Robot, Employment, and Population: Evidence from Articulated Robot in Japan's Local Labor Markets

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Abstract

We study the impacts of industrial robots on local labor markets in Japan, a leading country of robot production. Among structure classification of robots, articulated robots are particularly designed to replace human labor. We employ a unique data set that contains the cross table of robot deliveries by destination industry and robot structure. We leverage roughly 300 commuting zones (CZs) as units of analysis. To study the technology-induced causal effect, we employ the shift-share instrumental variable approach with penetration of robots in Germany, another leading country of robot production. Our novel findings include (i) using the articulated robot for the penetration measure, employment-to-population decreased in the areas highly exposed to the robot, as in Acemoglu and Restrepo (2017). However, (ii) the decrease is not caused by the reduction in employment, but by a *larger increase* in the population in CZ.

Keywords: inequality, automation, industrial robots, structure of robots, articulated robots, employment, jobs, labor, local population.

JEL Classification: J23, J24, R23, O33, R11.

1 Introduction

Academic researchers, policymakers, and journalists alike all discuss the concern that the penetration of new technology deprives jobs of human (Frey and Osborne, 2017). As an example of

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such new technology, growing literature examines the impact of industrial robots on labor market outcomes but have not arrived at a consensus. Graetz and Michaels (2018b) reported that robot penetration increased labor productivity as well as wages based on OECD country-industry level analysis. Acemoglu and Restrepo (2017) analyzed US regional labor markets and concluded that robot penetration to a local labor market reduces the employment-to-population rate and earnings of all workers regardless of skill levels implying that all workers are losers of robot penetration. In contrast, Dauth et al. (2018) analyzed German regional labor markets to find that the penetration of robots decreased the employment in the manufacturing sector but increased the employment of service sector, suggesting the coexistence of losers and winners in the local economies. These conflicting empirical results from two major economies, in addition to the theoretical discussion by Caselli and Manning (2018) that technological progress should benefit some workers under fairly standard assumptions, warrant further empirical study on other major economies based on the local labor market approach. This paper aims to analyze the effect of robot penetration on local labor markets of Japan, which is the most robot dense country measured by the robot stocks per worker. More importantly, it aims to attribute the seemingly contrasting results from US and German labor markets to the difference of the measurements in the outcome variables, either employment-population ratio or the total number of employment.

Our empirical strategy is based on the regional labor market approach similar to Acemoglu and Restrepo (2017) and Dauth et al. (2018) that exploits the difference in the impact of robot penetration by regions due to the initial heterogeneity in industrial composition. For example, the regions where automobile industry was concentrated are profoundly affected by the robot penetration because automobile industry has been a significant destination of robot shipments, whereas the regions where food processing industry was concentrated have virtually not been affected because robots are rarely shipped to the food processing industry.

To implement the empirical analysis, we draw on data set published by Japan Robot Association (JARA) that records the shipment of each type of robots to destination industries by year. JARA provides source data to the International Federation of Robots (IFR) whose data was widely used in the previous empirical studies (Graetz and Michaels, 2018b; Acemoglu and Restrepo, 2017; Dauth et al., 2018). The benefit of JARA's original data over IFR is its detailed classification of robot structures. According to IFR, the industrial robot is an automatically controlled, reprogrammable, and multipurpose machine. Since this definition covers a wide variety of complexities of robots, it cannot necessarily capture the recent development of robot technology that replicates human moves. This issue is particularly severe when we study the impact of robot penetration in Japan where the significant adaptation of robots started as early as the 1970s, particularly in welding tasks in the automobile assembly lines. Reflecting the early adaptation, the number of robot stocks has been almost constant from the early 1990s until recently in the IFS data set. However, behind the nearly constant stocks, more sophisticated robots have substituted for simple robots. To capture the penetration of robots that closely mimics human actions, we particularly focus on the articulated robots with multiple joints whose shipments have increased significantly in the 2000s and 2010s.

We assess the impacts of robot penetration on local labor markets using the Employment Status Survey, a large scale household surveys conducted in every five years between 2002 to 2017. This period covers the period we observe significant penetration of articulated robots in Japanese industries. The unit of analysis is roughly 300 commuting zones (CZs) defined by Adachi and Fukai (2019) based on commuting patterns available in the Population Census. This paper is the first application of such CZs in Japan. Exploiting the heterogeneous industrial structure as of 2002 by CZs and heterogeneous shipments of articulated robots across industries, we construct the measurements of robot exposures by CZs. To address the potential endogeneity of robot penetration caused by the industry-level demand shock that increases both the investment in robots as well as labor demand, we construct a shift-share-type instrumental variable drawing on German robot shipment by the industry as a measurement of price reduction of robots because Germany is another front runner in the robot production.[1].

The analysis reveals that robot penetration to the CZ increases employment, particularly that of non-university graduates. This result is somewhat consistent with Dauth et al. (2017) to the extent that they found the robot increased employment in service sectors in local labor markets in Germany. Our finding is also interpretable in light of recent theoretical development of the study of the general equilibrium effects of recent disruptive technologies such as robots and artificial intelligence. Acemoglu and Restrepo (2019) summarized the potential theoretical mechanisms through which the changes in the underlying production technologies associated with industrial robots affect local employment. Among them, displacement effect decreases the employment due to the reduction in labor demand that is substituted by the robots. On the other hand, productivity effect and reinstatement effect *increases* local labor demand, because the increased productivity due to robots implies larger local purchasing power, which results in larger labor demand, and simply because robot creates new tasks in which human labor has a comparative advantage, such as

[1]

robot market research, development, evaluation, among others. Therefore, if the latter set of effects dominates the former, technological advance in robot increases the local employment in aggregate.

Additional analysis of the robot penetration on local population shed new light on the proper measure of labor market outcomes; the analysis shows that robot penetration increases the total population of CZs. Since Japan's total population started to decline from the mid-2000s, especially in rural areas, this finding implies that robot penetration helps to maintain the population of the local community compared with other declining community. Since the impact of robot penetration on the local population is even larger than the effect on local employment, the penetration of robot to the local community decreases the employment-to-population ratio–a finding consistent with that of Acemoglu and Restrepo (2017).

The larger impact of robots on CZs' population than employment is arguably not by coincidence. To articulate the importance of manufacturing jobs in a local community, Moretti (2010) proposes the notion of local multiplier that conceptualizes the causal impact of local manufacturing-sector employment to local service-sector employment through the generation of local demand for non-tradable services by manufacturing sector workers who bring in incomes to the local community by producing the tradable goods. The productivity effect of Acemoglu and Restrepo (2019) is a theoretical model that suggests a presence of such a multiplier effect. We propose a similar multiplier effect from the local employment to the local population, including the dependent population. We argue that the sustained manufacturing sector employment in a local community induced by the penetration of robots generates sufficient demand for local service sector that helps to sustain local commercial facilities such as local retail grocery shops. Furthermore, sustained manufacturing-sector employment increases tax revenues of local governments that help to maintain local public goods such as public schools and hospitals. Another mechanism could be employment opportunities in a local community may help sustain regional social capital based on networks among residents. All these externalities motivate the non-working population to remain in the local community. Thus, despite the apparent negative impact of robot penetration on the employment-to-population ratio, we conclude that robot increases the employment and indirectly help sustain the local community in Japan.

2 Background

2.1 Structures of Robots

In this section, we discuss some technical detail of industrial robots. International Organization for Standardization (ISO) gives the definition of industrial robots as follows: "automatically controlled, reprogrammable multipurpose manipulator programmable in three or more axes.[2]" According to this definition, the first industrial robot at least dates back to 1938, when an "automatic block-setting crane" was introduced, and the first made-in-Japan industrial robot, Unimate, was released in 1969 by Kawasaki Heavy Industry. The first Unimate is a cartesian robot featureing five axes. This was a favorable property, in particular, to Transport machinery industry or more specifically the automobile industry. Machine with such features might potentially save human labor without losing the flexibility to accommodate the model changes that were frequent in these industries.[3] Japan quickly accepted the new technology beginning in 1970's.

Since then, technological improvement was made in terms of applicability of robots as the demand industries widen. Industrial robots are categorized. Indeed, in "agreement with the robot suppliers, robots should be classified only by mechanical structure as of 2004." (International Federation of Robotics, or IFR, 2016) Such mechanical structures are Linear robots (including cartesian and gantry robots), SCARA robots, Articulated robots, Parallel robots (delta), Cylindrical robots, Others, and Not classified. These structures are broadly classified according to how the articulation (or "degree of freedom") works, or specifically, how many articulations are set in which dimensions or directions. Formal definitions of each robot are summarized in Table 1. Among them, this section focuses on the structure of our primary interest, Articulated robots.

[2] `https://www.iso.org/obp/ui/#iso:std:iso:8373:ed-2:v1:en` (accessed on June 28, 2019)

[3] `https://robotics.kawasaki.com/ja1/xyz/jp/1806-01/` (accessed on June 28, 2019. Written in Japanese)

Table 1: Definitions of Structures

Classification	Definition
Cartesian robot	a robot whose arm has three prismatic joints and whose axes are coincident with a cartesian coordinate system
SCARA robot	a robot, which has two parallel rotary joints to provide compliance in a plane
Articulated robot	a robot whose arm has at least three rotary joints
Parallel robot	a robot whose arms have concurrent prismatic or rotary joints
Cylindrical robot	a robot whose axes form a cylindrical coordinate system

Articulated robots are robots whose arm have at least three *rotary* joints. Since the three joints are rotary, Articulated robots have a high degree of freedom in their operations. They can also perform operations that involve non-linear moves and avoiding the in-between objects, which give them comparative advantages in conducting tasks such as welding and painting in Transportation machinery. To the extent that many parts have to be welded to each other and painted, these features give the producers sizable cost-saving opportunities.

Importantly, the feature of more-than-three rotary joints means that Articulated robots are similar to the structure of human arms. Indeed, human body is equipped with several articulations including waist, shoulder, elbow, wrist, and those in hands. All of these articulations are rotary, which makes humans possible to perform fine tasks like those listed above. The characteristics of the human body resemble those of Articulated robots well.

This resemblance should be emphasized when matching the economic models with the real-world application. Theoretically, a growing factor demand models of production feature factor allocation to tasks (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2017, among others). In these models, factors such as human labor and robots are typically perfect substitutes in performing a certain task (e.g. welding parts together). This significantly helps the tractability of the model because then the producer problem boils down to assigning factors in each task exclusively, and assignment models are well-studied. In particular, the insights from Ricardian trade models, that a factor that has the comparative advantage in performing a task is assigned to the task. Therefore, it is crucial to employ the relevant group of robots in empirical application. Unfortunately, IFR does not provide the robot installment by structures. As we discuss in Section 3.2, our data has a benefit that we can access such variables.

2.2 Transport machinery industry in Japan

We discussed that the Transport machinery industry is a primary application of the industrial robots, in particular, Articulated robots. In Japan, the industry is clustered in southern coastal regions facing the Pacific Ocean. In particular, Tokai region (Shizuoka, Aichi, Gifu, and Mie prefectures) holds sizable amount of plants producing automobile machine and automobile parts. For example, Toyota city and Hamamatsu city are home to multinational automobile producers Toyota and Suzuki, respectively. Based on their high demand in the downstream, parts suppliers gather in these cities. Accordingly, these cities' employment shares in Transport machinery industries are high, where these data is discussed in Section 3. Since our empirical approach is by local labor market method, these cities which feature high employment shares in industries that intensively introduced industrial robots (or Articulated robots) are key in our identification and interpretation of the results that follow.

3 Data

Our main data set consists of three primary data sources–(i) 1987, 2002, and 2017 surveys of Employment Status Survey (ESS) administered by Japan Statistics Bureau, (ii) Robot Reports 1992-2017 by Japan Robot Association (JARA), and (iii) 1993 and 2007 data from the International Federation of Robotics (IFR). In short, from ESS, we obtain regional and industrial employment variables for each demographic group. From JARA, we take the shipment units and value of industrial robots for each *structure* and demand industry in Japan. From IFR, we acquire the industrial operation stock of industrial robots in countries other than Japan. We explain the details of each data source below. In addition, we also discuss how we construct the control variables in our analysis.

