Structural adjustment and changes to employment use in Japan

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Abstract

The following paper examines the determinants of structural adjustment in Japan. Unlike many other developed economies, firms in Japan rely more on changes to employment composition than mass layoffs as a method of structural change. Examining the drivers of changes in employee composition in Japan is therefore of interest to policy makers and academics alike. This research uses a novel plant-level dataset, which contains considerable detail on the types of employees used by Japanese manufacturers between 2001 and 2014. The results find a number of countervailing factors that explain the use of certain employment types. Growth in the diffusion of robotics is linked to the use of fewer non-regular employees. This appears to be partially driven by the fact that these machines positively predict the dismissal of certain types of non-regular workers. Offshoring from Japan leads to the use of a higher proportion of non-regular to regular workers, potentially due to increased competition faced by plants from abroad. Plant productivity however leads to the use of more regular to non-regular workers. Finally, establishments which experienced job dismissals in the past are substituting away from regular to non-regular workers in the present.

1. Introduction

Firms in a dynamic economy are continuously under pressure to adjust and evolve over time. Economic development, changing competitive conditions across economies, innovation and the emergence of new technologies and markets are a number of factors, which compel firms to change. The ability of businesses and sectors to adapt to these trends can influence their future competitive trajectory. Therefore, in order to remain economically viable, parts of the economy may at times need to undergo a process of structural adjustment i.e. reducing their workforce because they have greater numbers of employees for which is economically viable. This often requires a reallocation (adjustment) of resources from the least productive (or shrinking) to the most productive (or expanding) areas of economic activity, which can result in significant transformations of the labour market (OECD 2017).[1]

Historical evidence suggests that firms sometimes attempt to overcome these imbalances through mass layoffs. While mass layoffs affect a sizable number of workers, entailing significant human and social costs, they account for a relatively small fraction of all dismissals.[2] However, these events are "lumpy" both temporally and regionally. Mass lay-offs therefore represent a channel of adjustment that poses particular policy challenges. Recent work by OECD (2019) analyses the main economic factors associated with the intensity of "mass lay-offs" at country-industry level. Their results suggest that some of the important drivers of aggregate employment change (e.g. digitalisation and globalisation) are not necessarily linked to ML, once overall employment dynamics are taken into account. However, policy-induced distortions in international markets (in the form of subsidies or other forms of government support to firms and sectors) appear to be associated with ML.

Another channel through which firms can adjust is by substituting away from of the use of regular full-time employment to more temporary part-time workers. Doing so can provide firms with greater flexibility and lower labour costs, by reducing expenses associated with benefits such as pensions, housing assistance, commuting costs and so on (Asao 2011). This type of employment substitution may take place in the event/aftermath of an economic shock and/or as a gradual structural adjustment over a period of time.[3] One country where firms tend to adjustment more by employee composition as opposed to mass layoffs is Japan.

Mass layoffs in Japan are rare. The typical feature of Japan's labour market since the 1970s has been lifetime employment, promotion through seniority and the participation of company unions. After the macroeconomic shock of 1992, many firms found that their labour structures were no longer efficient and needed reform (Kambayashi 2017). In response, a considerably number of Japanese firms adjusted their employee

[1] The ability of firms to grow during fortunate times and shrink/exit during downturns is also important for aggregate productivity growth (Restuccia and Rogerson 2013).

[2] Recent OECD work on 7 European countries (Germany, Sweden, Denmark, Portugal, Finland, the United Kingdom, and France) indicates that mass layoffs account for only 15% of all layoffs (OECD 2019). The same study suggests that a comparable figure for the United States is around 20%.

[3] This however does not suggest that such changes have no adverse effects on the workforce.

composition[4] away from regular full-time employees towards non-regular workers. The two main types of non-regular workers in Japan are those on *part-time* and *haken* contracts. *Part-time* workers tend to be hired directly by the firm while *haken* workers are indirectly hired through employment agencies. Non-regular workers in general are paid considerably less than regular workers and they can be dismissed much more flexibly.

Understanding the determinants of employee composition as a mechanism for structural adjustment is relevant to policy makers for a number of reasons. Firstly, this may allow firms to restructure and increase competitiveness without firing workers, thereby reducing the shocks to local regions. Second, it may enable the economy to maintain similar levels of employment without considerably reducing consumer demand, particularly for vulnerable communities. At the same time, while firms may temporarily rely on non-regular workers to get through economic downturns, they may begin to favour these types of workers over regular staff, for the long-run. Given the social and economic implications this may have on the workforce, it is important to understand what type of characteristics drive these employment choices.

The objective of this paper is to assess the evolution of employment use for Japanese manufacturers and identify the main determinants of this form of structural change.[5] The paper starts by assessing descriptive analysis on the evolution of employment composition across years, industries and regions. Econometric techniques are used to identify how various plant and sector characteristics explain the employment of certain types of workers. Since worker composition is also influenced by the manner in which certain employees are fired, the analysis also examines the relationship between plant/sector characteristics and the dismissal of different types of workers. Moreover, in an attempt to identify the potential link between layoffs and employment composition, the paper also assesses whether layoffs in the past predict the employment of certain worker types today i.e. do firms that dismissed workers in the past rely more on non-regular or regular workers today.

The analysis finds that exposure to automation leads to the use of a greater proportion of regular workers partially driven by the fact that these technologies are linked to the dismissal of non-regular workers and the hiring of regular workers. On the other hand offshoring is correlated to a greater reliance on the share of non-regular workers. Productivity growth is associated with the use of greater numbers of both regular and non-regular workers in absolute terms. However more productive plants rely on a greater proportion of regular workers than non-regular workers. Interestingly, those that have achieved high productivity levels (irrespective of productivity growth), hire greater numbers of non-regular worker but are also more likely to dismiss them. Finally, the analysis finds that establishments that experienced job dismissals in the past are more likely to substitute away from regular to non-regular workers in the present.

The rest of the paper continues as follows. Section 2 provides a background on the nature of employment composition, recent policy changes concerning to employment contracts and the relating literature. Section 3 explains the main sources of data and presents some summary statistics. Section 4, introduces some descriptive analyses conducted on the

[4] In this paper, employee composition refers to the share of non-regular to regular employees.

[5] This report is a follow-up to OECD (2019), focusing predominantly on the economic effects of structural adjustment for manufacturing firms in Japan.

nature of employee use in Japan and assesses how this has changed across sectors, regions and time. Section 5 describes the methodological strategy of the paper and discusses the main results from the empirical analysis. Finally, Section 6 provides a summary of the paper.

2. Background on employment composition in Japan

Mass layoffs of regular workers is quite rare in the Japan because of lifetime employment systems driven employment practice and cultural norms (Kambayashi 2017). In particular, the reluctance to layoff regular workers is partly due to employers commitment to their workers and because labour laws make it difficult and costly to dismiss regular workers (OECD 2015). Seen in this light, mass-layoffs are relatively infrequent in the Japanese labour market (Sugeno and Yamakoshi 2014). Because of this convention, Japanese firms face challenges in the event of adverse shocks when needing to reduce costs. One of ways firms have attempted to reduce costs is through early retirement incentives, reduced overtime, less bonuses, hiring freezes and so on (Kambayashi and Kano 2011). Firms have also attempted to reduce labour costs by relying more on non-regular workers. Since adjustment costs of non-regular workers are considerably lower since they can be easily dismissed during economic downturn (Yokoyama et al. 2018) or employed gradually as firms and sectors undergo more gradual adjustments.

2.1. History of Haken law and Haken-layoffs

One of the most flexible forms a labour in Japan are haken workers. Unlike most contractual arrangements in Japan, haken workers sign an employment contract with a third party dispatch company, which provides labour to firms. The expansion of this type of employee classification was facilitated by *The Ordinance for Enforcement of the Act for Securing the Proper Operation of Worker Dispatching Undertakings and Improved Working Conditions for Dispatched Workers (hereinafter Worker Dispatch Law)* published in 1985 and enacted in 1986. The law allowed labour supply businesses to sign an employment contract with haken workers and dispatch them to other firms on the order of the haken company. At this time, these were in effect only for 16 specialised jobs including, *software developers, business machine operators, translator and stenographers, official administrators, filing clerks, research services, financial affairs, business document writers, executant or demonstrator of new products, tour conductors, building cleaners, operation and inspection (maintenance) of building equipment, receptionist at information desks, machine designers, broadcast machine operators, television and radio writers.*

In 1996, 10 new jobs were added to this classification including *research and development associates, planner and designer and implementer of business systems, editor and producer of books, advertising designers, interior coordinators, announcers, instructors of Office Automation (OA), telemarketers, sales engineers and production (set) of equipment for broadcast programmers*. Three years later in 1999, the Haken law was emended to encompass all tasks with the exception of *port transport, construction, security, medical treatment and manufacturers of objects*. Furthermore, in 2004, the law encompassed all operations and from 2007 contract lengths were extended from one year to three years.

The impact of the 2008 financial crisis heightened the public discussion about the economic and social implications of non-regular and haken contracts, particularly since these types of workers were considerably impacted during the economic downturn. Since firms are required to either directly hire haken workers as a regular worker or dismiss them after a set number of years, (during this period the time requirement was three years) many firms decided to let these workers go. These events were labeled "haken-layoffs". The number of workers involved in the haken-layoff in 2008 and 2009 was around 244,000 people while the layoff of regular workers was around 50,000 (Ministry of Health, Labour and Welfare 2009). A number of haken workers not only lost employment, but also lost their homes. In order to help around 500 people, labour unions and Non-Profit Organisations (NPOs) organised a camp in Hibiya Park in Tokyo to provide food services and bedding (Kojima 2010).

After the haken-layoffs, the Worker Dispatch Law was amended in 2012 to help support haken workers. The new law provided the followings provisions: *prohibition of daily haken workers (this refers to workers hired for only one day at a time), disclosure on the rate of margin for haken companies,*[6] *improvement of working conditions of haken workers including advance notice about wages, business operations and the haken contract, and the removal of the limit of employment durations.* The most recent amended Worker Dispatch Law published in 2015 aims to improve equality between haken workers and other types of workers (Kambayashi 2017).

