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Document de Travail
Working Paper
2015-28

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Computer technology and probable job destructions in Japan: an evaluation*

Benjamin David†

Abstract

This paper evaluates the risk of job destructions induced by computer technology in Japan. Relying on recent methodology, we find evidence that approximatively 55% of jobs are susceptible to be carried by computer capital in the next years. We also show that there is no significant difference on the basis of gender. On the contrary, non-regular jobs (those that concern temporary and part-time workers) are more vulnerable to computer technology diffusion than the others.

JEL Classification: C53, J21, O33.
Keywords: Computer technology, Japanese labor market, Automation, Random Forest

*We are grateful Professor Professor Valérie Mignon and Professor Ryo Kambayashi for helpful comments and suggestions.

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1 Introduction

In recent years, an important dissemination of computer and communication technologies has been observed in Japan and in other industrialized countries. This diffusion in economic activities is a broad and international movement with country specific timeline. According to Murata (2010), this process begins in Japan in the 1950s via the acquisition of a US computer (Bendix G-15) by the *Railway Technical Research Institute* (1957) and continued through the 1960s by the introduction of second and third generation of computers.[1] These machines which were both imported and produced locally, were progressively dedicated to special purpose terminals in manufacturing, distributions and financial industries in the 1970s. During the 1980s, Japan undergone a massive development of office automation benefiting from the invention of Personal Computer (PC) and other specific programs such spreadsheets or work processors.[2] The spread of computers has continued until now and they are used every day in a large range of economic activities. In parallel, technical advance and deregulation policies have caused the emergence of networks supported by computer infrastructure. This concerns the use of the fax machine in the 1980s and above all the development of the Internet and mobile phone in the 1990s and 2000s. Networks have hugely modified the modalities of communication and reduced their costs. The actual situation is characterized by a massive access to these networks: 90% of Japanese people have an access to Internet and the ownership rate of mobile phone is equal to 120% (International Telecommunication Union, 2015).

Another aspect of the actual technological diffusion is the massive development of robotics that can be viewed as a component of the computer revolution (Spong et al., 2012).[3] In this field, Japan is a key country both in terms of production and use to the point that it was labelled as ≪ robot kingdom ≫ (Schodt, 1988). Indeed, Japan has a long and fruitful history in this matter which began in the 1960s by the introduction of industrial robots dedicated to welding, assembling or painting, followed by the first mobile robots used in inspection, transport or spatial tasks in the 1980s (Kumaresan and Miyazaki, 1999). Production and use of robots continue at a large scale and were extented through the development of micro-robots and services robots.

[1] The second generation of computers is characterized by the introduction of transistors and the third by the use of integrated circuits.

[2] The first PC produced in Japan was the NEC PC 8001 (1979).

[3] They argue that ≪ The key element in the above definition is the reprogrammability of robots. It is the computer brain that gives the robot its utility and adaptability. The so-called robotics revolution is, in fact, part of the larger computer revolution≫.

Illustrations of this trend are the actual efforts in the humanoid robotic field initiated by researchers of Waseda University who created *Wabot 1* (1973) as well as other famous examples as *ASIMO* (Honda), *Wakamaru* (Mitsubishi), or *Pepper* (Aldebaran Robotics and Softbank). Data also show the importance of robotics diffusion in Japan. In 2013, this country has the second highest robot density in the world (323 units per 10000 workers) behind the Republic of Korea and has the most important robot density in the automotive industry with 1520 industrial robots per 10000 employees (International Federation of Robotics, 2014).[4]

All these digital devices share a common theoretical and technical background based on binary logic and basic electronic components such as transistor or microprocessor.[5] Many scholars suggest that this set is not a simple group of incremental innovations but constitute a ≪ Technological Revolution ≫ or a ≪ technological-discontinuity ≫ (Brynjolfsson and McAfee, 2011) able to ≪ transform profoundly the rest of the economy ≫ and produce a ≪ new economic paradigm ≫ (Perez, 2009).
Indeed, efforts of characterization of technologies in the literature suggest that innovations or interrelated cluster of innovations are not comparable in their scale and their degree. In this perspective, ICT can be viewed as a major technological set susceptible to produce large-scale impacts. In support of this vision, the literature on ≪ General Purpose Technology ≫ (GPT) (Bresnahan and Trajtenberg, 1995; Rosenberg and Trajtenberg, 2004) supposes that the most important technologies share the feature of generality. This crucial point was anticipated by Simon (1987) which stress that the higher is the level of generality of a technology, the higher is its potential because there is a very important number of possible applications. In the case of computer technology, the degree of generality is very high because all economic activities include information processing tasks.

This view is reinforced by the actual process of digitization of human activities which makes the amount of information available more and more important (≪ Big Data ≫). Furthermore, digitization is coupled with an impressive improvement of ICT capacities in information processing as well as in terms of transmission, storage and transformation of information (Nordhaus, 2007; Nagy et al., 2011; Koomey et al., 2010). Thus, it supposes that the field

[4] Moreover, Japan not only employs robots but is a major producer with 127491 robots produced in 2014 of which 98882 were exported (Japan Robotics Association, 2015).

[5] For this reason, we consider the following expressions as synonym: ≪ computer technology ≫, ≪ computer and communication technologies ≫, ≪ Information Technology (IT) ≫, ≪ Information and Communication Technologies ≫ (ICT).

of application of computer technology is growing, a characteristic that could have notable effects on many economic matters. Among the possible consequences of ICT adoption, an important aspect is its potential destabilising impact on employment. Indeed, labour activities do not escape this trend of digitization: in production activities, there are many tasks consisting of manipulation of information but also that some other tasks can be modeled as information flows. For example, accounting calculations is a task which consists of transferring, stocking and transforming information. On the other hand, some physical activities such as assembly, construction, transport can also be represented as information. Material elements, the space in which they are situated, and movements can be defined as mathematical objects. From this perspective, these tasks are susceptible of being carried out by robots within computer programs representing physical objects, environment and motions in information way. With this in mind, it could be expected that a large number of tasks in a wide variety of fields could be given over to computers now and in the near future. This perspective constitutes a biggest challenge for modern economies. Acknowledging the importance of this topic, our aim in this paper is to investigate the impact of ICT on job destructions in Japan.

The perspective from which a growing share of tasks will be performed by computer capital has strong implications for several Japanese specific economic questions especially those pertaining to the labor market. Among these issues, we can mention the ageing process sustained by gains in longevity, while life expectancy is already one the highest in the world, and low immigration flows. Even if this process concerns several countries in Europe (Germany, France) or in Asia (Korea, China), it is important to stress that ≪ Japan has the most rapidly aging population in the world ≫ (IMF, 2013). On the supply side of the labor market, significant consequences of this evolution are the massive reduction of the overall labor-force, or a dependency ratio reduction in the coming years and decades. A possible response face to this scenario is to call to the technological solution. Growth of ICT capital stock could contribute to maintain the level of production and to help in the care of elderly people. On the demand side, we note that the Japanese labor market has experienced the introduction of more flexibility from the 1980s. This situation originates in the labor law reform in a context of asset-inflated bubble economy collapse (Asao, 2011). The system characterized by job rigidity and wage flexibility (shūshinkoyō) has progressively left space for a growing number of non-regular jobs which represent roughly twenty millions people (Statistics Bureau, 2015). It is important to underline that if computer technology will replace workforce, it could do it differently according to the type of employment. Indeed, it is possible that computer technology destroys more easily non-regular employment either because dismissals are facilitated by legal disposition or because computer technology realizes rather tasks typically carried by non-regular workers. Inversely, if computer and communication tools threaten regular jobs, we can expect that the share of non-regular workers in overall active population increases significantly, thus profoundly affecting the structure of Japanese workforce. We also note that the computer revolution could have notable effects on other questions such as the participation of women in the workplace or could significantly modify the ≪ return to education ≫.