3.1 ESS

ESS is administered by Japan Statistics Bureau and conducted its survey in every five years that end with digit 2 or 7 since 1982. It samples around one million persons who live in Japan and is equal or above age 15, or roughly one percent of Japan's such population. We use 1987, 2002, and 2017 surveys of ESS data to obtain the regional and industrial employment and population variables for each demographic group. 1987 is used for constructing the instrumental variable (detailed below), 2002 for the base year, 2017 for the year after the change.[4] Therefore, in our primary specification, the robot installment between years 2002 and 2017 concerns.

For the employment variables, we consider the number of employed workers, their average hours worked, and their average yearly earnings. The variable of the number of employed worker is primary as it is used both as an outcome variables in the regression analyses and the industry-share variable in the construction of shift-share type regressor and instruments (Bartik, 1991; Card, 2001). Average hours and earnings are used as an outcome variables. The detail of constructing these variables from the survey instrument is set out in Section A.

Our definition of the regional units is commuting zones (CZs) in Japan. Tolbert and Sizer (1996) define the CZs in the US from the commuting flow data from the US Census 1990. Adachi and Fukai (2019) apply their method to Japan's Population Census 2005 to obtain 331 CZs in Japan. A benefit of using CZs is twofold. First, it tracts the local labor market better by relying on the information obtained by micro-level commuting flows than jurisdictional delineations. Second, the method of CZ creation yields the delineations that are mutually exclusive and collectively exhaustive. Namely, there is no single point in a country that does not locate in any CZs or more than one CZ. In particular, this implies that any rural regions are within the consideration of our analysis. This is an important feature to the extent that the industrial robots may be installed in rural regions rather than urban areas where service sector prevails.[5]

Our definition of the industries depends on the industry codes used in ESS, JARA, and IFR. ESS builds on Japan Standard Industry Classification (JSIC) in current survey years, whereas JARA on an original industry classification and IFR on ISIC. We take union of these codes and define 20 industries (13 manufacturing and 7 non-manufacturing) in Table 2. Since industrial robots are introduced intensively manufacturing industries, our definition captures fine divisions within manufacturing industries and relatively coarse definitions of non-manufacturing industries.

[4]The reason for the choice is because of the availability of JARA data. See Section 3.2 for detail.

[5]Kanemoto and Tokuoka (2002) propose an urban employment areas in Japan. The definition resembles that of Metropolitan Areas in the US, which does not cover the whole country, but focuses on delineating only urban areas.

Table 2: List of Industries

Steel	Plastic products
Non-ferrous metal	Ceramics, stone products
Metal products	Other manufacturing
General machinery	Agriculture, forestry, fishery
Electronic machinery	Power, gas, water supply
Precision and optics	Construction
Transport machinery	Transportation, warehouse, communication
Food, Beverage, Tobacco	Research and development
Paper, paper products, printing, publishing	Education
Chemical products	Other non-manufacturing

Our definition of demographic groups is three dimensional, by education, sex, and age groups. Education consists of four groups: (1) less than middle school graduate, (2) some high school or high school graduate, (3) some junior/technical college or junior/technical college graduate, (4) more than some college. To save the notation, we sometimes indicate a education category by the number in each of the parentheses. Sex groups are (1) male and (2) female. Age groups consist of five-year bins covering from age 15 to 79 and above 80. We then aggregate the person-level ESS observations to CZ-industry-demographic levels. We call these grouped unit as cells below. The person-level survey weights are used to aggregate the estimate of counts of people in the cell. In a nutshell, from ESS, we calculate CZ c-industry i-demographic group g-cell employment in year t as L^g_{cit}. From now, we will use a similar notation that lacks some of the sub- or superscript. For example, $L_{cit} \equiv \sum_g L^g_{cit}$ is demographic group-aggregate employment in CZ c, industry i, and year t.

Before we show the descriptive statistics, we discuss sample selection. Since our CZs contain sparsely populated rural regions, and since ESS is a sampling survey, there are some "cells" formed by our regional delineation, industry definition, and demographic groups. To create consistent samples across several analyses that follow, we focus on the following cells: We sum the cells by the age dimension. If the resulting CZ-industry-education-sex aggregate employment is zero, we drop such CZ-industry-education-sex groups. This procedure mainly drops some industry-demographic groups in a minor region and sustains more than 99 percent of original sum of the person weights. On the other hand, it significantly maintains the consistency of the analysis across specifications.

To better understand the data and Japan's labor market, some descriptive statistics follow. Figure 1 shows the distribution estimate of natural log of the employment across CZs for each industry.

The estimation is done by the kernel density method. To keep the distribution interpretable, the observations with more than one million observation is trimmed. The right-heavy tail of Other non-manufacturing industry indicates our selection of industry definition reflects the robot intensity at industry level–The more intensive the robot is installed, the finer the divisions of industries are. Moreover, within the manufacturing sector, Transport machinery industry has relatively right heavy-tailed distribution. This partly reflects the Japanese industrial specialization. As we see below, the industry installs the industrial robots intensively, which potentially affects sizable amount of workers who worked in the industry in the base year 2002.

Figure 1: 2002 Distribution of Employment

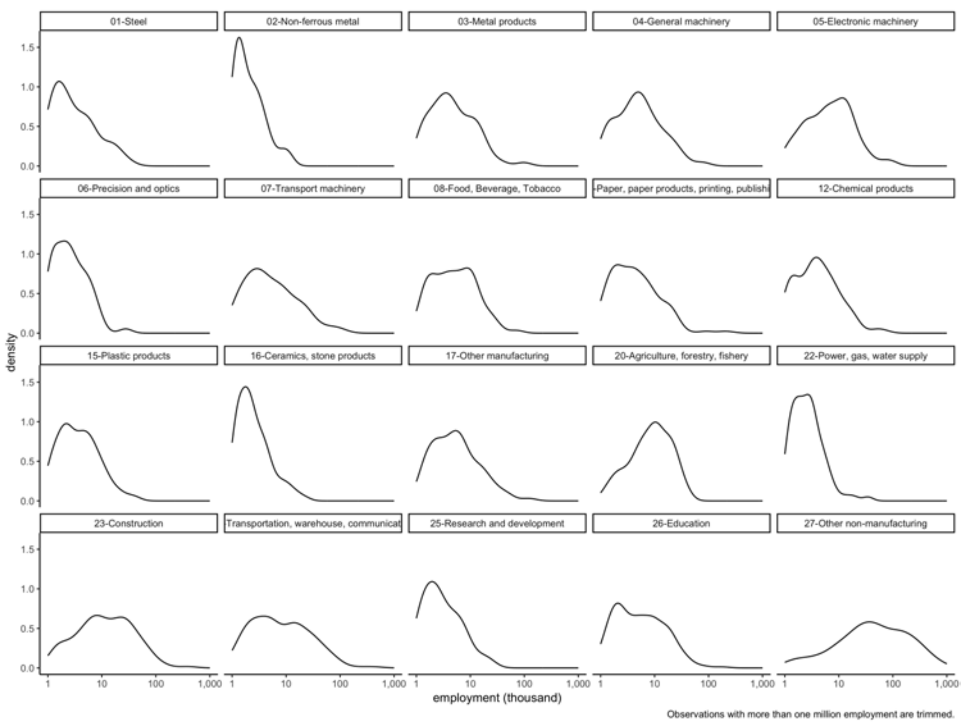
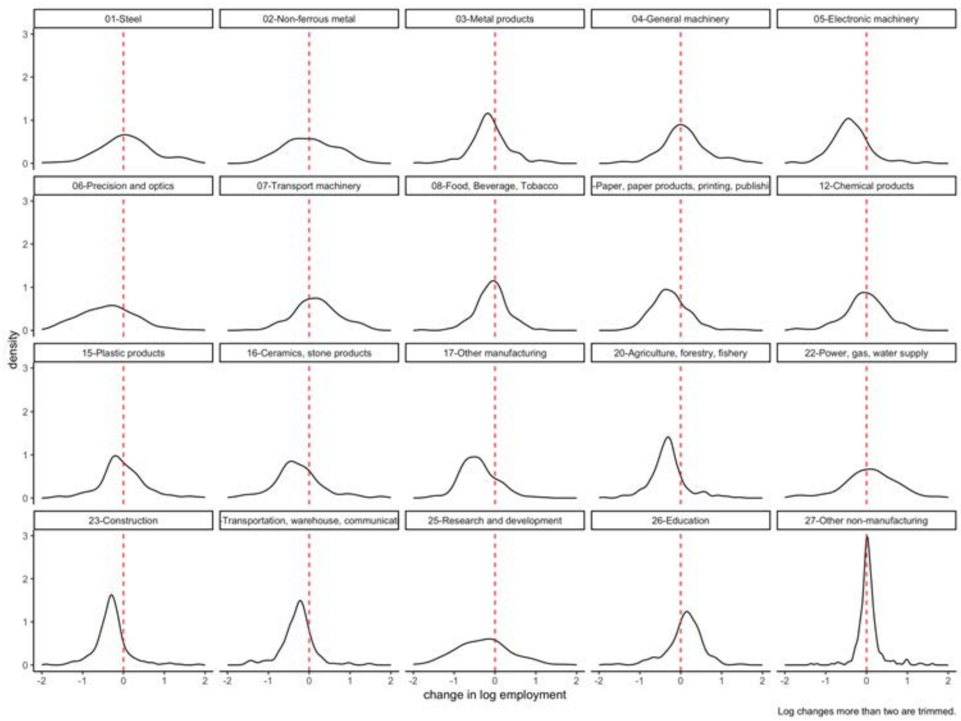


Figure 2 shows the distribution of changes in log employment between 2002 and 2017 across CZs for each industry. The observations with log changes of more than two are trimmed. The vertical dashed line shows zero change. These reservations also apply for figures below. Figure 2 tells us several key takeaways about the structural changes in Japanese labor market across industries in the period. For example, many manufacturing industries decreased the employment, including Electronic machinery. The same is the case for Agriculture, forestry, fishery. On the other hand, Education industry increased the employment. These patterns might emerge due to the structural change from the primary or secondary sectors to some of the tertiary sector. Interestingly, Transportation machinery does not join the group of employment-decreasing industries. Given that the industry absorbed many robots, one can see suggestive evidence that the robot installment does not necessarily decrease the employment at industry level.

Figure 2: Distribution of 2002-2017 Growth Rates of Employment



Figures 3 and 4 show the distributions of average hours worked and average income, respectively. Both measures are conditional on workers that report relevant variables. Again one can find no suggestive evidence that robot substantially reduced the labor demand in Japan's labor markets. For example, Transport machinery industry did not decrease the average hours worked or average income relative to other industries. These distributions by education groups are discussed in Section B.2.