2.2. Literature on the determinants of employee use

Technology change is perceived to influence employment choices, most notably the recent diffusion of industrial robotics (Acemoglu and Restreto 2017; Ford 2016; Brynjolfsson and McAfee 2014). In theory, robots and automation may take the place of many types of workers and may not be restricted to only lower skilled jobs. For example, work by Frey and Osborne (2017) suggests that roughly 47% of US employment is susceptible to automation and computerisation. Their results imply that the jobs most susceptible to robots are those composed of tasks, which require repetitive and rudimentary activities. This may include lower paying jobs like bicycle repairpersons and shoe mending operators, but also higher income jobs like real-estate brokers and accountants. Their work suggests that both skilled and unskilled jobs are vulnerable to robots.[7] Examining the impact of a specific type of autonomous technology, industrial robotics, Acemoglu and Restreto (2017) find that the adverse effects of these machines on wages and demand are more pronounced in blue-collar jobs and for workers with education below the college level. To date, much of the literature focuses on the impact of robotics on skilled versus unskilled workers. This paper contributes to this body of work by focusing on the impact of industrial robotics on the use of regular and non-regular workers.

[6] This refers to the difference between the revenue of the haken company and the salary of haken workers

[7] See Frey and Osborne (2017) on the types of tasks robots and automation may most likely undertake.

The extent to which firms are exposed to global competitive pressures may also determine how they use and dismiss workers. In particular, offshoring from developed economies is found to influence the demand of skilled workers more than unskilled employees. In addition, the evidence is quite consistent across countries. See for example Feenstra and Hanson (1999) for the US, Falk and Koebel (2002) for Germany, Strauss-Kahn (2003) for France and Hijzen et al. (2005) for the UK. Similarly, for Japan Kiyota and Maruyama (2016) and Ahn, et al (2008), find evidence that offshoring from Japan is linked to an increased demand in skilled workers for manufacturing plants. In our dataset we cannot directly identify skilled and unskilled workers, however there may be important insights regarding the effects of offshoring on regular versus non-regular employees.

Another obvious driver of the choice between regular and non-regular workers is how productive firms are. While not directly linked to the demand for regular and non-regular workers, recent empirical papers find a strong relationship between productivity and wages (which may suggest a positive correlation with the demand for regular workers). A recent paper by Berlingerie et al (2018) using aggregated micro data across 17 countries finds a close link between productivity and wages. Using micro data in Sweden Carlsson et al (2016) find that firms that obtain productivity shocks pay incumbent employees' higher wages. The extent to which productivity explains employee composition may differ however depending on where in the productivity distribution the firm resides. For example, large incumbents with high efficiency irrespective of productivity growth may favour more non-regular workers to remain competitive and as a cost buffer in the event of an economic shock. This paper attempts to test this hypothesis by also estimating the importance of a plants position within the productivity distribution for employee composition.

2.3. Economics literature on the use of non-regular workers in Japan

There are a number of papers, which have assessed the use of employment types in Japan. Such studies have typically focused on three main areas: the rise of non-regular workers in Japan, the effects of employment use on firms' performance and the impact of exogenous shocks on the structure and demand for regular and non-regular workers.

While non-regular contracts can allow firms to adjust more flexible to economic shocks, increased reliance on non-regular workers may lead to polarisation in task and wage. Kambayashi (2017) explores the polarisation and replacement regarding regular and non-regular workers by using data from the Employment Status Survey, which allow the author to determine individuals' employment status and income level. The paper clarifies that the number of non-regular workers grew between 1982 and 2012 in high-, middle- and low-income level jobs whereas that of regular workers with middle-wage jobs decreased in 2002-2012. The analysis also finds that the polarisation in income-level is occurring for the number of employment both at the high- and low-income level grew while middle-income jobs decreased as a whole. Other papers find that the rise in the number of non-regular workers influences the decline in long-term employment (Asano et al. 2013, Kawaguchi and Ueno 2013). More recently, Teruyama et al. (2018) finds that increases in the number of female and elderly labour supply is leading to a decline in the demand for *haken* workers.

In terms of firm performance and employee use, Matsuura et al. (2011) presents a theoretical framework, which suggests that trade liberalistion induces firms to reduce the number of goods they sale, thereby increasing the demand for non-regular since they involve no dismissal costs. Similarly, Tanaka et al. (2017) finds that new entrants in exporting markets achieve higher growth in the number of employees as well as a higher share of non-regular workers when compared to non-exporters in manufacturing sectors in Japan.

Examining the impact of exogenous shocks on the demand for workers, Yokoyama et al. (2018) assesses the effect of changes in exchange rates on the composition of regular and non-regular employees. They show that the employment of non-regular workers are negatively affected by the appreciation of Japanese Yen. This fact indicates that non-regular workers might be targeted for firing when firms face negative shocks to adjust their production costs. We examine this point further, by assessing the impact of offshoring from Japan on plant employment use.

3. Data

3.1. Data description

The following paper relies on information from three different datasets. The main data comes from the Census of Manufacturers (*Kougyou Toukei Chousa* in Japanese). This dataset contains plant level information on manufacturing firms for years 2001 to 2014.[8] [9]The dataset is quite rich in that it provides detailed information on each plant including performance, employment, location, sectoral affiliation and so on. Importantly, the dataset contains detailed information on types of employees within the plant. Two industry level variables are also are used in the analysis which measure offshoring[10] and the diffusion of industrial robot stock.[11] The offshoring measure is constructed from OECD Trade and Value Added dataset (TIVA) and robot stock is estimated with data from the International Federation of Robotics (IFR).

Table 1 Key variables and data sources

Variable	Short description	Source	Variation
composition	Share of non-regular workers over regular workers within the plant	CM	plant-time
regular	Headcount of the number of regular workers within the plant		
non-regular	Headcount of the number of non-regular workers (part-time+haken) within the plant		
part-time	Headcount of the number of part-time workers within the plant		
haken	Headcount of the number of haken workers within the plant		
layoff	Whether or not the plant has experienced considerable employment reduction (by type) within a year i.e. a reduction of 10% or more (0,1 dummy)		
productivity	Total factor productivity, estimated by Levinson-Petrin (2003)		
multi	Whether the plant is connected to a multi-plant firm (0,1 dummy)		
offshoring	Share of imported intermediate inputs (less energy) over total demand of intermediate inputs (less energy)	TIVA	industry-time
robot stock	Stock of industrial robotics, estimated with PIM assuming 10% annual depreciation	IFR	

Note: CM refers to the Census of Manufacturers, TIVA to the OECD-WTO Trade in Value Added dataset, IFR to the International Federation of Robotics.

[8] Note that this dataset does not contain information for the year 2011.

[9] The dataset collects information on two types of plants, those with 30 or more employees and those with 29 or less. Less information is collected on the small plants, therefore for this paper we focus on plants with 30 or more employees.

[10] Offshoring refers to the share of imported intermediates (less energy) over total intermediate inputs (Feenstra and Hanson 1996)

[11] The definition of industrial robots used by IFR comes from the International Organization for Standardization (ISO) 8373:2012: a robot refers to "a machine that embodies the following characteristics: can be reprogrammed, is multipurpose in function, allows for physical alteration, and is mounted on an axis."

3.2. Summary statistics

This sub-section presents summary statistics of the main variables used in the report (See Table 2 Descriptive statistics of main variables). Overall, the types of plants in our sample are medium to large with an average total employment of 117 and median number of workers of 64. Plants in the Japanese manufacturing sectors tend to employ more regular workers than non-regular workers.[12] For example, plants on average employ 86 regular, 30 non-regular workers, of which 20.2 are part-time and 9.1 are haken employees. The average share of non-regular to regular employees is around 0.25. The database also includes the value of revenue and its mean and median are 4,858 million JP yen and 1,071 million JP yen. In terms of robotic diffusion, the mean stock of industrial robotics by sector is 22,174 machines. While the number of robots is quite large, it is not surprising given that Japan is the largest user of these machines (in terms of absolute numbers) in the world (IFR 2017). In terms of offshoring, roughly 9% of total demanded inputs are imported, lower in comparison to other developed economies.

Table 2 Descriptive statistics of main variables

Variable	Mean	Median	SD	99%	1%
Log Revenue	11.85	11.70	1.25	15.20	9.40
Log TFP	8.09	8.00	1.07	10.82	5.84
Log Employment	4.35	4.16	0.77	6.76	3.40
Log Regular Employment	3.96	3.85	0.91	6.55	1.61
Log Non-regular Employment	2.49	2.64	1.45	5.73	0.00
Log Part-time Employment	2.02	2.08	1.46	5.41	0.00
Log Haken Employment	0.93	0.00	1.35	4.94	0.00
Employee Composition	0.25	0.20	0.56	2.58	0.00
Offshoring	0.09	0.08	0.03	0.18	0.04
Log Robot stock	8.88	9.43	1.80	11.73	4.22

Note: All variables are log-linearized asides for employee composition, which reflects the share of non-regular to regular employees in levels.

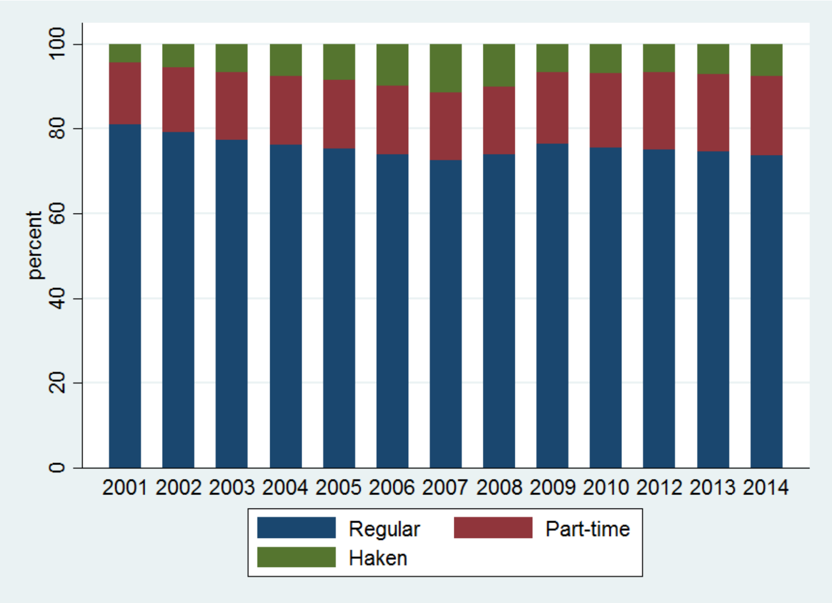
[12] Note that non-regular workers refer to any employee who is not on a regular full-time contract. The variable in this paper is constructed as the sum of part-time and haken workers within a plant.