Turning to methodological issues, in order to assess the potential risk for Japanese workers associated with the diffusion of computer technology, we use *Career matrix* data from the Japan Institute for Labour Policy and Training (JILPT) and we build a training sample containing occupations without doubt automatable and other occupations that could be considered as non-automatable. With this sample, we estimate a model explaining the probability of computerisation by the differential dotation in non-automatable skills. Estimation is achieved by using the ≪ Random Forest ≫ algorithm, which builds several uncorrelated decision trees from bootstrap samples from the training set and averages the results to obtain the final estimation. Then, by using our estimates and data from the Population Census (2010), we evaluate the number of jobs threatened by technology and we study the distribution of the probabilities by gender and type of employment.
Our results suggest that a large share of jobs could be performed by computer system in the coming years. More precisely, according to our estimates, one half of Japanese jobs are susceptible to be destroyed by computer technology. However, this global result masks differential effects according to the kind of workers since non-regular workers seem to be more exposed. On the contrary, we don't find results differentiated by gender. The rest of this paper is organized as follows. Section 2 briefly reviews the literature. Section 3 presents the methodology. Section 4 presents the results and section 5 concludes.

2 Literature review: employment and computer

A vast literature exists on the link between technology and employment, dating at least from classical economists such as Ricardo (1821) or Marx (1867). In this field, a recurrent question concerns the capacity of technology to re-

place workers in economic activities. The possibility of the realization of this capital/labor substitution may be interpreted from the economic perspective by the following alternative: compensation theory or ≪ technological unemployment ≫ (Keynes, 1930).
The first approach refers to the fact that there are ≪ compensation mechanisms that are triggered by technical change itself and which can counterbalance the initial labor saving impact of process innovation ≫ (Vivarelli, 2011).[6] In this perspective, technology is not a serious threat to employment level but it could produce a qualitative shift in jobs. Under technological pressure, some tasks are no longer carried out by workers whilst other appear because of new activities. The second view is more pessimistic because it supposes that even if there are some compensation mechanisms, a part of the workforce replaced by technology doesn't find new jobs and contributes to ≪ technological unemployment ≫. In this perspective, there is an inequality between the number of jobs destroyed and the number of jobs created.

Recently, this recurrent question has been raised again due to the diffusion of IT which seems capable of performing an ever-increasing share of tasks traditionally carried out by workers. In the recent literature, a major theoretical and empirical contribution in the understanding of the relationship between computer technology and the evolution of the distribution of occupations was made by Autor et al. (2003). They have developed an equilibrium model (≪ task model ≫) in which producers use two types of inputs: routine and non-routine labors.[7] They suppose that the first kind of labor input is perfectly substitutable by computer capital while the second constitutes a complement. The driving force of the model is the fall in prices of computer capital which produces differential evolution of each type of labor. Autor et al. (2003) provide econometrical evidences to support their model. A very similar study was written by Maurin and Thesmar (2004) who bring empirical arguments in favor of this hypothesis in France. Goos and Manning (2007) have extended this approach by showing that the non-routine tasks are mainly located in the top and the low level of wage distribution which can explain the polarization of the labor market observed in the UK. Many other works confirm the task-based polarization hypothesis for several economies such as Goos et al. (2009) or Autor and Dorn (2013).

With regard to the Japanese economy, Ikenaga (2009) uses the same frame-

[6] Vivarelli (2011) identify six types of compensation mechanisms.

[7] Each input is an aggregate. Routine tasks are composed of routine cognitive tasks and routine manual tasks. Non-routine tasks can be non-routine analytic tasks, non-routine interactive tasks or non-routine manual tasks.

work as Autor et al. (2003) and shows that since the 1990s, labor input of knowledge-intensive non-routine analytic tasks and low-skill non-routine manual tasks is growing, whereas, at the same time labor input of routine manual tasks has declined. In addition, Ikenaga identifies a complementary relationship between ICT capital and workers who carry out non-routine analytic tasks and a substitution trend with workers engaged in routine tasks. Ikenaga and Kambayashi (2010) also pay interest to the evolution of the input share of each type of tasks on the basis of a specific measure of ≪ task intensity ≫ in each occupation. Their analysis suggests that there is a long-term increase in non-routine task input and a long-term decrease in routine tasks between 1960 until 2005. In addition, they found a positive correlation between the average wage in an occupation and the routine cognitive task input, and a negative correlation with routine manual task input.

Recently, Frey and Osborne (2013) have renewed the analysis of the exposure of workers faced with recent technological diffusion. A starting point of their approach is that the identification between non-routine tasks and low susceptibility to automation is called into question by the improvements of computer tools in the fields of machine learning and mobile robots. Indeed, non-routine tasks can also be carried out by computer capital. A famous example is the autonomous driverless cars, now in development (but operational), and nonetheless considered as a good example of non-automatable tasks by Autor et al. (2003) (cited by Brynjolfsson and McAfee (2011)). On the basis of expert opinions and relying on the computer science literature, Frey and Osborne (2013) go beyond the distinction routine tasks/non-routine tasks and propose that computerisation[8] has strong limitations in perception and manipulation tasks, creative intelligence tasks, and social intelligence tasks. By using O*NET and SOC databases (from the US department of labor), the authors, helped by a panel of computer scientists, consider 70 occupations which are without doubt automatable or not in the next years. For example they consider that the cashier occupation is automatable, while childcare worker occupation is non-automatable. Then, they construct a probabilistic classification model with this training sample. The dependent variable is the probability of computerisation and the explicative variables are nine variables that representing the three ≪ bottlenecks ≫. They use this estimated model to predict the probabilities of automatization of the 702 occupations of their database. Then, they evaluate the number and the

[8] Frey and Osborne (2013) define Computerisation as follow: ≪ We refer to computerisation as job automation by means of computer-controlled equipment ≫. To avoid unpleasant repetitions, we also use the usual term of ≪ automation ≫.

distribution of jobs by sector now threatened by computer capital. Their results suggest that ≪ 47 percent of total US employment is at risk ≫ (by considering a threshold of probability equal to 0.7).