Figure 3: Distribution of 2002-2017 Growth Rates of Average Hours Worked

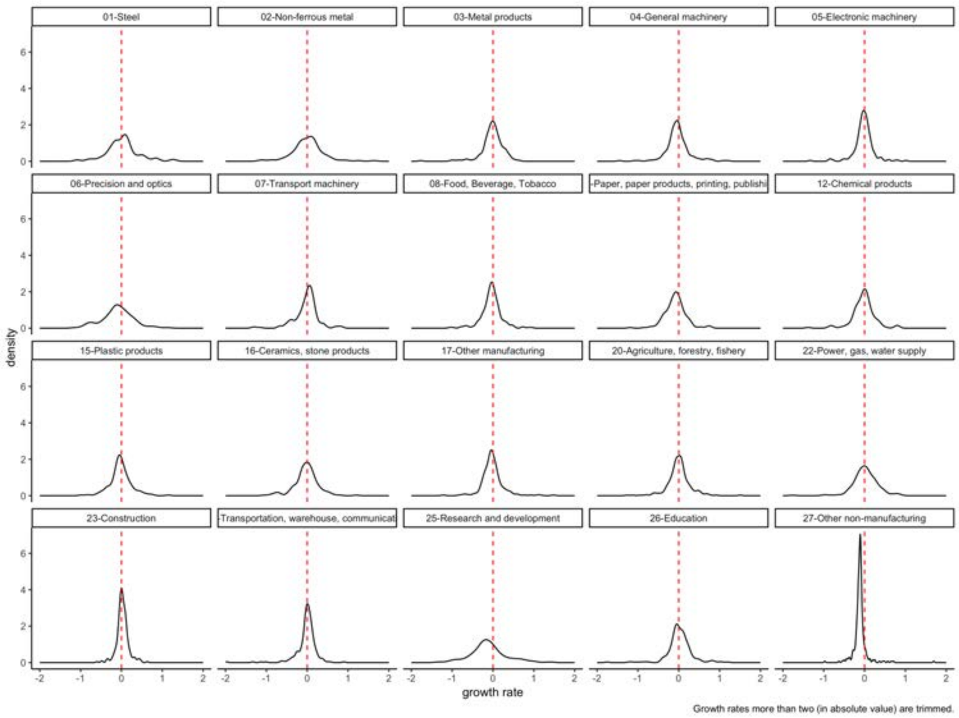
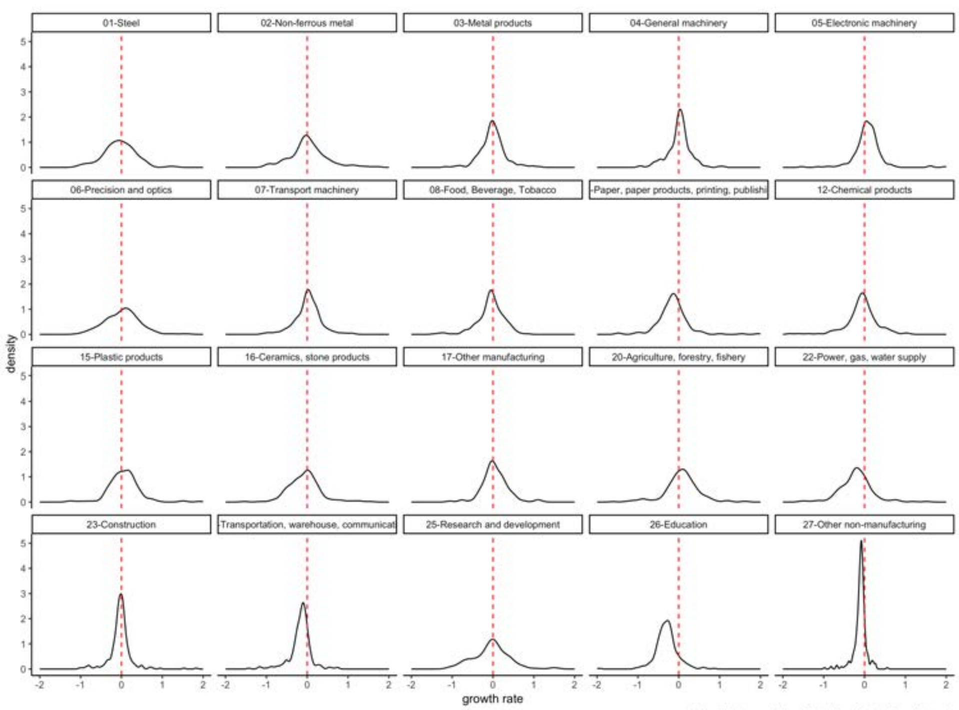


Figure 4: Distribution of 2002-2017 Growth Rates of Average Income



3.2 JARA

We now move on to the construction of the robot-side data. Our robot data consists of two data sources, JARA and IFR. IFR offers the industrial robot stock in each country between 1993 and 2016. JARA offers the data for Japan to IFR. In the original version of JARA data, we also have access to the variable that IFR does not collect, including the *structure* of robots and cross tables between the structure and industry or the type of robots and industry. As we detailed in Section 2.1, we primarily focus on the installment of *articulated robots*, which are expected to replace human labor. For this purpose, we focus on JARA data for Japan's robot installments, while we supplement this by IFR data when it is important to see the installment trends in other countries. In this section, we set out the construction of JARA data, while the next section is devoted for that of IFR data.

JARA is is an association of Japanese robot producers. As of June 2019, there are 53 full-member companies, 173 associate-member companies, and 113 supporting-member companies.[6] JARA distributes an questionnaire to the member companies to collect the unit- and value-sales of each type or structure of the industrial robots to each buyer industry. Annually, JARA publicize the summary tables of the survey results to their member companies. We obtain one of such publication for this paper. The dimensions of the summary tables differ by years. Importantly, the structure-buyer industry cross tables are available only since 2001. We therefore focus on the period after this year.

JARA data only has the flow absorption, whereas we are concerned of the stock of the robot capital and the impact on employment. To construct the capital stock, we follow the standard Perpetual Inventory Method, which is also applied in construction of capital stock measures in IFR. For detail, see C. We then calculate the structure-industry-level "penetration of robot" (Acemoglu and Restrepo, 2017) as follows:

$$PR^s_{i,(t_0,t_1)} \equiv \frac{R^s_{it_1} - R^s_{it_0}}{L_{it_0}}, \tag{1}$$

where $R^s_{i,t}$ is industry-i, structure-s, year-t stock of robot, and $t_0 \equiv 2002$ and $t_1 \equiv 2017$. In words, this measure calculates the per-worker change in structure-s robot stock between year t_0 and t_1. This can be caused by robot-producing technological change or other forces such as industry-i demand shocks. We will discuss this issue below.

[6] `https://www.jara.jp/about/index.html`, accessed on June 25, 2019.

Table 3 shows the list of $PRi, (t_0, t_1)^s$ for each industry i for structure of articulated robots. To facilitate interpretation, the measure is multiplied by a thousand. Therefore, the interpretation is the increase in the stock of robots per thousand workers. It is instructive to see that in many of the listed industries, articulated robots did not penetrate much. This indicates that the robot introduction was already saturated in Japan in year $t_0 = 2002$ in many industries. However, there is one important exception–Transport machinery industry increased the robot stock massively over the period. In fact, it overstocked 19 articulated robots per thousand workers between 2002 and 2017. Therefore, in our empirical application, the variation in the Transport machinery employment share across CZs matter significantly.

Table 3: Per-thousand-worker Penetration of Robot, Articulated Robot

Industry	Penetration of Robot
Steel	-2.681
Non-ferrous metal	-12.253
Metal products	-1.585
General machinery	-5.863
Electronic machinery	-3.861
Precision and optics	-7.481
Transport machinery	19.033
Food / Beverage / Tobacco	0.275
Paper / paper products / printing / publishing	-0.043
Chemical products	0.326
Plastic products	-3.743
Ceramics / stone products	-1.873
Other manufacturing	-4.846
Agriculture / forestry / fishery	-0.062
Power / gas / water supply	-1.938
Construction	-0.055
Transportation / warehouse / communication	-0.064
Research and development	-0.654
Education	-0.957
Other non-manufacturing	-0.013

3.3 IFR

To separate out the robot-producing technological change from our measure of penetration of robots, we employ the shift-share instrument strategy. Namely, we take local-level exogenous industry distributions in 1987, the year before the base year. By interacting industry-level robot installment growths in a counterpart country, we construct a CZ-level variation.[7] For this purpose, we employ the data from IFR. We will detail the empirical strategy in Section 4.

IFR collects the robot-operation stock data in each industry (based on ISIC revision 4) either directly from robot producers or associate institutes of member countries (including JARA). It reports the summary table through annual *World Robotics* publications from *World Robotics Wizard* from 1993 to 2016. The publication contains the robot stocks and flows in each country in each year. Although the division by types of robot and buyer industries are available individually, they are not *cross* tables. To make possible the use of the shift-share design by industry level, we do not leverage the type of robot variable from IFR, but only industry-level division.

We take the counterpart country as Germany. This is partly because our empirical application is Japan. Japan has had a number of frontier robot producers. For example, Dauth et al. (2017) report that out of 10 largest robot producers in the world, eight are Japanese firms.[8] On the other hand, Germany is also a leading robot producer. Indeed, Dauth et al. (2017) also reported that the remaining two largest producers "have German origin and mostly produce in Germany." To the extent that our instrumental variable is to take the trends of robot-technological changes that are concurrent with Japan, Germany is a relevant case for our purpose.

We thus take the robot stock in each industry in Germany in 2002 and 2016. We define the German penetration of robot as follows:

$$PR^{DEU}_{i,(t_0,t_1)} \equiv \frac{R^{DEU}_{it_1} - R^{DEU}_{it_0}}{L_{it_0}},, \tag{2}$$

where $R^{DEU}_{i,s,t}$ is industry-i, structure-s, year-t stock of robot in Germany, L^{DEU}_{it} is industry-i, year-t employment in Germany, and $t_0 \equiv 2002$ and $\widetilde{t_1} \equiv 2016$. We take German employment data in base year 2002 from EUKLEMS, Germany Basic 2017 File.[9]

[7]This method is close to the idea of Acemoglu and Restrepo (2017), with the reservation that we take a different country as the counterpart

[8]Another suggestive fact is that JARA assembles the industrial robot data of the type employed in this paper since 1970's, although this paper does not make use of it directly.

[9]Since the EUKLEMS data does not offer the breakdown of employment between Non-ferrous metal (ISIC 24) and Metal products (ISIC 25), we split the employment of the aggregate employment by half.

4 Empirical Strategy

In this section, we set out the empirical strategy by which we address our question of how specific-type industrial robots affected Japan's labor markets in 2002-2017, using our data set. We first discuss our main empirical specification in Section 4.1. Out of the specification, we overview some basic descriptive statistics of the variables used in the analysis in Section 4.2.

4.1 Specification

Armed with the data sets described in Section 3, we conduct empirical analyses regarding the impact of installments of the robots of each structure on several outcome variables. To do so, we begin by defining the measure of exposure to structure-s robots in each CZ as follows:

$$ER^{s}_{c,(t_0,t_1)} \equiv \sum_{i} l_{cit_0} PR^{s}_{i,(t_0,t_1)}, \tag{3}$$

where $l_{cit} \equiv \frac{L_{cit}}{\sum_{i'} L_{ci't}}$ is the industry-i share of employment in CZ c and year t. The motivation of the definition is that a CZ is exposed to robot more if it is intensive in industry where robots penetrate massively. In an economic theory with robot capital, the measure is the log-first order approximation to the effect of robot-technological improvement that enables robot to engage in tasks that were previously done exclusively by human labor. In fact, the base-year employment share l_{cit_0} works as the weight to averaging the log-approximated penetrations in each industry. This point is discussed in detail in Acemoglu and Restrepo (2017), who define a similar measure of exposure, but without the concept of structure s. For the sake of exposition, we occasionally drop (t_0, t_1) notation from now, when the analysis years are fixed and the dropping does not raise the risk of misinterpretation.

With this definition of exposure to robot, our main empirical specification is as follows: For each group g (including group-aggregate) and structure s,

$$y^{g}_{c} = \alpha^{gs} + \beta^{gs} ER^{s}_{c} + X'_{c}\gamma^{gs} + \varepsilon^{gs}_{c}, \tag{4}$$

where y^{g}_{c} is one of CZ c-demographic group g outcome variables, X_c is the (column) vector of control variables of CZ c, and ε^{gs}_{c} is the error term. Outcome variables are to be discussed below. Our coefficient of interest is β^{gs}, which can be interpreted as the effect of exposure to structure-s robot on the outcome variable of group g, upon identification discussed below. We take the control variables of the base-year characteristic variables of the demographic distribution such as working-age population shares and shares of employment by industry such as manufacturing, durable, and construction, following Acemoglu and Restrepo (2017).

To have a structural interpretation of β^{gs} introduced above, an uncorrelation assumption has to be satisfied with respect to the error term ε_c^{gs}. In equation (4), this assumption is problematic for a number of reasons. For example, suppose that the exchange rate depreciates and favors the export of Transport machinery disproportionately to other industries. This can be interpreted as a positive demand shock to the industry, which would increase the employment of both human labor and robots. This effect happens intensively in CZs with high initial employment shares of Transport machinery industry, such as Hamamatsu and Toyota CZs in Tokai region.[10] Then in equation (4), ER_c^s and ε_c^{gs} have a positive correlation, which violates the uncorrelation assumption.

