Automation and Offshoring on Wage Inequality in Japan *

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May 30, 2025

Abstract

I examine the effect of task displacement from automation technology and offshoring on wage inequality using data in Japan since 1980. First, I do not find evidence that task displacement from automation increases wage inequality, which contrasts with the finding for the US. Second, I find that the rise in offshoring has distributional consequences and is *progressive* after the mid-1990s. The surge in offshoring is concentrated in industries where ex-ante low-wage workers work and disproportionately increases their wages. This increase in wages is due to the increases in monthly payroll, decreases in hours worked, decreases in employment rate, and decreases in the share of offshorable occupations.

*I thank Daron Acemoglu, David Autor, and seminar participants at the Research Institute of Economy, Trade and Industry (RIETI) for their helpful comments. I also thank Satoshi Ichikawa and Sakito Tango for their excellent research assistance. This study is a part of the project "Macroeconomy and Automation" undertaken at RIETI. I acknowledge permission to access the micro-data of the following government statistics: the Employment Status Survey by the Ministry of Internal Affairs and Communications and the Basic Survey on Wage Structure by the Ministry of Health, Labor and Welfare. I am grateful to Keio University, where I worked on the empirical analyses using micro-data, for its hospitality during my visits. I thank RIETI for providing their help with the data access.

1 Introduction

Automation technology and globalization are two of the fundamental economic forces to be considered as the source of increasing inequality. There are many empirical papers, which show that they are regressive: automation and trade decrease wages for ex-ante low-wage workers and expand wage inequality (Autor et al., 2003, 2013; Acemoglu and Restrepo, 2022). However, theories do not provide any decisive conclusion on the direction of changes in wages in response to advances in automation technology and surges in globalization.

As pointed out in Acemoglu and Restrepo (2018), automation affects wages in two ways. On the one hand, automation displaces workers and decreases labor demand and wages. On the other hand, automation improves the productivity of workers and increases wages. Moreover, if automation encourages workers whose tasks are automated to move to higher-paid jobs, their wages increase after occupational switches. Therefore, the distributional consequences of automation are ambiguous, and they rely on how firms and workers respond.[1]

Globalization also has productivity effects that increase wages or displacement effects that decrease wages. There are many papers to examine the effect of globalization on wages, and the effect of China Shock, the surge in import penetration of Chinese manufacturing goods since the late 1990s, would be arguably the most extensively studied topic in this area. As Sasahara (2022) summarizes, the effects on wages in the US tend to be negative for ex-ante lower-paid workers while those in Japan are mixed.

In this paper, I use multiple confidential microdata in Japan to study how task displacement and offshoring affect wage inequality. I first document how wage inequality in Japan evolved since 1980 using the variance of wages and the Gini index. I show that wage inequality has shrunk over the last 40 years for overall workers as well as within a group of workers, differing by age, gender, and education. I also find that the wage gap is shrinking between different demographic groups, for example, college-educated and non-college-educated. This is consistent with the findings in the previous literature, including Otake (2005), Kambayashi et al. (2008), Kawaguchi and Mori (2016), and Kambayashi (2017). This pattern of wage inequality contrasts with the one in the US, which is reported in Autor (2019).

Second, I examine the effects of task displacement and offshoring on wage distribution in Japan. I find that offshoring exposures lead to increases in wages, especially after the mid-1990s. Since the offshoring exposures are larger for ex-ante low-wage workers, the surge in offshoring is *progressive* after the mid-1990s. I also find that the increase in wages is due to the increases in monthly payroll, decreases in hours worked, decreases in employment rate, and decreases in the share of offshorable occupations.

Related Literature This paper contributes to the broad literature, which studies the effect of technology on wage inequality, including Autor et al. (2003), Acemoglu and Autor (2011), Acemoglu and Restrepo (2022) among others. This paper studies the impact of labor-replacing technology (automation) on labor markets, which has also been studied extensively by the previous literature, including Graetz and Michaels (2018), Acemoglu and Restrepo (2020), and Dauth et al. (2021), Ace-

[1]For example, Kikuchi et al. (2023) show that, in the case of the Japanese labor market since the 1980s, automation decreased the share of routine occupation employment but did not decrease the overall employment rate or wages because workers moved to non-routine occupations. The effect also depends on the nature of technology. For instance, Noy and Zhang (2023) show that generative AI, specifically ChatGPT, increases the productivity of ex-ante low-wage workers and decreases wage inequality among workers.

moglu and Restrepo (2022). Several papers study the impact of technology on the Japanese labor markets. Ikenaga and Kambayashi (2016) show an industry-level correlation between ICT capital penetration and decreases in routine task score. Hamaguchi and Kondo (2018) study the implication of artificial intelligence. Dekle (2020) shows that industries that introduce more robots did not decrease labor demand. The closest papers are Adachi et al. (2022) and Kikuchi et al. (2023), which study the implication of robot penetration on overall employment across commuting zones. Compared to the paper, I study the effects on wages and in particular, general equilibrium wage structures as the difference articulated in Acemoglu and Restrepo (2022).[2] This paper specifically follows the specifications in Acemoglu and Restrepo (2022) but applies them to the Japanese labor market. I find that task displacement did not increase inequality, which is in contrast with the findings in Acemoglu and Restrepo (2022).

Second, this paper contributes to the literature, which examines the impact of international trade on wage inequality. (Feenstra and Hanson, 2003; Attanasio et al., 2004; Kambayashi et al., 2008; Autor et al., 2013). There is a large literature on the effect of offshoring on wages, including Ottaviano et al. (2013), Wright (2014), Endoh (2021). However, these papers focus on the effect of offshoring on wages at firm-, occupation-, or industry- level as opposed to labor market level. As Acemoglu and Restrepo (2022) point out in the context of the effect of automation on wages, these approaches cannot take equilibrium effects into account. Firms, occupations, or industries are not labor markets, and thus, one should not expect effects on wages in labor markets without assuming some frictions in labor markets. Instead, in this paper, I define a labor market as a pair of a prefecture, an age group, a gender group, and an education group. By doing so, this paper can study the effect of offshoring on wage inequality where wages are determined in a labor market.

2 Data and Variables

2.1 Basic Survey on Wage Structure (BSWS)

The main data source is the confidential microdata from the Basic Survey on Wage Structure conducted by the Ministry of Health, Labour and Welfare (MHLW) in Japan. The main purpose of the survey is to understand the wage structure of employees in major industries, including wage distribution by type of employment, type of work, industry, occupation, sex, age, and education.[3]

Variables I mainly use the following variables. First, for monthly earnings, I use contractual cash earnings, which is the before-tax amount of cash wages paid to employees, for the surveyed month of June. I then add a bonus by dividing annual special cash earnings, which are special wages including bonus and term-end allowance paid in the previous year, by 12. Second, I take the sum of the actual number of scheduled hours worked and the actual number of overtime worked for hours worked in a month. I then compute the hourly wages by dividing the monthly earnings by the hours worked.[4]

[2] Adachi et al. (2022) and Kikuchi et al. (2023) use the ESS data where data on wages and hours is in a few bins. Adachi et al. (2022) take mid-points of the bins, and Kikuchi et al. (2023) estimate conditional means and variances as functions of observables.

