krueger, 1980; Ram, 1987, 1990; World Bank, 1993). Trade liberalization in a developing country like Mexico may also facilitate the exploitation of scale economies due to an enlargement of effective market size, afford greater capacity utilization, and induce more rapid technological changes (Feder, 1983; Bliss, 1988; Pack, 1988; Edwards, 1993).

Traditional estimation of company-level production functions entails several endogeneity concerns. Transmission bias occurs when companies' managers optimize their input choices based on company and time-specific shocks that are observable to them but unobservable to the researcher (Ackerberg *et al.*, 2006; Eberhardt and Helmers, 2010; Beveren, 2012). However, by conducting estimations at the sector level, which entail a significant number of companies within each sector, this paper argues that transmission bias could be effectively mitigated.[8] However, incorporating heterogeneous sectors into a single production function comes with its costs. The constancy of factor

by total hours worked in the specific sector). Sector-level information is only available from 1999 onward, restricting the time window of the analysis.

[7] When also including FDI, an extra term $cov(y, \beta_4 FDI) = \beta_4 cov(y, FDI)$ is added to the equation. The covariance of $y$ and $\varepsilon$ is just equal to the variance of $\varepsilon$, when capital, education, trade (and FDI) are uncorrelated with the error term. In this setting, $\sigma^2(y)$ is known in the literature as the logarithmic variance.

[8] Eberhardt and Helmers (2010) decompose the log deviation of a company's labor productivity from its mean at a specific time into four components: a

elasticity across observations is an important assumption for identifying production functions in the literature. The failure of empirical findings to match this assumption remains a limitation of this analysis.[9] Therefore, to partially address sources of sectoral heterogeneity, Section 6 investigates three major shocks that disproportionately affected sectors during the period of interest: trade competition from China, increasing automation, and changes in import tariffs. The robustness of the estimates of the contribution of trade to between-sector inequality to these variations should strengthen confidence in the results.

The decomposition is based on a two-step procedure. In the first step, panel data are used to estimate the production function as presented in equation (8), yielding coefficients for various variables influencing output. Once the production function is estimated, the second step involves decomposing total inequality, represented by the term $\sigma^2(y)$, into its individual factors.

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company-specific effect, a time-specific effect, a company and time-specific effect, and a measurement error term. The third component relates to transmission bias. This paper argues that, by aggregating all company-level productivity functions across a given sector, the company- and time-specific effect and measurement error term could be effectively cancelled out by appealing to the Law of Large Numbers. This is an advantage of using sector-level data. Moreover, any potential endogeneity for the coefficient of trade openness, the object of this study, is likely to be far less significant than that of labor and capital. Eberhardt and Helmers (2010) note that the level of bias is positively dependent on the speed of adjustment of inputs in response to company- and time-specific shocks. Trade openness, in particular, is sluggish and difficult for companies to manipulate in response to those shocks.

[9] Marrocu *et al.* (2000) and Husain and Islam (2016) estimate production functions separately for each sector using company-level data in Italy and Bangladesh, respectively. They find differing factor elasticity for labor and capital across sectors. With the assumption of fixed factor elasticity violated, unaccounted heterogeneity may lead to bias in the estimated input coefficients, as it will be captured by the error component and be correlated with the input measures (Van Biesebroeck, 2007). However, estimating production functions at a more narrowly defined sector level does not seem to help, with Griliches and Mairesse (1995: 23) concluding that "the observed variability-heterogeneity does not really decline as we cut out data finer and finer. There is a sense in which different bakeries are just as different from each other, as the steel industry is from the machinery industry".

## 4. Data

The first part of the analysis exploits the National Urban Employment Survey (*Encuesta Nacional de Empleo Urbano*, ENEU), along with the subsequent National Survey of Occupation and Employment (*Encuesta Nacional de Ocupacion y Empleo*, ENOE), to facilitate the decomposition of total inequality into its between and within-group components.[10] These labor market surveys, collected by the Mexican Ministry of Labor and Social Welfare (STPS) and the National Institute of Statistics and Geography (INEGI), provide information on employment, earnings, and other socioeconomic characteristics in the population.

Although ENEU commenced in 1987, the construction of a consistent sample was only feasible from the third quarter of 1994 onwards, due to changes in the questionnaires. Additionally, the sample makes use of ENOE from the first quarter of 2005 to the third quarter of 2014. Over the years, the geographical coverage of both ENEU and ENOE has undergone evolution and alteration. In line with the criteria established by Villarreal (2014) and Duval-Hernández *et al.* (2017), this paper designates as urban those areas consistently present in both surveys.[11] On the other hand, rural areas encompass all other regions added over time, particularly starting with the introduction of ENOE, which also includes less populated rural hubs. Within this sample, the focus is narrowed down to individuals engaged in full-time employment (working more than 35 hours) and falling within the prime working age bracket of 25-64 years. Additionally, this analysis excludes individuals currently enrolled in education and those who represent extreme outlier cases, defined in terms of either hours worked or earnings.[12] Table A.6 presents, separately for urban and

[10] ENOE is the merger of ENEU and the National Employment Survey (*Encuesta Nacional de Empleo*, ENE).

[11] These areas include 28 cities: Mexico City, Guadalajara, Monterrey, Puebla, León, San Luis Potosí, Mérida, Chihuahua, Tampico, Veracruz, Acapulco, Aguascalientes, Morelia, Toluca, Saltillo, Villahermosa, Tijuana, Culiacán, Hermosillo, Durango, Tepic, Campeche, Cuernavaca, Oaxaca, Zacatecas, Colima, Querétaro, and Tlaxcala.

[12] Those individuals reporting that their monthly salary is below 99 Mexican pesos (MXN)–approximately 5 US dollars (USD) using the 2017 exchange rate–and those reporting that they work longer than 141 hours in any given week (more than 20 hours per day in a 7-day work week). Appendix A further presents the match between ENEU and ENOE.

rural areas, the sample of respondents in ENOE that are part-time workers (about 21% in urban areas and 25% in rural areas), and the respondents in the working age population that are enrolled in education (about 2.5% in urban areas and 1.8% in rural areas).

**Table 1**
*Summary statistics for the first stage of the analysis*

| | *Observations* | *Mean* | *St. Dev.* | *Min.* | *Max.* |
|---|---|---|---|---|---|
| *ENOE: 2005Q1 - 2014Q3* | | | | | |
| Monthly wages (log) | 19192064 | 8.1 | 0.8 | 4.6 | 13.7 |
| Hourly wages (log) | 19192064 | 2.8 | 0.8 | -1.1 | 8.4 |
| Sex (1 male, 2 female) | 19192064 | 1.3 | 0.5 | 1.0 | 2.0 |
| Age group (4 cat.) | 19192064 | 2.4 | 0.6 | 2.0 | 4.0 |
| Number of kids | 5579185 | 2.5 | 2.3 | 0.0 | 20.0 |
| Hours worked in a week | 19192064 | 50.7 | 12.2 | 35.0 | 140.0 |
| *ENEU: 1994Q3 - 2004Q4* | | | | | |
| Monthly wages (log) | 6939005 | 7.1 | 0.8 | 4.6 | 11.9 |
| Sex (1 male, 2 female) | 6939005 | 1.3 | 0.4 | 1.0 | 2.0 |
| Age | 6939005 | 38.4 | 10.7 | 25.0 | 98.0 |
| Number of kids | 1865014 | 2.3 | 2.4 | 0.0 | 23.0 |
| Hours worked in a week | 6939005 | 46.1 | 9.3 | 35.0 | 98.0 |

Notes: The four age groups in ENOE are: 1) 15y-24y; 2) 25y-44y; 3) 45y-64y; and 4) 65y and higher. In both ENOE and ENEU, all wages are expressed in MXN.

Source: Authors' calculations on the information provided by INEGI (ENOE and ENEU).

Descriptive statistics are presented in Table 1. The gender composition of the sample in both surveys is predominantly male, and the age distribution is skewed toward relatively young workers. ENEU, with its more detailed data, indicates an average age of 38.4 years. On average, participants have 2.5 children in ENOE and 2.3 children in ENEU, with a maximum of 23 children. Transitioning from ENEU to ENOE, there is a substantial increase in the number of hours worked, rising from 46.1 to 50.7. While this increase is considerable, it is in line with the Mexican reality, where extended working weeks are more the norm than the exception. For instance, despite the average annual working hours in OECD countries being 1,763 hours in 2016 (OECD, 2018), Mexico stands out as the country with the longest working hours, totaling 2,255 hours. In Korea and Greece, the next in line, people work an average of 2,069 and 2,035 hours per year, respectively.