To deal with the endogeneity problem, we follow a literature and consider a shift-share type of instrumental variable as follows:

$$ER_{c,(t_0,t_1)}^{DEU} \equiv \sum_i l_{cit_{-1}} PR_{i,(t_0,t_1)}^{DEU}, \tag{5}$$

where $t_{-1} \equiv 1987$ in our application. We call the year t_{-1} as the previous year to the base year. The motivation of the instrumental variable is twofold. First, to the extent that the employment share in the previous year is exogenous to the future demand shocks such as the exchange rate shocks after the base year, the instrument is uncorrelated with the error term ε_c^{gs} in equation (4). This maintains the instrument exogeneity. Second, to the extent that the robot technological innovation is correlated within the set of countries that are frontier in producing robots (e.g. Germany and Japan), the "shift" term of Germany penetration of robot in equation (5) works to correlate the Germany exposure to robot term, equation (4), with the (Japan's) exposure to robot, equation (3). This helps establishing the instrument relevance, which has positive correlation between the instrumental variable and the regressor, in particular. Formally, our identification assumption is that the previous year industry distribution $l_{cit_{-1}}$ is uncorrelated with the error term ε_c^{gs} (Goldsmith-Pinkham et al., 2018).

We close the current subsection by discussing the relationship among our coefficients with different demographic groups g. Since we analyze the regression specification (4) for different groups g, it is instructive to have their analytical relationships. After some algebraic derivations regarding linear regression, it turns out group-aggregate β coefficient can be expressed as the

[10] Following the convention in the US, we name a CZ with the most population-dense municipality (county in the US) in each CZ.

average-group employment share-weighted average of group-specific coefficient β^g, under the assumption that the base-year group employment share is exogenous. If this assumption does not hold, a correction term reflecting the endogeneity of the base-year group employment share emerges. In short, group-aggregate β is a weighted average of group-specific β^g's up to a correction term depending on underlying assumptions. Section D details.

4.2 Descriptive Statistics

Given our empirical specification and variables therein, we overview the descriptive statistics. In particular, in our main empirical specifications, the main outcome variables are employment-population ratio, growth rate of employment and population. Formally, these variables are defined as follows, respectively:

$$\Delta EP^g_{c,(t_0,t_1)} \equiv \frac{L^g_{c,t_1}}{P^g_{c,t_1}} - \frac{L^g_{c,t_0}}{P^g_{c,t_0}},\ r^{L,g}_{c,(t_0,t_1)} \equiv \frac{L^g_{c,t_1} - L^g_{c,t_0}}{L^g_{c,t_0}},\ r^{P,g}_{c,(t_0,t_1)} \equiv \frac{P^g_{c,t_1} - P^g_{c,t_0}}{P^g_{c,t_0}}. \tag{6}$$

We show the descriptive statistics including these variables in Table 4. First, overall, our sample consists of 305 CZs in total and 296 with those where Germany's exposure to robot variable is observed. The drop in the latter occurs because of the population change between 1987 and 2002 and some minor CZs were not well surveyed in 1987 ESS with minimal effects on our analysis. Note that this sample size is relatively large compared with the studies of Japan's local labor markets. For example, when one used the prefectures or Metropolitan Employment Areas (Kanemoto and Tokuoka, 2002) as the unit of analysis, (s)he would have smaller sample size such as 47 or 110 (2005 definition), respectively. Moreover, as we have discussed, robot installment could be potentially intensive in rural areas where service industry does not prevail. CZs capture these areas because the definition covers Japan in a mutually exclusive and collectively exhaustive manner. Therefore, our large sample size is suitable for our analysis both for the sample size and economic environment surrounding robots.

We then discuss each statistics in Table 4. Average employment and population in 2002 are 209 thousand and 352 thousand, respectively. Multiplying the sample size by these numbers result roughly in Japan's macroeconomic employment size and population equal or above age 15. Average weekly hours in 2002 and small standard deviation reveals majority of workers work at full time (40 hours a week). Average income in 2002 is reasonable or slightly overstating from the perspective of Japan's per-capita GDP and the labor share.[11] Our main outcome variables, changes or growth rates between 2002-2017, observe decreasing trends on average. Demographic changes including aging may partly explain these trends.

[11] 32,289.35 (2002 USD) × 125.14 (2002 JPY/USD) * 0.638 (Japan's labor share 2002) = 2.578 million JPY in 2002 (Source: World Bank, Bank of Japan, Adachi and Saito, 2019)

Table 4: Descriptive Statistics

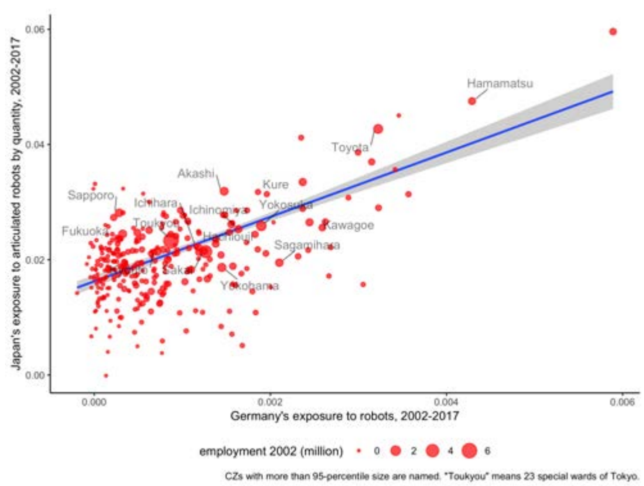
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
employment 2002 (thousand)	305	208.743	478.202	0.265	18.566	238.670	6,249.378
population 2002 (thousand)	305	351.771	784.606	0.349	34.452	400.459	9,929.337
average weekly hours 2002	305	37.857	3.973	21.106	36.135	39.209	56.860
average income 2002 (2002 million JPY)	305	3.111	0.559	0.896	2.765	3.396	5.939
exposure to robot	305	0.019	0.007	−0.0001	0.015	0.023	0.060
Germany's exposure to robot	296	0.008	0.008	−0.002	0.002	0.011	0.059
change of employment-to-population ratio 2002-2017	305	−0.007	0.066	−0.318	−0.030	0.010	0.249
growth rate of employment 2002-2017	305	−0.008	0.495	−0.790	−0.156	0.011	6.967
growth rate of population 2002-2017	305	−0.007	0.402	−0.731	−0.135	0.010	4.288
growth rate of average hours 2002-2017	305	−0.211	0.093	−0.527	−0.243	−0.195	0.387
growth rate of average income 2002-2017	305	−0.072	0.141	−0.501	−0.121	−0.034	0.837

5 Results

5.1 Main Results

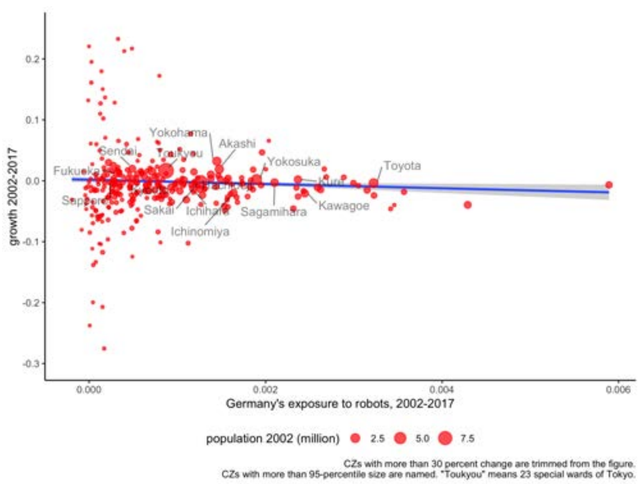
This section is devoted to discuss the empirical results of the regression specification (4). First, we focus on the articulated robot structure. Figure 5 shows the result of the first stage regression. The x-axis shows our instrumental variable of Germany's exposure to robot, while the y-axis shows our regressor of exposure to robot. In our plot analysis, the x-axis is the same variable for most of the time when not otherwise stated. The red bubbles show each CZ, while the size of them indicate the base-year population. The result of the base-year population-weighted regression is shown by the blue line and the gray region. For each point on x-axis, the blue line is the collection of the point estimates, whereas the gray area show the 95 percent confidence interval. Similar notes apply for the rest of the figures that follow. As one expects, there is strong positive correlation between the instrument and the regressor. In particular, the CZs intensive in robot-heavy industries (e.g. Transport machinery), such as Hamamatsu and Toyota, have high values to both of the variables Germany's exposure to robot and exposure to robot. This reflects two facts–that there CZs are both historically and currently such industry-intensive, and that both Germany and Japan experienced the innovation in robotics technology that are suitable to the application in such industries.

Figure 5: First Stage



We then proceed to the analysis of the reduced form of specification (4). We first analyze the outcome variable of the change in employment-population ratio, $\Delta EP^{g}_{c,(t_0,t_1)}$. Figure 6 shows the result. The y-axis is the outcome variable. To simplify the plot, CZs with the change of the outcome variable with more than 30 percent are dropped.[12] This sample selection in plots applies for the rest of the plots unless otherwise stated. As one can see, there is statistically significant negative association between the instrument and the outcome variable. Therefore, the identification assumption implies that the installment of robots *decreases* the employment-population ratio. We discuss the quantitative implication below when we show the regression tables. Qualitatively, our finding is consistent with that of Acemoglu and Restrepo (2017).

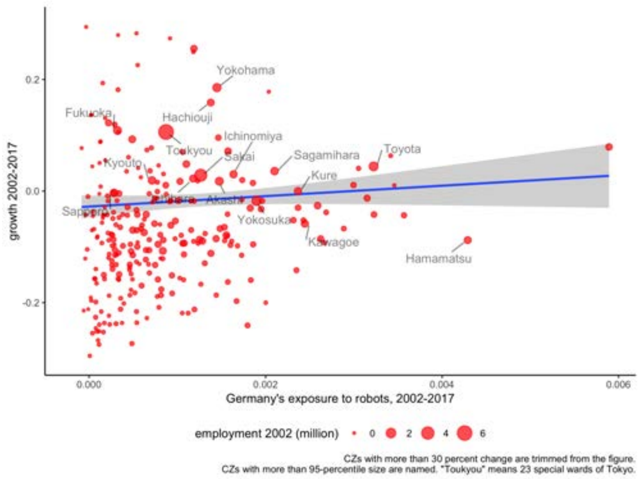
Figure 6: Reduced Form, Employment to Population Ratio



How does this negative relationship emerge? To approach, we explore the growth rate of employment growth rate $r^{L,g}_{c,(t_0,t_1)}$ and population growth rate $r^{P,g}_{c,(t_0,t_1)}$ separately. Figure 7 shows the result of the employment growth rate, which is on the y-axis. Interestingly, we do not observe the negative correlation that was found in Figure 6, but weak positive one. This reflects the fact that the robot does not necessarily reduce the employment *at level*.

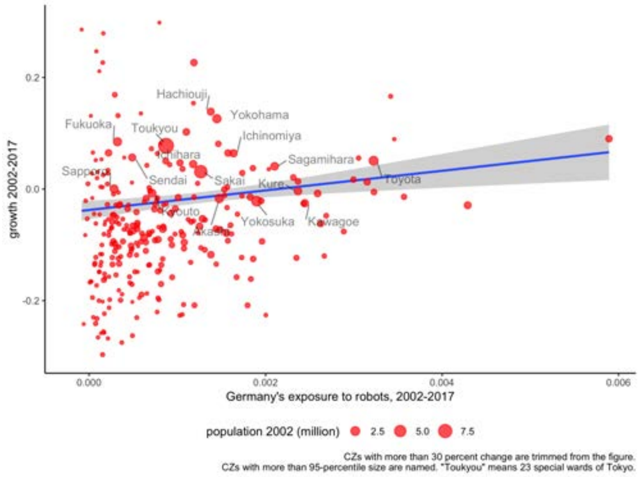
[12]Such extreme change in the outcome variable mostly occurs in minor CZs, where the denominator of the variable, base-year employment, is small. Thus it does not significantly affect the slope of the weighted fit line.