[3] The detailed data description is available here.

[4] See here for the detailed description of variables in BSWS (MHLW).

Sample Selection I use data from 1980 to 2019. Since the detailed demographic information is available only for full-time workers in this period, I focus on full-time workers. I also restrict my analysis to workers in the private sector, aged from 25 to 64, with non-missing data on occupation, industry, education, and wages. This ended up with 356,498 workers in 1980 and 343,584 workers in 2019.

2.2 Employment Status Survey (ESS)

I also use the microdata of the Employment Status Survey (ESS) by the Ministry of Internal Affairs and Communications. ESS aims to capture the employment status and occupation of workers at both regional and national levels. Since 1982, this survey has been conducted every five years. The survey is nationally representative, and the coverage is extensive: the survey in 2017, for instance, includes approximately 1.08 million individuals from 520,000 households residing in 33,000 survey districts around the nation, and past surveys have similar levels of coverage.

2.3 Japan O-NET Data

I use the Japanese O-NET data constructed by the Japan Institute for Labour Policy and Training (JILPT) to define routine intensity and offshorability for each occupation in Japan. I use Version 4.00.01, which includes work contents and work activities across occupations in Japan.

2.4 JIP Database

I also use the Japan Industrial Productivity Database 2015 (JIP), which is compliant with the EU-KLEMS dataset.[5] Since there was a major change in the classification of industry in JIP2018, I use both JIP2015 and JIP2023 (or JIP2021). I use data on value-added, labor inputs, capital stocks, and labor share from 1980 to 2018 as follows.

Capital Stock I obtain data on real IT capital stock from JIP2015 (1970-2012) and JIP2023 (1994-2020). Real IT capital stock is computed in these matrices as follows. In JIP2015, I sum up capital stocks of computer-related equipment, electric communication equipment, and made-to-order software. In JIP2023, I sum up capital stocks of communication, information, and software equipment.

Labor Share The data on labor share is available only in JIP2021 (1994-2018). Thus, for 1980-2012, I computed it using JIP2015 based on the same definition as JIP2021. In detail, it is derived as the proportion of nominal labor cost against nominal value added subtracted by net tax. Since net tax data is not contained in JIP2023, the labor share after 2018 cannot be obtained from JIP data.

When computing the labor share, data from the housing industry is dropped because it does not have net tax data in JIP2015 or JIP2021.[6]

[5] For details, see Fukao et al. (2007) and Fukao et al. (2021).

[6] Note that the nursing care industry also has no data on net tax or nominal value added from 1994 to 1999, it has dropped for the duration. However, when computing the changes in the labor share by industry from 1994 to 2018, that of the nursing care industry is computed by replacing data from 2000 to 1994.

Figure 1 and Figure 2 show the changes in labor share in Japan, from 1980 to 2012 and 1994 to 2018, respectively. Since the data sources are different, the patterns are not exactly the same. However, service sectors experienced a decrease in labor share between 1980 and 2000, while manufacturing sectors experienced a decrease more recently, particularly after 2000. Figures A.1, A.2, A.3, and A.4 in the Appendix show the changes in labor share by manufacturing and non-manufacturing industries, for 1980 to 2012 and 1994 to 2018, respectively, by industries.

Figure 1: Change in Labor Share in Japan (JIP2015)

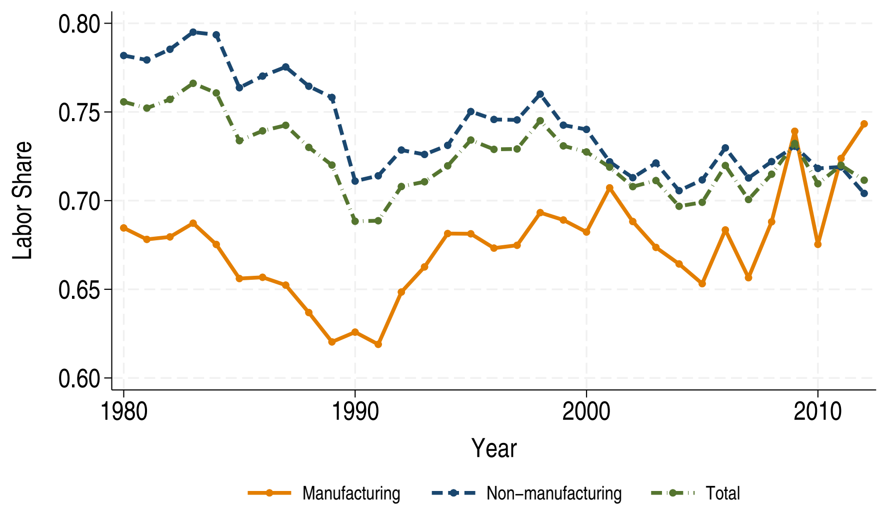
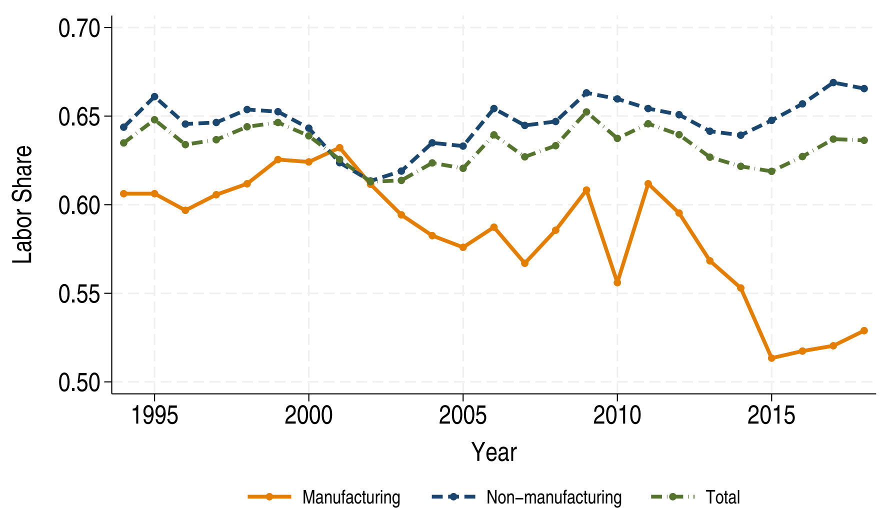


Figure 2: Change in Labor Share in Japan (JIP2021)



2.5 Comtrade Data

I use the UN Comtrade data to obtain bilateral trade flow across industries. I focus on manufacturing industries because service trade data is not available for a long time horizon. I use JSIC

3-digit industrial categories as a baseline. I summarize the steps to construct data below.

First, I take the data from UN Comtrade data. I take annual values of traded goods from 1980 to 2018 across industries categorized in SITC Rev. 2, 4-digit. I convert all trade flows into real 2015 JPY.