In the present paper, we aim at implementing a similar analysis about Japanese labor market by assessing the share of jobs which could be threatened by computer technology over the next few years. This approach is justified by the fact that the results obtained by Frey and Osborne (2013) for the United States are not fully transposable to the case of the Japanese labor market. Indeed, there are some differences in industry and occupational structures between these two countries. Industries have not the same weight in each economy and occupations are partially different (follows that US and Japanese classificatiosn are not the same). We note, for instance, the existence of Japanese specific occupations such as kimono dressing instructor, sushi chef, pachinko employee, Juku teacher, administrative scrivener and some differences in occupations which have not the same valuations of skills (Ikenaga and Kambayashi, 2010).
On the other hand, Japan is a country where the technological issue is particularly interesting. Even if the spread of computer devices is an international dynamic, there are country specific characteristics. As discussed above, Japan has a high level of technology diffusion and it is a major producer of innovations. If computer technology has a significant impact on the structure or on the level of employment, we can expect that it will be particularly important in this country, in particular due to the development and the dissemination of robots.

3 Methodology

3.1 Data

The first step of our analysis is to constitute a training sample with which we build our prediction model. The purpose is to select occupations, which can be undoubtedly, in the current state, performed or not by computer capital. We also need some information about the levels of skills required to perform each occupation.

For that purpose, we use data from *Career matrix*, a database created by the JILPT containing 499 occupations based on the Classification of Occupations for Employment Services (ESCO). It contains 35 variables that describe the level of different skills necessary for each occupation. These values are defined on the basis of surveys and range between 0 and 5, 0 being the lowest value and 5 the maximum value. Firstly, we select 61 occupations similar or very close to Frey and Osborne (2013) selection (which is itself based on computer science expert opinions). In order to expand our sample and ensure robust estimation, we add other automatable occupations identified on an empirical basis. This means that they are now subject to automation process or that a technology in an advanced development stage is susceptible to replace workers in these occupations. For example, we include in this sample the occupation ≪ Train Driver ≫ because there are already automatic trains in running in Japan. Finally, the training sample considered in this study contains 69 occupations representing roughly 14% of those of *Career Matrix* (tables 3, 4).

The second step in the constitution of our training sample is to select explanatory variables that determine the probability of automation. The baseline model supposes there are three limitations to automation: perception and manipulation tasks, creative intelligence tasks, and social intelligence tasks. Unfortunately, *Career matrix* doesn't contain variables for representing perception and manipulation tasks and creative intelligence tasks.
In order to overcome this problem, we create appropriate dummy variables for the two categories without data. Precisely, we define a dummy variable ≪ manual dexterity ≫ to reflect perception and manipulation tasks and two other to represent creative intelligence tasks: ≪ Fine Arts ≫ and ≪ Originality ≫. We prefer to create dummies and only three variables to reduce the risk to assign subjectively values between 0 and 5 for the other variables. For example, the occupation of surgeon takes a value of 1 to signify that it requires high level of manual dexterity, while the occupation of lawyer takes a value of 0 to signify the inverse. We consider that this approach is a convenient tradeoff between the accounting of important variables and the risk of subjective assignation.
To represent social intelligence tasks, we select, in *Career Matrix*, the following five variables: ≪ Coordination ≫, ≪ Persuasion ≫, ≪ Negotiation ≫, ≪ Instructing ≫ and ≪ Service orientation ≫. Lastly, by examining variables contained in *Career Matrix*, we select another variable that seems impossible for the moment to automatize: ≪ Judgment and decision making ≫. We call this task: Appreciation tasks. We present all data in table 5.

3.2 Random Forest

We aim to compute the probability of automation of occupations on the basis of the different dotations in non-computerisable tasks inputs by using the methodology of Frey and Osborne (2013): (i) considering a training sample of occupations which could be considered as clearly automatable or not, (ii) we build a model with this subsample, (iii) and we finally predict the probability of automation of all occupations. In this perspective, we have constituted a training sample as described in section 3-1. For the estimation, we rely on the ≪ Random Forest ≫ (RF) algorithm[9], a very useful method from machine learning framework.

The use of RF instead of a standard method requires explanation. In these kind of situation, when we consider a binary dependent variable, it is usual in applied economics to use logistic regression. However, in this case, for technical reasons, this seems impossible. Indeed, as suggested by Peduzzi et al. (1996), it is necessary to have at least 10 Events Per explanatory Variables (EPV) in order to perform logistic regression. Below this threshold, there are important risks of non-convergence, loss in terms of accuracy, or no normality of regression coefficients. In our case, we have 69 observations in the learning sample including 33 events (*i.e.* when the probability of automation is equal to one) and 10 explanatory variables (EPV = 3.3). Another potential difficulty is the correlation between several explanatory variables. For example, the persuasion and negotiation variables are highly correlated (r=0.8). In front of these problems, it seems difficult to expand the size of the learning sample or to remove some variables just on a subjective basis.

Initially, for simplicity and to circumvent these technical problems, we have been interested in using regression trees[10], specifically CART algorithm (Breiman et al., 1984), a simple nonparametric method consisting in splitting the subspace of predictors in different regions and model the response of the dependent variable as a constant in each region.[11] The main advantages of this approach are that no assumption on the functional form to linking the variables is required (that allows taking into account non-linearity), it produces easily readable results and it can avoid the multicolinearity problem between the variables in *Career Matrix*.

[9] For estimation, we use R Package *randomForest* version 4.6-10 (Liaw and Wiener, 2002). We consider a ≪ forest ≫ containing 100 trees. We doesn't need more iterations because the study of the execution of the algorithm shows that the Mean Square Error (MSE) stabilizes around 40 trees.

[10] Given the particular structure of data ($y = 1$ or $y = 0$), we could use classification tree but we would a more nuanced view. By using regression tree instead, we could get all values between 0 and 1.

[11] CART part of the "Top 10 Algorithm in data mining" (Wu et al., 2008).

However, regression trees, although being a very compelling method, suffer from a major drawback: instability (Breiman, 1996). If there is a small modification of the dataset, results will be altered substantially, constituting a key issue in terms of results'robustness. To overcome this major drawback, we rely here on another approach. Specifically, in order to stabilize trees and improve the accuracy of estimation, various methods have been developed, such as ≪ bagging ≫[12] (Breiman, 1996) and ≪ Random Forest ≫ (Breiman, 2001). We use the latter approach because this is a simple method that has interesting theoretical properties.

RF has three main components: tree ①, randomization ② and bagging ③. The first step is to consider a bootstrap sample b of the training data (one third of the sample is left out) and construct a tree ①. The difference with CART is that at each node p, we select randomly several variables for each node ② and we split the node in two child nodes, by considering the variable k and the split point s, that produce the best binary partition in terms of minimization of the residual sum of squares. Formally, the aim is to minimize the sum of squared errors from the two regions (R1 and R2):

$$min_{k,s}\left[min_{c1}\sum_{x_i\in R_1(p,k,s)}(y_i-c_1)^2+min_{c2}\sum_{x_i\in R_2(p,k,s)}(y_i-c_2)^2\right] \quad (1)$$

The best ≪ response ≫ in each m region ($\hat{c}_m$) is equal to the average value of the dependent variable. Since it is a regression tree, it is recommended that the number of k randomly selected variables is equal to the following floor function $\lfloor\frac{K}{3}\rfloor$ (Hastie et al., 2009) where K denotes the number of explanatory variables. The third step is to repeat this procedure on B bootstrap samples ③ and average the results of prediction to obtain the final estimation. It is important to stress that unlike CART, there is not ≪ pruning ≫ of the estimated tree.[13] At each step, the tree is constructed until it reaches its maximum size defined in advance. This procedure is summarized in figure 1.