Figure 7: Reduced Form, Employment Growth Rate



Given the results in Figure 6 and 7, it must be that the population measure strongly *positively* correlates with the instrument. Figure 8 confirms this by showing the result of the population growth rate $r^{L,g}_{c,(t_0,t_1)}$ on y-axis. Therefore, it can be said that since the population growths' positive association with the instrument is stronger than that of employment growths, the employment-to-population ratio is negatively correlated with the instrument in Figure 6. In other words, the negative relationship for employment growth is not a necessary condition for having negative relationship for employment-population growth. Indeed, the negative relationship for employment-population can emerge even with positive employment growth, so long as the population growth has *stronger* positive relationship than employment growth. A formal discussion between these measures can be found in Section E.

Figure 8: Reduced Form, Population Growth Rate



Tables 5 and 6 confirm the findings in Figures 5, 6, 7, and 8. In Table 5 in column 1, we can confirm that the first stage is strong–The F statistic is 267. Columns 2-4 simply reflects the correlation in Figures 6, 7, and 8. These result in the main regression results in Table 6, in which columns 1 and 2 compare the results of OLS and IV. Note that the IV coefficient is significantly negative whereas the OLS coefficient is positive and statistically significant. Recall that we discussed in Section 4, OLS may include positive bias caused by local factor demand shocks. Our results are consistent with this theoretical prediction. From Table 4 and column 2 of Table 6, we interpret that one standard deviation increase in exposure to robot (0.007) reduces the employment-to-population ratio by 0.45 percent point (= 0.64 * 0.007 * 100) at the point estimate. However, again, this effect emerges from relative population growth rather than employment shrink. From column 3 and 4, the similar calculation shows that the same increase in exposure to robot *increases* employment by 1.36 percent point *and* population by 2.25 percent point.

Next, we discuss the robots' implication on average hours worked and earnings. Figures 9 and 10 shows the reduced-form regression plots of workers' average hours worked and their average income, respectively. Neither plot shows clear pattern of the effect of Germany's exposure to robot. This can be confirmed by the instrumental variable regression shown in Table 7. To reconcile these results with the above results that shows an increased employment, it might be the case that those added to the employed group because of robots may work shorter and earn less than the average workers. Thus the composition effect might mask the overall effect of increasing labor demand found in Figure 7 and Table 6.

	First Stage	RF, $\Delta \frac{L}{P}$	RF, g_L	RF, g_P
(Intercept)	0.02^{***}	0.00	-0.03^{***}	-0.04^{***}
	(0.00)	(0.00)	(0.01)	(0.01)
Exposure to Robot	5.46^{***}	-3.44^{***}	11.26^{*}	17.51^{***}
	(0.33)	(1.31)	(6.51)	(5.53)
Num. obs.	296	296	296	296

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
First stage regresses the measure of exposure to robot on the instrumental variable of Germany's exposure to robot. RF stands for reduced form. The variables in the model name is the regressand, which is regressed on the same instrumental variable. $\Delta \frac{L}{P}$ is the change in the fraction of employment and population, while g_L and g_P are the growth rate of employment and population, respectively. See the text for detail.
All regressions are weighted by the base-year employment or population. See the text for detail.

Table 5

	OLS, $\Delta \frac{L}{P}$	IV, $\Delta \frac{L}{P}$	IV, g_L	IV, g_P
(Intercept)	-0.01^{*}	0.01^{**}	-0.06^{**}	-0.09^{***}
	(0.00)	(0.01)	(0.03)	(0.02)
Exposure to Robot	0.20	-0.64^{**}	1.94^{*}	3.21^{***}
	(0.17)	(0.26)	(1.12)	(1.01)
Num. obs.	305	296	296	296

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
IV model uses the instrumental variable of Germany's exposure to robot. $\Delta \frac{L}{P}$ is the change in the fraction of employment and population, while g_L and g_P are the growth rate of employment and population, respectively. See the text for detail.
All regressions are weighted by the base-year employment or population. See the text for detail.

Table 6

Figure 9: Reduced Form, Average Hours Growth Rate

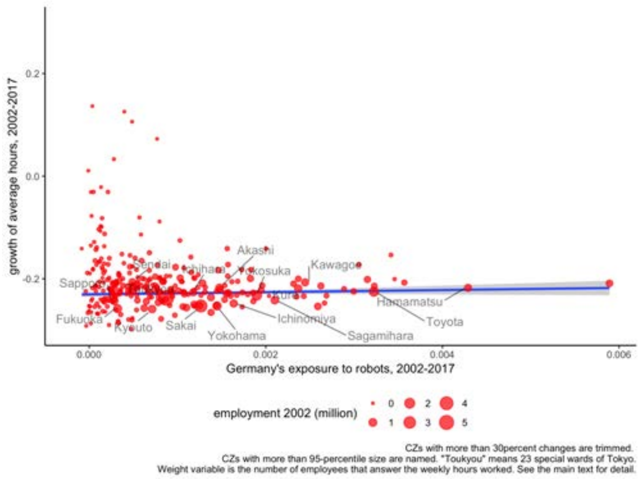
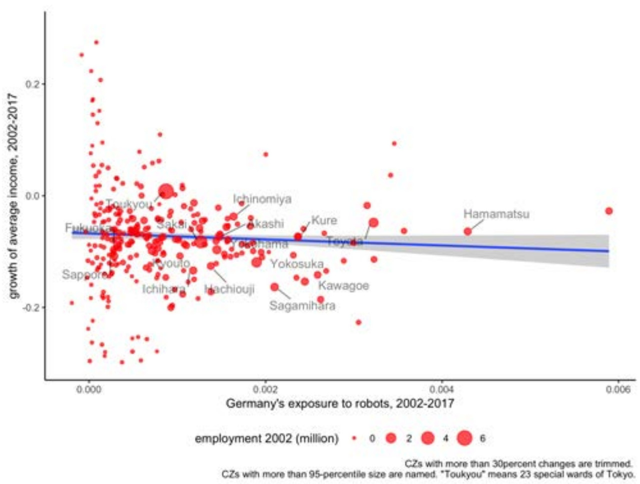


Figure 10: Reduced Form, Average Income Growth Rate



5.2 Results by Education Levels

Among different groups of people in CZs, which drive the pattern found in Section 5.1? To approach this question, we separate the educational and gender groups. We primarily focus on two major groups in Japan's labor markets, male some high school or high-school graduates (High-school Graduates or HSG, or education group 2 in Section 3.1) and male more-than-some four-year college (College Graduates or CG, or education group 4 in Section 3.1). Other demographic groups are

	Hours	Income
(Intercept)	-0.24^{***}	-0.05^{***}
	(0.01)	(0.01)
Exposure to Robot	0.43	-0.92
	(0.28)	(0.58)
Num. obs.	296	296

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
All regressions regress the outcome variable on the measure of exposure to robot with the instrumental variable of Germany's exposure to robot. Hours is the growth rate of average hours worked. Income is the growth rate of average income. See the text for detail.
All regressions are weighted by the base-year employment or population. See the text for detail.

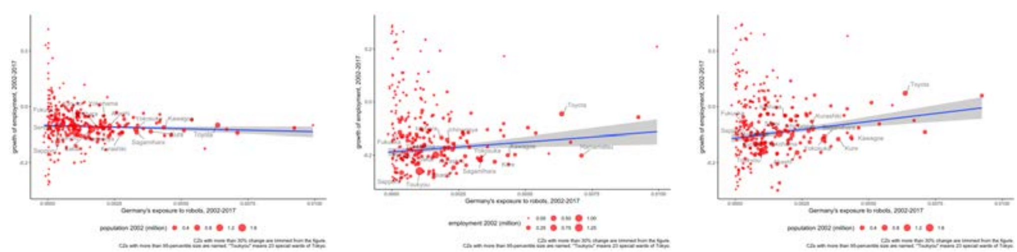
Table 7

discussed in detail in Section **??**. Since our regressor is the same across analyses as in equation (4), the first stage plot is the same as Figure 5.

Figure 11 shows the results for high-school graduates. From the left, subpanels show the result of different outcome variables, change in employment-to-population ratio, growth rate of employment, and that of population. One can see the qualitative similarity with the group-aggregate results in Figures 6, 7, and 8. Namely, although the employment-to-population ratio is decreasing in Germany's exposure to robot measure (panel a), the result is accompanied by the *positive* correlation for employment growth (panel b) rate and the even *stronger positive* correlation for population growth (panel c). Indeed, the positive association for the employment growth is now statistically significant at 5 percent (panel b).

Figure 11: Reduced Form Plots for High-school Graduates

(a) ΔEP_c^{HSG} (b) $r_c^{L,HSG}$ (c) $r_c^{P,HSG}$



However, this pattern is not observed for College Graduates. Figure 12 shows the results. The order of the subpanels are the same as Figure 11. Although we observe a negative relationship for

	HSG, $\Delta\frac{L}{P}$	HSG, g_L	HSG, g_P	CG, $\Delta\frac{L}{P}$	CG, g_L	CG, g_P
(Intercept)	-0.04^{**}	-0.29^{***}	-0.25^{***}	0.01	0.27^{***}	0.28^{***}
	(0.02)	(0.05)	(0.05)	(0.03)	(0.08)	(0.08)
Exposure to Robot	-2.46^{*}	9.44^{**}	13.24^{***}	-1.96	-4.66	-3.20
	(1.37)	(3.70)	(3.80)	(1.24)	(4.10)	(3.89)
Num. obs.	296	296	296	271	270	271

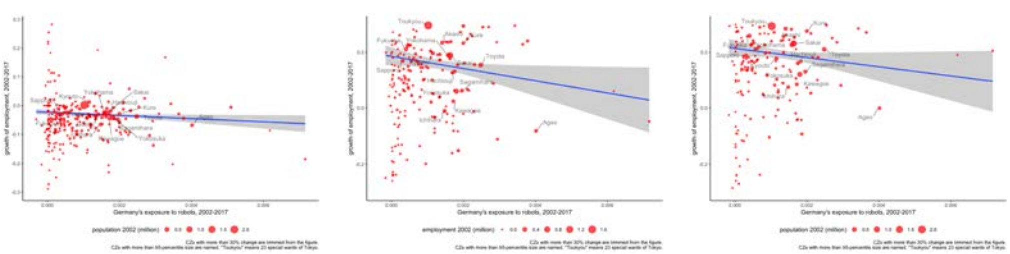
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
All regressions show the result of IV specification with the instrumental variable of Germany's exposure to robot. HSG and CG indicate the target group of the analysis. HSG stands for high-school graduates. CG stands for college graduates. $\Delta\frac{L}{P}$ is the change in the fraction of employment and population, while g_L and g_P are the growth rate of employment and population, respectively. See the text for detail. All regressions are weighted by the base-year employment or population. See the text for detail.

Table 8

the employment-to-population ratio (panel a), we do not see the positive relationship for either the employment growth rate or the population growth rate. In fact, although statistically insignificant, the relationship is negative, if any. Therefore, we interpret that the results in Section 5.1 primarily emerge from High-school Graduate groups.

Figure 12: Reduced Form Plots for College Graduates

(a) ΔEP_c^{CG} (b) $r_c^{L,CG}$ (c) $r_c^{P,CG}$



To confirm our findings in Figures 11 and 12, Table 8 shows the IV coefficients of high-school graduates and college graduates. Again, we observe that the exposure to robot reduces the employment-to-population ratio, and that both employment and population grew with the exposure, while the population grew more. This pattern is similar to the aggregate results in Table 6. We do not observe this pattern for college graduates.