Second, using a cleaner provided by Feenstra and Romalis (2014), I convert data at SITC Rev.2, 4-digit level across countries over time. This step gives primacy to importer's reports over exporter's reports where available, corrects values where UN values are known to be inaccurate, accounts for re-exports of Chinese goods through Hong Kong, and puts Taiwan back as an importer and an exporter.[7]

Third, I combine some of the countries, that reunify or report jointly for subsets of years in the database. I combine East and West Germany prior to reunification, Belgium and Luxembourg; the islands that formed the Netherlands Antilles; North and South Yemen; and Sudan and South Sudan.

Finally, I convert these SITC Rev.2, 4-digit industrial categories into HS 1996/2002 6-digit using the crosswalk provided by the UN and then into JSIC 3-digit.[8]

Offshoring I use the BEC classification to identify which products traded are intermediates. I then construct the offshoring measure as follows:

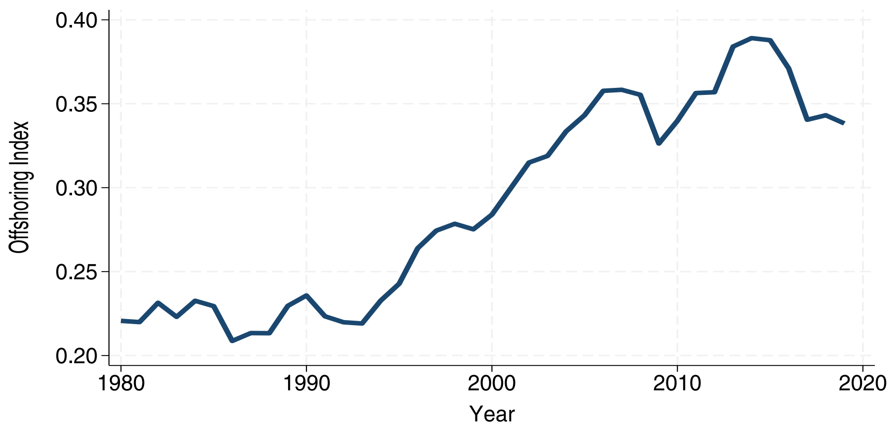
$$\text{OFS}_i \equiv \sum_{n \neq JP} \pi_{n,JP,i} = 1 - \pi_{JP,JP,i} \tag{1}$$

$\pi_{n,JP,i} = \frac{x_{n,JP,i}}{\sum_m x_{m,JP,i}}$ is the export share of country n to Japan in an intermediate industry i where $x_{m,JP,i}$ is the trade flow from country m to Japan in an industry i. $\pi_{JP,JP,i}$ is the Japanese domestic production share (relative to foreign countries' exports to Japan) in the intermediate goods industry i. Figure 3 shows the time series of the average of this offshoring measure across industries, weighted by the shares of intermediate goods in the total value of production in each industry. The offshoring measure has increased since the mid-1990s from 22% to 38% in 2016 then dropped recently around 35%.

[7] Their cleaner is available here.

[8] The crosswalk from SITC Rev2 to HS is available in the UNSD web page here.

Figure 3: Offshoring Index



Notes: The figure shows the offshoring measure in the Japanese manufacturing sector. The offshoring measure in each industry i is defined as one minus the Japanese domestic production share (relative to foreign countries' exports to Japan) in the intermediate goods industry i. The economy-wide offshoring measure in the figure is the weighted average of these industry-level measures, where the weights are the shares of intermediate goods in the total value of production in each industry.

3 Wage Inequality in Japan

I first document how wage inequality in Japan evolved since 1980. I restrict samples to full-time workers, working in the private sector, and aged 25 to 64. I compute hourly wages by dividing earnings by hours worked. I convert the hourly wage in real term (JPY in 2015) using CPI.[9]

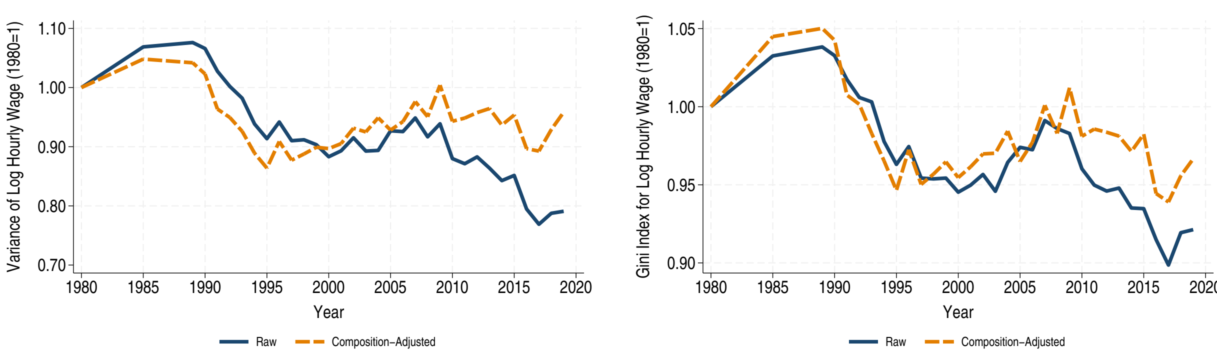
3.1 Aggregate Inequality Measures

Variance of Wages I first show the variance of wages over time. Figure 4a shows the variance of real log wages for full-time workers. The navy solid line shows the one for raw log wages while the orange dashed line shows the one where I adjust the composition of workers. I residualize a group fixed effects where each group is defined as one of the 1504 demographic groups based on prefectures (47), sex (2), age groups (8 five-year age bins, 25-29,...,60-64), and college education (2).

The patterns differ across specifications. The variance of raw wages has been decreasing since 1990 until recently. The variance of composition-adjusted wages followed a similar pattern until 2010 with a small increase between 1995 and 2010 but it did not decrease after 2010 as opposed to the raw data. This suggests that wage inequality across groups and wage inequality within groups experience different time trends, and the latter did not shrink as much as the former.

Figure 4: Variance and Gini Index of Real Log Wage for Full Time Workers

(a) Variance (b) Gini Index



Notes: The figures show the variance of log real hourly wages for full-time workers and the Gini Index of log real hourly wages for full-time workers. Data is from BSWS (MHLW).

Gini Index I second show the Gini Index of wages over time. Figure 4b shows the Gini Index of real log wages for full-time workers. The navy solid line shows the one for raw log wages while the orange dashed line shows the one where I adjust the composition of workers.

The pattern is the same as the variance of wages shown in Figure 4a. The raw wage inequality based on the Gini Index decreases over time while the composition-adjusted wage inequality slightly increased from 1995 until 2010 and decreased since then.

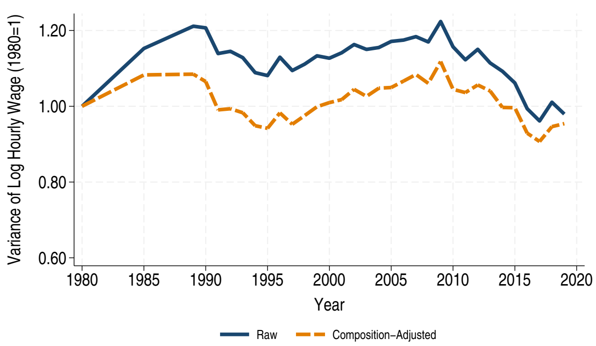
[9]CPI data from FRED is available here.

