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Kuznets in the twenty-first century

Mexico and United States compared

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Abstract: Building upon a multisectoral framework in light of the Kuznetsian paradigm, this paper analyses the relationship between structural transformation and income inequality. Empirical evidence is drawn using a large census dataset consisting of more than 22 million individuals from Mexico and the United States in 2000 and 2020. The Gini coefficient of income in Mexico decreased from 0.49 in 2000 to 0.43 in 2020, whereas it slightly increased in the US from 0.49 in 2000 to 0.51 in 2020. Movement of workers from other sectors to manufacturing and industry in the bottom income quantiles, and to services in the middle income quantiles, lowers the income disparity in Mexico. On the other hand, movement of workers from other sectors to manufacturing and industry in the top income quantiles, and to business and finance services in the upper middle income quantiles, appears to increase the income disparity in the US. Therefore, the type of services matters in explaining inequality dynamics—business services in a high income context and both business and non-business services in a middle income country context. The analysis suggests that we need to go beyond manufacturing in understanding the relevance of Kuznets in the twenty-first century.

Key words: Kuznets, structural transformation, manufacturing, services, inequality, Mexico, US

JEL classification: D31, O11, O57

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1 Introduction

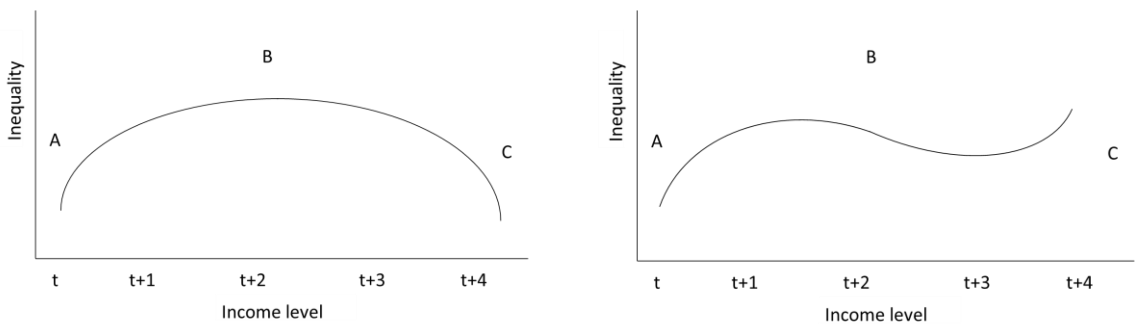
In 1955, in an influential study Kuznets (1955) predicted an inverted-U relationship between development through changes in the structure of production and inequality. The main aspects of structural transformation that Kuznets envisioned were a declining share of agriculture in total output, and migration from the low-income agricultural sector to the high-income industrial sector (Kuznets 1955) as depicted in Figure 1 (panel A). Though Kuznets used a two-sector formulation, he noted that 'several other conjectural conclusions could be drawn with additional variations in assumptions and multiplication of sectors beyond the two distinguished in the numerical illustration' (1955: 15).

We observe three distinguishing features of the process of structural transformation since the beginning of the second half of the 20th century. Firstly, many developed countries and an increasing number of developing countries witnessed a significant de-industrialization trend, and a hump-shaped nature of the manufacturing employment share, where the latter first increased with per capita income and then steadily fell after income crossed a certain threshold level (Fujiwara and Matsuyama 2020). Secondly, the service sector increasingly became an important provider of employment, with the employment share in services significantly exceeding that of manufacturing in most developed and developing countries by the 2010s (Sen 2023). Thirdly, within the services sector, there was a dual existence of high productivity financial and business services alongside a low productivity labour absorbing service sectors including wholesale and retail trade, hotels and restaurants, transportation, and the government sector (Rodrik and Sandhu 2024).

Figure 1: The Kuznets process

A. Inverted-U-shaped relationship

B. S-shaped relationship



Note: in panel a, at A, inequality is low as earnings are predominantly from agriculture. At B, inequality is high with structural transformation from agriculture to industry and growing earnings gap between agricultural and industry. At C, inequality is low when the economy fully transforms into an industrial economy.

Source: authors' illustration.

The increasing importance of services following the movement of workers *both* from agriculture and manufacturing to services suggests a more complex relationship between structural transformation and inequality than was conceived in the original Kuznets formulation. As such, an inverted U-shaped curve may no longer characterize the relationship between inequality and development, and one may postulate a different relationship such as a S-shape curve where inequality first decreases as the economy fully transforms into an industrial economy and increases again due to growing earnings gap within industrial economy (Figure 1, panel B). Extending the numerical example in Kuznets

(1955) from a two-sector to a three-sector framework, this complex process of changing income distribution can be explained by a widening per capita income differential between manufacturing, services, and agriculture, a rise in the relative weight of manufacturing and services in total employment in the economy, and the degree of inequality in the income distribution of manufacturing, services, and agricultural workers. This in turn would depend on which sector—manufacturing or services—workers from other sectors moved to, as well as which part of the income distribution the workers would be in after they move.

Early works on dual-sector models (Robinson 1976; Fields 1979; Anand and Kanbur 1993) explain the Kuznets motion in the presence of within-sector and between-sector inequality. For instance, the dual-sector (agriculture and non-agricultural) framework of Robinson (1976) analyses the Kuznets process in the presence of within-sector and between-sector income gap. Robinson's original work was based on the variance of log income, which was later extended by Anand and Kanbur (1993) to a range of inequality measures. However, these studies do not capture how movement of workers from one sector to another (i.e., the process of structural transformation) affects the change in income inequality over time. In this paper, we aim to address how the movement of workers into a particular sector (manufacturing versus services) affects the change in income over time at each quantile using census data from two countries: Mexico and the Unites States.

To assess the relationship between structural transformation and inequality, we use the well-known re-centered influence function (RIF) regression-based decomposition technique (Firpo et al 2009; Firpo et al 2018). The RIF decomposition method can produce decomposition results of the change in income into the change in the observable characteristics of income earners over time (the composition effect) and the change in the return to income when the observable characteristics remain unchanged over time (the structure effect) at each income quantile. As the RIF regression coefficients estimate only local approximations to the change in the distribution of workers across sectors, Firpo and Pinto (2016) approximate the counterfactual distributions and estimate the inequality treatment effects (ITEs) as long as the potential income is observed for each individual under the assumption of unconfoundedness (i.e., potential incomes are independent of the sectoral affiliation conditioned by observed characteristics) and overlapping support (i.e., comparable characteristics are observed for workers in different sectors) following the recent developments in parametric and nonparametric strategies to approximate the counterfactual distributions (Rothe 2010; Donald and Hsu 2014).

ITEs have been used in the empirical literature to assess the distributional outcomes of a given program intervention. Intuitively, ITEs estimate the changes in a range of inequality measures of the marginal distributions of the potential outcome of joining the program (receiving the treatment, based on observables) and not joining it (not receiving the treatment). Here, we use ITEs in an innovative way by assessing the potential outcome on income quantiles of a worker being 'selected' into manufacturing or services as compared to a worker who does not make such a move. By doing so, we can isolate the causal effect of the relocation of a worker into manufacturing or services on inequality, controlling for other covariates. Drawing upon a large census dataset consisting of more than 22 million individuals from Mexico and the United States, we estimate the ITE to examine the change in income inequality resulting from the ongoing process of structural transformation between 2000 and 2020.

There are four reasons why we chose to work with Mexico and the US. Firstly, Mexico and the US are at different stages of structural transformation, with a meagre 1.6 per cent of workers in agriculture in the US as compared to 19.2 per cent in Mexico in 2020, while the business services sector increasing in importance rapidly in US as compared to Mexico in the period of our study. Secondly, the Gini has fallen in Mexico over 2000–2020 as compared to an increase in the same measure for the US in the corresponding period. Therefore, both the process of structural transformation and evolution of inequality has differed across these two countries, which makes a comparison of Mexico and the US interesting from a Kuznetian perspective. Thirdly, both Mexico and the US are highly integrated with each other, both being members of the North American Free Trade Agreement (NAFTA), through movement of goods and services (labour intensive exports from Mexico to the US and capital-intensive exports from the US to Mexico). Finally, for both these countries, we have access to high quality unit record census data from IPUMS[1] for 2000 and 2020, which allows to maintain the same period of study for comparison.