6 Conclusion

We examined the impact of articulated robot penetration to commuting zone (CZ) on its employment and population in Japan. To capture the the penetration of robot to CZ, we constructed the shift-share variable constructed from the historical industrial composition and growth of robot shipment by industry. Exploiting the German robot shipment to each industry as the exogenous source of variation, we found that the penetration of robots to CZ decreases the employment to population ratio: a finding consistent with Acemoglu and Restrepo (2017). However, the separate analysis on employment and population reveals that the penetration of robots to CZ both increases CZ's employment as well as population. Since the impact on population exceeds the impact on employment, the penetration of robot apparently decreases the employment to population ratio. The impacts are particularly larger for the employment and population of less educated people. Overall, the penetration of robots help CZ sustain the employment and population through generating jobs for less educated people.

This result suggests that we should cautiously select the outcome variable to assess the impacts of exogenous change on regional employment. While the employment population ratio is widely used to measure the regional labor market outcomes to assess the impact of exposure to robots, information technology or international trade, we need to separately examine the impacts on employment as well as population.

While not substantiated by evidence at this stage, we speculate that the larger impacts of robot on local population than that on local employment is not by coincidence. With the backdrop of declining rural communities through the shrinkage of manufacturing employment in Japan, sustaining manufacturing employment could be a key to sustain the whole local community through various externally channels such as provision of local public goods through local tax revenue or sustaining local networks. The local multiplier of manufacturing jobs, intriguing concept introduced by Moretti (2010), goes well beyond the employment of service sector jobs, reaching to the total population including dependent population. Providing the direct evidence using local tax revenue, public goods provision, some measurement of social capital is left for future research.

References

Acemoglu, Daron and David Autor, "Skills, tasks and technologies: Implications for employment and earnings," in "Handbook of labor economics," Vol. 4, Elsevier, 2011, pp. 1043–1171.

— **and Pascual Restrepo**, "Robots and jobs: Evidence from US labor markets," Technical Report 2017.

— **and** — , "Automation and New Tasks: How Technology Displaces and Reinstates Labor," Technical Report, National Bureau of Economic Research 2019.

Adachi, Daisuke and Taiyo Fukai, "Commuting zones in Japan," 2019. mimeo.

— **and Yukiko U. Saito**, "Multinational productions and labor share," 2019. mimeo.

Bartik, Timothy J, *Who benefits from state and local economic development policies?*, WE Upjohn Institute for Employment Research, 1991.

Card, David, "Immigrant inflows, native outflows, and the local labor market impacts of higher immigration," *Journal of Labor Economics*, 2001, *19* (1), 22–64.

Caselli, Francesco and Alan Manning, "Robot Arithmetic: New Technology And Wages," *American Economic Review: Insights*, 2018, *1* (1), 1–15.

Dauth, Wolfgang, Sebastian Findeisen, Jens Südekum, and Nicole Woessner, "German robots-the impact of industrial robots on workers," Technical Report 2017.

— **,** — **, Jens Suedekum, and Nicole Woessner**, "Adjusting to Robots: Worker-Level Evidence," Technical Report Institute Working Paper 13 2018.

Frey, Carl Benedikt and Michael A. Osborne, "The future of employment: How susceptible are jobs to computerisation?," *Technological Forecasting and Social Change*, 2017, *114* (C), 254–280.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik instruments: What, when, why, and how," Technical Report, National Bureau of Economic Research 2018.

Graetz, Georg and Guy Michaels, "Robots at work," *Review of Economics and Statistics*, 2018, *100* (5), 753–768.

— **and** — , "ROBOTS AT WORK Georg," *The Review ofEconomics and Statistics*, 2018, *100* (5), 753–768.

Kanemoto, Yoshitsugu and Kazuyuki Tokuoka, "The proposal for the standard definition of the metro area in Japan," *Journal of Applied Regional Science*, 2002, *7*, 1–15.

Moretti, Enrico, "Local Multipliers," *American Economic Review*, 2010, *100* (2), 373–377.

Tolbert, Charles M and Molly Sizer, "US commuting zones and labor market areas: A 1990 update," Technical Report 1996.

A Variables in Detail

We set out the method to generate variables of yearly hours worked and income in the following paragraphs.

To construct hours worked, we use the variable of yearly days worked and weekly hours worked. Since these variables are categorical with bins, we take the median of the minimum and maximum thresholds if they exist. If the maximum threshold does not exist because of the maximum category, the weekly hours worked variable is the minimum threshold multiplied by 1.5 and the yearly days worked variable is set 365.[13] Write these variables as $days_p$ and $whours_p$ for respondent p. Then we define the yearly hours worked as

$$yhours_p \equiv \frac{days_p \times whours_p}{7}.$$

In variables $days_p$ and $whours_p$, there are two types of missings. One is non-answering and we simply drop these observation in calculating average hours worked. The other is missing due to non-applicability of the question that arises to variable $whours_p$. Namely, for those with less than 200 days worked per year (and with non-answering the question invoving $days_p$) *and* working in a non-regular manner (e.g. seasonal worker or non-regular worker), the question $whours_p$ is not asked. Therefore, if the margin of adjustment to technological shocks happens not at the margin of hours worked within workers working more than 200 days or regular workers (*i.e.*, *intensive margin*), but at that of workers becoming working less than 200 days and non-regular (*i.e.*, *extensive margin*), our $yhours_p$ variable, averaged at workers answering the question involving $whours_p$, understate the total effect of adjustment. In particular, such a variable captures the intensive margin but misses the extensive margin. To measure the effect on the extensive margin, we also define the following variable

$$D_p^{answerhours} = \mathbf{1}\left\{p \text{ answers the question involving } whours_p\right\}.$$

To construct earnings variable, we use the variable of before-tax yearly earnings. ESS asks workers before-tax yearly earnings from their primary job (and secondary one, if any) with discrete

[13]Note that the treatment of the maximum category of yearly days worked variable crutially depends on the level of the minimum threshold. Indeed, the thresholds of the maximum category vary by years. Importantly, they are 250 days until 2002 survey as opposed to 300 days since 2007 survey. Thus the comparison of aggregate distributions of yearly days worked across years may have biases due to the categorization errors. However, this does not have any critical errors in our OLS and IV analyses so long as these errors are uncorrelated with commuting zones.

choices with several bins of monetary values. Since these bins changes over survey years, we take consistent definition between 2002 and 2017 to eliminate errors due to the inconsistency. Table 9 shows the bins. For each observation, we take the midpoint of the bin to input the actual predicted value of yearly earnings. For the highest category 15+ million JPY (or 187.7 thousand USD in 2002), we multiply by 1.5 to impute the value.

Table 9: Consistent Earnings Bins

0-0.49 million JPY	3.00-3.99 million JPY
0.50-0.99 million JPY	4.00-4.99 million JPY
1.00-1.49 million JPY	5.00-6.99 million JPY
1.50-1.99 million JPY	7.00-9.99 million JPY
2.00-2.49 million JPY	10.00-14.99 million JPY
2.50-2.99 million JPY	15+ million JPY

B Data Appendix

B.1 Data in Detail

From the ESS, we drop non-existing prefecture-municipality codes in 1997, 14223, 21456, 21671, 35009, and 40223. XXX

Concordance of JIP and EUKLEMS should be explained in detail. XXX SEE ‘ess-jara-ifr.xlsx‘ AND EXPLAIN THE PROCESS. XXX

B.2 Detailed Statistics

Figures 13, 14, 15, and 16, show CZ-level distributions of growth rates of employment by education groups (1), (2), (3), and (4), respectively. Recall the education group classification: (1) less than middle school graduate, (2) some high school or high school graduate, (3) some junior/technical college or junior/technical college graduate, (4) more than some college.

Figure 13: Distribution of 2002-2017 Growth Rates of Employment, Less than High School

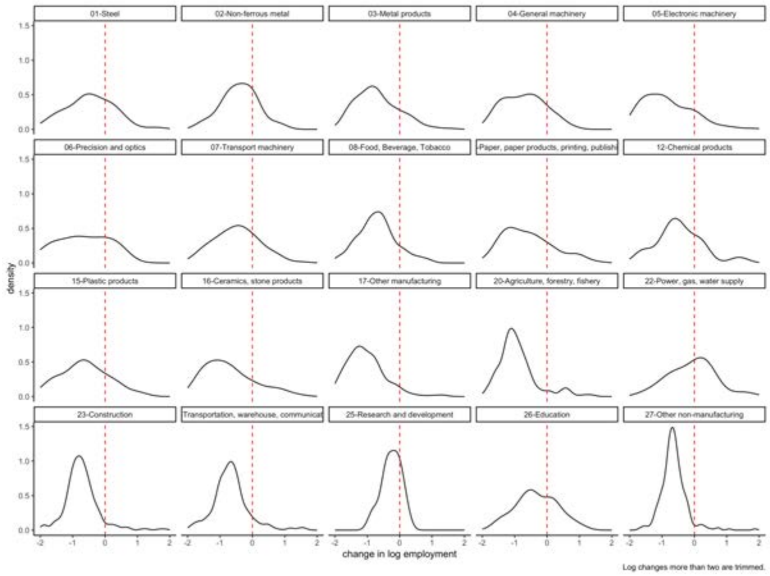


Figure 14: Distribution of 2002-2017 Growth Rates of Employment, High School Graduates

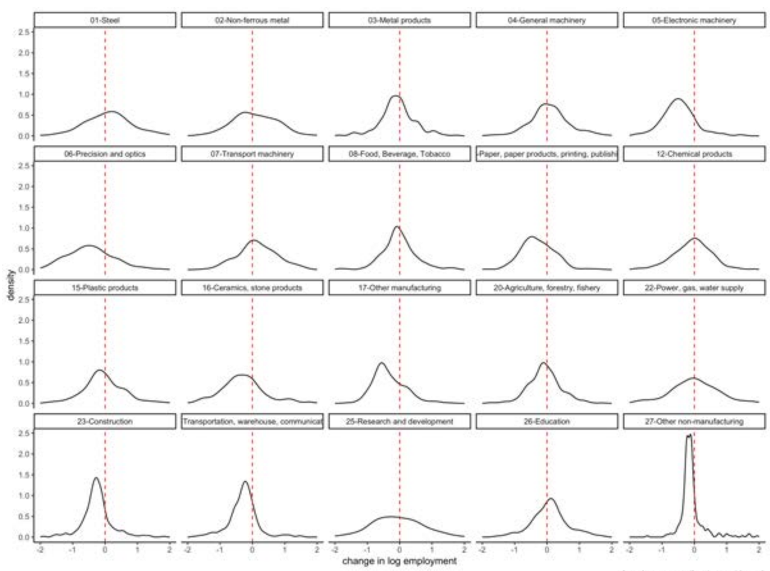


Figure 15: Distribution of 2002-2017 Growth Rates of Employment, Junior/Technical College

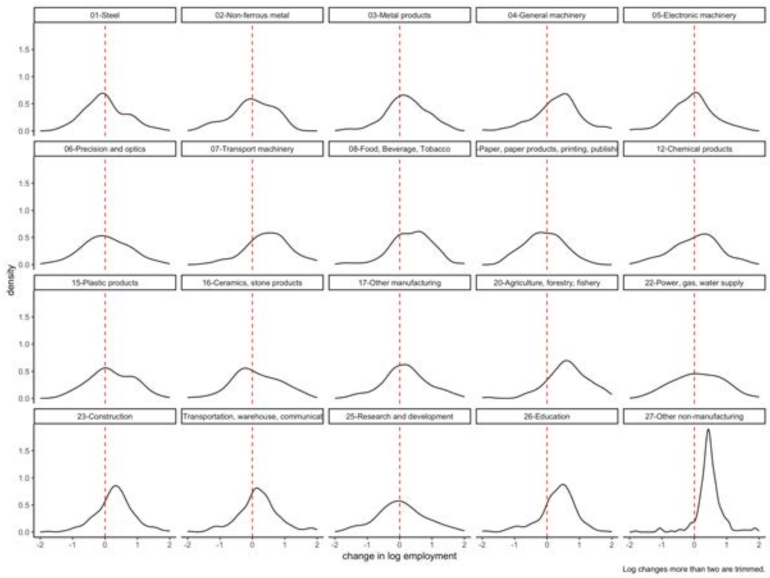
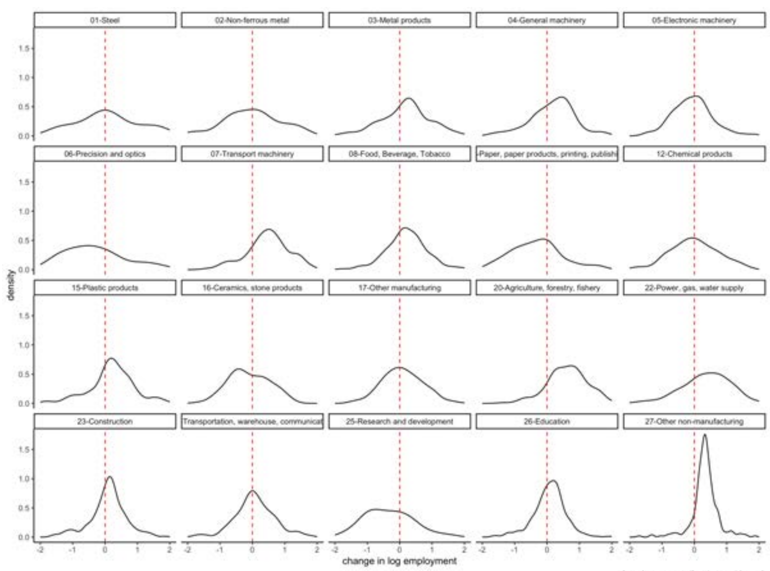


Figure 16: Distribution of 2002-2017 Growth Rates of Employment, College Graduate



Figures 17, 18, 19, and 20 show CZ-level distributions of growth rates of average hours worked by education groups (1), (2), (3), and (4), respectively.