**Table 2**

*Summary statistics for the second stage of the analysis*

| | *Observations* | *Mean* | *St. Dev.* | *Min.* | *Max.* |
|---|---|---|---|---|---|
| Output-to-labor | 260 | 84.5 | 153.5 | 9.7 | 969.5 |
| Capital-to-labor | 260 | 30.2 | 39.0 | 1.2 | 181.3 |
| Low skill (hours, thousand) | 260 | 320133.9 | 303253.3 | 10739.6 | 1250934.0 |
| Medium skill (hours, thousand) | 260 | 393378.9 | 291164.2 | 26264.5 | 1262175.0 |
| High skill (hours, thousand) | 260 | 97438.3 | 90188.6 | 17688.8 | 416411.3 |
| Trade-to-output | 260 | 58.6 | 40.3 | 5.8 | 186.1 |
| Trade-to-VA | 260 | 210.9 | 200.8 | 14.7 | 1040.5 |

Notes: The output, capital, trade (exports and imports), and value-added series are all in millions of USD, adjusted to constant 2008 prices.

Source: Authors' calculations on the information provided by the WIOD database (input-output table and socio-economic accounts) and INEGI (input-output table).

The second analysis of this paper considers sector-level information on output, capital, skill level, and trade from three different sources: 1) the input-output table of the World Input-Output Database (WIOD); 2) the socioeconomic accounts of the WIOD; and, 3) the input-output table (*matriz de insumo-producto*) provided by INEGI.[13] The WIOD has been released in two rounds, with the information for 1995-1999 being sourced from the first round, and the information for 2000-2014 from the second round.[14]

[13] When also taking into account the effect of FDI on sector inequality, the information on the flow of FDI from the world to Mexico by sector was obtained from the Secretariat of Economy of Mexico. This information is only available from 1999 onward, thus restricting the sample when it is included.

[14] The numbers have been checked and compared for consistency across the two waves.

The output level, sourced from the WIOD, was initially denominated in millions of USD at current prices. To facilitate analysis, this variable was deflated using the Consumer Price Index (CPI), with a base year set to 2008, thereby expressing the series in constant 2008 prices. The subsequent analysis considers the logarithm of output, scaled by total hours worked in each sector.[15] Data regarding the stock of capital in a sector is sourced from INEGI. Analogous to the treatment of output, this variable is expressed in constant 2008 prices and scaled by the total hours worked in the sector. Moreover, the logarithm of this ratio is taken into account. Regarding the skill level in a sector, this paper adheres to the 1997 International Standard Classification of Education (ISCED) and considers low-, medium-, and high-skilled labor.[16] The analysis examines the logarithm of the number of hours worked in a specific sector, differentiating between low-, medium-, and high-skilled workers. Lastly, the trade variable considered is the logarithm of the trade-to-output ratio.[17] Trade is defined as the sum of the yearly value (in millions of USD) of exports and imports in each sector, deflated to 2008 prices. Panel A of Figure A.2 illustrates the raw trends over time for these variables, with the year 1995 set as the baseline at 100. There has been a consistent upward trend in the measures of output, capital, trade-to-output, and trade-to-VA, while the size of the highly skilled workforce has remained constant. Panel B of Figure A.2 displays the evolution over time of the components of the trade-to-output variable: exports, imports, and output. The logarithm of these series, expressed in constant 2008 prices, demonstrates a general upward trend over time, with Mexican imports experiencing a greater increase compared to exports. Between 1995 and 2014, both exports and imports grew at a much faster pace than output, resulting in a steep rise in the trade-to-

[15] Scaling by sector-level total hours worked gives a measure for the labor productivity in the sector. This is a better measure than total output in order to compare sector-level differences.

[16] The categorization of skill levels is defined as follows. *Low-skill level* encompasses individuals with primary education or the first stage of basic education, as well as those with lower secondary or the second stage of basic education; *medium-skill level* individuals with (upper) secondary education and post-secondary non-tertiary education; and *high-skill level* individuals with the first stage of tertiary education and the second stage of tertiary education.

[17] As part of a robustness check, this paper explores the logarithm of the trade-to-value added (VA) ratio, with VA representing the value added in the economy. Notably, the results remain consistent across these alternative specifications.

output variable. Table 2 summarizes the key statistics of the variables just discussed.

## 5. Results

### 5.1 *A measure of inequality between and within-groups*

This analysis begins by introducing a metric for the variability of wages in Mexico. Panel A of Figure 1 illustrates the outcomes for total wage inequality. This measure is calculated based on the respondents of ENEU for 1994-2004, and on those of ENOE for 2005-2014. Due to limited data availability in ENEU, total wage inequality can only be separately calculated for urban and rural areas starting from 2005. From the beginning of the sample, there is a consistent and pronounced downward trend in wage inequality levels, and the pace of this decline seems to surpass that of more conventional measures, such as the Gini coefficient. Compared to 1994, the level of total inequality in urban areas dropped by over 30% over a twenty-year period, from 0.50 to 0.34. The drop in rural areas is measured at 25%, from 0.75 in 2005 to 0.56 in 2014. How much of this total wage inequality can be attributed to differences between groups?

Panel B of Figure 1 shows the decomposition of total inequality when considering 20 distinct sectors.[18] The primary observation drawn from panel B is that differences within sectors account for the majority of total inequality, surpassing differences between sectors. In urban areas, taking an average between 1994 and 2014, only 11.0% of total inequality is attributed to differences between sectors. However, this share has risen 4.3 percentage points over this period, from 8.6% in 1994 to 12.9% in 2014, and this sustained uptick in inequality between sectors began around the year 2000. In rural areas, the share of total inequality that is attributed to differences between sectors is significantly higher: on average 22.3% over 2005-2014, with negligible fluctuation observed over time (if anything, there has been a marginal decrease of 0.1 percentage points during these nine years). This discrepancy may be explained by the sector distribution of the rural regions, where several relatively low-income sectors play a more dominant role, potentially magnifying their impact on constructing

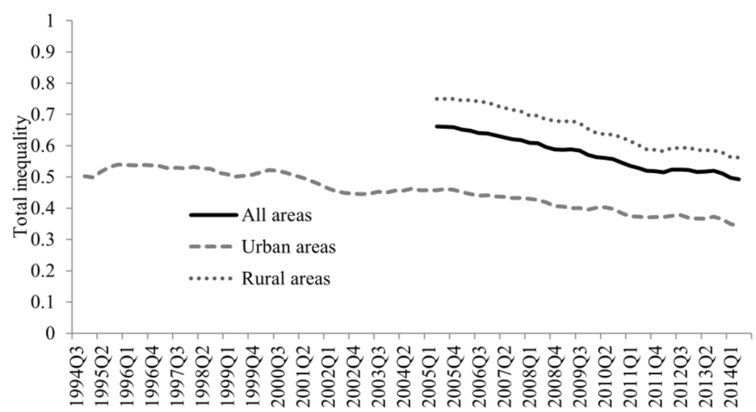
[18] Following the consolidation of ENEU with ENOE, 18 groups remain. See Appendix A for further details.

between-sector inequality levels. Overall, Panel B of Figure 1 suggests that labor markets in urban and rural regions indeed exhibit distinct characteristics.[19]