The income inequality in Mexico decreases by almost six percentage points, from 0.49 in 2000 to 0.43 in 2020, whereas the income inequality slightly increases in the US by two percentage points from 0.49 in 2000 to 0.51 in 2020. In both countries, we find a larger contribution to aggregate income inequality coming from within-sector inequality compared to between-sector inequality. A lower income inequality in 2020 compared to 2000 in Mexico is likely to be associated with selection into manufacturing, mining, construction, and utilities in the middle income quantiles, business and finance services in the bottom quantiles in Mexico, and other services in the middle quantiles in Mexico. On the other hand, a higher income inequality in the US is associated with selection into manufacturing, mining, construction, and utilities at the top income quantiles, and business and finance services in the middle income quantiles. Therefore, the process of structural transformation has led to differing outcomes on inequality in Mexico and the US, with the movement of workers into the business services sector augmenting inequality in the US and into other services mitigating inequality in Mexico.

The rest of the paper is organized as follows. In section 2, we formulate our main idea using a multisectoral Kuznetsian framework to analyse the relationship between structural transformation and inequality. Section 3 provides a description of the empirical methodology. In Section 4, we describe the IPUMS data and the stylized facts on structural transformation and sectoral inequality in Mexico and the US. The key empirical findings are summarized in Section 5, followed by some concluding remarks in Section 6.

2 Conceptual framework

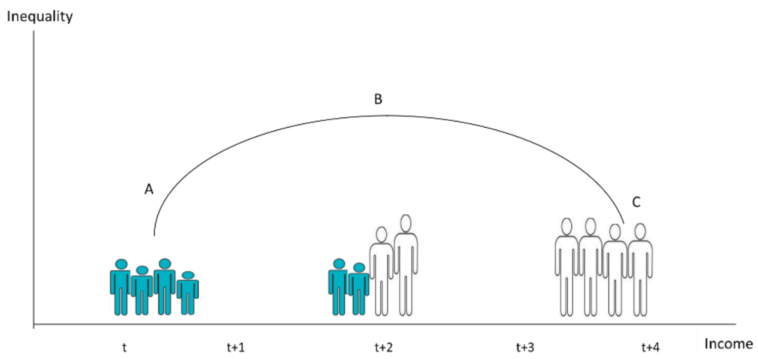
In an influential study, Kuznets (1955) predicted an inverted-U relationship between development through changes in the structure of production and inequality (Figure 2, panel A). The main aspects of structural transformation that Kuznets envisioned were a declining share of agriculture in total output, and migration of workers from the low-income agricultural sector to the high-income industrial sector. At point A, income inequality is low as earnings are predominantly from agriculture (workers in blue). As illustrated, the income gap is reflected through differences in the height of workers. At point B, inequality is high with structural transformation from agriculture to industry and growing earnings gap

[1] See **https://international.ipums.org/international/**.

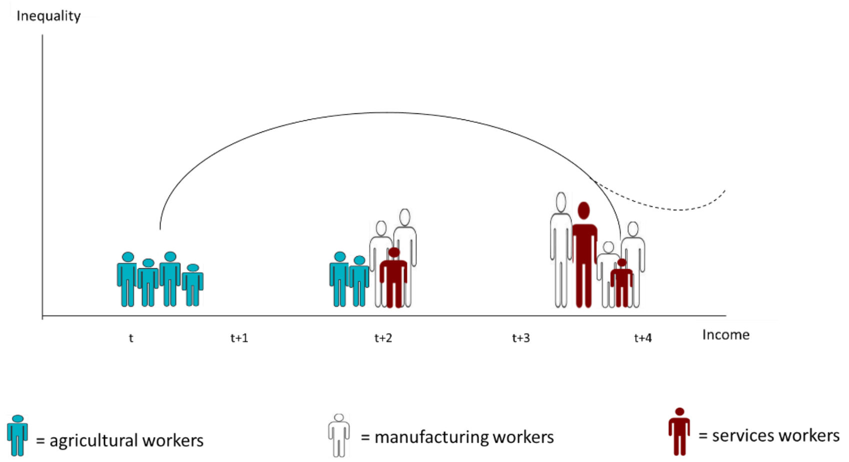
between agricultural (workers in blue) and industry (workers in white). Inequality is low again at point C, when the economy fully transforms into an industrial economy.[2]

Figure 2: The Kuznets curve

Panel A: Kuznets motion with agriculture and industry



Panel B: Kuznets motion with agriculture, manufacturing, and services



Source: authors' illustration.

In the original formulation of 'the Kuznets process', structural transformation was viewed as a movement of workers from agriculture to industry (Kuznets 1955), However, there were three distinguishing features of the process of structural transformation, beginning in the second half of the 20th century and intensifying in the 21st century, that suggested a more complex relationship between structural transformation and inequality than was conceived in the original Kuznets formulation. Firstly, many developed countries and an increasing number of developing countries witnessed a significant de-industrialization trend, and a hump-shaped nature of the manufacturing employment

[2] As Kuznets (1955: 18) noted, 'One might thus assume a long swing in the inequality characterizing the secular income structure: widening in the early phases of economic growth with the transition from pre-industrial to industrial civilization most rapid; becoming stabilized for a while, and then narrowing in the later phases'.

share, where the latter first increased with per capita income and then steadily fell after income crossed a certain threshold level (Fujiwara and Matsuyama 2020, Huneeus and Rogerson 2020, Sposi et al. 2021). In the case of several developing countries, the threshold level of income was significantly lower that observed earlier for the rich countries, leading to the phenomenon of 'premature de-industrialization' (Tregenna 2014, Rodrik 2016).

Secondly, the service sector increasingly became an important provider of employment, with the employment share in services significantly exceeding that of manufacturing in most developed and developing countries by the 2010s (Sen 2023). The increase in the relative importance of the services sector vis-à-vis the manufacturing sector could be attributed to the differentials in productivity growth rates between manufacturing and services (Huneeus and Rogerson 2020) along with a higher demand for services such as tourism and restaurant meals with increases in income (Nayyar et al. 2021).[3] Therefore, instead of the movement of workers from agriculture to manufacturing that was observed in the earlier stages of economic development, one saw a movement of workers *both* from agriculture and manufacturing to services.

Thirdly, within the services sector, there was a dual existence of high productivity modern financial and business services (a large component of which was tradable) along with a mostly non-tradable low productivity labour absorbing highly heterogenous service sectors such as trade, hotels and restaurants, transportation and the government sector (Rodrik and Sandhu 2024). In the richer economies, the financial and business services sector became increasingly important in total employment and value-added, while in the poorer economies, much of the growth in services employment occurred in the non-tradable non-business service sectors (Duarte and Restuccia 2020, Sen 2023). This implied that with the growth of the services sector in both developed and developing countries, both between-sector and within-sector inequality may have increased over time. Consequently, an inverted U-shaped curve may no longer characterize the relationship between inequality and development, and one may postulate a different relationship such as a S-shape curve as depicted in Figure 2, panel B.[4]

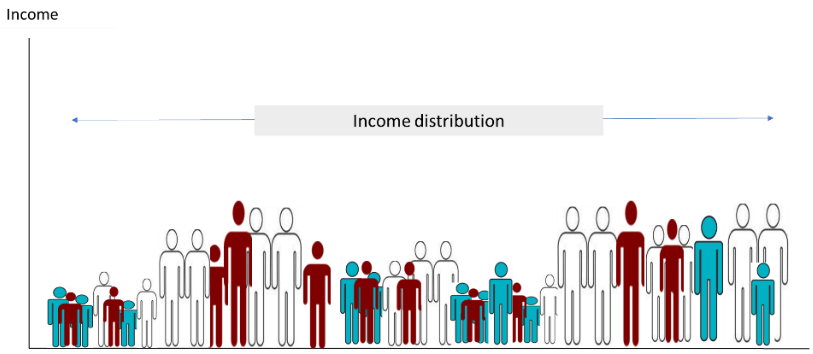
In summary, the increasing importance of services in the process of structural transformation in the second half of the 20th century, along with the unequal nature of incomes in the services sector suggests a more complex relation between structural transformation and inequality since the late 20th century and into the 21st century.

[3] As argued by Gollin (2018), the modern services sector had some of the features of manufacturing such as knowledge spillovers and agglomeration economies, and increasingly became the driver of structural transformation in many advanced and emerging economies rather than manufacturing (Baldwin and Forslid 2019).