3.2 Within Group Wage Inequality

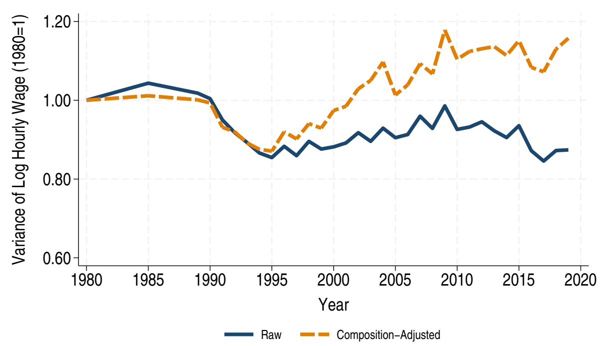
To understand this diversion of the time trend, I now split the samples of workers by gender and college education. Figure 5a, 5b, 5c, and 5d show the versions of Figure 4a for male non-college-educated, male college-educated, female non-college-educated, and female college-educated workers respectively. For all groups but male, college-educated workers, the patterns are consistent for raw and composition-adjusted wages. Figure 5a shows that male, non-college-educated workers saw increases in inequality until the late 2000s and decreases since then. Figure 5c shows that female, non-college-educated workers have seen steady declines in inequality since 1990 until now. Figure 5d shows that female, college-educated workers have seen decreases in inequality until 1995, then the variance has stayed constant until now. Figure 5b shows that male, college-educated workers have seen a decrease in inequality until 1995, then the composition-adjusted inequality increased since then while the raw wages inequality stayed constant. In sum, wage inequality within gender-education groups is not increasing, except for the composition-adjusted inequality for male, college-educated workers.

Figure 5: Variance of Real Log Wage for Full Time Workers within Groups of Gender and College-Education

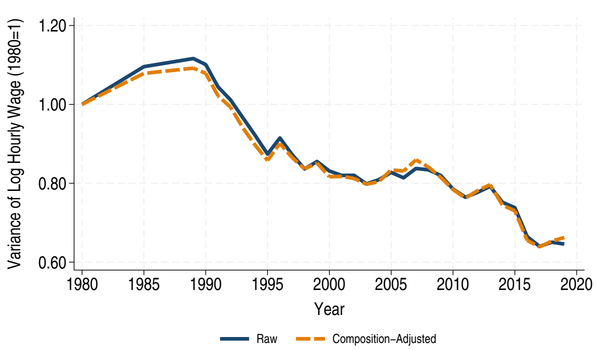
(a) Male, Non-College-Educated Workers



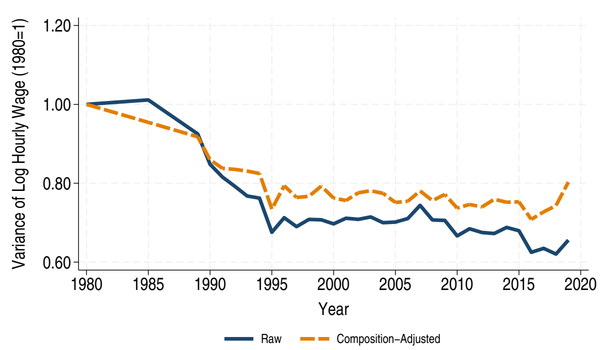
(b) Male, College-Educated Workers



(c) Femal, Non-College-Educated Workers



(d) Female, College-Educated Workers

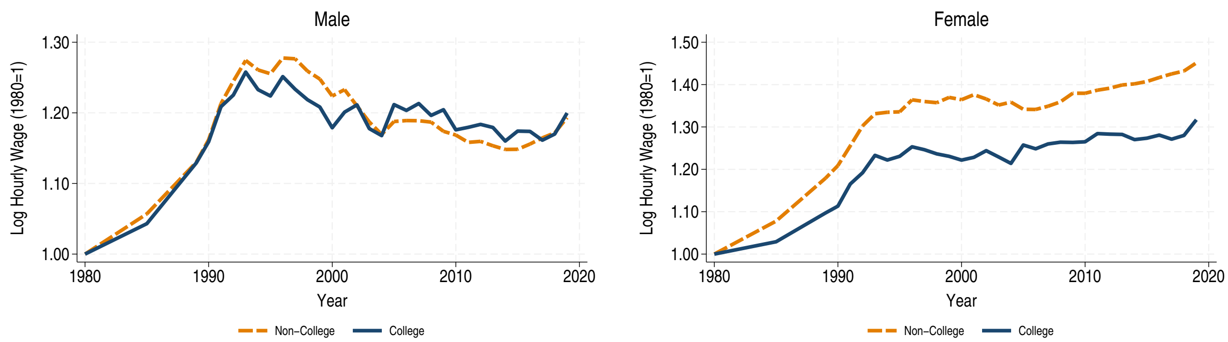


Notes: The figures show the variance of log real hourly wages for full-time workers by gender. Data is from BSWS (MHLW).

3.3 Across Group Wage Inequality

Real Wage Inequality Figure 6 shows the real log hourly wages for full-time workers since 1980. In each panel, two lines show wage paths for college-educated and non-college-educated workers separately. For male workers, both groups see increases in wages until the mid-1990s. Since then both wages have stagnated. For female workers, both groups have experienced increases in wages since 1980 until now albeit slowdowns since the mid-1990s. Also, non-college workers have experienced faster growth in wages throughout the periods.

Figure 6: Real Log Wage for Full Time Workers (1980=1)

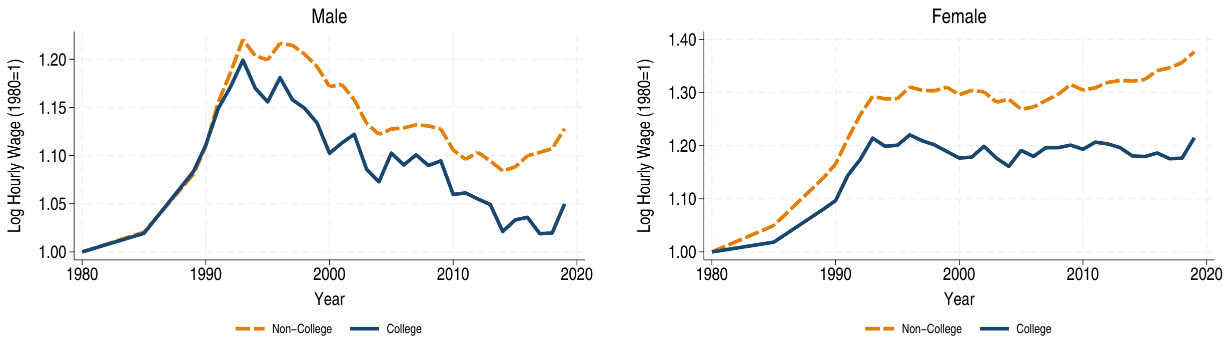


Notes: The figures show log hourly wages for male and female workers. In each panel, two lines show wage paths for college-educated and non-college-educated workers separately. Data is from BSWS (MHLW).