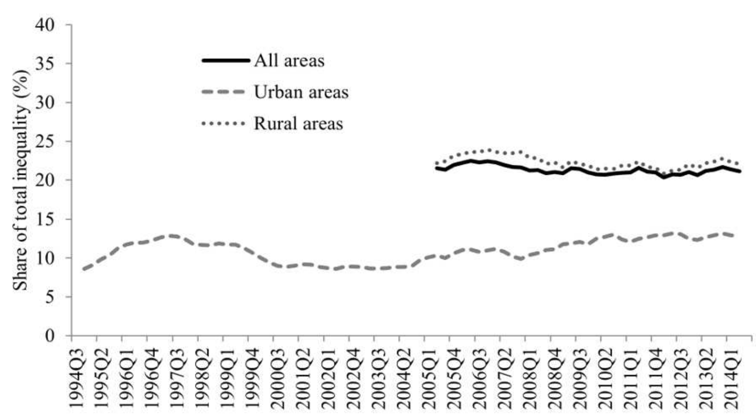
**Figure 1**

*Inequality measured through the variability of wages, 1994-2014*

*a) Total wage inequality*




*b) Differences between sectors*

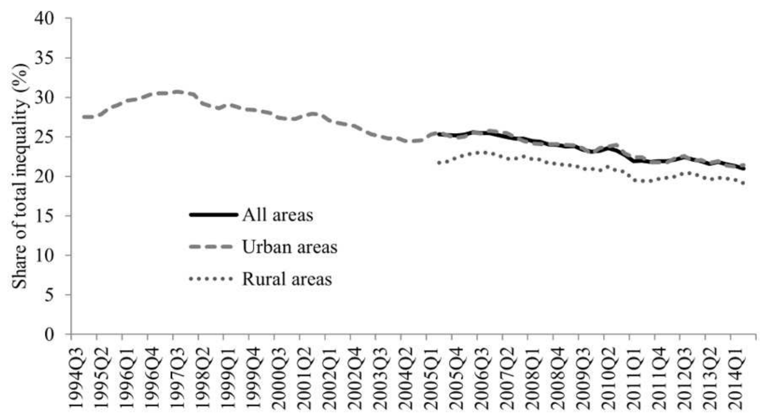



19 Table A.3 presents the breakdown of total employment by sector, separately for urban and rural areas.

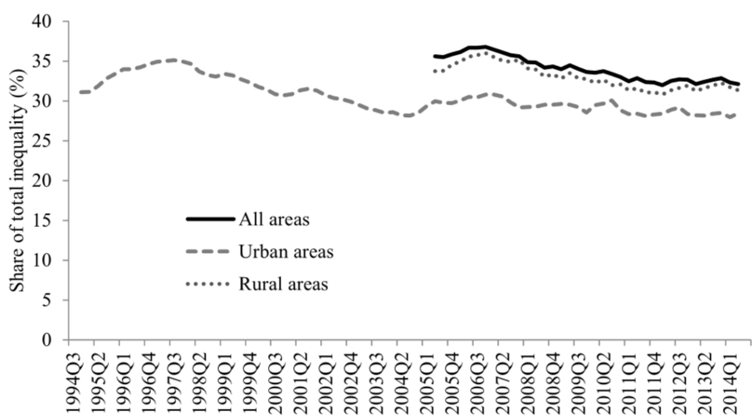
**Figure 1**

*(Continued)*

*c) Differences between education groups*




*d) Differences between sector-education groups*




Notes: Panel A shows the measure of total wage inequality. Panels B, C, and D illustrate the share (%) of total inequality that is attributed to differences between groups. For Panel B, the sector groups are those included in the variable SCIAN of ENOE: agriculture, forestry, fishing, and hunting; mining, quarrying and oil and gas extraction; utilities; construction; manufacturing; wholesale trade; retail sector; transportation and warehousing; information; finance and insurance; real estate and rental and leasing; professional, scientific, and technical services; management of companies and enterprises; administrative and support and waste management; educational services; healthcare and social assistance; arts, entertainment, and recreation; accommodation and food services; other services (excluding public administration); and public administration. For Panel C, the education groups are those included in the variable *CS P13 1* of ENOE: no education (*ninguno*); preschool (*preescolar*); primary (*primaria*); junior high school (*secundaria*); high school (*preparatoria o bachillerto*); teacher training college (*normal*); technical career (*carrera técnica*); professional (*profesional*); master's degree (*maestría*); and doctoral degree (*doctorado*).

Source: Authors' elaboration.

The decomposition of inequality between 10 distinct education groups is depicted in Panel C of Figure 1.[20] Corroborating the hypothesis of a significant education premium in Mexico, the variations between education groups outweigh those observed between sectors. In the urban sample, the share of total wage inequality that is attributed to differences between education groups is measured at 25.8% over 1994-2014 (23.5% over 2005-2014). However, when considering education in urban areas, there is a robust and consistent downward trend in the contribution of between-group inequality since the mid-1990s, in line with the prevailing consensus of a diminishing education premium over time. The share of total inequality that is attributed to differences between education groups decreases 6.1 percentage points, from 27.5% in 1994 to 21.4% in 2014. Notably, the between-group difference in education groups in rural areas is smaller than the observed difference across urban areas: on average 21.1% during 2005-2014. The reduction is also more modest: from 21.7% in 2005 to 19.1% in 2014. This finding is in line with the theory that urban areas are more likely to provide favorable opportunities to well-educated individuals. Figure A.4 confirms that the results are not driven by the choice of groups used to define education in Mexico. Reducing the categories to three groups (less than middle school, high-school level, and higher education) confirms the patterns observed when following the more granular classification of education offered in ENOE. Taking the average between 2005 and 2014, urban areas account for 21.3% of total wage inequality, compared to 16.1% in rural areas.

In a subsequent stage of the decomposition, the data is disaggregated into sector-education groups, considering each possible combination of education level and sector as a distinct group.[21] As illustrated in Panel D of Figure 1, the proportion of total inequality

[20] Following the consolidation of ENEU with ENOE, eight groups remain. See Appendix A for additional details.

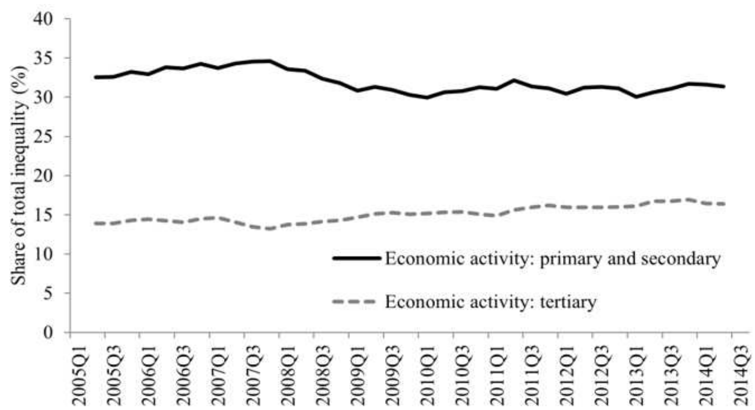
[21] Not all education groups are sufficiently represented in each sector, and the analysis is only conducted for the 176 groups with enough information to estimate the decomposition.

attributable to between-group inequality for education-sector groups has also diminished since the mid-1990s, with the rural and urban sectors converging in recent years. In urban areas between 2005 and 2014, the contribution averages 29.2% (compared to 33.0% in rural areas). The reduction over this period has been larger for rural areas compared to urban areas: 2.4 percentage points versus 1.5 percentage points.

**Figure 2**

*Differences between sectors by economic activity, 2005-2014*

*a) All areas*




*b) Urban areas*

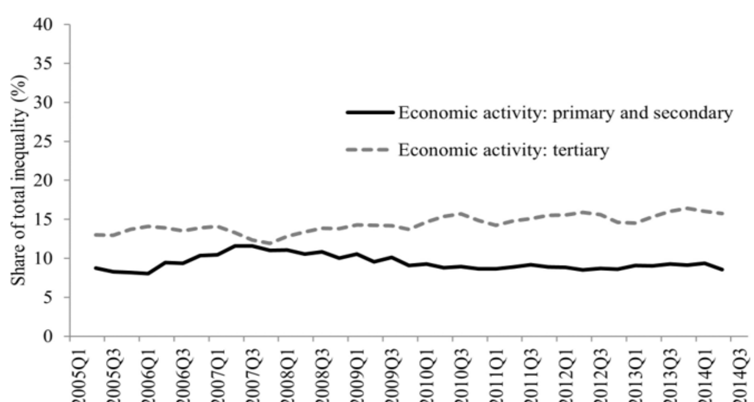
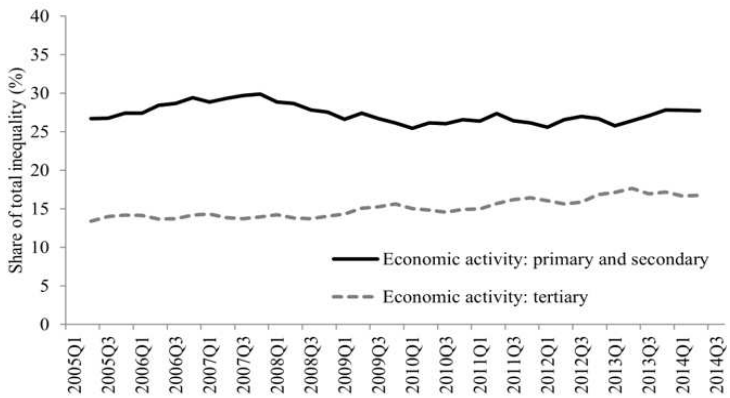


**Figure 2**
*(Continued)*
*c) Rural areas*




Notes: Panels A, B, and C illustrate the share (%) of total inequality that is attributed to differences between sectors, separately by economic activity. Panel A considers all areas. Panels B and C consider urban and rural areas, respectively. The variable SCIAN of ENOE categorizes economic activity into sectors based on the nature of the production process. These sectors have been split into two groups: 1) primary and secondary; and, 2) tertiary. Here is a breakdown of the SCIAN 20 categories according to these groups. Primary and secondary: agriculture, forestry, fishing, and hunting; mining, quarrying and oil and gas extraction; construction; and, manufacturing. Tertiary: utilities; wholesale trade; retail sector; transportation and warehousing; information; finance and insurance; real estate and rental and leasing; professional, scientific, and technical services; management of companies and enterprises; administrative and support and waste management; educational services; healthcare and social assistance; arts, entertainment, and recreation; accommodation and food services; other services (excluding public administration); and public administration..

Source: Authors' elaboration.