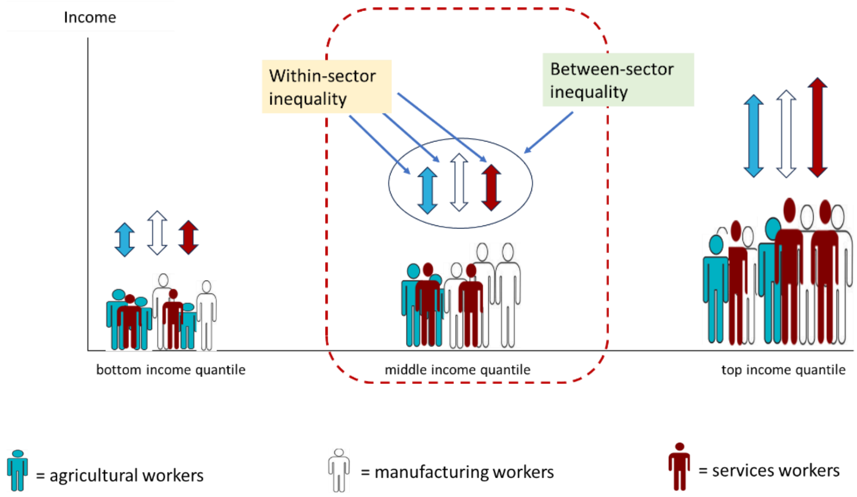
[4] In a related study, Paul (2018) using a growth incidence curve framework shows that alternate time periods of positive and negative growth incidence can produce similar S-shape curve.

Figure 3: Income distribution in period t+2

Panel A. Income distribution



Panel B. Income distribution, by income quantile



Source: authors' illustration.

It helps to understand the change in inequality in relation to a growing complexity in the process of structural transformation if we focus on the income distribution in a particular year, say period *t+2* (Figure 3, panel A). We continue with our model economy structured around three broad sectors: agriculture (workers in blue), manufacturing (workers in white), and services (works in brown). In panel B, we arrange them across three income quantiles: the bottom income quantile, the middle income quantile, and the top income quantile. The vertical arrows in each income quantile depicts the level of income inequality within each sector, also known as within-sector inequality. For instance, the inequality among workers in manufacturing is the largest in the bottom quantile, whereas it is the largest among workers in services sector in the top income quantile. On the other hand, the inequality across these sectors within each quantile can be termed as between-sector inequality. As depicted in the diagram (Figure 3, panel B), the overall inequality can then be approximated by the sum of within- and between-sector inequality in each quantile. How inequality will evolve from time period t to t+2 would depend on how within- and between-sector inequality changed in each quantile.

Early works on dual-sector models (Robinson 1976; Fields 1979; Anand and Kanbur 1993) explain the Kuznets motion in the presence of within-sector and between-sector inequality. For instance, the dual-sector (agriculture and non-agricultural) framework of Robinson (1976) analyses the Kuznets process in the presence of within-sector and between-sector income gap. Robinson's original work was based on the variance of log income, which was later extended by Anand and Kanbur (1993) to a range of inequality measures. However, these studies do not capture how movement of workers from one sector to another (i.e., the process of structural transformation) affects the change in income inequality over time. As shown by Kuznets (1955), through the help of a numerical example, changes in the income distribution would depend on a) whether per capita income differentials widen between manufacturing, services and agriculture, b) the rise over time in the relative weight of manufacturing and services in total employment in the economy, and c) the degree of inequality in the income distribution of manufacturing, services and agricultural workers.[5] This in turn would depend on which sector—manufacturing or services—workers from other sectors moved to, as well as which part of the income distribution the workers would be located in after they move.

In this paper, we aim to address how the movement of workers into a particular sector (manufacturing versus services) affects the change in income over time at each quantile using census data from two countries: Mexico and the Unites States. Before we describe the data and the empirical findings, we briefly discuss the empirical framework in the following section.

3 Empirical framework

To answer the question: how relocation of workers from one sector to another at each quantile affects the change in income over time, we have to overcome two challenges. First, we do not track workers over time (that is, we do not have panel data), which makes it difficult to trace workers moving from one sector to another over time. Second, the standard empirical frameworks based on unconditional estimation of the change in income at each quantile only provides the local effect of the change in the distribution of explanatory variables (Essama-Nssah and Lambert 2012). For instance, in the current context, the standard re-centered influence function (RIF) regression framework is incapable to estimate large changes in the distribution of manufacturing workers across income quantiles. We overcome both constraints following nonparametric strategies (Rothe 2010; Donald and Hsu 2014; Firpo and Pinto 2016) to create a counterfactual distribution of workers who are not observed in each period based on a re-weighting method. We then estimate the inequality treatment effects (ITE) using the re-weighted data of the treatment, i.e., selection of workers into a sector (e.g., manufacturing). Finally, the inequality treatment effect at each income quantile is achieved through the re-centered influence function (RIF) regression framework (Firpo 2007). Below, we provide an exposition of the RIF-based methodology that we use estimate the ITEs.

[5] Though Kuznets used a two sector formulation in his numerical example in the 1955 paper, he recognized that the example could be extended to more than two sectors—as he noted, 'several other conjectural conclusions could be drawn with additional variations in assumptions and multiplication of sectors beyond the two distinguished in the numerical illustration' (1955: 15).

3.1 Distributional statistics using RIF

Define a functional $h(.)$ that can be used to estimate any distributional statistics (mean, Gini, etc) of the log income (y) drawn from a finite sample of n individuals $Y = [y_1, y_2, \dots y_n]$ with F_y and f_y as the cumulative and probability density function of Y, respectively. Assume that the change in the distribution of services employment causes F_y to change to G_y, the ex-post distribution of Y with same properties as F_y. Then, the change in the distributional statistic can be summarized as

$$\Delta h = h(G_Y) - h(F_Y). \tag{1}$$

For unconditional estimation of the distributional statistic, we rely on *influence function* (IF) - a widely used tool for assessing the robustness of estimation methods in statistics.

The IF is a directional derivative showing the rate of change in $h(.)$ caused by a small change $(0 < \varepsilon < 1)$ in F_y in the direction of K_{y_i}, as follows:

$$IF\{y_i;\ h(F_Y)\} = \frac{\partial h\ (F_y \overset{\Delta}{\rightarrow} K_{y_i})}{\partial \varepsilon}, \tag{2}$$

where G_Y can be redefined as a combination of the distributions F_Y and K_{y_i}, as follows: $G_Y = (1 - \emptyset)F_Y + \ \emptyset K_{y_i}; 0 < \emptyset < 1$. Firpo et al (2009) define the (RIF) as the leading terms of a von Mises (1947) linear approximation of the associated functional. Given that the expected value of the influence function is equal to zero, the expected value of the RIF equals to the corresponding distributional statistic:

$$RIF\{y_i;\ h(F_Y)\} = h(F_Y) + IF\{y_i;\ h(F_Y)\} \tag{3}$$

Following Firpo et al (2009), we apply RIF to approximate Δh, i.e., the change in the unconditional distribution of any statistic of Y (log income) as unconditional partial effects resulting from small changes in the distribution of employment in services:

$$\Delta h = \int (RIF\{y_i;\ h(F_Y)\}|X = x)\, d(G_X - F_X)(X) \tag{4}$$

For example, $RIF\big(y;\ q_p\big) = \ \beta_0 + \beta_1 Manufacturing + \beta_2 Services + X'\gamma + \varepsilon$, where the unconditional or marginal quantile $q_p = \int (RIF\{y_i;\ h(F_Y)\}|X = x)\, d(G_X - F_X)(X)$. The main advantage of RIF-regression is that it allows for estimation of the partial effects at any unconditional quantile of the outcome variable and it has been applied to examine the change in the growth incidence curve over time (Essama-Nssah, Paul, and Bassole 2013).