Real Wage Inequality: Compositon-Adjusted Next, I residualize components in wages, such as age and tenure. In particular, following Autor (2019) and Acemoglu and Restrepo (2022), I regress log hourly wages on a quadratic in tenure and a quadratic in age, in each year and each demographic group separately.

Figure 7 shows the result. As before, in each panel, two lines show composition-adjusted (residualized) wage paths for college-educated and non-college-educated workers separately. For male workers, both groups see increases in wages until the mid-1990s. Since then both wages have stagnated, and, if any, college-educated workers have experienced decreases in wages. The stable path in Figure 6 comes from the fact that the composition of the workers has shifted older so that the average wage is biased upwards. For female workers, both groups have experienced increases in wages from 1980 until the mid-1990s. Non-college workers have experienced faster growth in wages afterward while college workers have experienced more modest wage growth. Comparing four groups of workers, college-educated male workers experienced around 5% of wage growth over the 40 years, while the growth is 13% for non-college-educated male workers, 21% for college-educated female workers, and 38% for non-college-educated female workers. These regressive paths are in sharp contrast to the patterns in the US documented in Autor (2019) that inequality has expanded since 1980.

Figure 7: Real Log Wage for Full Time Workers (1980=1): Composition-Adjusted



Notes: The figures show composition-adjusted log hourly wages for male and female workers. In each panel, two lines show wage paths for college-educated and non-college-educated workers separately. Log hourly wages of full-time workers are regressed on a quadratic in tenure and a quadratic in age, in each year and in each demographic group separately. Data is from BSWS (MHLW).

3.4 Summary of Facts

Over the last 40 years, wage inequality for all full-time workers has decreased while composition-adjusted wage inequality experienced smaller declines (Figure 4). Within each gender-education group, wage inequality remains constant for male workers and has decreased for female workers (Figure 5). Across education groups, wage inequality shrinks for males and females (Figure 6 and 7). This is opposite to the findings Autor et al. (2003) and Acemoglu and Restrepo (2022) for the US that wage inequality across education groups within each gender has increased in the last few decades. In the next section, I study how technology and trade affect this shrink in wage inequality.

4 Effects of Task Displacement and Offshoring on Wage Inequality

In this section, I study how task displacement and offshoring affect wage distribution in Japan. I first define task displacement and offshoring measures for each demographic group. Then, I examine the relationship between initial wage distribution, task displacement, and offshoring. Finally, I examine the relationship between changes in wage distribution and task displacement and offshoring.

4.1 Unit of Observation

Following Acemoglu and Restrepo (2022), I divide full-time workers into 1504 demographic groups based on prefectures (47), sex (2), age groups (8 five-year age bins, 25-29,...,60-64), and college education (2). As the categories of education are coarser and the data on foreign workers is limited, I added geographic information—prefectures—to define demographic groups.

4.2 Definition of Task Displacement and Offshoring

4.2.1 Task Displacement

Following Acemoglu and Restrepo (2022), I define task displacement measures for demographic group g as follows

$$\text{Task displacement}_{g} = \sum_{i \in \mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R} \cdot \left(-d \ln s_i^L\right) \tag{2}$$

where ω_g^i is the share of wage bills earned in industry i by group g relative to total wage bills earned by group g, ω_{gi}^R is the share of wage bills earned in industry i and routine occupation by group g relative to wage bills earned in industry i by group g, and ω_i^R is the share of wage bills earned in industry i and routine occupation relative to wage bills earned in industry i. $-d \ln s_i^L$ is the decline in labor share in industry i in log.

Routine Task Intensity To classify which occupations are routine occupations, I construct occupation-level routine task intensity. Following Komatsu and Mugiyama (2021), I first use the following three scores: "work according to the speed of equipment" in the Work Content measure, "repetitive work" in the Work Content measure, and "control machines and process of machine manufacture" in the Generalized Work Activities measure. As in Komatsu and Mugiyama (2021), I normalize these three scores so that the mean is zero with a standard deviation of one across 167 occupation classifications in 2012. I then sum up these three scores into one-dimensional scores and normalize them again.

Figure 8 shows the relationship between routine task intensity and log hourly wages in 1995 across occupation categories. Each dot represents an occupation, and its size represents the total hours worked. There is a weak, positive relationship: the slope is 0.08 with a standard error of 0.05.

I define an occupation to be a routine occupation if the routine task intensity is in the top 1/3 as in Autor et al. (2003).

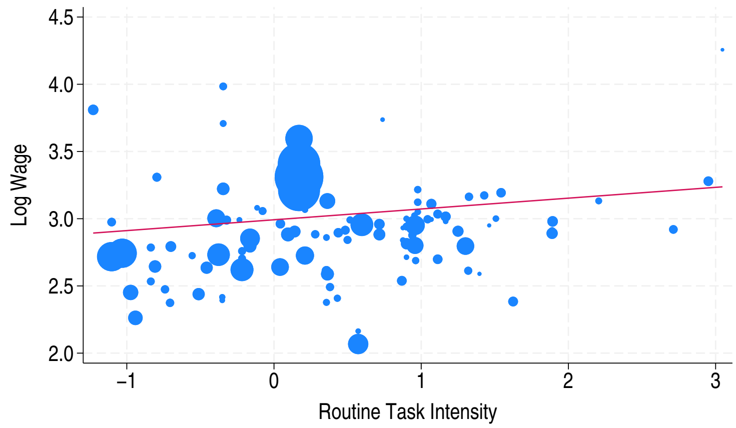
4.2.2 Offshoring Exposure

I define offshoring exposure to demographic group g as follows:

$$\text{Offshoring}_{g} = \sum_{i \in \mathcal{I}_{\mathcal{I}}} \omega_g^i \cdot \frac{\omega_{gi}^O}{\omega_i^O} \cdot \left(-d \ln \pi_{JP,JP,i}\right) \tag{3}$$

where ω_g^i is the share of wages bills earned by group g workers in intermediate goods industry i (relative to their total earnings). ω_{gi}^O is the share of wage bills earned in industry i and offshorable occupation by group g (relative to wage bills earned in industry i by group g), and ω_i^O is the share of wage bills earned in industry i, offshorable occupation (relative to wage bills earned in industry i). $(-d \ln \pi_{JP,JP,i})$ is the percent decline in the Japanese domestic production share (relative to foreign countries' exports to Japan) in the intermediate goods industry i. Note that we only consider industries producing intermediate goods, $i \in \mathcal{I}_{\mathcal{I}}$. For final goods or capital goods

Figure 8: Routine Task Intensity and Wage



Notes: The figure shows the relationship between routine task intensity and log hourly wages in 1995 in Japan. Each dot represents an occupation category, and its size represents the total hours worked. The fitted line is based on a weighted bi-variate linear regression. Data is from BSWS (MHLW).

industries and service sectors, we set these changes of offshoring to be zero to focus on the action in intermediate goods industries.