RF has several advantages, in addition to those generally associated with CART. First, using this method, we lose the possibility to summarize the estimation in a simple tree because with each bootstrap sample we estimate a new tree, but we eliminate the main problem of the instability of the results. Second, RF benefits from the randomization process because it allows to construct ≪ de-correlated trees ≫ which in turn lead to reduce the variance of the estimated model. Third, RF is a powerful method which performs

[12] Bagging refers to ≪ Bootstrap AGGregatING ≫.
[13] In CART, ≪ Weakest Link Pruning ≫ is used.

Figure 1: RF Algorithm

a-Consider a b bootstrap sample from the original data. b-At each node, select randomly several splitting variables c-Split current node into two child nodes	NODE $\Downarrow$
Repeat steps a, b, c until the tree reaches a maximum size	TREE $\Downarrow$
Repeat steps 1 and 2 on B bootstrap samples Average predictions	FOREST

well when the sample has limited size and even if the number of observations is lesser than the number of predictor variables[14]. Lastly, RF permits also to compute a value which provides information on the importance of the variables in the estimation by using the $\ll$ Mean Decrease in Accuracy(MDA) $\gg$ criteria. For that purpose, we consider the Out-Of-Bag (OBB) sample, *ie* data that are not used for constructing the b tree, and proceed as follows:

- Compute the error of a b tree on its OBB sample.
- Permute randomly the value of the variable k from the training sample and compute new OBB error.
- Average all the OBB errors to obtain the MDA (the value is normalized by standard deviation).

The underlying idea of this algorithm is to detect if the permutation involves a decrease in the accuracy of the model. If a variable is not important the decrease will be weak while it will be significant if a variable is important.

4 Results

4.1 General results: classification of occupations

Before commenting and studying the probabilities of computerisation and their economic implications, it is necessary to evaluate the accuracy of our model. A simple approach is to check how many predictions of the adjusted model are correct by looking at the confusion matrix (not reported here). If we consider a standard threshold of 0.5 for assigning a class to each occupation, the estimated model achieves accurate prediction in approximately

[14] See examples in Verikas et al. (2011).

88% of cases.
A more efficient measure of accuracy in classification problems is the Area Under Curve (AUC) that corresponds to the evaluation of the area situated under the Receiving Operating Curve (ROC). This tool enables to situate the quality of a classifier over two references, a perfect and a random classifier which have respectively an AUC value of 1 and 0.5. The model considered in our analysis has a value of AUC equal to 0.955, suggesting that it has a very good level of performance that allows us to have a relative confidence in the probabilities computed.[15]
Application of the RF algorithm permits to obtain a probability of automation for all occupations considered (see tables 7 to 21 in appendix). Given that there are 499 occupations, we cannot comment precisely all the results, but we could give an overview of the findings by selecting the top ten, bottom ten and some intermediate occupations (table 1). As shown, in the top 10 occupations, there are only occupations that require high level of creativity, manual dexterity or social intelligence. This is reflected in the variable importance measure that highlights the significant weight of the variables ≪ originality ≫ and ≪ manual dexterity ≫ , ≪ instructing ≫ and ≪ negotiation ≫ in the estimation (table 6 in appendix).
Logically, occupations in the bottom ten are poorly endowed in non computerisable skills. A part of results is plausible with, for example, the probable disappearance of mail deliverer or cashier occupations. On the contrary, some occupations such as model or truck driver is difficult to appear as risky because no replacement process has now began.

4.2 Detailed results

Beyond the results by occupation, it is very interesting to draw lessons at different economic levels. Our aim is to study the number, the distribution and the properties of the jobs which could be destroyed by computer devices in the next years. The drawback is that *Career matrix* contains data on skills by occupation but no information on the number and the characteristics of workers who perform each occupation. To alleviate this problem, we rely on the data of the last population census (2010) that provides detailed information on the number, the type of employment and the gender of people which perform each job.
Our strategy is to construct a new data set combining interesting information from these two sources. Since Population Census considers only 232 occupations, we include all *Career Matrix* occupations in population cen-

[15] Note that Frey and Osborne (2013) model has AUC equal to 0.894.

Table 1: Overview of results

Top 10 occupations	Probability
Speech therapist	0.014
Lawyer	0.019
Stylist	0.021
Classical Musician	0.025
Theatre Decorator	0.025
Stage director	0.031
High school teacher	0.033
Vocational school teacher	0.033
Make-up artist	0.035
Radio director	0.038
Some intermediate occupations	**Probability**
Dentist	0.118
Tourist guide	0.200
Programmer	0.365
Radiology technologist	0.424
Nutritionist	0.510
Cargo handler	0.628
Car Assembler	0.694
Postal clerk	0.783
Train driver	0.874
Taxi Driver	0.954
Bottom 10 occupations	**Probability**
Packing worker	0.972
Truck driver	0.972
Hotel worker	0.974
Tourist Bus Driver	0.974
Road patrol worker	0.974
Computer-Assisted-Design operator	0.982
Data entry keyer	0.982
Industrial waste collection and transportation worker	0.982
Mail Deliverer	0.982
Computerized typesetting operator	0.982

sus categories and average the values of all variables. In some cases, this approach is quite simple because occupations are similar (pharmacist, architectural engineers, childcare workers...) which led no loss of information. However, in other cases, we must insert several occupations from *Career Matrix* in Population census categories. For example, in the category ≪ Motor vehicle drivers ≫, we include taxi drivers, truck drivers, tourist bus drivers and bus drivers. For few cases, we have not any *Career matrix* occupation to introduce. Our solution is to compute the mean of all variables from the occupations included in the same occupation group. For example, for ≪ house cleaning workers ≫, we average the values of the variables of building cleaning workers, waste treatment workers and other cleaning workers. Lastly, when there is no possible correspondence, we drop the corresponding occupation. We also put aside the category ≪ Workers not classifiable by occupation ≫ because it contains too heterogeneous components.[16] Finally, our new dataset contains 88% of employed population. By predicting probabilities of automation with this new sample, we get (i) the total number of jobs which are threatened by actual technological advance, and (ii) a detailed view by type of employment and by gender.

Frey and Osborne (2013) present their results by decomposing the total of jobs in three categories: high, middle and low risk of automation. These groups are delimited by two thresholds equal to 0.7 and 0.3 and serve as the basis for the determination of the number of jobs currently threatened by computer technology (they evaluate that 47% of US employment is at risk). If we consider the same thresholds, our results suggest that approximatively 55% of employment in Japan has a highly susceptibility to be replaced by technological equipment, namely 8 points higher than in the US (see table 2). Our predictions also state that roughly 25% of jobs are in the intermediate category and 19% can be considered as non-automatable in the next years. These estimates are consistent with the US results but the share of at risk jobs is higher. The difference of the estimated share of automatable occupations can be explained by several factors. Firstly, it is a possible that this result comes from methodological issues. Indeed, the aggregation procedure for combining *Career Matrix* and data from population census could lead to loss of information causing an underestimation of the number of jobs susceptible to be computerised. For example, some Population census categories contain a large number of workers such as ≪ Other general clerical workers≫ or ≪ Comprehensive clerical workers ≫. If we had data at a more detailed level, it would have been possible that a share of occupations in-

[16] It represents approximatively 6% of the employed population.