Figure 17: Distribution of 2002-2017 Growth Rates of Average Hours, Less than High School

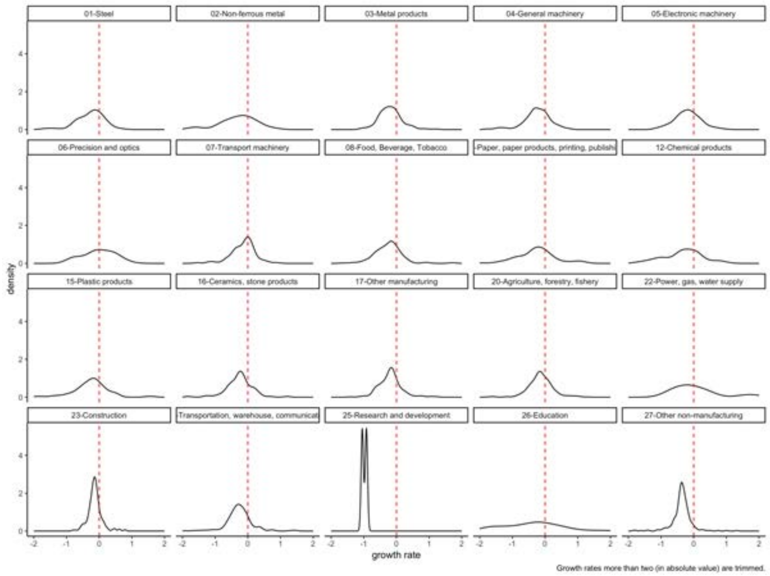


Figure 18: Distribution of 2002-2017 Growth Rates of Average Hours, High School Graduates

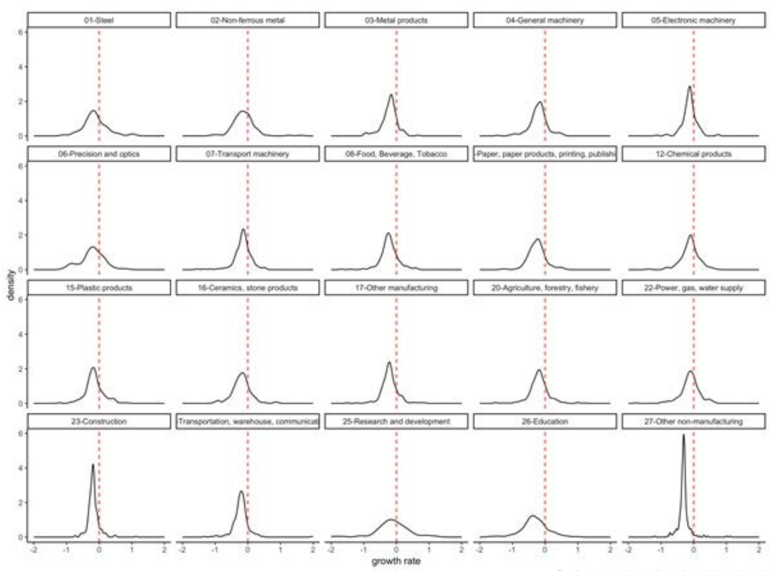


Figure 19: Distribution of 2002-2017 Growth Rates of Average Hours, Junior/Technical College

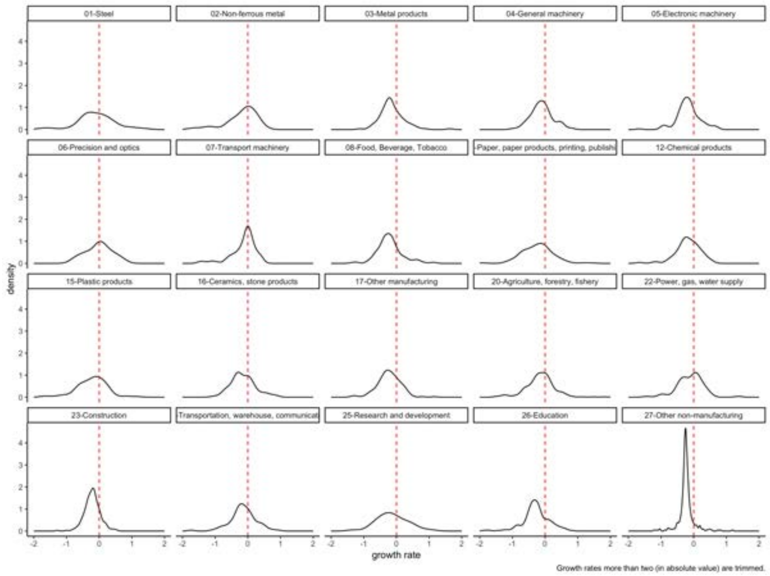
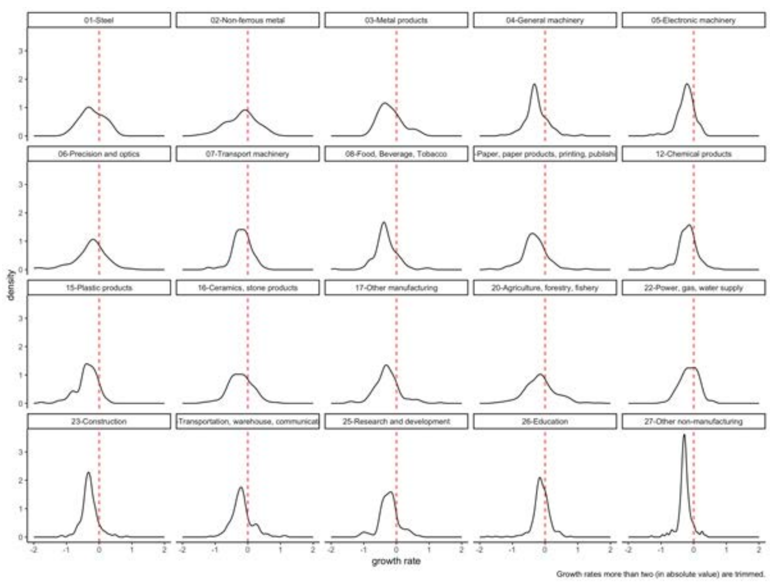


Figure 20: Distribution of 2002-2017 Growth Rates of Average Hours, College Graduate



Figures 21, 22, 23, and 24 show CZ-level distributions of growth rates of average income by education groups (1), (2), (3), and (4), respectively.

Figure 21: Distribution of 2002-2017 Growth Rates of Average Income, Less than High School

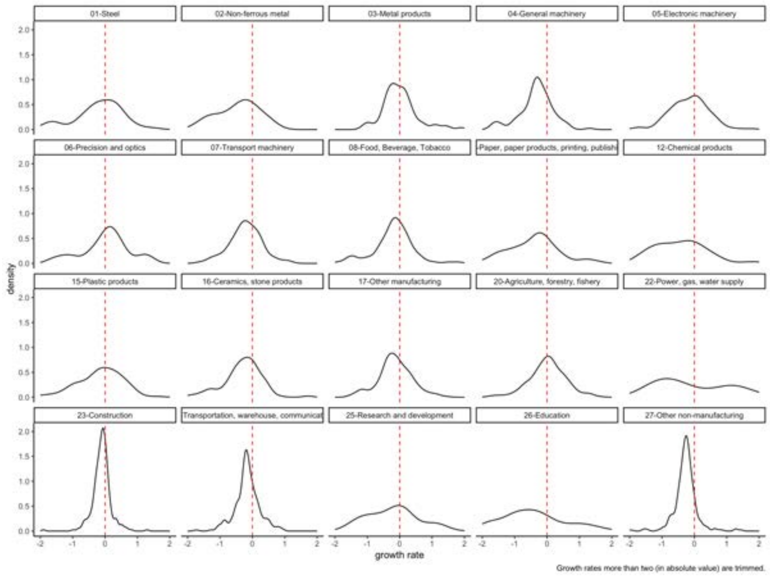


Figure 22: Distribution of 2002-2017 Growth Rates of Average Income, High School Graduates

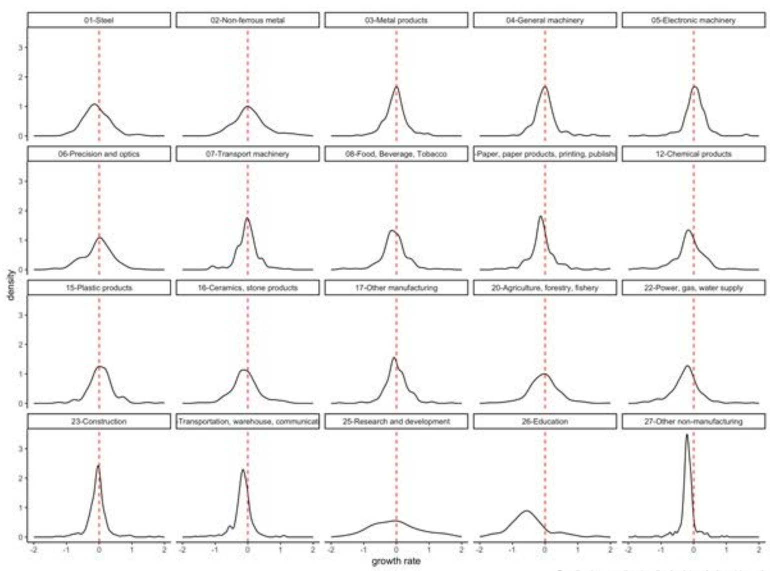


Figure 23: Distribution of 2002-2017 Growth Rates of Average Income, Junior/Technical College