Offshorability To classify which occupations are offshorable occupation, I construct an occupation-level offshorability score. Following Autor et al. (2003), I first use the following two scores: "in-person communication" and "physical proximity to others" in the Work Content measure. As in Autor et al. (2003), I normalize these two scores so that the mean is zero with a standard deviation of one across 167 occupation classifications in 2012. I then sum up these two scores into one-dimensional scores and normalize them again.

Figure 9 shows the relationship between offshorability score and log hourly wages in 1995 across occupation categories. Each dot represents an occupation, and its size represents the total hours worked. There is a negative relationship: the slope is -0.19 with a standard error of 0.03.

I define an occupation to be an offshorable occupation if the offshorable is in the top 1/3 as in Autor et al. (2003).

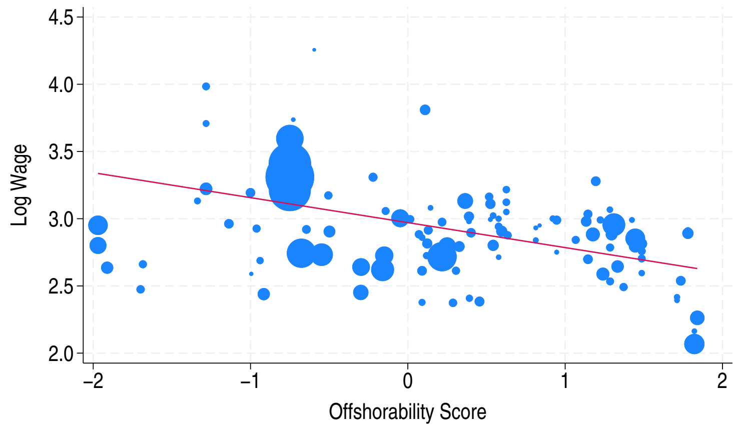
4.2.3 IT Investment

I use an IT technology control as a covariate because it is shown as one of the most important industry-level determinants of wage inequality (Autor et al., 2003; Ikenaga and Kambayashi, 2016). I define them for demographic group g as follows:

$$\mathrm{IT}_g = \sum_{i \in \mathcal{I}} \omega_g^i \cdot (d \ln IT_i) \tag{4}$$

where ω_g^i is the share of wage bills earned in industry i by group g relative to total wage bills earned by group g, and $d \ln IT_i$ is the log changes in real IT capital stock from JIP data.

Figure 9: Offshorability and Wage



Notes: The figure shows the relationship between offshorability score and log hourly wages in 1995 in Japan. Each dot represents an occupation category, and its size represents the total hours worked. The fitted line is based on a weighted bi-variate linear regression. Data is from BSWS (MHLW).

4.3 Relationships to Initial Wage Distributions

I use the following specification to examine the relationship between initial wage distribution and task displacement and offshoring:

$$\begin{aligned} \ln w_g =& \beta_1 \text{ Task displacement }_g + \beta_2 \text{Offshoring }_g + \beta_3 IT_g \\ &+ \eta_{sex(g)} + \eta_{age(g)} + \eta_{edu(g)} + \eta_{pref(g)} + \varepsilon_g. \end{aligned} \tag{5}$$

where $\ln w_g$ is the log initial wage of demographic group g, Task displacement $_g$ is the task displacement measure for g, Offshoring$_g$ is the offshoring measure for g, IT_g is the IT investment exposure, and η are fixed effects for demographic groups.

Table 1 shows the results for 1980-1994, and Table 2 shows the results for 1995-2018. For both tables, as the running variables, Columns (1), (3), and (4) include the task displacement measure. Columns (2), (3), and (4) include the offshorability measure. All the columns include prefecture-fixed effects, gender-fixed effects, age-group-fixed effects, and college-education fixed effects. Column (4) includes real IT capital stocks. Each observation is weighted by its initial total hours worked. Robust standard errors are shown in parentheses.

The results show that the initial wage is not related to task displacement from automation technology. However, the initial wage is negatively associated with offshoring. This means that the surge in offshoring is concentrated in industries where ex-ante low-income workers work.

4.4 Relationships to Changes in Wage

Now, I examine the relationship between changes in wage distribution and task displacement and offshoring. I use the following specification:

$$\begin{aligned} \Delta \ln w_g =& \beta_1 \text{ Task displacement }_g + \beta_2 \text{Offshoring }_g + \beta_3 IT_g \\ &+ \eta_{sex(g)} + \eta_{age(g)} + \eta_{edu(g)} + \eta_{pref(g)} + \varepsilon_g \end{aligned} \tag{6}$$

Table 1: Initial Log Hourly Wage and Task Displacement and Offshoring: 1980-1994

	Dep. Var. Log Hour Initial Wage			
	(1)	(2)	(3)	(4)
Task Displacement	-0.096		-0.103	-0.094
	(0.080)		(0.080)	(0.084)
Offshoring		-0.063	-0.067	-0.070
		(0.034)	(0.034)	(0.033)
IT Investment				-0.002
				(0.000)
Observations	1,088	1,088	1,088	1,088
Pref. FE	✓	✓	✓	✓
Demographic FE	✓	✓	✓	✓

Notes: This table shows the relationship between task displacement, offshoring, and wages across demographic groups in Japan. Demographic groups are defined as a pair of prefectures (47), sex (2), age groups (8 five-year age bins, 25-29,...,60-64), and college education (2). The dependent variable is the log hourly wages in 1980 for each demographic group. As the running variables, Columns (1), (3), and (4) include the task displacement measure. Columns (2), (3), and (4) include the offshorability measure. All the columns include prefecture-fixed effects, gender-fixed effects, age-group-fixed effects, and college-education fixed effects. Column (4) includes real IT capital stocks. Each observation is weighted by its initial total hours worked. Robust standard errors are shown in parentheses.

Table 2: Initial Log Hourly Wage and Task Displacement and Offshoring: 1995-2018

	Dep. Var. Log Hour Initial Wage			
	(1)	(2)	(3)	(4)
Task Displacement	0.066		0.061	0.061
	(0.036)		(0.036)	(0.036)
Offshoring		-0.088	-0.085	-0.063
		(0.036)	(0.035)	(0.034)
IT Investment				0.627
				(0.083)
Observations	1,325	1,325	1,325	1,325
Pref. FE	✓	✓	✓	✓
Demographic FE	✓	✓	✓	✓

Notes: This table shows the relationship between task displacement, offshoring, and wages across demographic groups in Japan. Demographic groups are defined as a pair of prefectures (47), sex (2), age groups (8 five-year age bins, 25-29,...,60-64), and college education (2). The dependent variable is the log hourly wages in 1995 for each demographic group. As the running variables, Columns (1), (3), and (4) include the task displacement measure. Columns (2), (3), and (4) include the offshorability measure. All the columns include prefecture-fixed effects, gender-fixed effects, age group-fixed effects, and college-education fixed effects. Column (4) includes real imports and real IT capital stocks. Each observation is weighted by its initial total hours worked. Robust standard errors are shown in parentheses.

where $\Delta \ln w_g$ is the changes in log hourly wages of demographic group g.