4. The evolution of employee composition

4.1. Employment composition by year

Figure 1 illustrates the average proportion of employee types (regular, part-time and haken) across plants for each year of the sample period. Regular workers represent the largest proportion of employee types used. However, the figure suggests that plants overall are relying on a smaller proportion of regular works in 2014 compared to 2001, although the trend is quite gradual from 78.60% in 2001 to 71.71% in 2014. Over the sample period, the proportion of part-time and haken workers increases from 15.77% to 19.57 and 5.62% to 8.71%, respectively. Marked declines in the proportion of haken workers are observed in the years corresponding to the Great Recession (from 12.54% in 2007 to 7.78% in 2009) consistent with the literature discussed above. The recession however appears to have had less of an impact on part-time employees, which may be due to the fact that haken employees can be dismissed easier than other types of labour and because Worker Dispatch Law required firms to either hire them as regular employees or dismiss them.

Figure 1 Share of average employee types by year



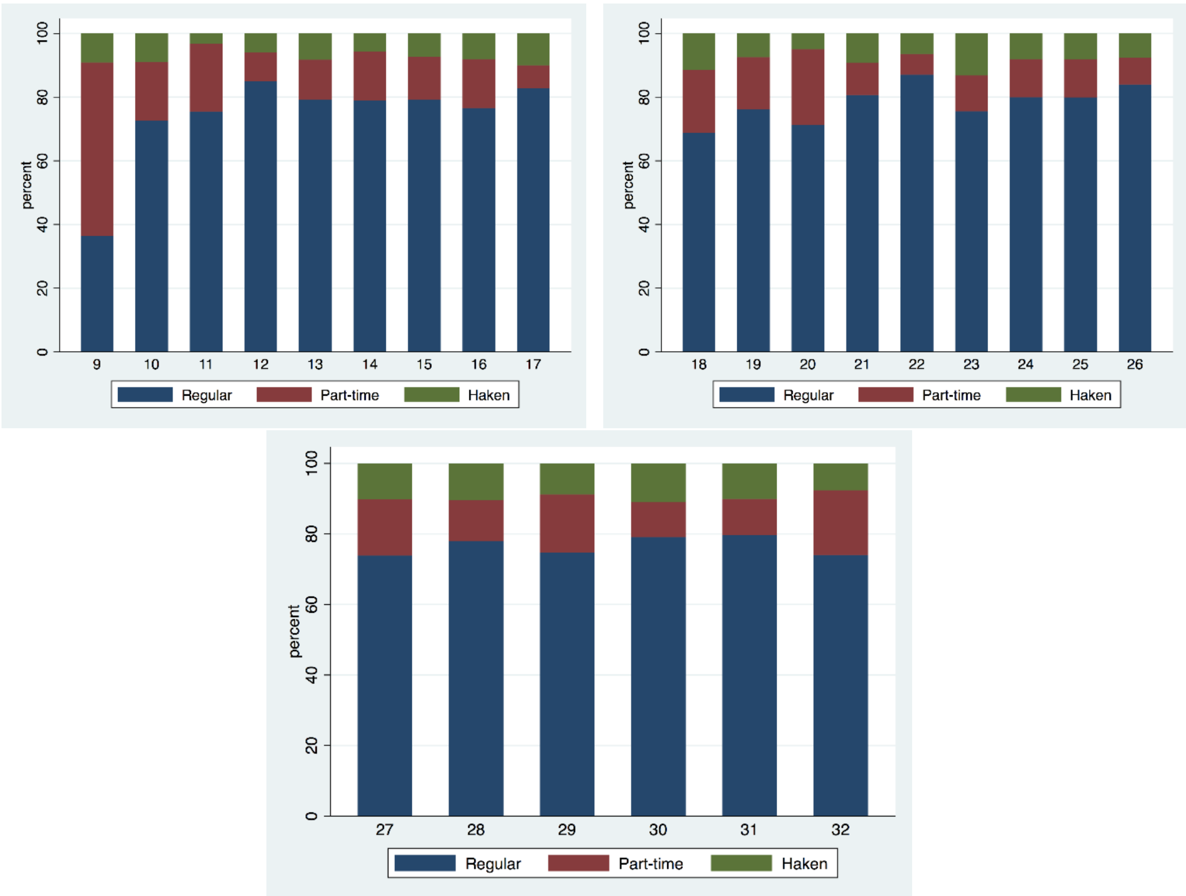
Note: The following figure illustrates averages in employee type by year.
Source: Census of Manufacturers, calculations by authors.

4.2. Employment composition by sector

Average employee composition across industries is considerably heterogeneous (see Figure 2). For some sectors such as Food Manufacturing, for the average firm roughly 60% of their employment were part-time and haken workers in 2014. At the same time, for the average plant in Plastics and Non-Ferrous Metals industries, (classification 18 and 23, respectively), more than 90% of their employees are regular workers. Moreover, the proportion of employee types across sectors has not been constant overtime (see

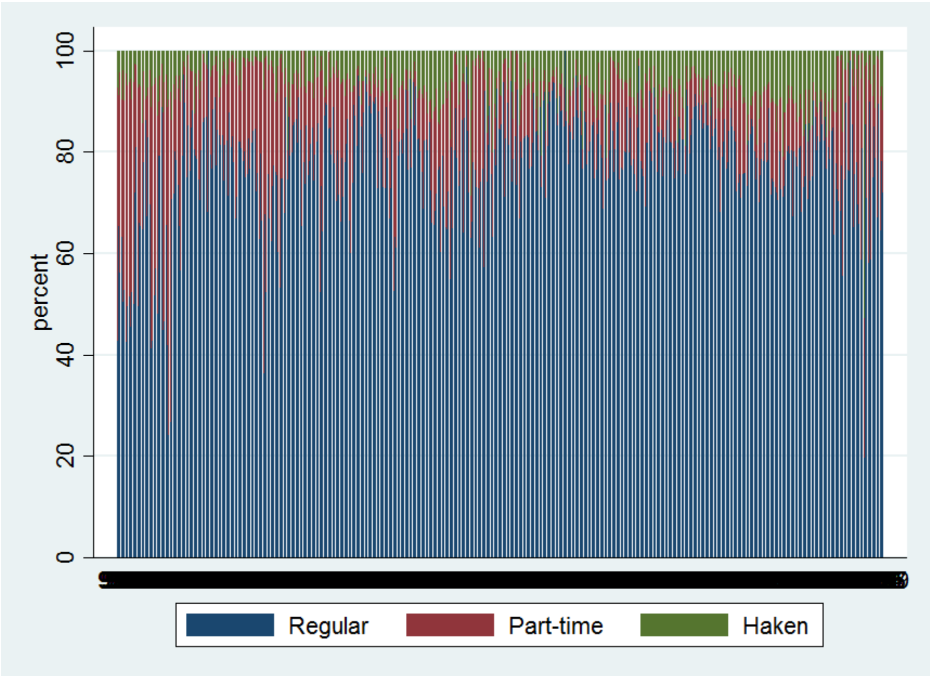
Figure 8 Share of average employee types by 2-digit sector, 2001 in the appendix). In order to explore further the degree of heterogeneity of employment use, Figure 3 illustrates the proportion of worker types at the 4-digit sectoral level. Disaggregating the statistics demonstrates even greater differences in employment composition across narrowly defined sectors. For example, in the Spinning, Cotton sector, roughly 80% of their workforce are part-time and haken while for the Medical instruments and Apparatus sector close to all of their employees are regular workers. The figures here demonstrate the need for micro data (to control for the host of unobservable characteristics) in order to have a detailed understanding of the determinants of employee composition while at the same time allowing for an examination of heterogeneity across plants characteristics. This is our main motivation for using plant-level data.

Figure 2 Share of average employee types by 2-digit sector, 2014



Note: The following figure illustrates averages in employee type by 2-digit sector for the year 2014. Sector classifications are the Japanese Standard Industrial Classification.
Source: Census of Manufacturers, calculations by authors.

Figure 3 Share of average employee types by 4-digit sector, 2014



Note: The following figure illustrates averages in employee type by 4-digit sector for the year 2014. Sector classifications are the Japanese Standard Industrial Classification.
Source: Census of Manufacturers, calculations by authors.