3.2 Inequality treatment effects (ITE)

By construction, the RIF regressions can only estimate the local effect, i.e., RIF regression coefficients estimate only local approximations to the change in the distribution of employment in manufacturing and services. Parametric and nonparametric strategies (Rothe 2010; Donald and Hsu 2014; Firpo and Pinto 2016) have been developed to approximate the counterfactual distributions and estimate inequality treatment effects (ITE) using RIF regressions. If potential outcomes can be observed for every firm, then following Firpo and Pinto (2016), ITE can be defined as

$$\Delta h = h(\theta_{Y_1}) - h(\theta_{Y_0}), \tag{5}$$

where θ_{Y_0}captures the relationship between potential outcomes Y_0 and Y_1, a set of explanatory factors X, and a binary treatment T. Assuming unconfoundedness (i.e., potential outcomes are independent of the treatment conditioned by observed characteristics) and overlapping support (i.e., comparable characteristics are observed in treated and control groups), the overall treatment effect can be written as

$$\Delta\hat{h} = \left(\int \left(RIF\{y;\ h(\hat{\theta}_{Y_1})\}\middle| X = x\right) \widehat{w}_1(X) d\left(\theta_{X|T=1}\right)(X)\right) - h\left(\int \left(RIF\{y;\ h(\hat{\theta}_{Y_1})\}\middle| X = x\right) \widehat{w}_0(X) d\left(\theta_{X|T=0}\right)(X)\right), \tag{6}$$

where $\widehat{w}_1$ and $\widehat{w}_1$ are reweighting factors defined as $w_k = \frac{P(T=k)}{P(T = k|X = x)}$. The RIF regressions allow us to observe the change in the distribution of independent variables by including them as controls in the model.

4 Data and stylized facts

The empirical evidence in this paper is drawn based on the IPUMS data Ruggles et al. (2023a, 2023b). We compare the change in income inequality over time between Mexico and the United States. Census data is available for both countries for multiple years covering a long period of time starting in the 1960.[6] Prior to 1990, the IPUMS data suffer from measurement problems and comparability issues across countries. Due to the Peso crisis in the early 1990s in Mexico, we also drop the year 1990 and consider post-1990 rounds. In 2010, the US census data was less than 20 per cent of the average sample size across other census rounds. To avoid any comparability issues, we also drop 2010 round for both years. This leaves us with the choice of comparing the change in income inequality between 2000 and 2020, i.e., over a period of 20 years.

[6] See: **https://www.ipums.org/**. The original producers of the data are the National Institute of Statistics, Geography, and Informatics (Mexico) and the Bureau of the Census (United States).

Table 1: Sectoral employment shares, Mexico versus the United States

	Mexico		United States	
	2000	2020	2000	2020
Observations	**2,734,299**	**4,804,116**	**7,401,156**	**7,986,142**
Sectoral share				
Agriculture	15.69	19.24	2.80	1.62
Manufacturing	19.28	14.79	14.91	9.93
Mining, Construction and Utilities	10.25	11.06	8.40	7.68
Business and Finance	4.62	5.05	11.70	15.23
Other Services	50.18	49.86	62.19	65.54

Note: agriculture includes agricultural activities, fisheries, forestry, and mining. Manufacturing includes all manufacturing activities, construction, and utilities.

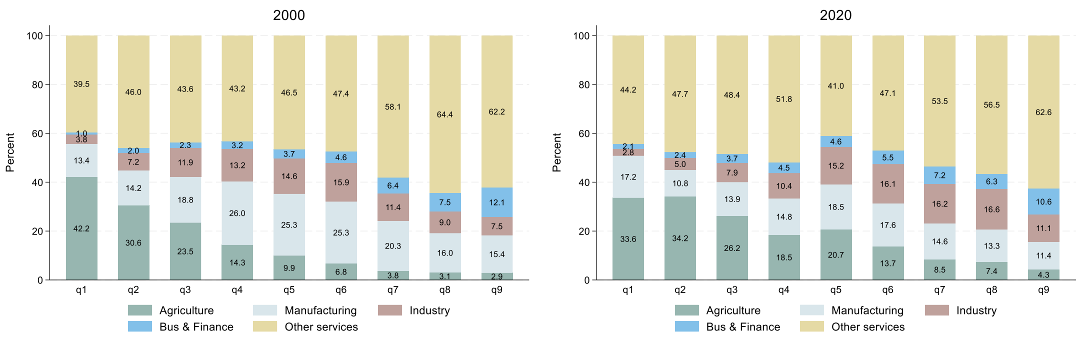
Source: authors' estimates based on the IPUMS data.

As reported in Table 1, the observations for Mexico in 2000 and 2020 are 2.7 and 4.8 million, respectively. The sample size for the US is over 7.4 million in 2000 and 7.9 million in 2020. Table 1 presents the distribution of working population across sectors. We observe very different processes of structural transformation between Mexico and the US. We first consider Mexico. In 2000, nearly 16 per cent of the working population was in agriculture, and it increased to 19 per cent in 2020. The share of manufacturing dropped from 19.3 per cent in 2000 to nearly 15 per cent in 2020, reflecting the phenomenon of 'premature de-industrialization' (Rodrik 2016). On the other hand, the share of services sector (business and finance, and other sector) remains roughly at 55 per cent throughout the period (with the employment share of business services a paltry 5 per cent in 2020), suggesting an unusual reverse process of structural transformation from primarily manufacturing to agriculture.

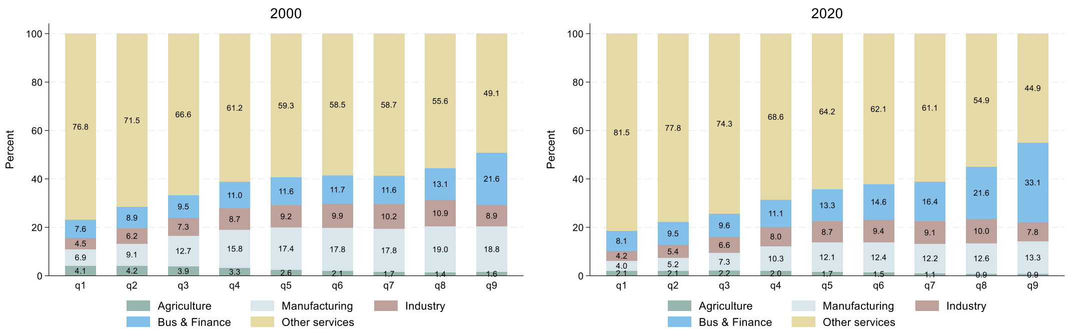
Turning to the US, the employment share in agriculture remains negligible around 2 per cent over the period. While we observe a similar drop in the share of manufacturing from 15 per cent in 2000 to 10 per cent in 2020 (though at much higher levels of per capita income than Mexico), it is primarily the share of services sector that gained. The share of employment in business and finance increased from 11.7 per cent in 2000 to 15 per cent in 2020, where the share of other services also increased by roughly 3 percentage points from 62 per cent in 2000. Therefore, as noted in Section II, business and financial services played a much more important role in employment creation for a high income economy such as the US as compared to Mexico. Overall, the process of structural transformation in the US suggests dominance of services, reaching nearly 8 per cent in 2020, at the cost of manufacturing. The differences in the process of structural transformation between Mexico and the US makes the comparison of the change in income inequality more interesting.

Figure 3: Employment shares by income quantile, Mexico versus the United States

A. Mexico



B. United States



Note: agriculture includes agricultural activities, fisheries, and forestry. Manufacturing includes all manufacturing activities, Industry includes mining, construction, and utilities.

Source: authors' estimates based on the IPUMS data.

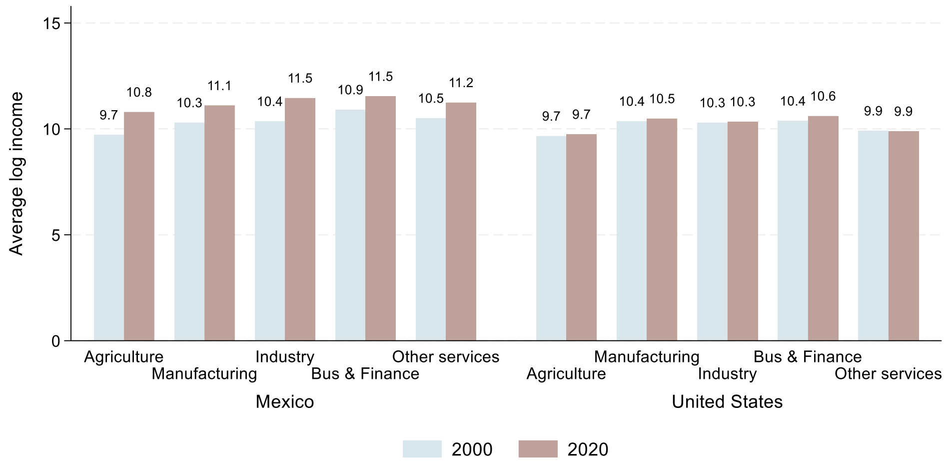
Figure 3 presents the sectoral employment shares by income quantiles for Mexico (panel A), and the United States (panel B). We first discuss Mexico's case. In 2000, agriculture dominated the distribution of employment in the bottom three income quantiles, employment in manufacturing and industry was more prevalent in the middle three income quantiles, whereas employment in services sectors largely concentrated in the top three income quantiles. In 2020, employment in agriculture became more evenly spread in the bottom five income quantiles. The employment share in manufacturing and industry increased in the top four income quantiles at the cost of a decline in employment share in services sectors. This suggests that much of the concentration of income was in the manufacturing and industry over time, as compared to the business services and other services sectors.