Tables 3 and 4 show the results for 1980-1994 and 1995-2018, respectively. For both tables, as the running variables, Columns (1), (3), and (4) include the task displacement measure. Columns (2), (3), and (4) include the offshorability measure. All the columns include prefecture-fixed effects, gender-fixed effects, age-group-fixed effects, and college-education fixed effects. Column (4) includes real IT capital stocks. Each observation is weighted by its initial total hours worked. Robust standard errors are shown in parentheses.

The results show that the changes in log hourly wages are not related to task displacement from automation technology, which contrasts with the findings in Acemoglu and Restrepo (2022). However, the changes in log hourly wages are positively associated with offshoring for the period between 1995 and 2018, when the offshoring accelerated. This means that the surge in offshoring disproportionately increases the income of groups of workers who initially work at offshorable jobs.

Table 3: Effects of Task Displacement and Offshoring on Wages: 1980-1994

	Dep. Var. Log Changes in Hourly Wage			
	(1)	(2)	(3)	(4)
Task Displacement	0.050		0.053	0.054
	(0.043)		(0.044)	(0.044)
Offshoring		0.028	0.029	0.029
		(0.021)	(0.021)	(0.021)
IT Investment				-0.000
				(0.000)
Observations	1,088	1,088	1,088	1,088
Pref. FE	✓	✓	✓	✓
Demographic FE	✓	✓	✓	✓

Notes: This table shows the relationship between task displacement, offshoring, and changes in wages across demographic groups in Japan. Demographic groups are defined as a pair of prefectures (47), sex (2), age groups (8 five-year age bins, 25-29,...,60-64), and college education (2). The dependent variable is the changes in log hourly wages from 1980 to 1994 for each demographic group. As the running variables, Columns (1), (3), and (4) include the task displacement measure. Columns (2), (3), and (4) include the offshorability measure. All the columns include prefecture-fixed effects, gender-fixed effects, age-group-fixed effects, and college-education fixed effects. Column (4) includes real IT capital stocks. Each observation is weighted by its initial total hours worked. Robust standard errors are shown in parentheses.

4.5 Understanding the Wage Changes

Table 4 shows that the log hourly wages increase for demographic groups with more offshoring. In this subsection, I examine the source of this change. Increases in hourly wages can be either from the increases in monthly payroll or the decreases in hours worked. Thus, I first study the effect of offshoring on both monthly payroll and hours worked.

At the same time, there can be the case that the increase in hourly wages is due to the composition changes or extensive margins, that is, the decreases in employment rate with only high-skill *within* each demographic group surviving. Thus, I also study the effect of offshoring on the employment rate.

Table 4: Effects of Task Displacement and Offshoring on Wages: 1995-2018

	Dep. Var. Log Changes in Hourly Wage			
	(1)	(2)	(3)	(4)
Task Displacement	-0.016		-0.013	-0.013
	(0.024)		(0.024)	(0.024)
Offshoring		0.062	0.061	0.050
		(0.024)	(0.024)	(0.023)
IT Investment				-0.309
				(0.055)
Observations	1,325	1,325	1,325	1,325
Pref. FE	✓	✓	✓	✓
Demographic FE	✓	✓	✓	✓

Notes: This table shows the relationship between task displacement, offshoring, and changes in wages across demographic groups in Japan. Demographic groups are defined as a pair of prefectures (47), sex (2), age groups (8 five-year age bins, 25-29,...,60-64), and college education (2). The dependent variable is the changes in log hourly wages from 1995 to 2018 for each demographic group. As the running variables, Columns (1), (3), and (4) include the task displacement measure. Columns (2), (3), and (4) include the offshorability measure. All the columns include prefecture-fixed effects, gender-fixed effects, age group-fixed effects, and college-education fixed effects. Column (4) includes real IT capital stocks. Each observation is weighted by its initial total hours worked. Robust standard errors are shown in parentheses.

Finally, as the mechanism, I study the effect of automation and offshoring on occupational switches. In particular, I examine whether offshoring exposures encourage workers to move out of offshorable occupations.

Table 5 shows the results. Column (1) uses changes in log monthly payrolls, Column (2) uses changes in log hours worked in a month, Column (3) uses changes in employment rate, and Column (4) uses changes in the share of offshorable occupations as the dependent variable, respectively. All the columns include prefecture-fixed effects, gender-fixed effects, age-group-fixed effects, and college-education fixed effects. All the columns include real imports and real IT capital stocks. Each observation is weighted by its initial total hours worked. Robust standard errors are shown in parentheses.

The estimates suggest that offshoring leads to increases in average monthly payroll, decreases in hours worked, decreases in employment rate, and decreases in the share of offshorable occupations.

5 Conclusion

In this paper, I show that the surge in offshoring in Japan is associated with a decrease in wage inequality. This is consistent with the findings in the US (Ottaviano et al., 2013; Wright, 2014). The results suggest that the surge in offshoring in Japan is concentrated in industries where ex-ante low-income workers work. This is consistent with the fact that the surge in offshoring in Japan is concentrated in manufacturing industries, which are traditionally low-wage industries.

There are several directions for future research. One of the most exciting avenues would be to study the consequences of offshoring in a more detailed manner using employer-employee-matched datasets with firm-level offshoring data. That will allow researchers to study whether

Table 5: Effects of Task Displacement and Offshoring on Different Outcomes: 1995-2018

	Dep. Var. Log Changes in			
	Montly Payroll	Hours Worked	Employment Rate	Share in Ofs. Occ.
	(1)	(2)	(3)	(4)
Task Displacement	-0.015	-0.041	0.037	0.145
	(0.021)	(0.074)	(0.012)	(0.126)
Offshoring	0.078	-0.164	-0.044	-0.301
	(0.022)	(0.076)	(0.013)	(0.129)
IT Investment	-0.268	1.387	-0.046	1.508
	(0.047)	(0.164)	(0.027)	(0.279)
Observations	1,045	1,045	1,045	1,045
Pref. FE	✓	✓	✓	✓
Demographic FE	✓	✓	✓	✓

Notes: This table shows the relationship between task displacement, offshoring, and changes in wages across demographic groups in Japan. Demographic groups are defined as a pair of prefectures (47), sex (2), age groups (8 five-year age bins, 25-29,...,60-64), and college education (2). The dependent variable is the changes from 1995 to 2018 for log monthly payroll, log hours worked in a month, employment rate, and the share of offshorable occupation in Columns (1), (2), (3), and (4), respectively. All the columns include prefecture-fixed effects, gender-fixed effects, age-group-fixed effects, and college-education fixed effects. Each observation is weighted by its initial total hours worked. Robust standard errors are shown in parentheses.

offshoring relocates workers within or across firms.