The analysis presented in Figure 1 is based on a sample of individuals working more than 35 hours per week and earning more than 99 MXN per month. Figure A.5 checks the results when expanding the set of ENOE respondents to include all workers, regardless of hours worked and earnings. Expanding the sample to include individuals working fewer hours per week, and declaring earnings below 99 MXN per month, raises the contribution of between-group inequality to total wage inequality. Comparing Panel B of Figure 1 with Panel A of Figure A.5, both based on the same decomposition with 20 categories of sectors, confirms the central result that between-sector inequality has increased over time. In the expanded sample of respondents, the 2005-2014 share of total wage inequality that is attributed to differences between sectors is measured at 22.1% in urban areas, and 27.8% in rural areas. The rise over time has been especially marked in urban areas (11.0 percentage points to 27.8%) compared to rural areas (2.8 percentage points to 28.5%). When looking at the impact of between-group difference in education groups, the average contribution to total wage inequality is higher in the urban sample (32.3%) compared to the rural sample (28.0%). Mirroring the fast rise in between-sector inequality, urban areas have also experienced an increase in between-education inequality (5.5 percentage points to 35.6%), compared to the steadier measure across rural areas (-0.4 percentage points to 27.2%).

As depicted in Figure 1, there has been a notable increase in income inequality between sectors over time. To what extent did specific sectors contribute to this upward trend? Figure 2 shows the proportion of total inequality attributed to differences between sectors, categorized by economic activity. This analysis divides the 20 sectors previously outlined in Figure 1 into two distinct groups: 1) primary and secondary sectors; and 2) tertiary sectors.[22] For each of these two economic groups, the portion of total wage inequality attributed to differences between sectors has been computed. For instance, this analysis determined the share of total wage inequality within the primary and secondary sectors stemming from distinctions among agriculture, mining, construction, and manufacturing. This analysis was conducted separately for both urban and rural areas. When looking at all areas (Panel A), the share of total inequality that is attributed to differences between sectors is much higher for primary and secondary sectors (an average of 32.0% between 2005 and 2014) compared to tertiary sectors (15.1%). In urban areas (Panel B), the two groups perform more similarly, and tertiary sectors have a higher share in

[22] Primary and secondary sectors include: agriculture, forestry, fishing, and hunting; mining, quarrying and oil and gas extraction; construction; and manufacturing. Tertiary sectors include: utilities; wholesale trade; retail sector; transportation and warehousing; information; finance and insurance; real estate and rental and leasing; professional, scientific, and technical services; management of companies and enterprises; administrative and support and waste management; educational services; healthcare and social assistance; arts, entertainment, and recreation; accommodation and food services; other services (excluding public administration); and public administration.

total inequality compared to primary and secondary sectors: 14.4% versus 9.4%, respectively. Rural areas instead mirror the pattern observed for all areas, with the share of total inequality being 27.3% for primary and secondary sectors, and 15.1% for tertiary sectors (Panel C). When considering the trend over time, the contribution of tertiary sectors to total inequality rose between 2005 and 2014 in all three geographies considered: by 2.5 percentage points in all areas, by 2.7 percentage points in urban areas, and by 3.4 percentage points in rural areas. On the other hand, the share of total inequality that is attributed to differences between sectors in the group of primary and secondary sectors fell over time in all areas (by 1.2 percentage points) and urban areas (by 0.2 percentage points), whereas it rose by 1.0 percentage points in rural areas.

On the whole, the surge in between-sector inequality observed between 2005 and 2014 appears to be primarily propelled by distinctions between sectors within the tertiary sector. Were there any notable shifts in the number of workers employed in primary, secondary, and tertiary sectors? Focusing on full-time workers, the proportion of employment within these broad sectors of economic activity remained remarkably stable over time. The tertiary sector in urban areas employed 70% of the workforce at the start of 2005, compared to 56.2% in rural areas. In 2014, the corresponding figures stood at 69.3% for urban areas and 57.9% for rural areas.

### 5.2 *Drivers behind the rise in between-sector inequality*

After confirming an increase in between-sector inequality over time, particularly prominent in the urban sample, the subsequent step in the analysis aims to identify the primary drivers behind this upward trend.

Initially, the production function of equation 8 is estimated using alternative specifications. Columns (1), (3),(5), and (7) of Table 3 present results without time fixed effects. Although the results remain robust, specification tests suggest that time dummies should always be included in this model. Therefore, columns (2), (4), (6), (8), (9), and (10) are preferred.[23] Time dummies are particularly helpful in eliminating unobserved effects that are year-specific and common to all sectors. Moreover, recognizing the potential spill-over

[23] The hypothesis that the coefficients for all years are jointly equal to 0 was tested and rejected, suggesting that time fixed effects should be included in the analysis.

effects of foreign investments on labor productivity, the analysis introduces FDI as an additional control variable. However, sources of endogeneity might arise. In the Mexican case, foreign investments are found to gravitate towards low-productivity labor-intensive industries to benefit from cross-border differences in labor costs, best exemplified by the Maquiladoras program (Jordaan, 2011).[24]

The robustness of the results persists across various specifications, and all coefficients exhibit the anticipated signs. Notably, scaling the trade variable by either output (trade-to-output) or value added (trade-to-VA) results in significant and positive effects. Specifically, for every 1% increase in the trade ratio measure, labor productivity experiences a growth ranging from 0.09% to 0.11%. Moreover, after accounting for FDI, the positive impact of the trade ratio on labor productivity becomes more pronounced, yielding a range between 0.21% and 0.25%.

The presence of a more educated workforce, as indicated by the level of high-skilled workers, appears to have a large effect on labor productivity. Specifically, there are increases of approximately 0.30% for every 1% increase in the education variable. This underscores the relevance of human capital considerations for the Mexican economy. The results for the capital-to-labor ratio reveal that, for every 1% increase in this variable, labor productivity experiences a rise of 0.26%. This coefficient remains consistent across all specifications, with the exception of the final two columns where FDI is also included, resulting in a decrease of 0.09%. The estimation of the elasticity with respect to capital hovering around 0.3 is reassuring, in line with values often found in cross-sectional studies.

[24] The Maquiladoras program entails predominantly US-owned factories situated in Mexico, typically in close proximity to the border. These factories import materials and equipment duty-free for assembly or manufacturing, subsequently exporting the finished products. The primary advantage lies in leveraging lower labor costs. However, these companies generally contribute relatively low value added to the production process.

**Table 3**

*The production function*

| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* | *(8)* | *(9)* | *(10)* |
|---|---|---|---|---|---|---|---|---|---|---|
| Capital | 0.522*** | 0.263*** | 0.416*** | 0.259*** | 0.544*** | 0.262*** | 0.434*** | 0.257*** | 0.175*** | 0.172** |
| | (0.052) | (0.069) | (0.054) | (0.071) | (0.052) | (0.069) | (0.053) | (0.071) | (0.067) | (0.069) |
| High skill | 0.525*** | 0.347*** | | | 0.505*** | 0.320*** | | | 0.271*** | |
| | (0.084) | (0.088) | | | (0.085) | (0.088) | | | (0.104) | |
| Med & high skill | | | 0.479*** | 0.194*** | | | 0.473*** | 0.167* | | -0.043 |
| | | | (0.073) | (0.094) | | | (0.074) | (0.093) | | (0.103) |
| Trade-to-output | 0.197*** | 0.107*** | 0.173*** | 0.111*** | | | | | | |
| | (0.035) | (0.036) | (0.036) | (0.037) | | | | | | |
| Trade-to-VA | | | | | 0.146*** | 0.085*** | 0.130*** | 0.093*** | 0.213*** | 0.251*** |
| | | | | | (0.029) | (0.029) | (0.029) | (0.029) | (0.045) | (0.045) |
| FDI | | | | | | | | | 0.028* | 0.032* |
| | | | | | | | | | (0.017) | (0.017) |
| Year fixed effects | No | Yes | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Adj. R-Square | 0.55 | 0.63 | 0.56 | 0.61 | 0.54 | 0.63 | 0.55 | 0.62 | 0.51 | 0.49 |
| N | 260 | 260 | 260 | 260 | 260 | 260 | 260 | 260 | 189 | 189 |

Notes: The dependent variable is output-to-labor. All variables are in logarithmic form and all variables (except hours of work) are expressed in constant 2008 prices. When FDI is included, the sample is reduced, starting in 2000. As this paper rejects the null hypothesis that the coefficients for all years are jointly equal to 0, including time fixed effects in the specifications is preferred. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Author's elaboration.