The change in the distribution of sectoral employment across income quantiles appears to follow a different process in the United States. The share of agriculture and industry remain within 10 per cent in both periods. We observe a drop in the share of manufacturing and other services in each income quantile. The drop in the manufacturing employment share is on average between one to two percentage points across income quantiles. However, the largest loss in employment share was in other services and the biggest gainer of employment share was business and finance. Especially in the top three income quantiles, the gain in employment share in business and finance was on average seven to nine percentage points.

The composition of employment in services starkly differs between Mexico and the United States. In Mexico, the total employment share increases with movement from a lower to a higher income quantile, which remains almost constant across income quantiles at around 80 per cent in the United States. However, the employment share in business and finance becomes larger with movement from a lower income quantile to a higher income quantile in the US, which appears less prominent for Mexico. These differences within services sector and concentration of agriculture in the bottom income quantiles highlights the differences in the pattern of structural transformation in these two countries. While the process of structural transformation affects the sectoral distribution of employment at each income quantile, its consequences on income distribution depends on the change in both within-sector and between-sector inequality at each income quantile as depicted in Figure 2.

We next compare the average real income over time. Since the IPUMS income data is available in local currencies (current prices), we convert the US income data using the variable **CPI99**, which provides an easy way to adjust dollar amounts to constant 2010 US dollars.[7] We use the Mexican Peso to the US dollar conversion rate to change the income figures for Mexico into 2010 US dollars. After converting the income figures into constant terms, the average log income in 2000 in Mexico and the US becomes 10.35 and 10.05, respectively (Figure 4). In 2020, the average log income for Mexico increases to 11.18, whereas it remains almost at the same level (10.07) in the US. Since our goal is to compare the statistics within countries over time, these statistics do not pose any threat to our main conclusions.

Figure 4: Average sectoral income, Mexico versus the United States



Note: agriculture includes agricultural activities, fisheries, and forestry. Manufacturing includes all manufacturing activities, Industry includes mining, construction, and utilities.

Source: authors' estimates based on the IPUMS data.

[7] See **IPUMS USA** for more information, **https://usa.ipums.org/usa/cpi99.shtml**.

In 2000, the average income in Mexico was highest in business and finance, followed by other services, industry, manufacturing and then agriculture. This sectoral ranking based on the average income remained the same in 2020. In the US, we observe a slightly different trend. The average income is the highest in manufacturing and business and finance, followed by other services, industry, and agriculture. The intersectoral income gap is lower in the US compared to Mexico, which suggests that any movement of workers from one sector to another is likely to have a smaller effect on the change in inequality in the US compared to Mexico.

As a final step, in Table 2, we compare the Gini coefficient of income inequality in Mexico and the US. The income inequality in Mexico decreases by almost six percentage points, from 0.49 in 2000 to 0.43 in 2020, whereas the income inequality slightly increases in the US by two percentage points from 0.49 in 2000 to 0.51 in 2020. We next analyse how this divergence in the pattern of the change in aggregate income inequality is associated with sectoral income equality trends over time.

Table 2: The Gini coefficient of income, Mexico versus the United States

	Mexico		US	
	2000	2020	2000	2020
Agriculture	0.47	0.38	0.54	0.53
Manufacturing	0.46	0.44	0.43	0.44
Mining, Construction and Utilities	0.49	0.36	0.43	0.44
Business and Finance	0.52	0.47	0.52	0.50
Other Services	0.43	0.39	0.50	0.51
All sectors	**0.49**	**0.43**	**0.49**	**0.51**
Between-sector	0.21	0.18	0.20	0.21
Within-sector	0.28	0.25	0.29	0.30

Note: agriculture includes agricultural activities, fisheries, forestry, and mining. Manufacturing includes all manufacturing activities, construction, and utilities.

Source: authors' estimates based on the IPUMS data.

In Mexico, we observe a drop in income inequality in each sector. Between 2000 and 2020, the Gini coefficient of income lowers by 9 percentage points in agriculture, by only two percentage points in manufacturing, by almost 13 percentage points in mining, construction, and utilities, and on average by roughly 4.5 percentage points across services sectors. Due to dominance of services sectors in total employment, the change in income inequality at the aggregate level is like that in services. It is noteworthy to mention, between-sector and within-sector inequality also lowers in Mexico. While within-sector inequality plays a dominant role in both periods, the Gini coefficient for it drops from 0.28 to 0.25, and we observe a similar drop by three percentage points from 0.21 for between-sector inequality.

In the US, the sectoral patterns of the change in inequality suggest a rather diverse picture. The Gini coefficient of income has dropped in agriculture by one percentage point and in business and finance by two percentage points, whereas in other sectors it has increased by one percentage point each. As almost 65 per cent of workers are employed in other services, the direction of the change in aggregate income inequality closely corresponds to that in other services. It is interesting to note that both within-sector and between sector component equally share the burden of the increase in inequality in the US between 2000 and 2020. In both countries, we find a larger contribution to aggregate income inequality coming from within-sector inequality compared to between-sector inequality.

A comparison of the descriptive evidence in this section sets the stage for an in-depth analysis of the link between movement of workers between sectors and the change in income inequality at different quantiles on income. We analyse the empirical outcomes of RIF-based estimation of ITE in the following section.

5 Empirical outcomes

We first present the RIF regression outcomes for different income quantiles and income inequality measures. We estimate $RIF(y;\ q_p) = \beta_0 + Sector'\beta + X'\gamma + \varepsilon$, where β represents the vector of coefficients for four sectors (manufacturing, industry, business and finance, and other services) and γ represents the vector of coefficients for control variables (gender, dummy variables for marital status, education qualification, and occupation). See appendix Table A1 for summary statistics for these variables.

The RIF regression outcomes for Mexico are presented in Table A2 (year 2000) and Table A3 (year 2020). The first three columns show the outcomes for 10^{th}, 50^{th} and 90^{th} quantile of incomes. The last three columns show the outcomes for three inequality measures, the variance, interquartile range (90-10 IQR) and the Gini coefficient of income. We focus on the estimated coefficients of the sectors of employment (agriculture is the omitted category). The coefficient of employment in all sectors (compared to agriculture) suggest a positive association with the income level at the 10^{th}, and the 50^{th} quantiles of income, however for the 90^{th} quantile the correlation is positive only for the services sectors. The outcomes in 2020 reveal different degree of association between sectoral affiliation and income. For instance, the returns (income) to all sectors are almost five times larger at the 10^{th} quantile in compared to 2000. The results are comparable in both rounds for the 50^{th} quantile, whereas the association between income and sectoral participation becomes positive and statistically significant for all sectors in the 90^{th} quantile.

The above findings suggest that movement of workers between sectors at each income quantile could possibly lead to a different set of effects on income distribution. To understand the net effect on income inequality we next analyse the outcomes for inequality measures. We observe that an increase in the participation in manufacturing and industry produces dampening effects on the income inequality in both periods. However, an increase in employment in the services sectors has the dampening effect only in 2020, but not in 2000. In terms of the sign, the results are robust across different measures of income inequality. The magnitude of the negative correlation is lower for the variance and the IQR compared to the Gini coefficient of income.

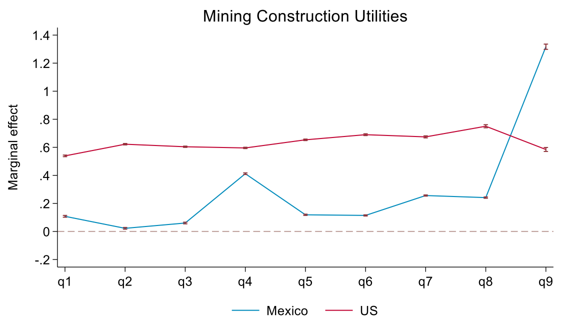
A higher return to manufacturing and services at the 10^{th} quantile compared to the 90^{th} quantile in 2020 (compared to 2000) is one possible reason why the inequality measures accompany a larger drop in 2020 compared to 2000. As the Gini coefficient is more sensitive to the change in the middle of the distribution, it could be the reason why the effect of the higher returns to these sectors at the 10^{th} quantile does not corresponds to an even larger drop in the Gini coefficient between 2000 and 2020. These outcomes resonate with the summary statistics on the Gini coefficient presented in Table 2 for Mexico, which shows the positive association between the change in the within-sector Gini and the overall Gini coefficient of income between 2000 and 2020.