Table 2: Share of employment by level of risk(%)

Level of risk	Total	Men	Women	Regular jobs	Temporary jobs	Part-time jobs
High risk	55.611	55.827	55.018	56.147	73.120	55.587
Middle risk	25.413	24.643	26.424	21.572	20.876	34.439
Low risk	18.977	19.530	18.559	22.281	06.004	09.973

cluded in this group could be considered as non-computerisable which may lower the share of employment threatened. A second type of explanation is linked to the specificities of the Japanese labor market, such as the presence of differences in skills for some occupations and differences in occupational structures. Lastly, we can notice, dealing also with US data, the estimations by Pajarinen and Rouvinen (2014) give a value of 49.2% thus reducing the difference observed between the two coutries.

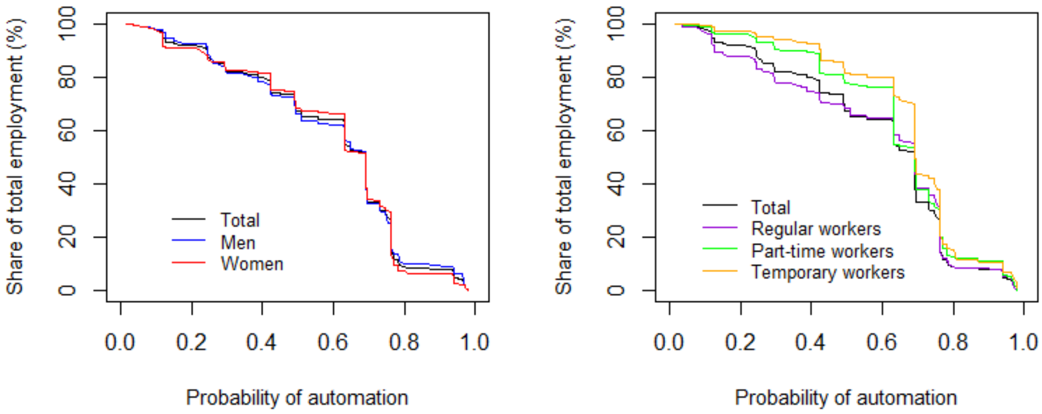
Beyond the determination of the share of jobs threatened by computer technology, we can also draw lessons at a more detailed level (table 2, figure 2). As shown, the vulnerability face to technological pressure is roughly similar between men and women since their respective curves are both quite close to the total curve. However, we identify a significant difference according to the type of employment. Indeed, we find evidence that the type of employment determines the exposure to ICT capital. The non-regular jobs (temporary and part-time employment) appear to be more vulnerable to computer technology at any level of probability (figure 2). This situation concerns part-time workers and is even more pronounced for temporary workers.

4.3 Comments

Althought this study has some methodological limitations mainly related to the lack of some variables and to the aggregation procedure[17], we can draw several interesting conclusions. Our findings suggest that the diffusion of computer technology will have an important effect on employment in the next years and decades. This is caused by the fact that a growing number of economic tasks could be technically and economically performed by computer devices (they become feasible at admissible costs). From this point of view, it is expected that some occupations and jobs in Japan (and in other

[17] We have also used the median instead of the mean in the aggregation procedure. We obtain similar results

Figure 2: Detailed results



industrialized countries) will disappear in short or medium term. Although, the assessment of the exact share of jobs concerned is difficult to evaluate, our analysis shows that this share is around one half of the total employment.

These estimates are based on a technological background, and the effective realization of these predictions will finally depend on many factors technological, economic and cultural factors. A first determinant is the technological advance in terms of capacities, quality and cost offered by the future technology which will create the opportunities of investment for producers. This is indeed on this technological basis and its cost that their choices will be made. Furthermore, an important element will be the institutional and social ≪ response ≫ face to this technological wave. In this respect, the attitude of public authorities will play a key-role by promoting or not the technological diffusion. The observation of the part and recent situation suggest that they will act in favor of development and adoption of ICT. Indeed, historically, the Japanese government has supported the development of computer and robotic technologies since its beginning through the Ministry of Internal Affairs and Communication (MIC), the Ministry of Economy, Trade, and Industry (METI) or The New Energy and Industrial Technology Organization (NEDO) and continues to promote actively innovation in these fields (Kitano, 2005; Lechevalier et al., 2010; Murata, 2010). One example of this continuity is the call, in May 2015, for a ≪ robot revolution ≫ by the Prime Minister Abe. These efforts are also made by firms and universities and likely to be continued due to ageing and because ICT constitute a challenge for competitiveness in a context of regional competition with China and the Republic of Korea.

On the other hand, the availability of a technology is obviously not a sufficient condition for its adoption. It is important to emphasize that a crucial determinant of the future automation is the social acceptation of technology by producers and consumers. For instance, it must be noted that a large share of jobs which could be probably automated in the future will be through robots with an important share of humanoid robots. We further observe that there are already experimentations with the introduction of these machines in shops such as *Pepper* robot in Omotesando *Softbank* shop or the *Toshiba* robot (*Chihira Aico*) in Mitsukoshi department store. A key determinant of this kind of computerisation will be the public reception. Some scholars suggest that Japanese people are more willing to accept these new technologies than western people that might encourage automation. For example, Kaplan (2004)[18] suggests that this better acceptance is due to the fact that from a western point of view, there is a clear distinction between the natural and the artificial which generates a feeling of strangeness or aversion about this kind of robot. Conversly, in the Japanese culture, there is not such distinction but rather a representation which emphasises a network of beings. This type of analysis suggests that Japanese producers and consumers may display a more positive attitude about robots, and more broadly, toward information technologies that may foster job destructions.

Another very important clarification to do about these results is that these possible destructions of jobs are not equal to future unemployment. Indeed, as pointed in section 2, the development of new technologies also supports the creation of jobs by several compensation mechanisms. Existence or importance of technological unemployment will depend on the extent of these unpredictable dynamics. One possibility is that this technological diffusion produces no unemployment, but a deep restructuring of the production apparatus. Another positive point is specific to the Japanese situation and is linked to the decline in the population and its consequence in terms of reduction of labor participation. This dynamics might offset the potential negative impact of computer technology because it is possible that computer capital will replace the individuals who enter retirement instead of the available workers. The convergence of these two phenomena might create a historical opportunity susceptible to avoid the risk of technological unemployment. On the contrary, a more pessimistic view could be supported by the fact that ICT tools seem able to perform a very large kind of tasks. The range of application seems to be unprecedented and it appears that technological limits are continually broken the barriers to capital labor/substitution. This advance

[18] See also Kitano (2005).

could cause serious problems by putting forward a clear risk of technological unemployment in the short run during a transition period, but also in the long run if the compensation mechanisms are insufficient.

5 Conclusion

The aim of this paper is to assess the number of jobs which could be replaced by computer technology in Japan in the near future. Relying on a recent methodology, our findings suggest that 55% of actual jobs in Japan could be destroyed by computer technology diffusion and that non regular workers are more subject to this risk. The decline in the working population, the support in ICT development by public authorities, firms and universities, and the possible positive attitude about technology by Japanese people, suggest that this capital/labor substitution process could play a key role in Japan.