**Table 4**

*Decomposition of the contributing factors to changes in inequality in Mexico, 1995-2014*

| | | (1) | | | | (2) | | | | (3) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Year* | *Total inequality* | *Capital* | *Med. & high skill* | *Trade-to-output* | *Other* | *Capital* | *High skill* | *Trade-to-output* | *Other* | *Capital* | *High skill* | *Trade-to-VA* | *Other* |
| 1995 | 0.77 | 0.24 | -0.06 | -0.03 | 0.63 | 0.24 | -0.04 | -0.03 | 0.60 | 0.24 | -0.03 | 0.00 | 0.57 |
| 1996 | 0.78 | 0.24 | -0.06 | -0.03 | 0.62 | 0.24 | -0.04 | -0.03 | 0.61 | 0.24 | -0.04 | 0.00 | 0.58 |
| 1997 | 0.77 | 0.24 | -0.05 | -0.03 | 0.62 | 0.24 | -0.04 | -0.03 | 0.61 | 0.24 | -0.04 | 0.00 | 0.58 |
| 1998 | 0.73 | 0.24 | -0.06 | -0.03 | 0.58 | 0.24 | -0.04 | -0.03 | 0.56 | 0.24 | -0.04 | 0.00 | 0.52 |
| 1999 | 0.69 | 0.24 | -0.05 | -0.03 | 0.54 | 0.24 | -0.04 | -0.03 | 0.52 | 0.24 | -0.04 | 0.00 | 0.49 |
| 2000 | 0.75 | 0.24 | -0.07 | -0.01 | 0.58 | 0.25 | -0.05 | -0.01 | 0.56 | 0.24 | -0.05 | 0.02 | 0.53 |
| 2001 | 0.73 | 0.24 | -0.06 | -0.01 | 0.57 | 0.25 | -0.06 | -0.01 | 0.55 | 0.24 | -0.05 | 0.02 | 0.52 |
| 2002 | 0.71 | 0.24 | -0.06 | -0.01 | 0.54 | 0.25 | -0.05 | -0.01 | 0.53 | 0.24 | -0.04 | 0.01 | 0.50 |
| 2003 | 0.72 | 0.24 | -0.05 | -0.01 | 0.55 | 0.24 | -0.04 | -0.01 | 0.53 | 0.24 | -0.04 | 0.02 | 0.50 |
| 2004 | 0.83 | 0.24 | -0.06 | -0.02 | 0.66 | 0.24 | -0.05 | -0.02 | 0.65 | 0.24 | -0.04 | 0.01 | 0.62 |
| 2005 | 0.89 | 0.24 | -0.07 | -0.01 | 0.73 | 0.24 | -0.05 | -0.01 | 0.71 | 0.24 | -0.05 | 0.04 | 0.66 |
| 2006 | 0.98 | 0.23 | -0.08 | -0.01 | 0.84 | 0.24 | -0.06 | -0.01 | 0.81 | 0.24 | -0.05 | 0.01 | 0.79 |
| 2007 | 0.99 | 0.23 | -0.07 | 0.00 | 0.83 | 0.23 | -0.05 | 0.00 | 0.81 | 0.23 | -0.05 | 0.03 | 0.78 |
| 2008 | 1.14 | 0.23 | -0.07 | 0.00 | 0.98 | 0.23 | -0.04 | 0.00 | 0.95 | 0.23 | -0.04 | 0.03 | 0.92 |
| 2009 | 0.98 | 0.23 | -0.07 | 0.01 | 0.80 | 0.24 | -0.04 | 0.01 | 0.77 | 0.24 | -0.04 | 0.04 | 0.74 |
| 2010 | 1.06 | 0.24 | -0.07 | 0.01 | 0.88 | 0.24 | -0.05 | 0.01 | 0.86 | 0.24 | -0.05 | 0.04 | 0.83 |
| 2011 | 1.11 | 0.23 | -0.07 | 0.01 | 0.94 | 0.24 | -0.05 | 0.01 | 0.91 | 0.24 | -0.04 | 0.04 | 0.88 |
| 2012 | 1.12 | 0.23 | -0.07 | 0.01 | 0.95 | 0.23 | -0.05 | 0.01 | 0.93 | 0.23 | -0.05 | 0.04 | 0.89 |
| 2013 | 1.05 | 0.23 | -0.07 | 0.00 | 0.88 | 0.23 | -0.04 | 0.00 | 0.86 | 0.23 | -0.04 | 0.04 | 0.82 |
| 2014 | 1.00 | 0.23 | -0.06 | 0.00 | 0.84 | 0.23 | -0.04 | 0.00 | 0.81 | 0.23 | -0.03 | 0.03 | 0.77 |
| Contribution (%) | 100.00 | -3.99 | 0.20 | 14.05 | 89.74 | -4.05 | 0.31 | 13.56 | 90.18 | -4.04 | 0.29 | 15.74 | 88.01 |
| Growth (%) | 30.40 | | | | | | | | | | | | |

Notes: Total inequality is the log of the variance of the labor productivity measure. The decomposition (1) is based on the regression output from column (4) of Table 3. The decomposition (2) is based on the regression output from column (2) of Table 3. The decomposition (3) is based on the regression output from column (6) of Table 3. All columns (except for Total inequality and Other) are based on the multiplication of the covariance with the corresponding estimated coefficient, which represents the contribution of each term to total inequality.

Source: Author's elaboration.

The quantification of the contribution of factor components to total inequality between sectors is derived from the regression coefficients. Table 4 presents the breakdown into contributing factors based on three different specifications, corresponding to the coefficients from columns (4), (2), and (6) of Table 3, respectively. This decomposition yields very similar results, and the average is considered. It is essential to note that a significant portion of inequality, even after accounting for capital, education, and economic openness, remains unexplained. This limitation is a consequence of the study's focus on heterogeneity between sectors rather than individuals.[25] The inequality measure, represented by the log of the variance of the labor productivity term, exhibits a steady increase over time, rising from 0.8 in 1995 to 1.0 in 2014. This is in line with the earlier findings indicating a growing significance of differences between sectors. The trend suggests that the disparity in sector-level labor productivity in Mexico widened over the 20-year period of study (Satchi and Temple, 2009; McMillan and Rodrik, 2011). In the observed widening of inequality, trade emerges as the most substantial contributor, explaining approximately 14.5% of the total increase. This implies that NAFTA, by increasing economic openness and trade between Mexico and its northern neighbors, is associated with higher income inequality.[26] The impact of education on inequality is also positive, although the magnitude remains very small. In contrast, capital stands out as the only equalizing factor among the three considered, making a contribution to total inequality of around -4.0%.

Finally, the results from both analyses can be synthesized as follows. First, total wage inequality has exhibited a declining trend since the late 1990s and early 2000s. Second, this decline has been coupled with increasing differences between sectors, rather than within-sector inequality. This trend is particularly noteworthy for urban areas. Third, the primary factor contributing to the heightened differentiation between sectors is economic openness, above all through the trade channel.

[25] A follow-up analysis includes FDI in the decomposition, based on the coefficients of column (9) of Table 3. The influence of economic openness on total inequality, through the FDI channel, is minimal and does not alter the contribution of the other three factors included.

[26] Although Hakobyan and McLaren (2016) do not directly investigate inequality, their work identifies significant sector income shifts in the US in response to NAFTA.

## 6. Additional mechanisms

### 6.1 *China's accession to the WTO*

The surge in trade from China, leading to intensified competition in the US market, may have had important effects on income inequality in Mexico. Using data from 2004 to 2017 on 56 metropolitan areas, Vargas (2020) demonstrates that the overall impact on Mexican employment has been marginal, and that manufacturing unemployment in Mexico has not increased due to heightened competition with China in the US market, although wages have been negatively affected. However, this finding is contradicted by Blyde *et al.* (2023), who find a negative effect of increased Chinese-import competition on local manufacturing employment in the short and medium run. The adjustment in the labor market, which mostly affected small- and medium-sized companies, took various forms: for example, a decline in the number of paid employees and a substitution of some formal wage employees with informal wage employees.

**Table 5**
*Additional mechanisms*

| | *China* | | *TFP* | *Tariffs* | | |
|---|---|---|---|---|---|---|
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* |
| Capital | 0.263*** | 0.252*** | 0.231*** | 0.479*** | 0.605*** | 0.737*** |
| | (0.069) | (0.07) | (0.07) | (0.095) | (0.063) | (0.063) |
| High skill | 0.347*** | 0.496*** | 0.159 | 0.761*** | 0.460*** | 0.308*** |
| | (0.088) | (0.091) | (0.102) | (0.145) | (0.104) | (0.094) |
| Trade-to-output | 0.107*** | 0.116*** | 0.090** | 0.280*** | 0.175*** | -0.073 |
| | (0.036) | (0.035) | (0.037) | (0.044) | (0.038) | (0.058) |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. R-Square | 0.63 | 0.66 | 0.64 | 0.53 | 0.57 | 0.68 |
| N | 260 | 260 | 260 | 140 | 220 | 120 |

Notes: The dependent variable is output-to-labor. Robust standard errors in parenthesis are adjusted for clustering at the state level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Author's elaboration.