In Table A3 and A4, we present the RIF regression outcomes for the same set of dependent variables for the US. Unlike Mexico, participation in both manufacturing and services are positively correlated with the income level at different quantiles of income in both years in the US. In 2000, the return to other services is lower compared to returns to other sectors, and this gap widens in 2020. However, the gap in returns across income quantiles is comparable for most of the sectors. Turning to the inequality measures, participation in all sectors is associated with a lower income inequality in 2000. The results are less robust in 2020. Participation in business and finance and other sectors is in fact associated with a higher inequality when measured using the IQR; for the variance and the Gini coefficient, the results still suggest a dampening effect on inequality in 2020.

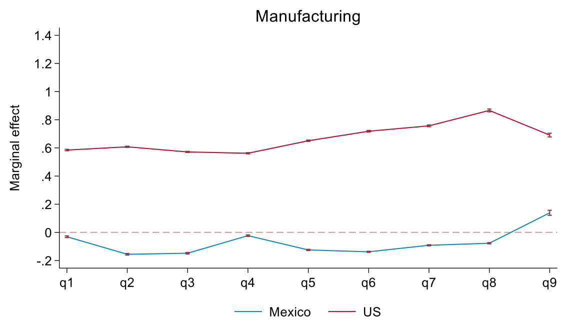
Between 2000 and 2020, inequality decreased in Mexico, but it increased in the US. Armed with the RIF regression outcomes discussed above, we next analyse how the inequality treatment effects (ITE) help understand these outcomes based on the returns to sectoral participation at different income quantiles. The panel A and B of Figure 5 presents the outcomes for industry (mining, construction, and utilities) and manufacturing, respectively. The magnitude of the ITE for industry is positive across all income quantiles for both countries. The return to industry is higher in the US compared to Mexico in across all income quantiles except the 90th income quantile. It is important to note that at the 40th income quantile, the gap in returns to industry between Mexico and the US becomes the smallest. Turning to manufacturing, we observe similar outcomes for the US (Panel B). However, the return to manufacturing is negative across all income quantiles except the 90th income quantile in the case of Mexico. The ITE outcomes on industry suggests that the industrial non-manufacturing sector produces an upward thrust to the change in income inequality in both countries. In contrast, manufacturing contributes to an increase in inequality in the US but a decline in inequality in Mexico (except the 90th quantile, where the effect is positive).

Figure 5: Inequality treatment effect: industry and manufacturing, Mexico versus US

A.



B.



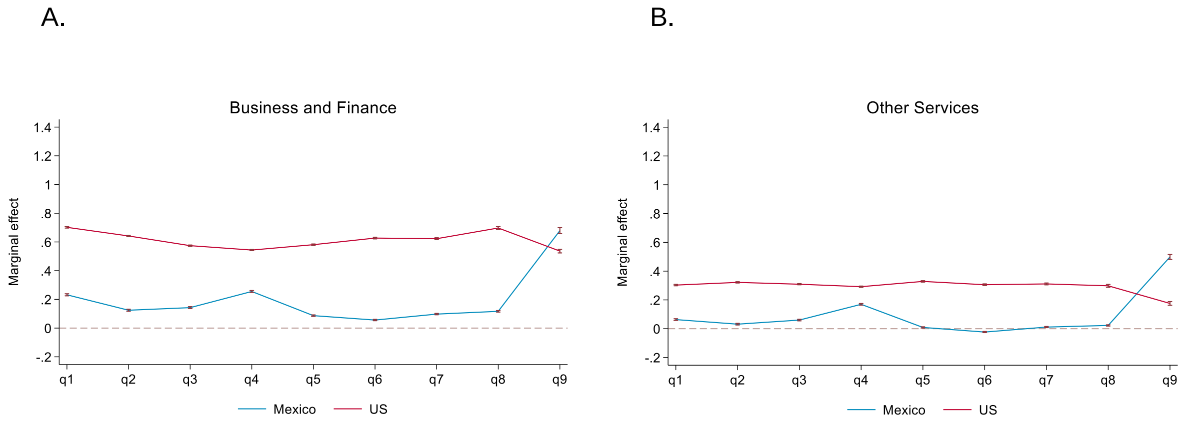
Note: manufacturing includes all manufacturing activities; industry includes mining, construction, and utilities.

Source: authors' estimates based on the IPUMS data.

The ITE outcomes for business and finance suggest positive returns across the income quantiles for both countries (Figure 6, panel A). For the bottom four income quantiles, the average return to participation in business and finance for Mexico averages around 0.2, whereas it remains almost three times larger for the US. For the next four income quantiles up to the 80th, the gap in returns widens as the returns fall to 0.1 for Mexico. The result is strikingly opposite for the 90th quantile, with a return for Mexico compared to the US. On the other hand, the average return to other services in

Mexico is negligible except for the 10th, the 40th and the 90th income quantile (Figure 6, panel B). The same for the US stays around 0.3 for the entire distribution.

Figure 6: Inequality treatment effect: business, finance, and other services, Mexico versus US



Source: authors' estimates based on the IPUMS data.

We summarize the key takeaways from the ITE outcomes. A lower income inequality in 2020 compared to 2000 in Mexico is likely to be associated with selection into manufacturing, mining, construction, and utilities in the middle income quantiles, business and finance services in the bottom quantiles in Mexico, and other services in the middle quantiles in Mexico. In other words, movement of workers from other sectors to manufacturing and industry in the bottom income quantiles, and movement of workers from other sectors to business and non-business services in the bottom and the middle income quantiles appears to lower the disparity in income between 2000 and 2020. On the other hand, a higher income inequality in the US is associated with selection into manufacturing, mining, construction, and utilities at the top income quantiles, and business and finance services in the middle income quantiles. To put it differently, movement of workers from other sectors to manufacturing and industry in the top income quantiles, and movement of workers from other sectors to business and finance services in the upper middle income quantiles appears to increase the disparity in income between 2000 and 2020 in the US.

As depicted in Figure 3, we indeed observe a greater concentration of the share of employment in industry and business and finance in the middle income quantiles, and the share of employment in other services in the bottom and middle income quantiles in 2020 compared to 2000 in Mexico. Similarly, in the US, the share of employment in business and finance becomes more concentrated in the upper middle income quantiles in 2020 compared to 2000.

Overall, our results suggest that differences in the process of structural transformation in Mexico and the US—a greater increase in business services along with the concentration of workers in this sector in the higher income quantiles in the US, and the increasing concentration of business and non-business services in the lower income quantiles in Mexico, can explain the evolution of income inequality in Mexico and the US, over 2000–2020. Therefore, the Kuznetian proposition of changes in income inequality with structural transformation applies more to services than to manufacturing in these two countries in the twenty-first century (see also Baymul and Sen 2020).

6 Conclusion

Inequality persists, and so does a global concern over it. The inverted-U relationship between inequality and development through the process of structural transformation has been under the lens of researchers since the influential study by Kuznets (1955). As the second half of the 20th century marked the global slowdown in the pace of industrialization, and services became the primary destination for labour and capital flow, this study revisits the Kuznets paradigm in light of a multisectoral framework. Using a simple conceptual framework, we postulate that the change in income inequality between two points in time can be understood from the movement of workers from one sector to another at each quantile of the income distribution.

Empirical evidence is drawn using a large census dataset consisting of more than 22 million individuals from Mexico and the United States for two periods: 2000 and 2020. The Gini coefficient of income in Mexico decreases from 0.49 in 2000 to 0.43 in 2020, whereas it slightly increases in the US from 0.49 in 2000 to 0.51 in 2020. Using the RIF decomposition approach to isolate the causal effect of structural transformation (that is, the movement of workers into manufacturing and services) on income inequality, we find that movement of workers from other sectors to manufacturing and industry in the bottom income quantiles, and to services in the middle income quantiles, lowers the income disparity in Mexico. On the other hand, movement of workers from other sectors to manufacturing and industry in the top income quantiles, and to business and finance services in the upper middle income quantiles, appears to increase the income disparity in the US.