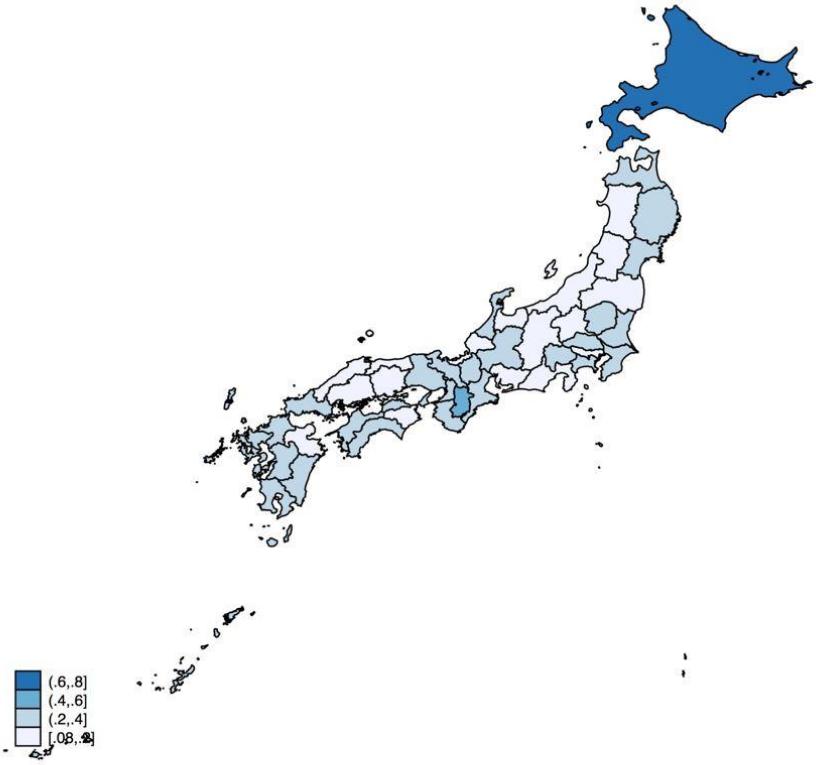
4.3. Employment composition by region

While the use of part-time and haken workers has increased overtime, Figure 4 and Figure 5 further demonstrates that these trends have been experienced across most of Japan. At the same time, certain regions appear to use part-time and haken employees more intensively than others. Prefectures in the Kanto and Kansai region as well as Kinki region use these types of employees more intensively than say in the Tohoku and Shikoku prefectures. Some of the determinants explaining regional concentration of employment types are due to spatial factors but may also be industrial composition and firm characteristics (OECD 2019).

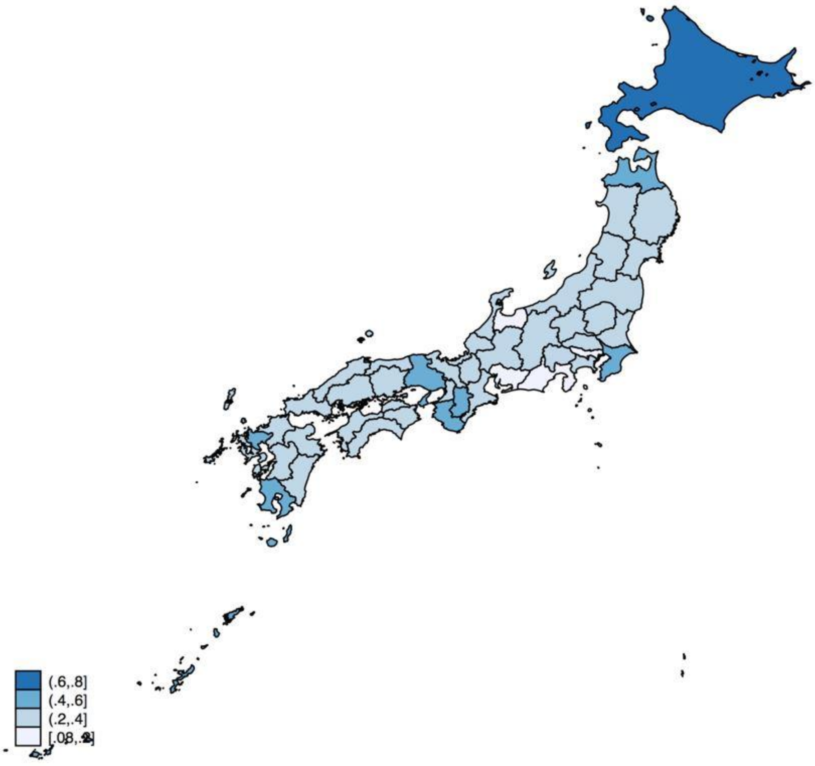
Disaggregating regional employee composition further, Figure 6 and Figure 7 illustrate the share of part-time to regular and haken to regular workers at the municipality level for Kanto and Kansai prefectures. In terms of part-time workers, Hayama-machi and Oiso-machi, and Higashiyoshino-mura and Nose-cho municipalities have the highest intensity of part-time workers in the Kanto and Kansai regions. As for haken employees, Ranzan-machi and Tamamura-machi, and Kusatsu-shi and Osaka-shi, Konohana-ku have the highest intensity of part-time workers in these regions.

Figure 4 Share of part-time to regular workers

2001



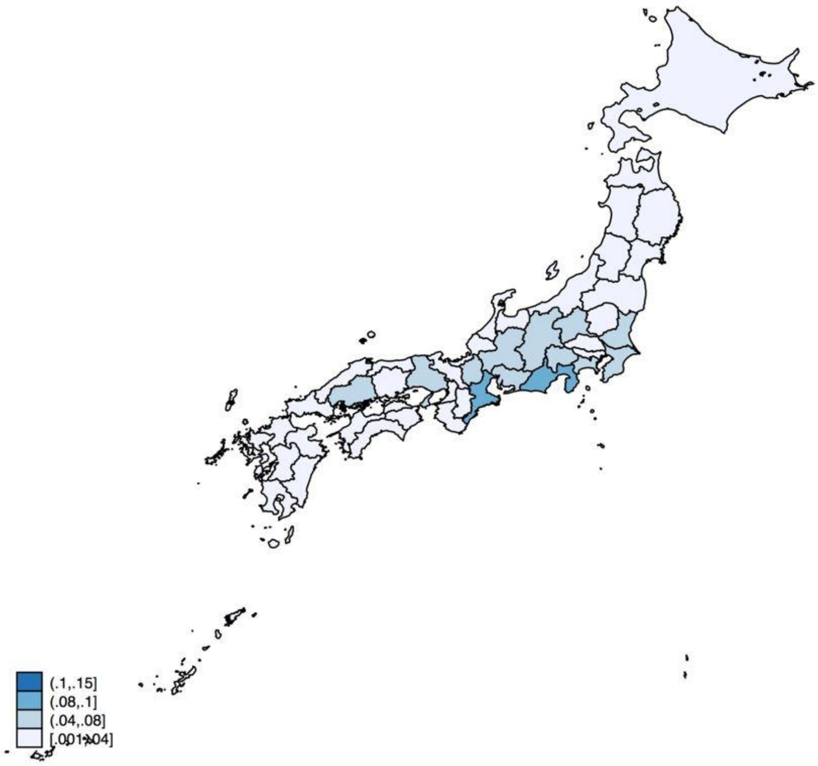
2014



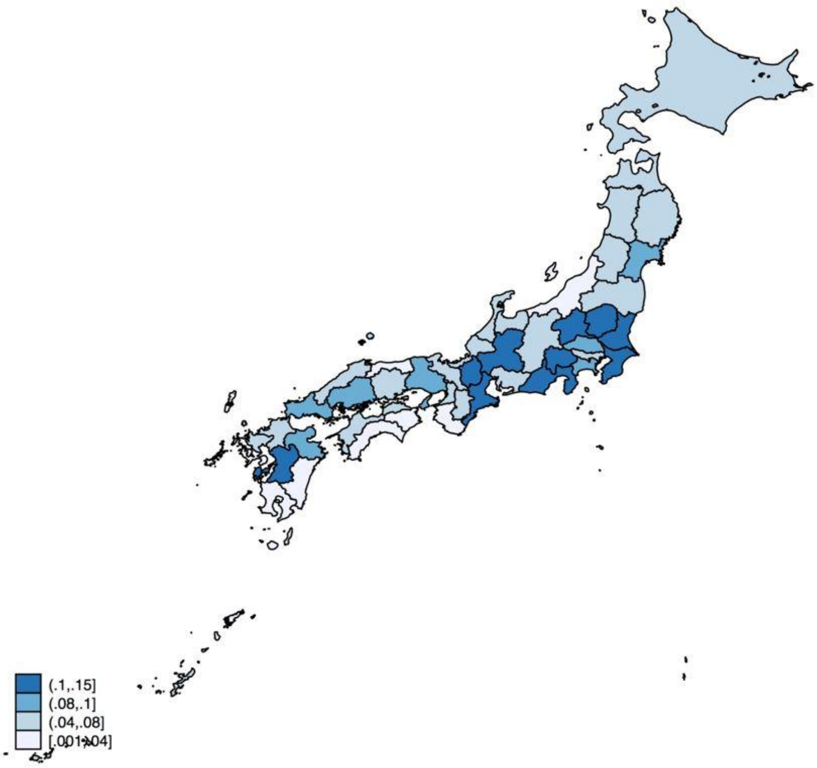
Note: The following figure illustrates share of part-time to regular employee by prefecture, 2001 and 2014
Source: Census of Manufacturers, calculations by authors.