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6 Appendix

Table 3: Training sample: Automatable occupations

Frey and Osborne (2013) based selection		
Communication Equipment Assembler and repairer	Human Ressources clerk	Newspaper deliverer
Camera Assembler	Parking Lot Attendant	Deliverer
Data entry keyer	Tractor Operator	Taxi driver
Technical Writer	Cook	Bus driver
Surveyor	Maid	Truck driver
PC Assembler	Seamstress	Tour bus driver
Machine Assembler	Cashier	
Sheet metal worker	Meter Reader	
Empirical selection	Technology	Examples
Toll Road Worker	Self-checkout	Open-source self-chek (Google)
Fighter Pilot	Drone	Northrop Grumman RQ-4 Global Hawk
Train Driver	Automatic train	New Transit Yurikamome
Model	Humanoid Robot	HRP-4C, Geminoid
Taxi dispatcher	Computer Reservations Systems (CRS)	Axess
Building cleaning worker	Robotic vacuum cleaner	Roomba, 360 Eye (Dyson)
Warehouse Worker	Warehouse mobile robot	Kiva Systems (Amazon)
Secretary	Office automation	emails, word processor softwares...
Train cleaning worker	Robotic vacuum cleaner	Roomba, 360 Eye (Dyson)

Table 4: Training sample (Non-Automatable Occupations)

Professional golfer	Hairdresser
Professional Football Player	Prosecutor
Professional Baseball Player	Judge
Jockey	Landscape Architects
Professional cyclists	Lawyers
Sumo Wrestler	Child Counsellor
Sushi Cook	Surgeon
Chefs and Head cooks	Obstetrician, Gynaecologist
Childcare Workers	Pediatrician
Civil Engineers	Physician
Clergy	Physicists
Concierges	Plumbers
Dentists	Preschool teacher
Economist	Nurses
Electrical Engineers	School Nurses
Fashion Designers	Transport Managers
Flight Attendants	Waiters, Waitresses
Nail artist	Zoologist
Makeup artist	

Table 5: Variables description

Tasks	Variable	Definition	Definition source	Data source
Perception and manipulation	Manual dexterity	The ability to make very precise manipulation with hands	Author	Author
Creative intelligence	Fine arts	Knowledge of theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture	FO (2013)	Author
	Originality	The ability to come up with unusual or clever ideas about a given topic or situation,or to develop creative ways to solve a problem	FO (2013)	Author
Social intelligence	Social perceptiveness	Being aware of others' reactions and understanding why they react as they do	Ikenaga and Kambayashi (2010)	Career Matrix
	Coordination	Adjusting actions in relation to others' actions	Ikenaga and Kambayashi (2010)	Career Matrix
	Persuasion	Persuading others to change their minds or behavior	Ikenaga and Kambayashi (2010)	Career Matrix
	Negotiation	Bringing others together and trying to reconcile differences	Ikenaga and Kambayashi (2010)	Career Matrix
	Instructing	Teaching others how to do something	Ikenaga and Kambayashi (2010)	Career Matrix
	Service orientation	Actively looking for ways to help people	Ikenaga and Kambayashi (2010)	Career Matrix
Appreciation	Judgment and decision making	Considering the relative costs and benefits of potential actions to choose the most appropriate one	Ikenaga and Kambayashi (2010)	Career Matrix

Table 6: Variable importance

Rank	Variables	Type of tasks	% increase in MSE
1	Originality	Creative intelligence	8.06676
2	Manual dexterity	Perception and manipulation	7.01464
3	Instructing	Social intelligence	5.41735
4	Negotiation	Social intelligence	4.56105
5	Persuasion	Social intelligence	3.09784
6	Judgment and decision making	Appreciation	2.18357
7	Fine Arts	Creative intelligence	1.04819
8	Social perceptiveness	Social intelligence	0.96448
9	Coordination	Social intelligence	0.42546
10	Service orientation	Social intelligence	-2.58361

Table 7: Probability of Automation by Occupation

Index	Occupation	Probability
1	Speech therapist	0.014
2	Lawyer	0.019
3	Stylist	0.021
4	Classical Musician	0.025
5	Theatre Decorator	0.025
6	Stage director	0.031
7	High school teacher	0.033
8	Vocational school teacher	0.033
9	Make-up artist	0.035
10	Radio director	0.038
11	Hairdresser	0.043
12	Nail Artist	0.058
13	Teacher to deaf and blind people	0.062
14	Artistic Director	0.068
15	Midwife	0.071
16	Illustrator	0.073
17	Fashion Designer	0.073
18	Sports Instructor	0.077
19	Ballet Dancer	0.081
20	Junior high school teacher	0.083
21	Floral designer	0.084
22	Chef and Head Cook	0.084
23	Primary school teacher	0.084
24	Sushi chef	0.088
25	Japanese Teacher	0.104
26	Pre-school Teacher	0.104
27	Interior Designer	0.107
28	Film director	0.107
29	Clinical engineer	0.108
30	Ship engineer	0.114
31	Forging engineer	0.114
32	Fair Trade Commission employee	0.114
33	Professional footballer	0.118
34	Surgeon	0.118
35	Nurse	0.118

Table 8: Probability of Automation by Occupation

Index	Occupation	Probability
36	Obstetrician, Gynaecologist	0.118
37	Dentist	0.118
38	Veterinary	0.118
39	Pediatrician	0.118
40	Physician	0.118
41	System Engineer (project manager)	0.124
42	Video games creator	0.124
43	System engineer (IT consultant)	0.124
44	System engineer (application specialist)	0.124
45	System engineer (Software creator)	0.124
46	Food coordinator	0.124
47	Recording Engineer	0.124
48	Musician	0.127
49	Book designer	0.129
50	Occupational therapist	0.145
51	Retirement home instructor	0.145
52	School Nurse	0.145
53	Construction engineer	0.148
54	Automobile Engineer	0.148
55	Information engineering researcher	0.148
56	Civil construction engineer	0.148
57	Civil engineer	0.148
58	Judge	0.154
59	University and college teacher	0.157
60	Forestry technician	0.157
61	Clergy	0.160
62	Psychiatrist	0.160
63	Legal instructor	0.177
64	Graphic Designer	0.179
65	Stage lighting technician	0.183
66	Pastry cook	0.183
67	Career advisor	0.184
68	Care Manager	0.184
69	Family investigator	0.184
70	Industrial counselor	0.184

Table 9: Probability of Automation by Occupation

Index	Occupation	Probability
71	Engine engineer	0.184
72	Polymer chemical engineer	0.184
73	Music teacher	0.191
74	Medical researcher	0.198
75	Nuclear Engineer	0.198
76	Tourist guide	0.200
77	Jewelry Designer	0.201
78	System engineer (IT architect)	0.207
79	Aerospace Engineer	0.211
80	Metal refining engineer (iron and steel)	0.211
81	Telecommunication engineer	0.211
82	Fast food manager	0.213
83	Dog Trainer	0.213
84	Vocational training instructor	0.213
85	Zoologist	0.216
86	Senior volunteer	0.217
87	Land self defense force	0.217
88	Childcare Worker	0.221
89	Fashion creator	0.226
90	Glass artist	0.236
91	System engineer (IT specialist)	0.239
92	Electronical engineer	0.239
93	Goldsmith	0.241
94	Sculptor	0.241
95	Outdoor Instructor	0.244
96	Administrative scrivener	0.244
97	Supermarket manager	0.244
98	Supervisor	0.244
99	Department store purchasing staff	0.244
100	Medical Inspector	0.244
101	Print sales clerk	0.244
102	Japan Coast Guard Officer	0.244
103	Bank branch manager	0.244
104	Airport clerk	0.244
105	Certified Public Accountant	0.244