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A More Figures

Figure A.1: Change in Labor Share by Manufacturing Industries 1980-2012 (JIP2015)

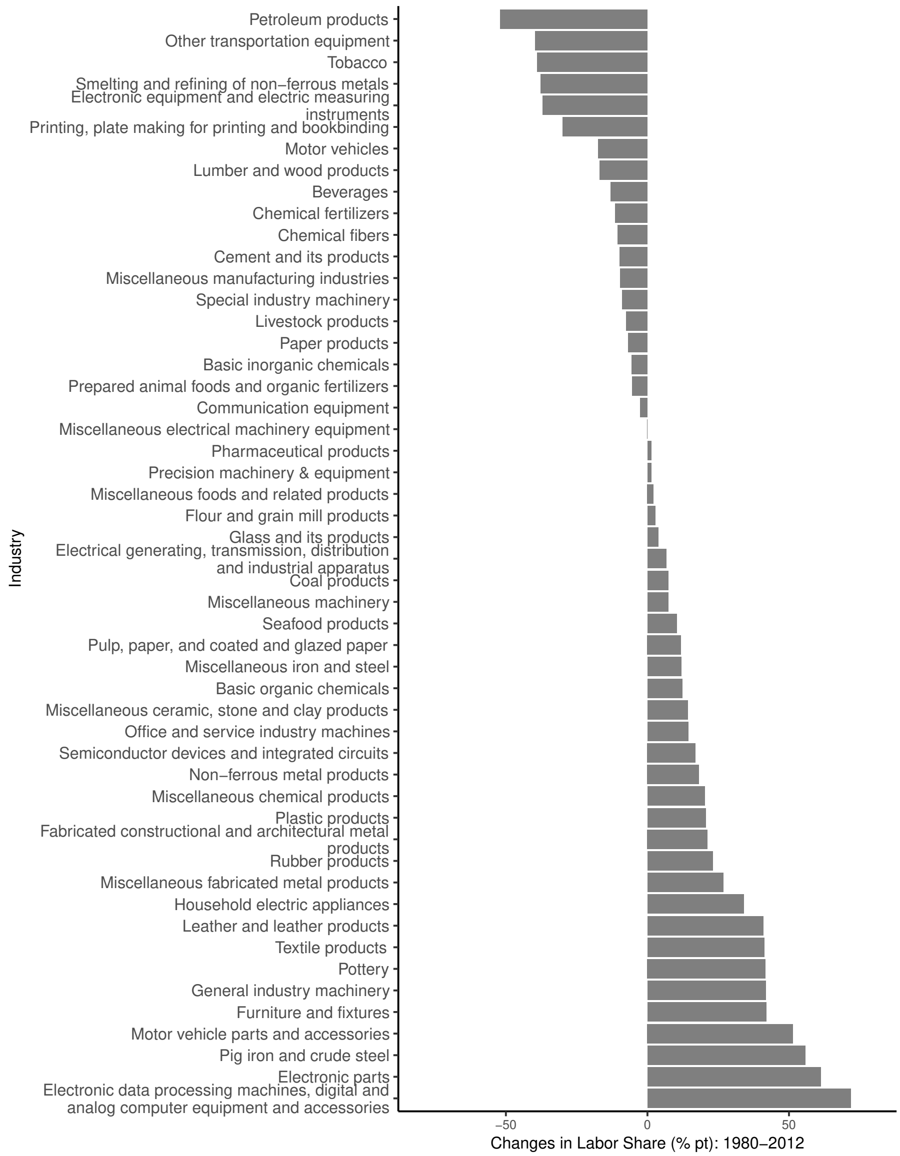

Figure A.2: Change in Labor Share by Non-manufacturing Industries 1980-2012 (JIP2015)

Figure A.3: Change in Labor Share by Manufacturing Industries 1994-2018 (JIP2021)

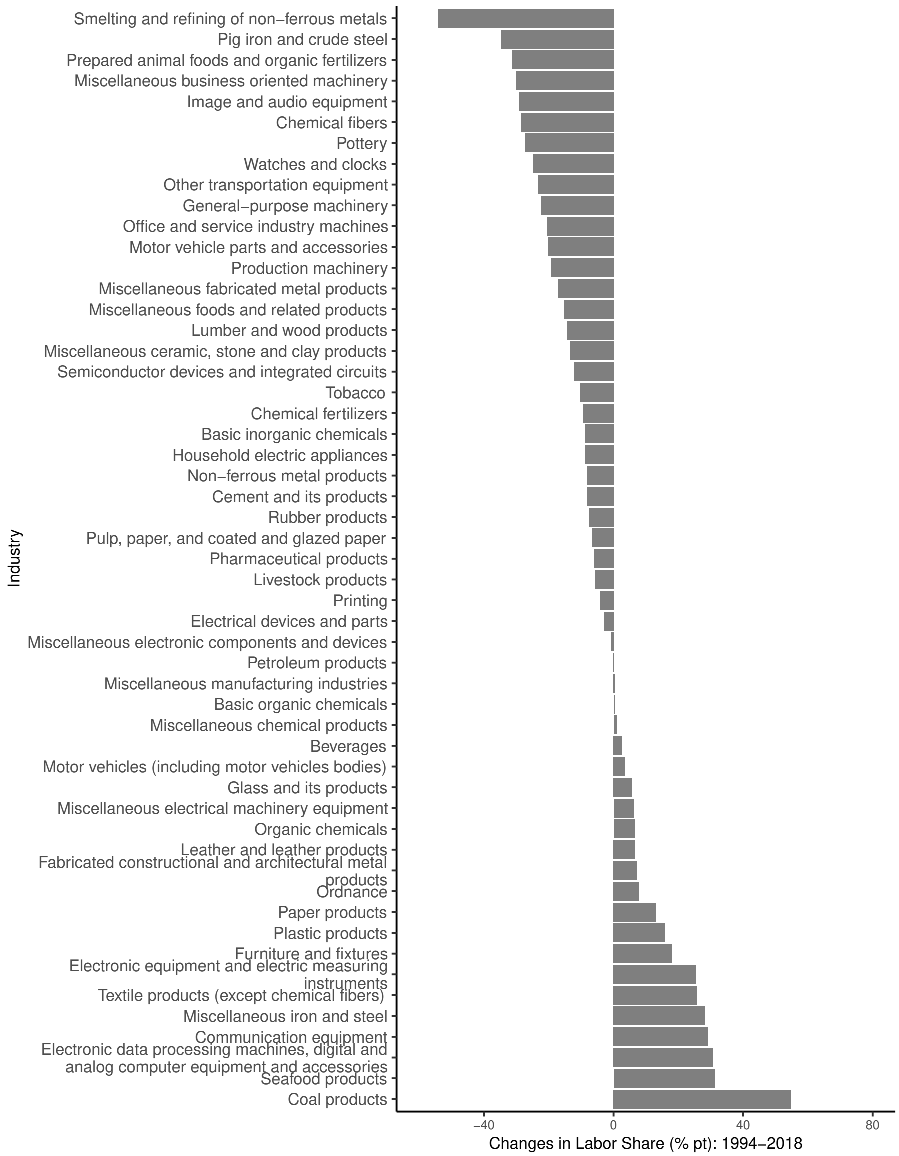

Figure A.4: Change in Labor Share by Non-manufacturing Industries 1994-2018 (JIP2021)