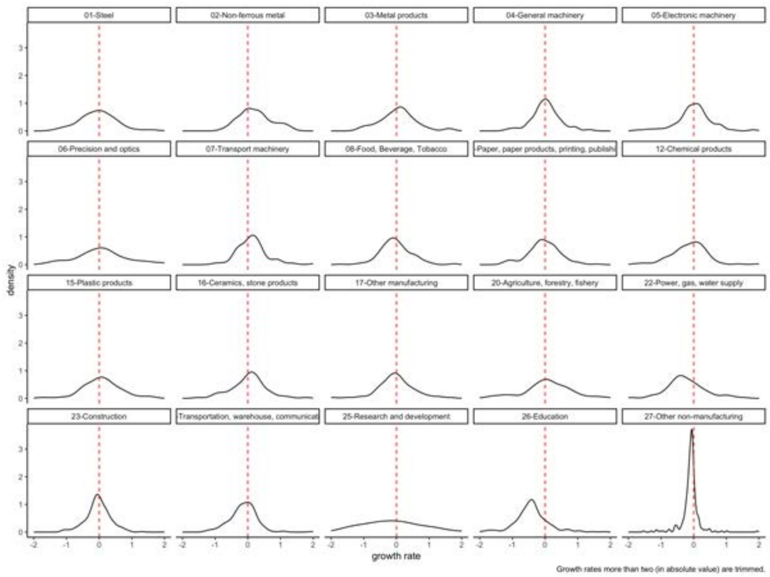
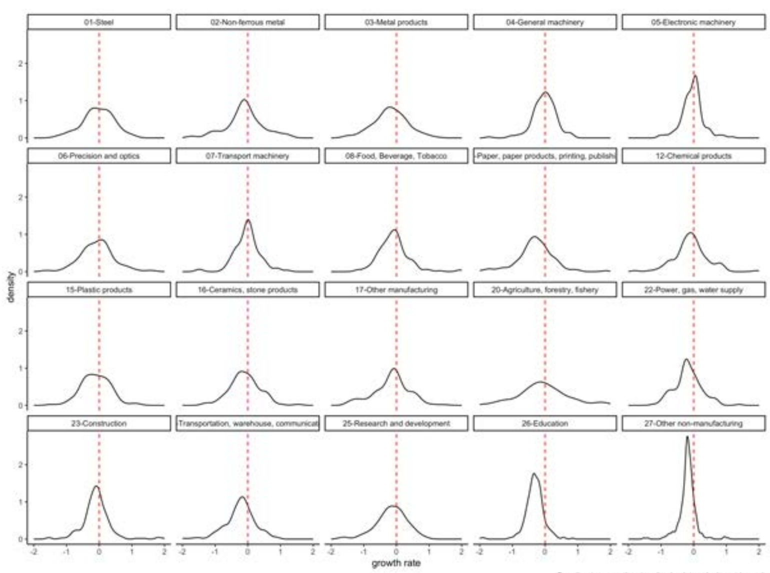


Figure 24: Distribution of 2002-2017 Growth Rates of Average Income, College Graduate



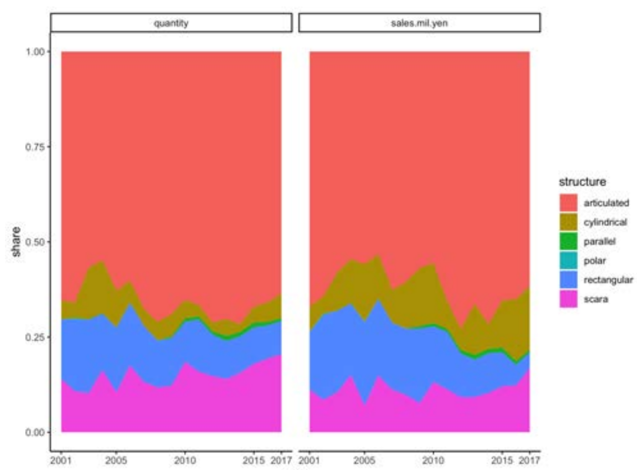
C Constructing Robot Stock

IFR calculates the operational stock by "the sum of robot installations of the last 12 years." Following this method, we calculate the capital stock of structure s, K_t^s as follows $K_t^s = \sum_{\tau=0}^{12} I_{t-\tau}$.[14] Note that we observe variable I_t for $t \geq 2001$. To obtain ones before year 2000, we estimate by dividing the aggregate investment values I_t proportionately by observed by-structure installments:

$$I_t^s = \frac{\overline{I^s}}{\sum_s \overline{I^s}} I_t.$$

Figure 25 shows the trend of shares of deliveries of each structure. The left panel shows that of delivered quantity, while the right panel of delivered sales by million current JPY. We observe stable delivery values both in quantity and sales for articulated robots. In 2001, articulated robot consisted 65.3 percent of total delivered quantity and 67.0 percent of total delivered sales, whereas in 2017, the corresponding values are 63.5 percent and 61.5 percent. We also observe two changes: a gradual structural change from rectangular robot to SCARA robot and emergence of parallel robot since late 2000s. Given these observations, we take the 2001 share of deliveries for the year before 2001.

Figure 25: Delivery Shares of Robot Structure



[14]Graetz and Michaels (2018a) assume ten percent of depreciation in their main specification.

D Properties of Group-specific Variables

Consider the two types of regressions of growth of employment on the measure of exposure to robot. One is the regression with aggregate variables. Write $\widetilde{Y_{ct}} \equiv \left(L_{c,t+1} - L_{ct}\right)/L_{ct}$, $\widetilde{X_{ct}} \equiv \sum_i l_{cit} PR_i^{JPN}$, $\widetilde{Z_{ct}} = \sum_i l_{ci,t-1} PR_i^{DEU}$, where L_{ct} is the employment in commuting zone c in year t, $l_{cit} \equiv \frac{L_{cit}}{\sum_i L_{cit}}$ is industry-i employment share in (c, t), PR_i^{JPN} and PR_i^{DEU} are industry-i penetration of robot in Japan and corresponding other countries (e.g. Germany), respectively. We then regress

$$Y_{ct} = X_{ct}\beta + \varepsilon_{ct}, \tag{7}$$

with the instrument Z_{ct}, where the variables without tilde indicate the covariates (including constant)-partialled-out variables.

The other is group-specific regressions. Write $\widetilde{Y_{ct}^g} \equiv \left(L_{c,t+1}^g - L_{ct}^g\right)/L_{ct}^g$, where L_{ct}^g is the group-g employment in commuting zone c in year t. Note that $\sum_g L_{ct}^g = L_{ct}$. We then regress, for each g,

$$Y_{ct}^g = X_{ct}\beta^g + \varepsilon_{ct}^g, \tag{8}$$

with the instrument Z_{ct}, where, again, the variables without tilde indicate the covariates (including constant)-partialled-out variables. Our concern is the relationship between β and β^g's. This is established by the following result.

Lemma 1. *Write group-g employment share in (c, t) as $s_{ct}^g \equiv \frac{L_{ct}^g}{L_{ct}}$. Then*

$$\beta = \sum_g E\left[s_{ct}^g\right]\beta^g + \sum_g \frac{Cov\left(s_{ct}^g, Z_{ct}Y_{ct}^g\right)}{E\left[Z_{ct}X_{ct}\right]}, \tag{9}$$

where the expectation and covariances are taken at (c, t)-level for each fixed g.

Proof. With slight abuse of notation, consider all the variables as post partialled out of covariates. Note that by definitions of Y_{ct} and Y_{ct}^g, we have

$$Y_{ct} = \frac{\left(L_{c,t+1} - L_{ct}\right)}{L_{ct}} = \sum_g \frac{L_{ct}^g}{L_{ct}} \frac{\left(L_{c,t+1}^g - L_{ct}^g\right)}{L_{ct}^g} = \sum_g s_{ct}^g Y_{ct}^g.$$

By applying the instrumental variable regression formula to equation (7), we have

$$\beta = \frac{E\left[Z_{ct}Y_{ct}\right]}{E\left[Z_{ct}X_{ct}\right]} = \frac{E\left[Z_{ct}\sum_g s_{ct}^g Y_{ct}^g\right]}{E\left[Z_{ct}X_{ct}\right]} = \sum_g \frac{E\left[s_{ct}^g Z_{ct} Y_{ct}^g\right]}{E\left[Z_{ct}X_{ct}\right]}. \tag{10}$$

With the covariance formula,

$$\begin{aligned}\frac{E\left[s_{ct}^g Z_{ct}Y_{ct}^g\right]}{E\left[Z_{ct}X_{ct}\right]} &= \frac{E\left[s_{ct}^g\right]E\left[Z_{ct}Y_{ct}^g\right] + Cov\left(s_{ct}^g, Z_{ct}Y_{ct}^g\right)}{E\left[Z_{ct}X_{ct}\right]} \\ &= E\left[s_{ct}^g\right]\beta^g + \frac{Cov\left(s_{ct}^g, Z_{ct}Y_{ct}^g\right)}{E\left[Z_{ct}X_{ct}\right]},\end{aligned}$$

where the second line follows by the instrumental variable regression formula applied to equation (8). □

Note that $\sum_g E\left[s_{ct}^g\right] = E\left[\sum_g \frac{L_{ct}^g}{L_{ct}}\right] = 1$. Therefore, the first term in equation (9) can be interpreted as *average-share* $E\left[s_{ct}^g\right]$ *weighted average of group-specific coefficients* β^g. However, the coefficients in aggregate regression β involves an additional correction term, which emerges in the second term in equation (9). This term summarizes the group-average correlation between share s_{ct}^g and the term involving the correlation of exogenous robot exposure and group-g employment growth $Z_{ct}Y_{ct}^g$. Intuitively, if commuting zone-year pair (c, t) has high group g-share of employment and high correlation between robot exposure and group-g employment growth, such positive correlation should be reflected in the aggregate coefficient β in a positive force. However, since average shares $E\left[s_{ct}^g\right]$ and group-specific coefficients β^g miss such correlation, the correction should be made to match these two sets of coefficients.

When does such correction term go away? A short answer is when the group-specific error terms are independent of the group employment shares as well as the instrument. Formally, the following result establishes.

Lemma 2. *Assume* $E\left[\varepsilon_{ct}^g | s_{ct}^g, Z_{ct}\right] = 0$. *Then* $\beta = \sum_g E\left[s_{ct}^g\right]\beta^g$.

Proof. By the same token as the above lemma, equation (10) is derived. Then we have

$$\begin{aligned}\frac{E\left[s_{ct}^g Z_{ct}Y_{ct}^g\right]}{E\left[Z_{ct}X_{ct}\right]} &= \frac{E\left[s_{ct}^g Z_{ct}\left(X_{ct}\beta^g + \varepsilon_{ct}^g\right)\right]}{E\left[Z_{ct}X_{ct}\right]} \\ &= E\left[s_{ct}^g\right]\beta^g + \frac{E\left[s_{ct}^g Z_{ct}\varepsilon_{ct}^g\right]}{E\left[Z_{ct}X_{ct}\right]}.\end{aligned}$$

By the iterated expectation formula,

$$\frac{E\left[s_{ct}^{g} Z_{ct} \varepsilon_{ct}^{g}\right]}{E\left[Z_{ct} X_{ct}\right]} = \frac{E\left[s_{ct}^{g} Z_{ct} E\left[\varepsilon_{ct}^{g} | s_{ct}^{g}, Z_{ct}\right]\right]}{E\left[Z_{ct} X_{ct}\right]} = 0.$$

Hence the desired equality holds. □

E Relationships between Employment and Population Variables

To relate the change in employment-to-population ratio

$$\Delta\left(\frac{L_t}{P_t}\right) \equiv \frac{L_{t+1}}{P_{t+1}} - \frac{L_t}{P_t}$$

and employment and population growths

$$g_t^L \equiv \frac{\Delta L_t}{L_t}, g_t^P \equiv \frac{\Delta P_t}{P_t},$$

the log-first order approximation $g_t^X \approx \Delta \ln X_t$ for any variable X implies

$$\begin{aligned}
g_t^L - g_t^P &\approx \Delta \ln L_t - \Delta \ln P_t \\
&= \ln L_{t+1} - \ln L_t - (\ln P_{t+1} - \ln P_t) \\
&= \ln L_{t+1} - \ln P_{t+1} - (\ln L_t - \ln P_t) \\
&= \Delta \ln \frac{L_t}{P_t} \\
&\approx \frac{\frac{L_{t+1}}{P_{t+1}} - \frac{L_t}{P_t}}{\frac{L_t}{P_t}} = \left(\frac{L_t}{P_t}\right)^{-1} \Delta\left(\frac{L_t}{P_t}\right),
\end{aligned}$$

or $\Delta\left(\frac{L_t}{P_t}\right) \approx \frac{L_t}{P_t}\left(g_t^L - g_t^P\right)$. Therefore, the change in employment-to-population ratio is, to the first order, the difference between the employment growth and the population growth, adjusted by base-year employment-to-population ratio.