Figure 5 Share haken to regular workers

2001



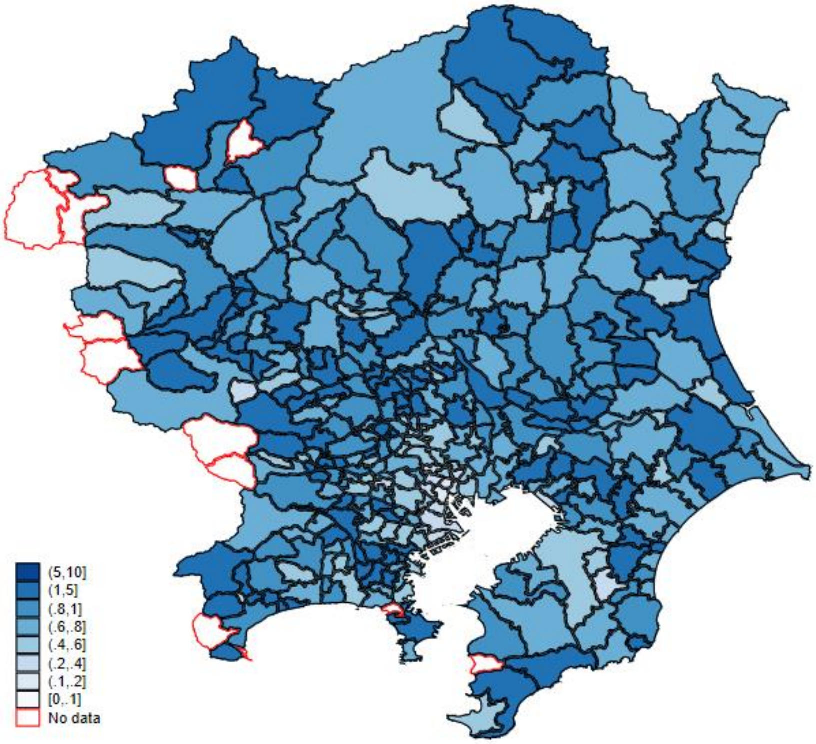
2014



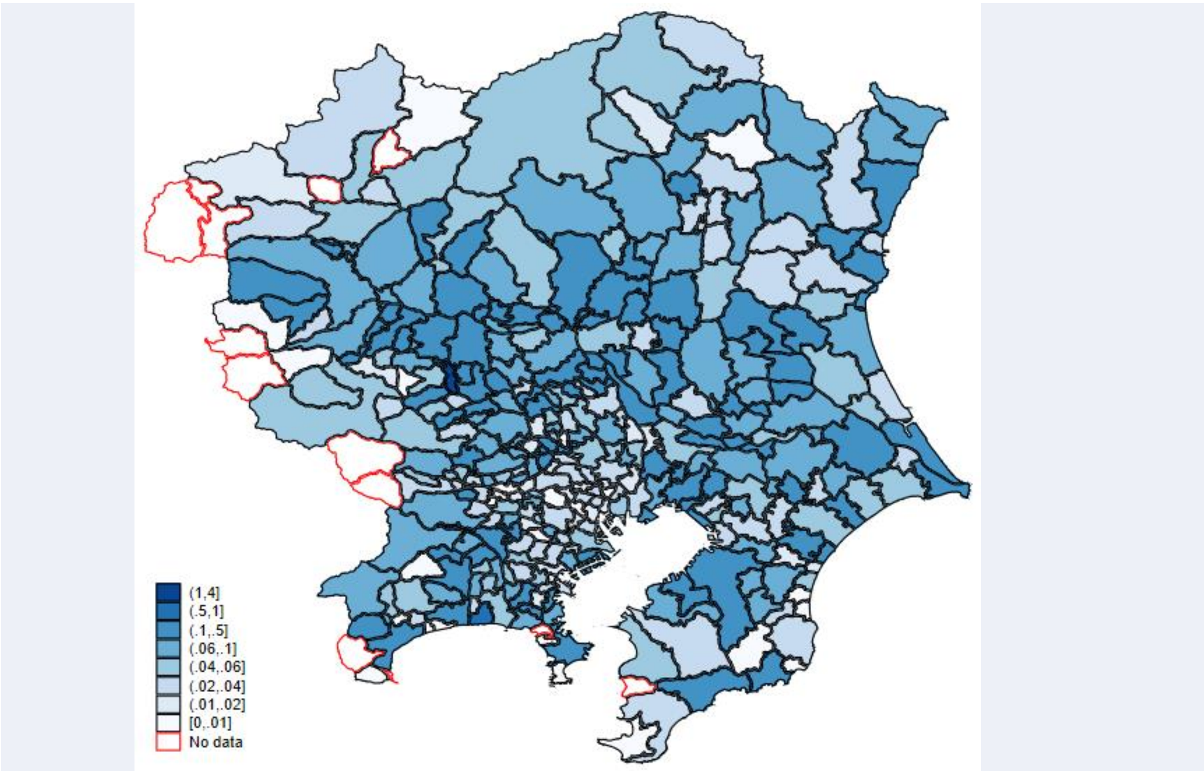
Note: The following figure illustrates share of haken to regular employee by prefecture, 2001 and 2014
Source: Census of Manufacturers, calculations by authors.

Figure 6 Share of part-time and haken to regular workers in Kanto region, 2014

Share of Part-time to Regular Workers



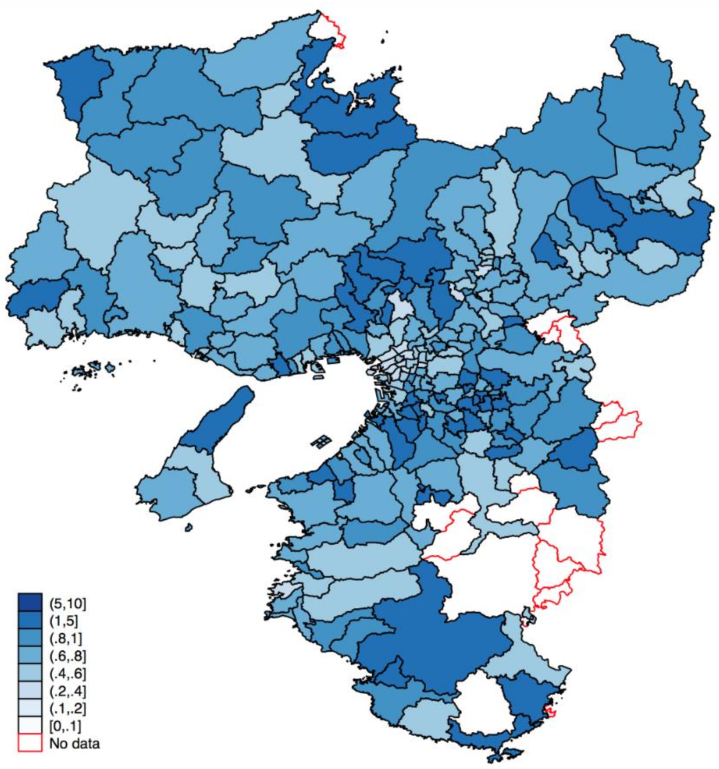
Share of Haken to Regular Workers



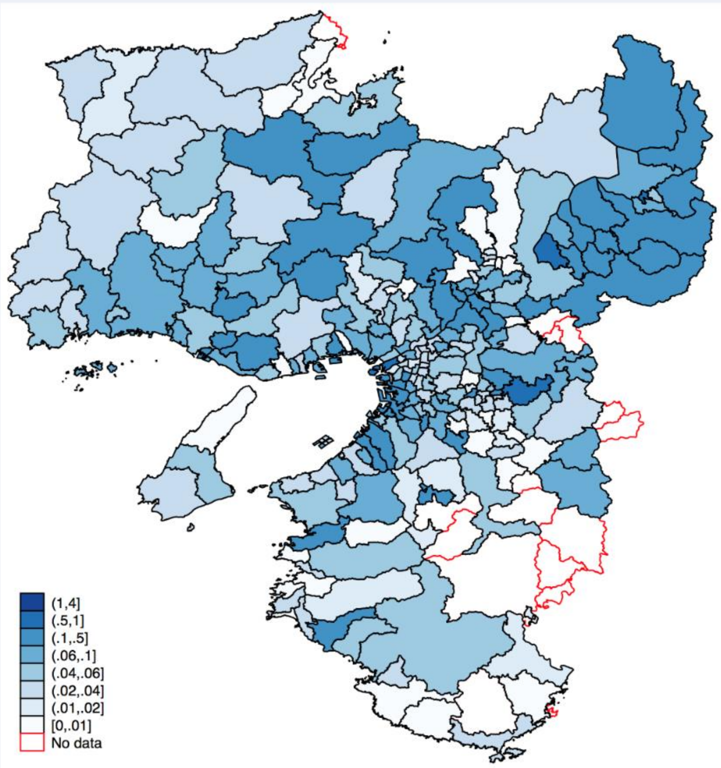
Note: The following figure illustrates share of part-time and haken to regular employee in the Kanto prefecture, 2014
Source: Census of Manufacturers, calculations by authors.

Figure 7 Share of part-time and haken to regular workers in Kansai region, 2014

Share of Part-time to Regular Workers



Share of Haken to Regular Workers



Note: The following figure illustrates share of part-time and haken to regular employee in the Kansai prefecture, 2014
Source: Census of Manufacturers, calculations by authors.

5. Empirical results

5.1. Determinants of compositional change and employee use

The following section conducts a number of empirical exercises in order to understand the nature and determinants of employee composition in Japan. The first part of this analysis assesses plant and sectoral determinants of employee use, including the share of non-regular to regular workers and the numbers of regular, non-regular, part-time and haken workers. Another factor, which influences the types of employees used within the firm, are the types of employees that are dismissed overtime. Although mass layoffs are uncommon in Japan, layoffs do occur, therefore the second section assess how various firm and industry characteristics determine the dismissal of certain types of workers. The final section explores whether instances of plant layoffs in the past influence the types of workers used in the present. Firms for example may use layoffs as an opportunity to adjust composition of the labour they hire. To shed light on this, the final section examines the extent to which instances of layoffs in the past result in greater reliance of non-regular workers in the present.

5.1.1. What are the predictors of compositional change and employee use?

The first section looks to assess how various plant and sector characteristics determine the use of employment types within the plant. Our measure of employee composition (similar to Matsuura et al 2011) is the share of non-regular employees over regular employees at establishment i in sector s at time t illustrated in Equation 1. [13] Composition along with the number of different employment types (regular, non-regular, part-time and haken) are the main dependent variables signified by y_{ist} and shown in Equation 2. These are regressed separately on firm productivity tfp_{ist}[14] and size s_{ist} (measure by whether the plant is connected to a multi-plant firm). The framework also includes two sector controls, offshoring[15] and robot stock[16] signified by δ_{st}. A host of other factors are also controlled for in the model, signified by χ_{it} comprising of year, city, 4-digit sector and plant fixed effects. The inclusion of year and plant fixed effects means that the regressions are capturing within firm changes.

Another interesting and relevant question, particularly to policy makers is what types of employment decisions do plants make at different locations on the productivity distribution irrespective of productivity growth. For example, plants which increase productivity year on year, may favour greater numbers of all types of workers due to their growth needs. Those at the top or bottom quartile of the productivity distribution may however require considerably different employment types. In order to assess this, the paper builds off Equation 2 including TFP along with TFP interacted with dummy variables indicating a plants quartile position within the productivity distribution at the start of the sample period, 2001 (See Equation 3). Since the purpose here is to assess

[13] Non-regular employees refer to the sum of part-time and haken workers.