Table 10: Probability of Automation by Occupation

Index	Occupation	Probability
106	Advertising sales clerk	0.244
107	Judicial scrivener	0.244
108	Car salesman	0.244
109	Director for Social Education	0.244
110	Work and social security solicitor	0.244
111	Trading company salesman	0.244
112	Firefighter	0.244
113	Life insurance sales representative	0.244
114	Licensed tax accountant	0.244
115	Funeral director	0.244
116	Railway operation planning and operation management member	0.244
117	Caseworker	0.244
118	Welfare equipment and professional advisor	0.244
119	Pharmacist	0.244
120	Travel agency clerk	0.244
121	colour coordinator	0.251
122	Esthetician	0.252
123	Aircraft pilot	0.252
124	Acupuncture-moxibustion	0.252
125	Prosthetist	0.252
126	Bonesetter	0.252
127	Sumo Wrestler	0.252
128	Legal researcher	0.257
129	Painter (art)	0.258
130	Interior Decorator	0.260
131	Comedian	0.260
132	Foreign Correspondent	0.261
133	Maritime self-defense force	0.261
134	Prosecutor	0.261
135	Drug enforcement officer	0.261
136	Mangaka	0.266
137	Fine ceramics engineer	0.267
138	Mathematician	0.268
139	Medical-social welfare worker	0.274
140	Retirement home employee	0.274

Table 11: Probability of Automation by Occupation

Index	Occupation	Probability
141	Architectural engineer	0.279
142	Mangaka Anime	0.282
143	Website Creator	0.282
144	Marketing researcher	0.282
145	Private detective	0.282
146	Coffeehouse clerk	0.285
147	Bartender	0.285
148	Hotel receptionist	0.285
149	Screenwriter	0.285
150	Japan Overseas Cooperation Volunteer	0.289
151	Astronomer	0.290
152	Power line worker	0.295
153	House painter	0.299
154	Jockey	0.300
155	Economist	0.303
156	TV reporter	0.303
157	English teacher	0.304
158	Juku teacher	0.304
159	Janitor	0.308
160	System engineer (sale)	0.310
161	Driving school instructor	0.315
162	Diplomat	0.316
163	Lift Installer	0.317
164	Electrician	0.317
165	Plumber	0.320
166	Livestock science researcher	0.320
167	Livestock technician	0.320
168	Cook (Ramen)	0.324
169	Police officer	0.325
170	Local legislator	0.333
171	Precision machinery engineer	0.337
172	Technical Writer	0.338
173	Plant design engineer	0.339
174	Seismologist	0.339
175	Perfumer	0.339

Table 12: Probability of Automation by Occupation

Index	Occupation	Probability
176	Flight Attendant	0.347
177	Air self-defense force	0.354
178	Racing driver	0.355
179	Fighter pilot	0.355
180	Composer	0.355
181	Go player	0.355
182	Shogi player	0.355
183	Japanese confectionery worker	0.358
184	Baseball referee	0.359
185	Ryokan manager	0.359
186	Paratrooper	0.359
187	International cooperation expert	0.359
188	Small business consultant	0.359
189	TV, radio engineer	0.365
190	Programmer	0.365
191	Rolling process worker	0.365
192	Landscape Architect	0.365
193	Civil engineering and construction engineering researcher	0.365
194	Prison guard	0.371
195	Tax accountant	0.371
196	Immigration control officer	0.371
197	Electrical Engineer	0.372
198	Piano Tuner	0.373
199	Tailor (childrens' and women clothes)	0.384
200	Taxi dispatcher	0.387
201	Wedding staff	0.387
202	Child Counsellor	0.387
203	Guide-interpreter	0.387
204	Physiotherapist	0.387
205	Sash installer	0.400
206	Carpenter	0.400
207	Political scientist	0.412
208	Aviation mechanic	0.420
209	Biotechnology researcher	0.420
210	Chemist	0.420

Table 13: Probability of Automation by Occupation

Index	Occupation	Probability
211	Fishery technician	0.420
212	Horse trainer	0.420
213	Ceramic engineer	0.420
214	Agronome	0.420
215	Physicist	0.420
216	Cook	0.421
217	Soba Cook	0.421
218	Beautician	0.421
219	Pension manager	0.424
220	Radiology technician	0.424
221	Waste disposal engineer	0.424
222	Bacteriologist	0.424
223	Food engineer	0.424
224	Casting engineer	0.424
225	Analytical chemistry engineer	0.424
226	Sommelier	0.430
227	Weather forecaster	0.430
228	Bicycle sales clerk	0.430
229	Pyrotechnician	0.430
230	Poet	0.437
231	Customer Engineer	0.439
232	Theatre actor	0.441
233	Voice actor	0.441
234	Actor	0.441
235	Jewelry maker	0.441
236	Industrial designer	0.445
237	International officer	0.449
238	Shipwright	0.449
239	Children's novelist	0.455
240	Novelist	0.455
241	Miner	0.460
242	Soy sauce manufacturing worker	0.460
243	Freelance journalist	0.461
244	Mecatronic researcher	0.461
245	Public relations assistant	0.461

Table 14: Probability of Automation by Occupation

Index	Occupation	Probability
246	Editor	0.461
247	Photojournalist	0.461
248	Mason (interior)	0.463
249	Cooks (Chinese food)	0.463
250	opérateur Computer-Assisted-Design	0.472
251	Botanist	0.472
252	Fine art restoration worker	0.482
253	Tofu producer	0.487
254	Professional golfer	0.489
255	Production and quality control engineer	0.489
256	Dental hygienist	0.493
257	Chinese Masseur	0.503
258	Chiropractor	0.503
259	Computer equipment saleman	0.510
260	Service station worker	0.510
261	Game center employee	0.510
262	Park ranger	0.510
263	Nutritionist	0.510
264	Breeding staff member (zoo)	0.510
265	Parking Lot Attendant	0.510
266	Electrical appliance salesperson	0.510
267	Veterinary technician	0.510
268	Amusement park worker	0.510
269	Swordsmith	0.537
270	Numerical controled milling machine operator	0.537
271	Fruit grower	0.537
272	Furniture worker	0.537
273	Sign language interpreter	0.547
274	Dispatcher	0.554
275	Housing and property sales assistant	0.554
276	Credit union liaison officer	0.554
277	Damage service clerk	0.554
278	Actuary	0.557
279	Estate Agent Valuer	0.557
280	Advertising photographer	0.558