Between 1994 and 2014, Mexico's contribution to total US imports increased by 5.1 percentage points (from 7.5% to 12.6%).[27] As illustrated in Figure A.3, this increase primarily occurred during the initial eight years, having risen 4.1 percentage points by 2001. With China joining the World Trade Organization (WTO) on December 11, 2001, Mexico's share of exports in total US imports dropped from 11.6% in 2002 to 10.2% in 2005, before recovering to 12.6% by the end of the sample period. In contrast, China's share in total US imports steadily increased from 5.8% in 1994 to 9.0% in 2001–a difference of 3.2 percentage points–before reaching 19.9% by 2014.

Overall, Mexico's export competitiveness–defined by its share in the US import market–increased between 2004 and 2014, although China held a better position. Notably, the year 2002, with China's WTO accession, marked a decline in Mexico's competitiveness. In an initial attempt to isolate the impact of increased trade from China on income inequality in Mexico, the analysis in Section 5 is replicated, including an indicator that divides the sample into two periods on either side of China's WTO accession in 2002: 1994-2001 and 2002-2014. As indicated in column (1) of Table 5, the coefficient on this indicator is positive but does not reach statistical significance when estimating the production function. However, once the impact of China's WTO accession is controlled for, the impact of trade on the total change in between-sector income inequality rises to 19.8%, as shown in column (1).

Increased competition from China may have affected different exporting sectors in Mexico, potentially replacing Mexico's role as a US supplier in specific industries. Utilizing data from ECLAC (2020), this paper creates an indicator measuring the change in export competitiveness for each industry between 2002 -the year of China's WTO accession- and 2014. This indicator is based on a matrix that distinguishes, on one hand, whether products are dynamic (growing at a higher rate than the average of total US imports) or stagnant and, on the other hand, whether they have gained or lost market share as US imports.[28] Including this differentiation does not alter the direction of the estimation results in the production function, as shown in column (2) of Table 5, but increases the impact of trade on inequality

[27] These calculations are based on data from ECLAC (2020).

[28] Products can be classified as rising stars (dynamic products gaining market share), lost opportunities (dynamic products losing market share), waning stars (stagnant products gaining market share), and withdrawals (stagnant products losing market share).

to 21.5%. Trade remains the primary contributor to widening income inequality in Mexico.

### 6.2 *Rising automation*

Another potentially transformative event shaping the Mexican economy is the emergence of automation, which has likely impacted specific sectors to varying degrees. This constitutes a potential source of endogeneity, especially since this paper has incorporated heterogeneous sectors into a single production function. Sectors more prone to automation may experience a disproportionate shift in factor elasticity, with a decrease in labor elasticity and an increase in capital elasticity over time. This might have important labor market consequences. In particular, Autor and Salomons (2018), using a panel dataset of 19 developed countries and 28 market industries for 1970-2007, observe a strong negative relationship between Total Factor Productivity (TFP) growth and both the contemporaneous log employment growth and changes in log labor share at the industry level. This suggests a strong labor-replacing effect of automation. Ramos, Garza-Rodríguez, and Gibaja-Romero (2022) corroborate this finding, concluding that labor demand decreases for Mexican occupations with a high risk of automation. To account for the dynamic effect of automation, this paper makes use of Socio-Economic Accounts (SEA) data from the WIOD to create a sector-level measure of TFP growth between 2000 and 2014.[29] Employing TFP as a measure of technological progress addresses the challenge of consistent measurement posed by the extensive heterogeneity of innovation across sectors and periods. It is particularly relevant to this analysis as it encapsulates the ultimate impact of automation. All facets of technological progress contribute to an elevation in TFP, whether by enhancing the efficiency of capital or labor in production, or by reallocating tasks from labor to capital, or vice versa (Autor and Salomons, 2018).

Column (3) of Table 5 presents the production function estimate with the inclusion of a dummy indicator set to 1 for sectors with TFP growth above the median of the distribution. After controlling for increasing automation using this TFP measure, the impact of trade on the total change in between-sector income inequality is 13.0%, as shown in column (3).

[29] TFP growth is the portion of output growth not explained by the growth in labor and capital. In constructing this measure, the standard weighting of 0.7 for labor and 0.3 for capital are used.

### 6.3 *Import tariffs*

This paper also investigates the impact of import tariffs, a critical aspect since, at the implementation of NAFTA, numerous Mexican industries–producing thousands of commodities–already enjoyed the benefits of zero-import tariffs under the Generalized System of Preferences (GSP) (Agama and McDaniel, 2002). Starting in 1974, the GSP conferred a tariff advantage to Mexico over its competitors in the US market.

This section leverages the fact that NAFTA addressed both tariffs and non-tariff barriers to trade and investment over a 15-year period (Besedes *et al.*, 2020). For each sector in the analysis, the Ad Valorem Equivalent (AVE) tax rate on imported goods is calculated, expressed as a percentage of the import value.[30] The sample is then categorized into three groups based on their 1994 and 2014 AVE rates: sectors that consistently had low tariffs, sectors that transitioned toward a low-tariff environment, and sectors that continued to face high tariffs.

The results of this analysis are presented in columns (4), (5), and (6) of Table 5. Encouragingly, the most significant contribution to Mexican inequality comes from products that already enjoyed GSP status before NAFTA and that maintained low-tariff rates by the end of the sample. In column (4), the impact of trade on inequality for this group is notably larger, estimated at 51.8%. Column (5), reflecting an increase in exports over time due to lower import tariffs post-NAFTA, shows that the trade component in the group transitioning to a low-tariff environment is responsible for 32.9% of the total change in between-sector income inequality. Conversely, in the group facing high import tariffs throughout the sample period, the trade component does not reach statistical significance at conventional levels, possibly due to the lower role of trade across these sectors.

## 7. Conclusions

The question of whether NAFTA, and the growing influence of trade in the Mexican economy, has adversely impacted income inequality is

[30] Using data from ECLAC (2020), the AVE rate is obtained by dividing the value of the tariff collected from a country-product by the value of the imports of that country-product subject to the payment of a tariff to enter the US market.

challenging to address. Over the course of the trade agreement, total inequality increased until 2000 and has since slightly declined. Critics attribute the rise in income inequality to NAFTA, particularly when considering subgroups of the economy. Consistent with this perspective, this study reveals that income inequality between sectors has indeed increased during NAFTA's tenure, indicating that its benefits have not been uniformly distributed across the whole economy.[31] The escalation of inequality between sectors is a crucial finding, raising important policy questions.

In an effort to disentangle the drivers behind the surge in between-sector inequality, this study estimates the proportion attributable to fluctuations in trade patterns compared to variations in capital intensity, educational attainment, and FDI. The results indicate that trade has had the most substantial impact, explaining around 14.5% of the total change in between-sector income inequality. Although modest, this result establishes a direct link between NAFTA's existence and an increase in income inequality within Mexico, suggesting winners and losers at the sector level, and emphasizing the need for further redistribution. Given the increasing inequality between sectors, policymakers must recognize and capitalize on the opportunities created. For example, encouraging retraining for workers interested in transitioning across sectors and facilitating shifts from low-productivity, low-income sectors to high-productivity, high-income sectors could potentially boost Mexican productivity.

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[31] The unequal regional distribution of these benefits persists, with prior research confirming that the northern states in Mexico have reaped more advantages than the south and southeast regions of the country (ECLAC, 2016; Dussel-Peters, 2018).

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## Appendix

A.1 *Data sources and definitions*

In the first analysis of this paper, based on the work of Akerman *et al.* (2013) and Helpman *et al.* (2017), the main groups of interest in the decomposition are the employment sectors and the education levels.

*Sector Variable*

In ENOE, there are 20 categories used to classify the sector of employment. These are reported in Table A.1 and follow the North American Industry Classification System 2007 (*Sistema de Clasificación Industrial de América del Norte*, SCIAN). In ENEU, the classification used is at a more disaggregated level (INEGI, 1994) and must be aggregated to be comparable to ENOE. This correspondence is reported in Table A.1, and the match between the two samples is presented in Table A.2. For this comparison, categories 6 and 7 in ENOE (Wholesale trade and Retail sector, respectively) have been combined into a single category, whereas categories 13 (Management of companies and enterprises, corresponding to 0.1% of the sample) and 14 (Administrative and support and waste management, 3.5% of the sample) in ENOE do not have a corresponding classification in ENEU. Table A.3 presents the breakdown of total employment by sector, separately for urban and rural areas.

*Education Variable*

There are 10 categories in ENOE used to describe educational attainment, ranging from no education to doctoral level. In ENEU, the disaggregation follows a more complex system, with a 5-digit code to describe every possible educational outcome in the Mexican system (INEGI, 1995). The correspondence between the two surveys is reported in Table A.4 and the quality of the match in Table A.5. For both preschool education (0.0% of the sample in ENOE) and teacher training college (0.7% of the sample), no corresponding category exists in ENEU.[32]

[32] The latter category trains high school graduates for a career in teaching.