The positive relationship between structural transformation and inequality that was postulated by Kuznets in his landmark 1955 article still seems to hold with more recent data from the 2000s. However, unlike in the previous Kuznets case, where industrialization was the main driver of changes in inequality, here we find that services is playing an increasingly important role in the evolution of inequality both in a developed and developing country context. We also find the type of services also matters in explaining inequality dynamics—business services in a high income context and both business and non-business services in a middle income country context. Our paper suggests that we need to go beyond manufacturing in understanding the relevance of Kuznets in the twenty-first century.

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Appendix tables

Table A1: Summary statistics

	Mexico		United States	
	2000	**2020**	**2000**	**2020**
Female	0.310	0.343	0.470	0.479
Married	0.626	0.641	0.580	0.542
Primary education	0.748	0.652	0.131	0.072
Secondary education	0.152	0.225	0.626	0.571
Higher education	0.101	0.123	0.243	0.357
Managers	0.030	0.017	0.086	0.079
Professionals	0.084	0.091	0.182	0.234
Technicians	0.029	0.043	0.064	0.089
Clerks	0.064	0.044	0.072	0.076
Service	0.247	0.194	0.327	0.277
Agricultural workers	0.154	0.170	0.010	0.008
Craftsmen	0.170	0.153	0.058	0.047
Operators	0.050	0.087	0.132	0.087
Other services	0.121	0.187	0.069	0.077

Source: authors’ estimates based on the IPUMS data.

Table A2: RIF regression outcomes for Mexico—2000

2000	Quantile 10	Quantile 50	Quantile 90	Variance	IQR 10/ 90	Gini
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Log age	-0.057***	0.156***	0.632***	0.569***	0.077***	1.198***
	(0.003)	(0.001)	(0.007)	(0.010)	(0.001)	(0.016)
Female	-0.523***	-0.240***	-0.116***	0.857***	0.060***	1.643***
	(0.002)	(0.001)	(0.006)	(0.008)	(0.001)	(0.013)
Married	0.135***	0.174***	-0.263***	-0.691***	-0.048***	-1.044***
	(0.002)	(0.001)	(0.006)	(0.008)	(0.001)	(0.012)
Secondary education	0.342***	0.425***	0.759***	0.101***	0.035***	0.332***
	(0.002)	(0.001)	(0.008)	(0.010)	(0.001)	(0.015)
Higher education	0.358***	0.622***	2.800***	0.591***	0.256***	2.179***
	(0.002)	(0.002)	(0.014)	(0.015)	(0.002)	(0.022)
Manufacturing	0.146***	0.142***	-0.048***	-0.353***	-0.026***	-0.592***
	(0.009)	(0.004)	(0.018)	(0.025)	(0.002)	(0.039)
Industry	0.322***	0.131***	-0.244***	-0.759***	-0.072***	-1.518***
	(0.009)	(0.004)	(0.018)	(0.025)	(0.002)	(0.040)
Business and finance	0.312***	0.266***	0.884***	0.177***	0.053***	0.243***
	(0.009)	(0.004)	(0.022)	(0.028)	(0.003)	(0.044)
Other services	0.254***	0.256***	0.343***	0.223***	0.002	0.150***
	(0.009)	(0.004)	(0.018)	(0.025)	(0.002)	(0.039)
Managers	0.042***	0.249***	2.546***	0.709***	0.272***	2.271***
	(0.002)	(0.002)	(0.023)	(0.024)	(0.003)	(0.037)
Professionals	0.018***	0.107***	-1.222***	-1.844***	-0.136***	-2.498***
	(0.003)	(0.002)	(0.016)	(0.017)	(0.002)	(0.026)
Technicians	0.049***	0.139***	-1.508***	-2.252***	-0.172***	-3.268***
	(0.004)	(0.003)	(0.015)	(0.017)	(0.002)	(0.026)
Clerks	0.249***	0.026***	-1.654***	-2.595***	-0.215***	-4.287***
	(0.003)	(0.002)	(0.011)	(0.014)	(0.001)	(0.022)
Service workers	-0.391***	-0.302***	-0.877***	-1.327***	-0.041***	-1.546***

	(0.003)	(0.002)	(0.009)	(0.012)	(0.001)	(0.019)
Agricultural workers	-0.931***	-0.496***	-0.717***	-0.194***	0.051***	0.634***
	(0.009)	(0.004)	(0.018)	(0.025)	(0.002)	(0.040)
Craftsmen	-0.210***	-0.075***	-0.750***	-0.837***	-0.053***	-1.068***
	(0.003)	(0.002)	(0.008)	(0.011)	(0.001)	(0.017)
Operators	0.382***	0.029***	-0.923***	-1.800***	-0.154***	-3.292***
	(0.003)	(0.003)	(0.010)	(0.014)	(0.001)	(0.022)
Constant	9.370***	9.367***	9.766***	1.163***	1.037***	3.778***
	(0.014)	(0.006)	(0.028)	(0.041)	(0.003)	(0.065)
Observations	2,818,999	2,818,999	2,818,999	2,818,999	2,818,999	2,818,999
R-squared	0.105	0.247	0.095	0.032	0.071	0.048

Note: robust standard errors within parentheses (0.01 = ***, 0.05 = **; 0.10 = *)

Source: authors' estimates based on the IPUMS data.

Table A3: RIF regression outcomes for Mexico—2020

2020	**Quantile 10**	**Quantile 50**	**Quantile 90**	**Variance**	**IQR 10/ 90**	**Gini**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Log age	-0.250***	0.015***	0.310***	0.354***	0.060***	0.872***
	(0.007)	(0.001)	(0.002)	(0.004)	(0.001)	(0.007)
Female	-1.532***	-0.154***	-0.258***	0.238***	0.156***	0.895***
	(0.005)	(0.000)	(0.002)	(0.003)	(0.001)	(0.006)
Married	0.332***	0.074***	0.144***	-0.032***	-0.025***	-0.103***
	(0.005)	(0.000)	(0.001)	(0.003)	(0.001)	(0.005)
Secondary education	0.873***	0.109***	0.337***	0.030***	-0.070***	-0.164***
	(0.005)	(0.001)	(0.002)	(0.003)	(0.001)	(0.006)
Higher education	0.996***	0.238***	1.271***	0.692***	0.008***	1.365***
	(0.006)	(0.001)	(0.004)	(0.008)	(0.001)	(0.011)
Manufacturing	0.644***	0.118***	0.194***	0.068***	-0.057***	-0.157***
	(0.014)	(0.001)	(0.003)	(0.007)	(0.002)	(0.013)

Industry	2.107***	0.287***	0.288***	-0.361***	-0.221***	-1.421***
	(0.014)	(0.001)	(0.003)	(0.007)	(0.002)	(0.013)
Business and finance	1.111***	0.123***	0.342***	0.094***	-0.098***	-0.201***
	(0.015)	(0.001)	(0.005)	(0.010)	(0.002)	(0.017)
Other services	0.873***	0.089***	0.199***	-0.082***	-0.084***	-0.407***
	(0.014)	(0.001)	(0.003)	(0.006)	(0.002)	(0.012)
Managers	0.948***	0.295***	1.446***	0.731***	0.031***	1.651***
	(0.010)	(0.001)	(0.009)	(0.017)	(0.001)	(0.025)
Professionals	0.971***	0.244***	0.606***	0.047***	-0.055***	0.003
	(0.008)	(0.001)	(0.005)	(0.009)	(0.001)	(0.013)
Technicians	0.534***	0.160***	0.368***	0.030***	-0.027***	-0.012
	(0.009)	(0.001)	(0.004)	(0.007)	(0.001)	(0.012)
Clerks	1.439***	0.231***	0.106***	-0.292***	-0.160***	-1.114***
	(0.008)	(0.001)	(0.004)	(0.008)	(0.001)	(0.012)
Service workers	0.258***	0.043***	0.085***	-0.034***	-0.022***	-0.121***
	(0.008)	(0.001)	(0.002)	(0.004)	(0.001)	(0.008)
Agricultural workers	-0.423***	-0.038***	0.008***	0.186***	0.051***	0.513***
	(0.014)	(0.001)	(0.003)	(0.006)	(0.002)	(0.012)
Craftsmen	-0.671***	0.026***	-0.008***	0.197***	0.079***	0.615***
	(0.008)	(0.001)	(0.002)	(0.005)	(0.001)	(0.009)
Operators	1.203***	0.196***	0.189***	-0.225***	-0.124***	-0.848***
	(0.007)	(0.001)	(0.003)	(0.005)	(0.001)	(0.009)
Constant	10.044***	11.039***	10.497***	-0.497***	1.046***	1.143***
	(0.029)	(0.002)	(0.006)	(0.014)	(0.003)	(0.028)
Observations	4,822,733	4,822,733	4,822,733	4,822,733	4,822,733	4,822,733
R-squared	0.072	0.180	0.155	0.016	0.046	0.036

Note: robust standard errors within parentheses (0.01 = ***, 0.05 = **; 0.10 = *)

Source: authors' estimates based on the IPUMS data.