[14] TFP is calculated with Levinsohn and Petrin (2003).

[15] Offshore measure is the share of imported intermediate inputs (less energy) over today demanded inputs (less energy) (Feenstra and Hanson 1996).

[16] Robot stock is estimated similarly to DeStefano et al (2018) and Graetz and Michaels (2018) using PIM and assuming a 10% annual depreciation.

differences in employment needs across different productivity levels (rather than changes), plant fixed effects are excluded.

$$comp_{ist} = \frac{non_{reg_{ist}}}{reg_{ist}} \tag{1}$$

$$y_{ist} = \alpha_0 + \alpha_1 tfp_{ist} + \alpha_2 s_{ist} + \alpha_3 \delta_{st} + \alpha_4 \chi_{ist} + \varepsilon_{it} \tag{2}$$

$$y_{it} = \alpha_0 + \alpha_1 tfp_{ist} + \alpha_2 tfp_{ist} * q1 + \alpha_3 tfp_{ist} * q2 + \alpha_4 tfp_{ist} * q3 + \alpha_5 tfp_{ist} * q4 + \alpha_6 s_{ist} + \alpha_7 \delta_{st} + \alpha_8 \chi_{ist} + \varepsilon_{it} \tag{3}$$

Empirical results

The results presented in Table 3 examine the links between changes in plant and sector characteristics on changes in employment use. Productivity is positively linked with greater use in the proportion of regular workers to non-regular workers, signified by the negative coefficient of the composition variable. At the same time, more productive plants employee greater numbers of all employee types, including non-regular, part-time and haken workers. This is not surprising given that productivity is positively correlated with firm size.[17] This is also somewhat consistent with our size measure i.e. those connected to a multi-plant firm, for regular and non-regular workers.[18] It is important to note that the weak effect found for the multi-plant variable is arguably driven by the inclusion of plant fixed effects, which washes out the predictive power from variables, which tend to be time invariant.

The diffusion of industrial robotics, is correlated with an increase in the use of regular workers and a decline in the numbers of non-regular and part-time workers. As a result, increases in robot stock lead to a greater proportion in the use of regular to non-regular workers. The mechanism for why this is occurring is not entirely clear. One explanation may be that firms are using robots to carryout activities that were traditionally done my non-regular workers. To explore this further, the section below will examine the extent to which robotics are linked with the dismissal of non-regular and regular workers.[19]

Offshoring is positively correlated with greater numbers of all types of employees (i.e. regular, non-regular, part-time and haken workers). In terms of composition, the offshoring coefficient is negative however the relationship is not statistically significant. Much of the literature on offshoring and labour demand focuses on skilled vs unskilled labour while here we are examining regular vs non-regular employment.[20] In fact, when one considers the list of jobs that can be undertaken say by haken workers (stipulated by the *Worker Dispatch Law*) many of these are positions require employees that are medium to highly skilled. On the one hand, the results are somewhat similar to

[17] Not surprising, plant output also consistently predicts greater numbers of all employee types including non-regular, part-time and haken workers (See Table 10 in the Appendix).

[18] Out of possible concerns for endogeneity bias the results a re-run taking lagged TFP both for time t-1 and t-2 (see Table 11 Determinants of Employee Use, lagged TFP the Appendix). The results are consistent with what is found in Table 3.

[19] Note that the results in Table 3 are also robust to the inclusion of measures of regular and non-regular worker wages (See Table 10 in Appendix).

[20] It is not possible to identify skilled and unskilled employee in each employment types with the Census of Manufacturers dataset.

Matsuura et al 2012, which find that trade liberalization induces firms to reduce the number of goods they sale, thereby increasing the demand for non-regular since they involve no dismissal costs are low. On the other hand, we cannot confirm from these results whether firms are substituting away from regular to non-regular workers as a result of changes in offshoring and/or competition from abroad.

Table 3 Determinants of Employee Use

Dependent variable	Composition	Regular	Non-Reg	Part-time	Haken
TFP	-0.020***	0.204***	0.150***	0.111***	0.134***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Multi-plant	0.000	0.014***	0.013**	0.006	0.009
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Offshoring	-0.001	0.078***	0.145***	0.151***	0.168***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)
Robot stock	-0.020***	0.052***	-0.053***	-0.056***	0.011
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fixed effects					
Plant	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓
4 digit industry	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓
R-squared	506,501	507,666	507,666	507,666	507,666
Observations	0.895	0.937	0.817	0.834	0.701

Note: Composition refers to the share or non-regular to regular workers. Regular, non-regular, part-time and haken represent the number of employee types by plant. Fixed effects included in each model listed in the table. Regressions are clustered at the plant-year level with robust standard errors in parenthesis. Level of significance are *** 1%, ** 5%, * 10%.

While TFP is significantly linked to the composition of employment across plants, there may be heterogeneous effects depending on where a plant resided within the productivity distribution. In order to assess this, we interact TFP with dummy variables, which corresponds to the productivity quartiles of the TFP distribution where the plant resides (at the start of the sample period 2001). The non-interacted term reflects the effects of TFP for plants in the bottom quartile, and each interacted term shows the additional effect (over the bottom quartile) for each of these higher quartiles.

Similar to the previous results, TFP is negatively correlated with employee composition, however we find that those located at the top productivity quartile use significantly less non-regular to regular workers than plants located on lower rungs of the productivity distribution (see Table 4). This is consistent with the result found for the number of regular employees used, i.e. plants at the top quartile use regular workers more in terms of numbers than those at the bottom quartile. The results for non-regular workers more nuanced and somewhat polarising. For example, plants located at the bottom and top quartiles are found to use greater numbers of non-regular and part-time workers, while those located on the 25^{th} – 50^{th} and 50^{th}- 75^{th} quartiles (for non-regular workers) and 25^{th} – 50^{th} (for part-time workers) use less. For haken, those at the bottom quartile use the most while those located above the bottom quartile use less. Taken together the results suggest that initial TFP maters for the types of labour employed, where the most productivity plants appear to use a greater proportion of regular workers than non-regular staff.

Table 4 Heterogeneous effects of TFP on employee use by quartile

Dependent variable	Composition	Regular	Non-Reg	Part-time	Haken
TFP	-0.066***	0.465***	0.264***	0.008***	0.441***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TFP* 25th-50th percentile	-0.015***	0.012***	-0.027***	-0.007***	-0.028***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TFP* 50th-75th percentile	-0.012***	0.020***	-0.012***	0.008***	-0.022***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TFP* 75th-100th percentile	-0.008***	0.047***	0.011***	0.024***	-0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Multi-plant	0.049***	-0.016***	0.062***	0.052***	0.006**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Offshoring	0.008	-0.007	0.102***	0.160***	0.116***
	(0.00)	(0.01)	(0.02)	(0.02)	(0.02)
Robot stock	-0.043***	0.041***	-0.123***	-0.140***	0.016
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Fixed effects					
Year	✓	✓	✓	✓	✓
4 digit industry	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓
Observations	514,727	515,876	515,876	515,876	515,876
R-squared	0.331	0.529	0.262	0.257	0.198

Note: Composition refers to the share or non-regular to regular workers. Regular, non-regular, part-time and haken represent the number of employee types by plant. Fixed effects included in each model are listed in the table. Regressions are clustered at the plant-year level with robust standard errors in parenthesis. Level of significance are *** 1%, ** 5%, * 10%.

5.1.2. Determinants of employee dismissals?

Another factor which may influence changes in employee composition relates to the types of workers firms choose to dismiss. In order to shed light on this, the following section assesses the link between firm characteristics and the types of employee dismissals. One way to approach this question empirically would be to simply look at changes in employment of a plant year on year. However, differences may not actually reflect layoffs but rather lags between hiring or relocating employees to different plants within the firm.[21] In order to capture considerable changes in employment (which is less likely to be result of hiring lags), a layoff is classified to have occurred if the employment of the plant decreased by 10% or more (see Equation 4).[22] This layoff definition is consistent with the classification used in OECD (2019).

$$layoff_{it} = 1 \ if \ \Delta emp_{it} \leq -10\%$$
$$layoff_{it} = 0 \ if \ \Delta emp_{it} > -10\% \tag{4}$$

The empirical model used to estimate the determinants of layoffs of manufacturing firms in Japan is illustrated in Equation 5. $layoff_{ist}$ is a dummy variable reflecting whether a plant experienced a decline (of 10% or more) in total employment, between time t-1 to t. The same plant (tfp_{ist} & s_{ist}) and sector (δ_{st}) determinants used in Equation 2 are included along with plant, year, region and sector fixed effects. Moreover, in order to assess whether there is heterogeneity in the effects of TFP on dismissals at different productivity quartiles, we augment the model including the TFP-quartile interaction terms (see Equation 6) and excluding plant fixed effects.

$$layoff_{ist} = \alpha_0 + \alpha_1 tfp_{ist} + \alpha_2 s_{ist} + \alpha_3 \delta_{st} + \alpha_4 \chi_{ist} + \varepsilon_{it} \tag{5}$$

$$\begin{aligned} layoff_{ist} = \alpha_0 + \alpha_1 tfp_{ist} + \alpha_2 tfp_{ist} * q1 + \alpha_3 tfp_{ist} * q2 + \alpha_4 tfp_{ist} * q3 \\ + \alpha_5 tfp_{ist} * q4 + \alpha_6 s_{ist} + \alpha_7 \delta_{st} + \alpha_8 \chi_{ist} + \varepsilon_{it} \end{aligned} \tag{6}$$

[21] Ideally one would assess the question using firm level data however, it does not appear possible to construct firm identifiers for the plants in the dataset at this moment.

[22] The results presented below are consistent with the use of different layoff thresholds (including plant employment declines by 5%, 15% and/or 20%.