**Table A.1**

*Correspondence between ENEU and ENOE: Sectors*

| *ENEU* | *ENOE* | |
|---|---|---|
| *Classification of Economic Activity* | *SCIAN USA* | *SCIAN Mexico* |
| 1 Classif. 01-04 | Agriculture, forestry, fishing, and hunting | Agricultura, ganadería, aprov. forestal, pesca y caza |
| 2 Classif. 05-10 | Mining, quarrying and oil and gas extr. | Minería |
| 3 Classif. 61 | Utilities | Electricidad, agua y suministro de gas |
| 4 Classif. 60 | Construction | Construcción |
| 5 Classif. 11-59 | Manufacturing | Industrias manufactureras |
| 6 Classif. 62 | Wholesale trade | Comercio al por mayor |
| 7 Classif. 62 | Retail sector | Comercio al por menor |
| 8 Classif. 64 | Transportation and warehousing | Transportes, correos y almacenamiento |
| 9 Classif. 65 | Information | Información en medios masivos |
| 10 Classif. 66 | Finance and insurance | Servicios financieros y de seguros |
| 11 Classif. 67 | Real estate and rental and leasing | Servicios inmobil. y de alquiler de bienes |
| 12 Classif. 68 | Professional, scientific, and technical services | Servicios profesionales, científicos y técnicos |
| 13 No corresp. classif. | Management of companies and enterprises | Dirección de corporativos y empresas |
| 14 No corresp. classif. | Admin. and support and waste management | Apoyo a los negocios y manejo de desechos |
| 15 Classif. 69 | Educational services | Servicios educativos |
| 16 Classif. 70 | Healthcare and social assistance | Salud y asistencia social |
| 17 Classif. 71 | Arts, entertainment, and recreation | Esparcimiento culturales y deportivos |
| 18 Classif. 63 | Accommodation and food services | Alojam. temporal, preparación de alimentos y bebidas |
| 19 Classif. 72 | Other services (ex. public administration) | Otros servicios ex. actividades del gobierno |
| 20 Classif. 73, 74, and 88 | Public administration | Activid. del gobierno, organismos internac. y extraterr. |

Notes: The table reports the correspondence of the classifications used in ENEU and ENOE.

Source: Author's elaboration.

**Table A.2**
*Correspondence between ENEU and ENOE: Sectors (% of total population)*

| | *ENEU* | | *ENOE* | |
|---|---|---|---|---|
| | *All Sample* | *2004Q4* | *All Sample* | *2005Q1* |
| 1 | 1.81 | 1.45 | 1.13 | 1.35 |
| 2 | 0.46 | 0.27 | 0.59 | 0.63 |
| 3 | 0.69 | 0.60 | 0.66 | 0.65 |
| 4 | 6.20 | 6.70 | 9.52 | 9.25 |
| 5 | 19.57 | 16.96 | 18.56 | 18.81 |
| 6 and 7 | 21.30 | 22.89 | 20.14 | 20.39 |
| 8 | 4.95 | 4.77 | 6.34 | 6.68 |
| 9 | 0.61 | 0.63 | 1.13 | 1.09 |
| 10 | 1.09 | 1.00 | 1.28 | 1.17 |
| 11 | 0.30 | 0.31 | 0.69 | 0.77 |
| 12 | 4.05 | 4.67 | 2.59 | 2.90 |
| 13 | Missing | Missing | 0.10 | 0.04 |
| 14 | Missing | Missing | 3.47 | 2.59 |
| 15 | 6.38 | 6.65 | 4.23 | 4.62 |
| 16 | 3.90 | 4.13 | 4.25 | 4.35 |
| 17 | 1.46 | 1.54 | 0.69 | 0.73 |
| 18 | 6.62 | 7.30 | 6.44 | 5.81 |
| 19 | 13.76 | 13.36 | 9.62 | 9.41 |
| 20 | 6.86 | 6.78 | 8.58 | 8.73 |
| Total | 100 | 100 | 100 | 100 |

Notes: The table reports the share of the population in each sector, according to the classification of sectors used in ENOE.

Source: Author's elaboration.

**Table A.3**
*Share of employment by sector*
*(% of total population)*

| | ENOE | | | |
|---|---|---|---|---|
| | *Urban Areas* | | *Rural Areas* | |
| | *All Sample* | *2005Q1* | *All Sample* | *2005Q1* |
| 1 | 1.13 | 1.35 | 16.61 | 18.12 |
| 2 | 0.59 | 0.63 | 1.08 | 1.03 |
| 3 | 0.66 | 0.65 | 0.70 | 0.73 |
| 4 | 9.52 | 9.25 | 10.69 | 10.35 |
| 5 | 18.56 | 18.81 | 14.19 | 14.34 |
| 6 | 3.71 | 3.92 | 2.70 | 2.62 |
| 7 | 16.43 | 16.47 | 15.21 | 15.43 |
| 8 | 6.34 | 6.68 | 5.04 | 5.00 |
| 9 | 1.13 | 1.09 | 0.57 | 0.50 |
| 10 | 1.28 | 1.17 | 0.69 | 0.51 |
| 11 | 0.69 | 0.77 | 0.51 | 0.65 |
| 12 | 2.59 | 2.90 | 1.31 | 1.34 |
| 13 | 0.10 | 0.04 | 0.02 | 0.00 |
| 14 | 3.47 | 2.59 | 2.02 | 1.39 |
| 15 | 4.23 | 4.62 | 3.31 | 3.57 |
| 16 | 4.25 | 4.35 | 2.72 | 2.85 |
| 17 | 0.69 | 0.73 | 0.55 | 0.53 |
| 18 | 6.44 | 5.81 | 6.60 | 6.19 |
| 19 | 9.62 | 9.41 | 8.22 | 7.61 |
| 20 | 8.58 | 8.73 | 7.25 | 7.23 |
| Total | 100 | 100 | 100 | 100 |

Notes: The table reports the share of the population in each sector, according to the classification of sectors used in ENOE.

Source: Author's elaboration.

**Table A.4**
*Correspondence between ENEU and ENOE: Education*

| | *ENEU* | *ENOE* |
|---|---|---|
| | *Classification of Educational Attainment* | |
| 1 | Classif. 96-98 | No education |
| 2 | No corresp. classif. | Preschool |
| 3 | Classif. 11-16, 21, 22 and 1N | Primary |
| 4 | Classif. 23, 31, 32, 1T and 2N | Junior high school |
| 5 | Classif. 33, 41-43 and 3N | High school |
| 6 | No corresp. classif. | Teacher training college |
| 7 | Classif. 2T and 3T | Technical career |
| 8 | Classif. 44, 45, 4T and 51 | Professional |
| 9 | Classif. 52, 5T and 61 | Master's degree |
| 10 | Classif. 62, 63 and 6T | Doctoral degree |

Notes: The table reports the correspondence of the classifications used in ENEU and ENOE.

Source: Author's elaboration.

**Table A.5**
*Correspondence between ENEU and ENOE: Education (% of total population)*

| | *ENEU* | | *ENOE* | |
|---|---|---|---|---|
| | *All Sample* | *2004Q4* | *All Sample* | *2005Q1* |
| 1 | 5.00 | 4.46 | 4.19 | 5.29 |
| 2 | Missing | Missing | 0.04 | 0.03 |
| 3 | 39.80 | 35.46 | 28.41 | 31.98 |
| 4 | 25.10 | 27.20 | 26.88 | 24.15 |
| 5 | 10.29 | 13.21 | 15.19 | 12.89 |

**Table A.5**
*(Continued)*

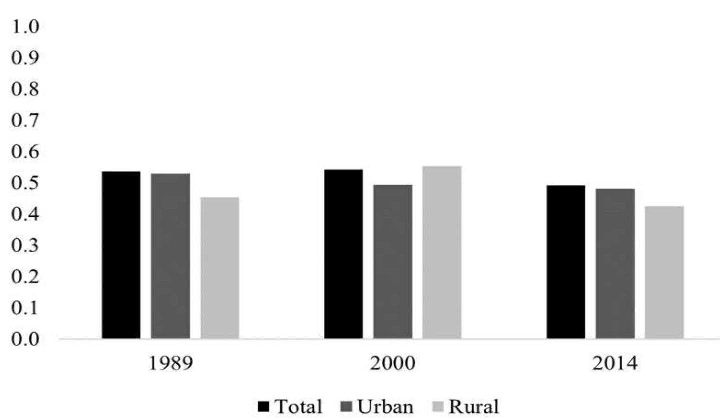
| | *ENEU* | | *ENOE* | |
|---|---|---|---|---|
| | *All Sample* | *2004Q4* | *All Sample* | *2005Q1* |
| 6 | Missing | Missing | 0.67 | 0.87 |
| 7 | 8.64 | 6.69 | 6.50 | 7.51 |
| 8 | 10.45 | 11.93 | 16.66 | 15.94 |
| 9 | 0.70 | 0.95 | 1.29 | 1.15 |
| 10 | 0.04 | 0.10 | 0.17 | 0.17 |
| Total | 100 | 100 | 100 | 100 |

Notes: The table reports the share of the population in each category of education, according to the classification of education used in ENOE.