Table A4: RIF regression outcomes for the United States—2000

2000	Quantile 10 (1)	Quantile 50 (2)	Quantile 90 (3)	Variance (4)	IQR 10/ 90 (5)	Gini (6)
Log age	1.736***	0.514***	0.277***	-0.794***	-0.246***	-2.556***
	(0.005)	(0.001)	(0.001)	(0.004)	(0.001)	(0.009)
Female	-0.460***	-0.484***	-0.445***	-0.086***	0.022***	0.128***
	(0.003)	(0.001)	(0.001)	(0.002)	(0.000)	(0.005)
Married	0.349***	0.204***	0.128***	-0.117***	-0.041***	-0.475***
	(0.003)	(0.001)	(0.001)	(0.002)	(0.000)	(0.005)
Secondary education	1.727***	0.497***	0.050***	-1.259***	-0.270***	-3.423***
	(0.005)	(0.001)	(0.001)	(0.005)	(0.001)	(0.009)
Higher education	2.062***	0.973***	0.673***	-0.914***	-0.251***	-2.876***
	(0.006)	(0.002)	(0.002)	(0.005)	(0.001)	(0.011)
Manufacturing	0.749***	0.654***	0.545***	-0.225***	-0.056***	-0.896***
	(0.011)	(0.003)	(0.003)	(0.011)	(0.002)	(0.021)
Industry	0.664***	0.638***	0.490***	-0.182***	-0.049***	-0.770***
	(0.011)	(0.004)	(0.004)	(0.012)	(0.002)	(0.022)
Business and finance	0.696***	0.580***	0.599***	-0.026**	-0.041***	-0.392***
	(0.011)	(0.003)	(0.003)	(0.011)	(0.002)	(0.022)
Other services	0.223***	0.383***	0.310***	-0.006	0.000	-0.129***
	(0.010)	(0.003)	(0.003)	(0.011)	(0.002)	(0.021)
Managers	0.095***	0.483***	0.814***	0.643***	0.080***	1.306***
	(0.006)	(0.002)	(0.003)	(0.005)	(0.001)	(0.012)
Professionals	-0.149***	0.276***	0.223***	0.283***	0.050***	0.547***
	(0.006)	(0.002)	(0.002)	(0.005)	(0.001)	(0.011)
Technicians	0.355***	0.330***	0.394***	0.180***	-0.011***	0.158***
	(0.007)	(0.002)	(0.002)	(0.006)	(0.001)	(0.013)
Clerks	-0.842***	-0.188***	0.174***	0.719***	0.155***	2.085***
	(0.008)	(0.002)	(0.002)	(0.007)	(0.001)	(0.014)
Service workers	-0.447***	-0.036***	0.164***	0.439***	0.091***	1.149***

	(0.006)	(0.002)	(0.001)	(0.005)	(0.001)	(0.010)
Agricultural workers	-0.097***	-0.040***	0.266***	0.219***	0.046***	0.813***
	(0.019)	(0.005)	(0.004)	(0.017)	(0.003)	(0.035)
Craftsmen	0.143***	-0.009***	-0.109***	-0.168***	-0.036***	-0.460***
	(0.007)	(0.003)	(0.003)	(0.006)	(0.001)	(0.014)
Operators	0.186***	0.103***	-0.049***	-0.154***	-0.035***	-0.517***
	(0.006)	(0.002)	(0.002)	(0.005)	(0.001)	(0.011)
Constant	0.419***	7.443***	9.621***	5.205***	2.426***	18.312***
	(0.021)	(0.005)	(0.004)	(0.019)	(0.003)	(0.039)
Observations	7,401,156	7,401,156	7,401,156	7,401,156	7,401,156	7,401,156
R-squared	0.116	0.233	0.170	0.044	0.081	0.082

Note: robust standard errors within parentheses (0.01 = ***, 0.05 = **; 0.10 = *)

Source: authors' estimates based on the IPUMS data.

Table A5: RIF regression outcomes for the United States—2020

2020	Quantile 10	Quantile 50	Quantile 90	Variance	IQR 10/ 90	Gini
	(1)	(2)	(3)	(4)	(5)	(6)
Log age	1.332***	0.441***	0.250***	-1.156***	-0.184***	-3.120***
	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.009)
Female	-0.213***	-0.349***	-0.396***	-0.163***	-0.013***	-0.070***
	(0.002)	(0.001)	(0.001)	(0.003)	(0.000)	(0.006)
Married	0.352***	0.309***	0.194***	-0.210***	-0.033***	-0.759***
	(0.002)	(0.001)	(0.001)	(0.003)	(0.000)	(0.005)
Secondary education	1.206***	0.370***	0.004***	-1.611***	-0.194***	-3.671***
	(0.005)	(0.001)	(0.001)	(0.008)	(0.001)	(0.014)
Higher education	1.590***	0.929***	0.642***	-1.430***	-0.179***	-3.669***
	(0.005)	(0.002)	(0.001)	(0.008)	(0.001)	(0.014)
Manufacturing	0.632***	0.668***	0.647***	-0.483***	-0.024***	-1.318***
	(0.010)	(0.005)	(0.005)	(0.021)	(0.002)	(0.032)

Industry	0.602***	0.693***	0.590***	-0.428***	-0.026***	-1.201***
	(0.010)	(0.005)	(0.005)	(0.021)	(0.002)	(0.033)
Business and finance	0.520***	0.598***	0.782***	-0.139***	0.010***	-0.477***
	(0.010)	(0.005)	(0.005)	(0.021)	(0.002)	(0.032)
Other services	0.186***	0.298***	0.302***	-0.212***	0.006***	-0.389***
	(0.010)	(0.004)	(0.005)	(0.021)	(0.002)	(0.032)
Managers	0.215***	0.507***	0.545***	0.311***	0.031***	0.276***
	(0.003)	(0.002)	(0.003)	(0.006)	(0.001)	(0.011)
Professionals	-0.080***	0.245***	-0.032***	0.109***	0.009***	0.027***
	(0.003)	(0.002)	(0.002)	(0.005)	(0.001)	(0.010)
Technicians	0.381***	0.310***	0.242***	-0.126***	-0.032***	-0.588***
	(0.004)	(0.002)	(0.002)	(0.006)	(0.001)	(0.011)
Clerks	-0.499***	-0.214***	0.018***	0.516***	0.082***	1.573***
	(0.005)	(0.002)	(0.002)	(0.007)	(0.001)	(0.014)
Service workers	-0.287***	-0.126***	-0.069***	0.282***	0.038***	0.732***
	(0.004)	(0.002)	(0.002)	(0.005)	(0.001)	(0.010)
Agricultural workers	0.079***	-0.042***	0.110***	-0.207***	0.001	-0.128***
	(0.016)	(0.006)	(0.005)	(0.026)	(0.003)	(0.046)
Craftsmen	0.077***	-0.155***	-0.417***	-0.426***	-0.062***	-0.955***
	(0.005)	(0.003)	(0.003)	(0.008)	(0.001)	(0.015)
Operators	0.203***	0.050***	-0.345***	-0.503***	-0.074***	-1.317***
	(0.004)	(0.002)	(0.002)	(0.006)	(0.001)	(0.011)
Constant	1.840***	7.691***	9.936***	7.806***	2.237***	22.782***
	(0.016)	(0.006)	(0.006)	(0.028)	(0.003)	(0.048)
Observations	7,986,142	7,986,142	7,986,142	7,986,142	7,986,142	7,986,142
R-squared	0.115	0.243	0.161	0.043	0.063	0.081

Note: robust standard errors within parentheses (0.01 = ***, 0.05 = **; 0.10 = *)

Source: authors' estimates based on the IPUMS data.