Empirical results

The results in Table 5 illustrate the link between firm and sector characteristics on the layoffs of all types of workers, regular, part-time and haken employees. TFP is negatively correlated with the dismissal of any types of workers. This is not surprising since more productivity plants tend employ their factors of production more efficiently and therefore may be less adversely impacted by shocks. Robotics diffusion are negatively related to the dismissal of regular workers but positively link to the layoffs non-regular work types. These results are consistent with what was found previously i.e., growth in robot diffusion is linked with fewer non-regular and more regular workers (See Table 3). Taking these two results together suggest that industrial robotics may be used in placed of certain types of non-regular workers. Interestingly, plants residing in sectors more exposed to offshoring are less likely to layoff either regular or any non-regular types of employment.

Table 5 Determinants of layoffs by employment type

Dependent variable	Layoff All	Layoff Reg	Layoff Non-Reg	Layoff PT	Layoff H
TFP	-0.212***	-0.212***	-0.081***	-0.064***	-0.036***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Multi-plant	-0.018***	-0.017***	-0.003	-0.000	0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Offshoring	-0.125***	-0.112***	-0.041***	-0.035***	-0.027***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Robot stock	-0.047***	-0.067***	0.026***	0.030***	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fixed effects					
Plant					
Year	✓	✓	✓	✓	✓
4 digit industry	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓
Observations	507,666	507,666	507,666	507,666	507,666
R-squared	0.141	0.138	0.115	0.127	0.223

Note: Layoff all, Reg, Non-Reg, PT and H refer to instance in a decline of all, regular, non-regular, part-time and haken workers, respectively by 10% or more at the plant. Fixed effects included in each model are stated in the table. Regressions are clustered at the plant-year level with robust standard errors in parenthesis. Level of significance are *** 1%, ** 5%, * 10%.

The impact of TFP on layoffs by employee types appears to be heterogeneous depending on the position plants reside on the productivity distribution. Interestingly, firms at the top of the productivity distribution are more likely to dismiss all types of workers, bother regular and non-regular than firms located on lower rungs of the productivity distribution. At the same time, TFP is still negatively correlated with the likelihood of the dismissals for all employees and regular workers with coefficients of -0.010 and -0.022 (-0.029+0.004+0.006+0.009= -0.010) and (-0.038+0.003+0.005+0.008=-0.022), respectively. When one considers heterogeneous effects for non-regular worker types, we find that those firms are the top are the most likely to dismiss non-regular types of employees. This is the case for both part-time and haken worker. However the size of the effects is markedly larger for the dismissal of haken workers with a coefficient of 0.044 (0.037+0.00001+0.003+0.004=0.044) than for part-time workers with a coefficient of 0.005 (-0.009+0.004+0.005+0.005=0.005). Considering the results in both Table 4 and Table 6 implies that the most productive plants may use certain types of non-regular worker as a flexible form of labour to adjust to economic environmental changes.

Table 6 Heterogeneous effects of TFP on layoffs by employment type, by TFP quartile

Dependent variable	Layoff All	Layoff Reg	Layoff Non-Reg	Layoff PT	Layoff H
TFP	-0.029***	-0.038***	-0.001	-0.009***	0.037***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TFP* 25th-50th percentile	0.004***	0.003***	0.003***	0.004***	0.000**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TFP* 50th-75th percentile	0.006***	0.005***	0.005***	0.005***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TFP* 75th-100th percentile	0.009***	0.008***	0.006***	0.005***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Multi-plant	0.019***	0.017***	0.000	-0.000	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Offshoring	-0.136***	-0.121***	-0.057***	-0.048***	-0.041***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
Robot stock	-0.043***	-0.059***	0.006	0.008*	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fixed effects					
Year	✓	✓	✓	✓	✓
4 digit industry	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓
Observations	515,876	515,876	515,876	515,876	515,876
R-squared	0.013	0.012	0.012	0.008	0.043

Note: Layoff all, Reg, Non-Reg, PT and H refer to instance in a decline of all, regular, non-regular, part-time and haken workers, respectively by 10% or more at the plant. Fixed effects included in each model are stated in the table. Regressions are clustered at the plant-year level with robust standard errors in parenthesis. Level of significance are *** 1%, ** 5%, * 10%.

5.1.3. Are layoffs a mechanism for employee composition

Another important question relating to structural adjustment is how firms reorganise themselves after downsizing. In particular, what types of employees do firms use after experiencing layoffs? Firms that need to reduce costs by dismissing workers may prefer more flexible forms of employment, such as part-time and haken workers. This may be particularly true given the cost of dismissing regular workers in Japan as discussed previously. This section therefore examines the extent to which layoffs in the past influence employ use in the present.

The estimation method uses a standard OLS framework illustrated in Equation (7). y_{ist} represents the various employment measures at the plant including composition, and numbers of regular, non-regular, part-time and haken workers. The explanatory variable of interest $layoff_{ist}$ is a dummy variable reflecting whether a plant experienced a decline (of 10% or more) in total employment at time $t-3, t-4, t-5$. The rationale for starting with $t-3$ and ending with $t-5$ is to ensure that the lag is far enough in the past that the relationship is not endogenous to decisions made in the present and not too distance from the present that it lacks predictive power.[23] The model includes the same plant and sector level controls) along with the same fixed effects used in Equations 2 and 5.

$$y_{ist} = \alpha_0 + \alpha_1 layoff_{ist-5} + \alpha_2 \chi_{ist} + \alpha_3 \delta_{st} + \varepsilon_{it} \qquad (7)$$

Empirical results

[23] Robustness tests using longer lags find that the predictive strength of α_1 weakens for longer time differences.

Table 7 presents the econometric results on the impact of past layoffs on the contemporaneous share of non-regular to regular workers. The results suggest that plants, which experienced a layoff in 3 to 5 years in the past, use more non-regular to regular workers today. In addition, the effects appear to strengthen overtime, illustrated by the size of the composition coefficients in time t-5 of 0.012. The relationships are robust to the different layoff definitions, such as declines of employment by 5% to 20% and for longer lagged period.[24] These results are consistent to what is found when we look at the numbers of employee types used in the present after a layoff in the past. Specifically, plants, which experienced layoffs in the past employ fewer regular workers and more non-regular, part-time, and haken workers in the present (See

[24] These additional results are excluded for brevity.

Table 8). In addition, the magnitudinal effect of the layoff appears to have the largest positive effect on haken use, signified by the size of the coefficient 0.050.[25] These results demonstrate that plants, which experienced downsizing in the past, are favouring more low cost and flexible workforce away from full-time regular workers.

[25] This does not however mean that the effect between haken and other non-regular workers is statistically different.

Table 7 Effects of layoffs (t-3, t-4, t-5) on present employee composition

Dependent variable	Composition	Composition	Composition
Layoff, t-3	0.010**		
	(0.00)		
Layoff, t-4		0.012***	
		(0.00)	
Layoff, t-5			0.012***
			(0.00)
TFP	-0.008***	-0.005***	-0.002
	(0.00)	(0.00)	(0.00)
Multi-plant	0.001	0.001	-0.000
	(0.00)	(0.00)	(0.00)
Offshoring	-0.016***	-0.015***	-0.006
	(0.00)	(0.00)	(0.00)
Robot stock	-0.022***	-0.015***	-0.013***
	(0.00)	(0.00)	(0.00)
Fixed effects			
Plant	✓	✓	✓
Year	✓	✓	✓
4 digit industry	✓	✓	✓
Region	✓	✓	✓
Observations	295,044	286,730	247,484
R-squared	0.917	0.919	0.923

Note: Composition refers to the share or non-regular to regular workers. Layoff refers to a reduction of total employment of the plant for 10% or more between times t-3, t-4 and t-5. Fixed effects included in each model are stated in the table. Regressions are clustered at the plant-year level with robust standard errors in parenthesis. Level of significance are *** 1%, ** 5%, * 10%.

Table 8 Impact of layoffs (t-5) on present employment use

Dependent variable	Regular	Non-Reg	Part-time	Haken
Layoff, t-5	-0.011**	0.043***	0.017***	0.050***
	(0.00)	(0.00)	(0.00)	(0.00)
TFP	0.148***	0.169***	0.131***	0.152***
	(0.00)	(0.00)	(0.00)	(0.00)
Multi-plant	0.010***	0.014*	0.024***	0.012
	(0.00)	(0.00)	(0.00)	(0.00)
Offshoring	0.013	0.088***	0.099***	0.096***
	(0.00)	(0.00)	(0.00)	(0.00)
Robot stock	0.024***	-0.073***	-0.025*	-0.071***
	(0.00)	(0.01)	(0.01)	(0.01)
Fixed effects				
Plant	✓	✓	✓	✓
Year	✓	✓	✓	✓
4 digit industry	✓	✓	✓	✓
Region	✓	✓	✓	✓
Observations	247,899	247,899	247,899	247,899
R-squared	0.958	0.857	0.869	0.756

Note: Composition refers to the share or non-regular to regular workers. Regular, non-regular, part-time and haken represent the number of employee types by plant.. Layoff refers to a reduction of total employment of the plant for 10% or more between time t-5. Fixed effects included in each model are stated in the table. Regressions are clustered at the plant-year level with robust standard errors in parenthesis. Level of significance are *** 1%, ** 5%, * 10%.

6. Conclusion

Firms in a dynamic market are continuously under pressure to adjust and evolve over time. The ability of firms to adapt to these competitive and technological factors can influence their growth trajectory. One of the ways in which firms have attempted to overcome these imbalances is through mass layoffs (Silva et al 2019). Another mechanism that a business can use to adjust is by substituting away from regular full-time employment to non-regular workers. Doing so may allow businesses to become more flexible and reduce labour costs (Asao 2011). Both methods can result in adverse effects to labour market participants.

The objective of this paper is to assess the evolution of employment composition for Japanese manufacturers and identify the main determinants of this style of structural change. Descriptive statistics show that plants are using greater proportions of non-regular workers to regular workers across regions, sectors and time. At the same time, the use of employee type is considerably heterogeneous across narrowly defined sectors and firms.

The econometric evidence identifies a number of countervailing factors, which influence the use of employment types. In terms of technology change, growth in the diffusion of robotics is linked to the employment of fewer non-regular employees. This appears to be partially driven by the fact that these machines are also related to the dismissal of certain types of non-regular workers. Offshoring to Japan leads to the use of a higher proportion of non-regular to regular workers, potentially due to increased competition faced by plants from abroad.