Source: Author's elaboration.

## A.2 *Additional results*

**Figure A.1**
*The Gini coefficient in Mexico*



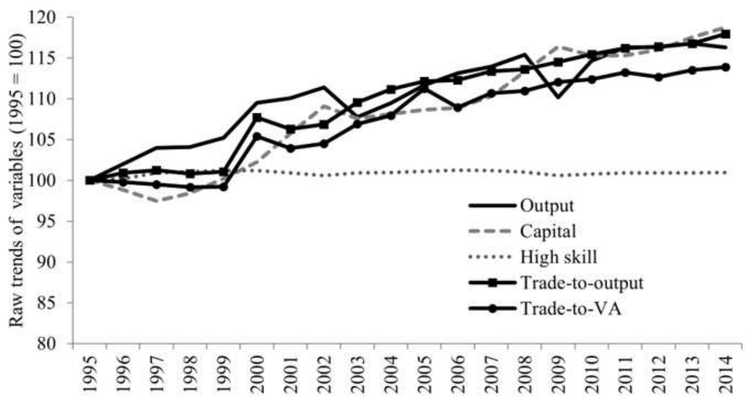

Notes: Using data from ECLAC (2024), the Gini coefficient is calculated for three time periods: 1989, 2000, and 2014. The figure presents the index separately for urban and rural areas.

Source: Author's elaboration.

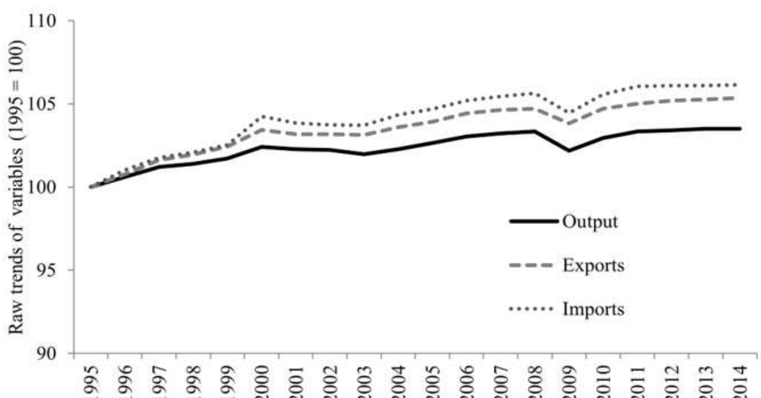
**Figure A.2**

*Raw trends over time for the factors driving inequality considered in Section 5.2*

*a) Output, capital, high skill, and trade*




*b) Trade-to-output*

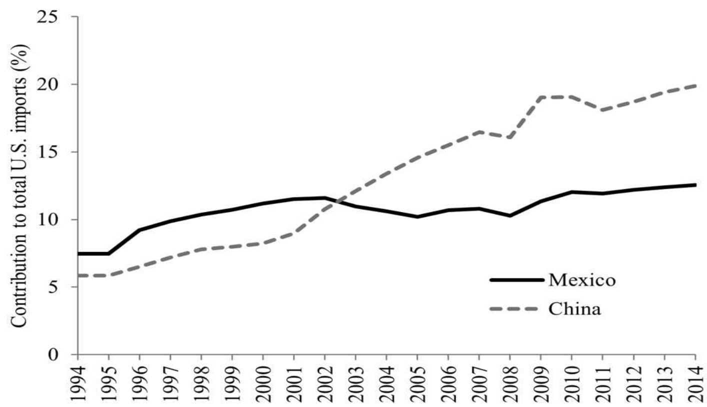



Notes: The figure reports the raw trends over time for the factors driving inequality, as discussed in Section 5.2.

Source: Author's elaboration.

**Figure A.3**

*Contributions of Mexico and China to total U.S. imports*

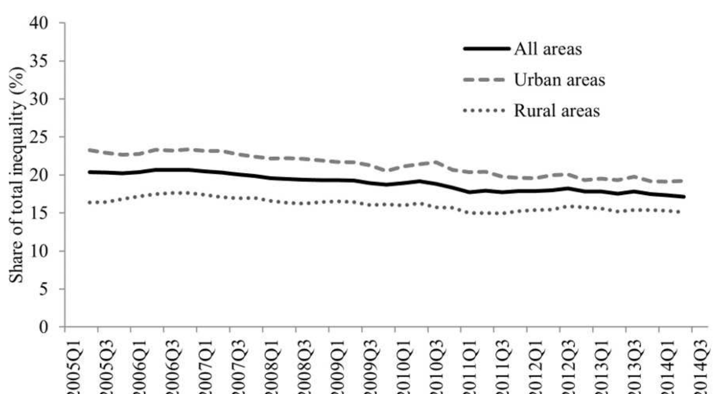



Notes: Using data from ECLAC (2020), the figure presents the contributions of Mexico and China to total U.S. imports.

Source: Author's elaboration.

**Figure A.4**

*Total inequality measured through the variability of wages, 1994-2014. Differences between education groups*



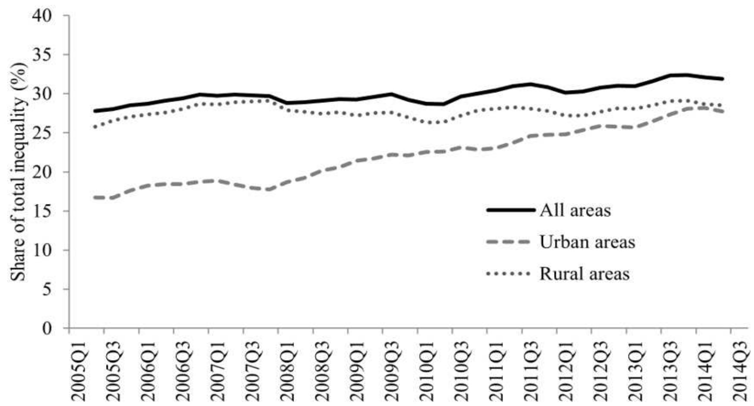

Notes: The figure illustrates the share (%) of total inequality that is attributed to differences between three groups of education: less than middle school, high-school level, and higher education.

Source: Author's elaboration.

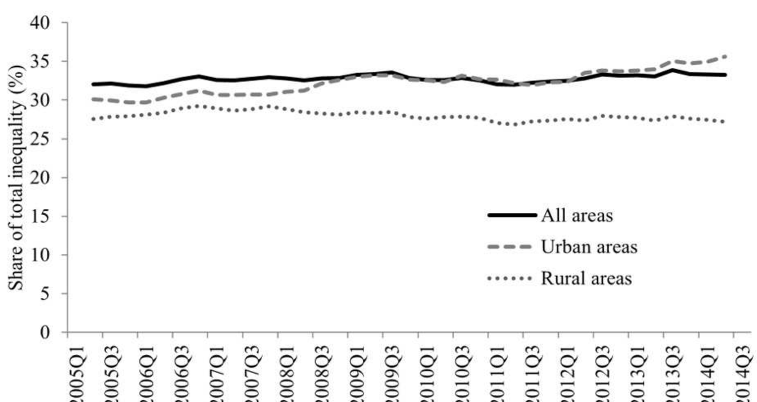
**Figure A.5**

*Total inequality measured through the variability of wages, 1994-2014*

*a) Differences between sectors*




*b) Differences between education groups*




Notes: Panels A and B illustrate the share (%) of total inequality that is attributed to differences between groups. Compared to Figure 1, this analysis expands the set of individuals considered, based on both hours worked and earnings. Figure 1 is based on a sample of individuals working more than 35 hours per week and earning more than 99 MXN per month. This analysis does not exclude individuals that work fewer than 35 hours per week but includes all workers regardless of hours worked. Furthermore, it does not exclude workers reporting monthly salaries of less than 99 MXN, but includes all workers regardless of earnings. Similarly to the analysis of Figure 1, the sector groups are those included in the variable SCIAN of ENOE, and the education groups are those included in the variable CS P13 1 of ENOE.

Source: Author's elaboration.

**Table A.6**

*Part-time workers and respondents enrolled in education*

| *ENOE* | | | | | | | |
|---|---|---|---|---|---|---|---|
| *Urban Areas* | | | | *Rural Areas* | | | |
| *Part-time Workers* | | *Enrolled in Education* | | *Part-time Workers* | | *Enrolled in Education* | |
| 2005Q1 | 2014Q3 | 2005Q1 | 2014Q3 | 2005Q1 | 2014Q3 | 2005Q1 | 2014Q3 |
| 21.71 | 21.01 | 2.48 | 2.46 | 24.40 | 25.46 | 1.92 | 1.78 |

Notes: The table shows, separately for urban and rural areas, the shares of ENOE respondents in the working age population that: 1) declare working fewer than 35 hours a week; and 2) are enrolled in education.

Source: Author's elaboration.