Firm productivity is also an important determinant for the types of employees used. Increases in plant productivity leads to greater numbers of regular and non-regular workers in absolute numbers, but a greater proportion of regular workers. When considering the position of plants within the productivity distribution, we find that those at the top of the productivity quartile hire greater numbers of non-regular workers but they are also more likely to dismiss these same types of workers than plants located on lower rungs of the distribution. These results may suggest that more productive firms may be using certain types of non-regular worker as a flexible form of labour as a cost buffer in the event of a macro shock. Finally, the analysis finds that establishments, which experienced job dismissals in the past, substitute away from regular to non-regular workers in the present.

While the following work provides some interesting insights regarding the nature of employee composition and what is driving this change, future work is need. Linking plants to firms within the Census of Manufacturers would allow researchers to more fully understand how employees are being reallocated across plants within a firm overtime. Assessing the determinants of these changes, identifying the types of employees that are being reallocated and understanding where they are being reallocated to would be particularly insightful to policy makers.

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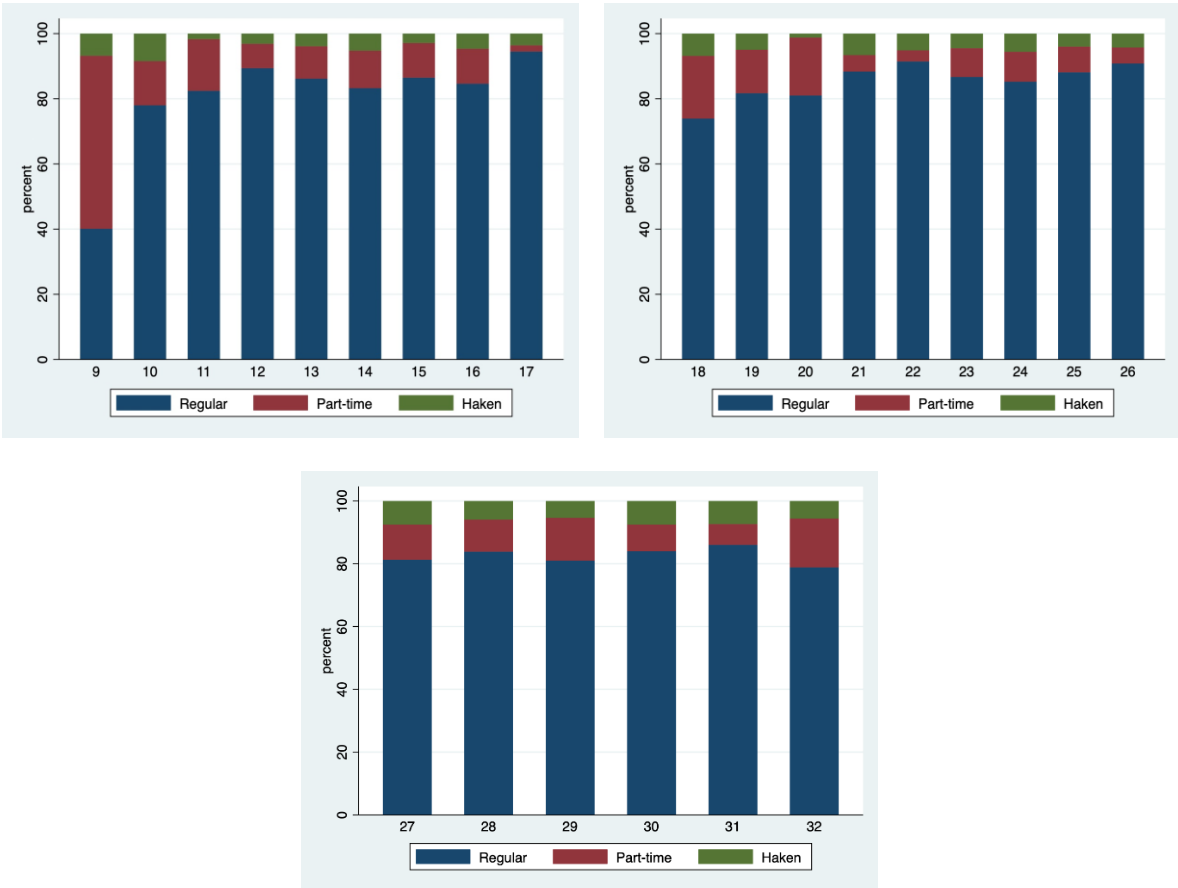
8. Appendix

Table 9 Sectoral classifications

Sic Code	Description
9	MANUFACTURE OF FOOD
10	MANUFACTURE OF BEVERAGES,TOBACCO AND FEED
11	MANUFACTURE OF TEXTILE PRODUCTS
12	MANUFACTURE OF LUMBER AND WOOD PRODUCTS, EXCEPT FURNITURE
13	MANUFACTURE OF FURNITURE AND FIXTURES
14	MANUFACTURE OF PULP, PAPER AND PAPER PRODUCTS
15	PRINTING AND ALLIED INDUSTRIES
16	MANUFACTURE OF CHEMICAL AND ALLIED PRODUCTS
17	MANUFACTURE OF PETROLEUM AND COAL PRODUCTS
18	MANUFACTURE OF PLASTIC PRODUCTS, EXCEPT OTHERWISE CLASSIFIED
19	MANUFACTURE OF RUBBER PRODUCTS
20	MANUFACTURE OF LEATHER TANNING, LEATHER PRODUCTS AND FUR SKINS
21	MANUFACTURE OF CERAMIC, STONE AND CLAY PRODUCTS
22	MANUFACTURE OF IRON AND STEEL
23	MANUFACTURE OF NON-FERROUS METALS AND PRODUCTS
24	MANUFACTURE OF FABRICATED METAL PRODUCTS
25	MANUFACTURE OF GENERAL-PURPOSE MACHINERY
26	MANUFACTURE OF PRODUCTION MACHINERY
27	MANUFACTURE OF BUSINESS ORIENTED MACHINERY
28	ELECTRONIC PARTS, DEVICES AND ELECTRONIC CIRCUITS
29	MANUFACTURE OF ELECTRICAL MACHINERY, EQUIPMENT AND SUPPLIES
30	MANUFACTURE OF INFORMATION AND COMMUNICATION ELECTRONICS EQUIPMENT
31	MANUFACTURE OF TRANSPORTATION EQUIPMENT
32	MISCELLANEOUS MANUFACTURING INDUSTRIES

Note: Sector classifications are 2-digit Japanese Standard Industrial Classification.

Figure 8 Share of average employee types by 2-digit sector, 2001



Note: The following figure illustrates averages in employee type by 2-digit sector for the year 2001. Sector classifications are the Japanese Standard Industrial Classification.
Source: Census of Manufacturers, calculations by authors.

Table 10 Determinants of Employee Use, controlling for output and wages

Dependent variable	Composition	Composition	Regular	Regular	Non-Reg	Non-Reg	Part-time	Part-time	Haken	Haken
Output	-0.013**		0.305**		0.321**		0.186**		0.314**	
	(0.00)		(0.00)		(0.00)		(0.00)		(0.00)	
TFP		-0.053**		0.244**		0.156**		0.093**		0.146**
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Multi-plant	-0.000	0.000	0.006**	0.009**	0.005	0.011+	0.003	0.006	0.004	0.009
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Offshoring	-0.015**	-0.009	0.060**	0.082**	0.039*	0.080**	0.123**	0.146**	0.105**	0.147**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)
Robot stock	-0.018**	-0.017**	0.044**	0.048**	-0.026**	-0.018*	-0.010	-0.005	-0.048**	-0.040**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
lnwage_full	0.396**	0.404**	-0.462**	-0.452**	0.408**	0.440**	0.608**	0.626**	0.118**	0.151**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
lnwage_nonfull	-0.015**	-0.014**	-0.000	-0.001**	-0.130**	-0.129**	-0.131**	-0.130**	0.011**	0.012**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fixed effects										
Plant	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
4 digit industry	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	305,480	305,480	305,480	305,480	305,480	305,480	305,480	305,480	305,480	305,480
R-squared	0.912	0.913	0.964	0.960	0.851	0.846	0.850	0.849	0.726	0.723

Note: Composition refers to the share or non-regular to regular workers. Regular, non-regular, part-time and haken represent the number of employee types by plant. Fixed effects included in each model listed in the table. Regressions are clustered at the plant-year level with robust standard errors in parenthesis. Level of significance are *** 1%, ** 5%, * 10%.

Table 11 Determinants of Employee Use, lagged TFP

Dependent variable	Composition	Composition	Regular	Regular	Non-Reg	Non-Reg	Part-time	Part-time	Haken	Haken
TFP, t-1	-0.021***		0.173***		0.091***		0.064***		0.086***	
	(0.00)		(0.00)		(0.00)		(0.00)		(0.00)	
TFP, t-2		-0.024***		0.137***		0.035***		0.029***		0.030***
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
Multi-plant	0.001	0.000	0.010***	0.011***	0.012*	0.015***	0.002	0.009	0.008	0.014
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Offshoring	-0.013*	-0.009	0.089***	0.054***	0.097***	0.062***	0.138***	0.108***	0.136***	0.091***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	(0.02)
Robot stock	-0.019***	-0.018***	0.042***	0.036***	-0.055***	-0.050***	-0.058***	-0.040***	0.003	-0.014*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fixed effects										
Plant	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
4 digit industry	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.903	0.910	0.944	0.949	0.828	0.835	0.845	0.852	0.721	0.729
Observations	388,883	333,867	389,679	334,467	389,679	334,467	389,679	334,467	389,679	334,467

Note: Composition refers to the share or non-regular to regular workers. Regular, non-regular, part-time and haken represent the number of employee types by plant. Fixed effects included in each model listed in the table. Regressions are clustered at the plant-year level with robust standard errors in parenthesis. Level of significance are *** 1%, ** 5%, * 10%.