Table 15: Probability of Automation by Occupation

Index	Occupation	Probability
281	Goods purchasing clerk	0.560
282	Numerical controled turning machine operator	0.567
283	Mould maker	0.567
284	Cytotechnologist	0.567
285	Electrical discharge machinist	0.567
286	Journalist	0.570
287	Travel writer	0.571
288	Magazine journalist	0.571
289	Product development staff worker	0.572
290	Administrative clerk (country)	0.574
291	Shoe Fitter	0.585
292	Fruit and vegetable producer	0.586
293	Professional Cyclist	0.590
294	Surveyor	0.597
295	Trade clerk	0.598
296	Trimmer	0.600
297	TV cameraman	0.628
298	Cargo handler	0.628
299	Navigator	0.628
300	Human Ressources clerk	0.628
301	Steelworker	0.628
302	Power plant and substation worker	0.628
303	Librarian	0.630
304	Communication Equipment Assembler and Repairer	0.630
305	Appliance repair technician	0.630
306	Bag manufacturing worker	0.630
307	Tailor	0.630
308	PC Assembler	0.630
309	Patterner	0.630
310	Professional baseball player	0.630
311	Miso manufacturing process worker	0.630
312	Forensic expert	0.630
313	Racing boat driver	0.630
314	Joiner	0.630
315	Dental technician	0.630

Table 16: Probability of Automation by Occupation

Index	Occupation	Probability
316	Mason	0.630
317	Dry cleaner	0.632
318	DIY seller	0.632
319	Aromatherapist	0.632
320	Kombini employee	0.632
321	Sport articles salesperson	0.632
322	Financial planner	0.632
323	Bakery sales assistant	0.632
324	Vynil, CD, salesperson	0.632
325	Car rental clerk	0.632
326	Curator, librarian	0.632
327	Air traffic controller	0.632
328	Bookshop seller	0.632
329	Merchandise clerk	0.632
330	Sake manufacturing process worker	0.632
331	Sailor	0.632
332	Zoo breeding staff	0.632
333	Baking expert	0.632
334	Waterproofness worker	0.646
335	Machine assembler	0.646
336	Violin maker	0.651
337	Printing operator	0.692
338	Industrial glassmaking worker	0.692
339	Cement production operator	0.692
340	Fish auction worker	0.692
341	Tire manufacturing process worker	0.692
342	Technical illustrator	0.692
343	Ham sausage manufacturing process worker	0.692
344	Prepress operator	0.692
345	Wine manufacturing process worker	0.692
346	Medical imaging equipment assembler	0.692
347	Rice farmer	0.692
348	Sign-board production worker	0.692
349	Toy manufacturing process worker	0.692
350	Footwear manufacturing worker	0.692

Table 17: Probability of Automation by Occupation

Index	Occupation	Probability
351	Accountancy clerck	0.692
352	Plywood worker	0.692
353	Lacquerware worker	0.692
354	Drink dispenser supply worker	0.692
355	Steel worker	0.692
356	Lumber industry worker	0.692
357	Binding worker	0.692
358	Fruit and vegetable store clerk	0.692
359	Senshokuko	0.692
360	Fiber wholesale clerk	0.692
361	Greengrocer, fishmonger, butcher shop owner	0.692
362	Non-destructive testing technician	0.692
363	Patent attorney	0.692
364	Pipe laying worker	0.692
365	Spinning worker	0.692
366	Tunnel construction worker	0.693
367	Bread production worker	0.694
368	Integrated circuit manufacturing operator	0.694
369	Foundry worker	0.694
370	Tin can production worker	0.694
371	Tile manufacturing worker	0.694
372	Tobishoku	0.694
373	Video rental clerk	0.694
374	Pet shop sales assistant	0.694
375	Pharmaceutical production employee	0.694
376	Mover	0.694
377	Chemical production operator	0.694
378	Cosmetic manufacturing process worker	0.694
379	Cook (school canteen)	0.694
380	Carpenter	0.694
381	Construction worker	0.694
382	Sheet metal worker	0.694
383	Administrative clerk (county municipality)	0.694
384	Car Assembler	0.694
385	Petroleum refinery operator	0.694

Table 18: Probability of Automation by Occupation

Index	Occupation	Probability
386	Railway line construction worker	0.694
387	Dairy products worker	0.694
388	Paving worker	0.694
389	Textile machinery technician	0.694
390	Frozen processed food manufacturing process worker	0.694
391	Technical writer	0.709
392	Optician	0.709
393	Dealer	0.710
394	Department store clerk	0.732
395	Patchinko employee	0.732
396	Orthoptist	0.732
397	Station employee	0.732
398	Cosmetic sales clerk	0.732
399	Cosmetic home sales assistant	0.732
400	Emergency Medical Technician	0.732
401	Security guard	0.732
402	Train conductor	0.732
403	Bicycle manufacturing process worker	0.740
404	Numerical controled grinding machine operator	0.746
405	Beer manufacturing process worker	0.746
406	Plastic product molding worker	0.746
407	Machine center operator	0.746
408	Plating worker	0.746
409	Printing worker	0.746
410	Flower producer	0.746
411	Metal press worker	0.746
412	Metal products inspector	0.746
413	Metal processing inspector	0.746
414	Metal heat treatment worker	0.746
415	Measuring machine assembler	0.746
416	Block worker	0.746
417	Folding carton manufacturing process	0.746
418	Image processing operator	0.746
419	Industrial weaver	0.746
420	Flight meal production worker	0.754

Table 19: Probability of Automation by Occupation

Index	Occupation	Probability
421	Medical technician	0.754
422	Train cleaning worker	0.754
423	Coastal fisherman	0.761
424	Toy store clerk	0.761
425	Used book salesperson	0.761
426	Diver	0.761
427	Building cleaning worker	0.770
428	Boiler operator	0.770
429	School clerk	0.770
430	Dormitory janitor	0.770
431	Construction machine operator	0.770
432	Plasterer	0.770
433	Fisheries manufacturing process worker	0.770
434	Surveyor	0.770
435	Forging worker	0.770
436	Secretary	0.781
437	Kimono dressing instructor	0.783
438	Bellhop	0.783
439	Waiter, Waitresse	0.783
440	Bus tour guide	0.783
441	Intern	0.783
442	Postal clerk	0.783
443	Aquaculture worker	0.783
444	Ceramic worker	0.783
445	Dairy farmer	0.783
446	Toll road worker	0.787
447	Camera Assembler	0.788
448	Sewing machine operator	0.788
449	Auto mechanic	0.788
450	Welder	0.788
451	Stenographer	0.791
452	Photo shop employee	0.793
453	Telecommunicator	0.801
454	Groom	0.810
455	Fashion salesperson	0.812

Table 20: Probability of Automation by Occupation

Index	Occupation	Probability
456	Financial analyst	0.814
457	Flower shop clerk	0.849
458	Bank cashier	0.849
459	Customs officer	0.862
460	Postal Sales Representative	0.862
461	Unloading Worker	0.868
462	Train driver	0.874
463	Financial securities sales clerk	0.937
464	Chief medical information officer	0.939
465	Refuse Collector	0.941
466	Department store out-of-store saleperson	0.941
467	Meter Readers	0.941
468	Newspaper Deliverer	0.941
469	Warehouse worker	0.941
470	Prepared food manufacturing process worker	0.941
471	Cashier	0.950
472	Golf caddie	0.954
473	Hostess	0.954
474	Supermarket employee	0.954
475	Taxi Driver	0.954
476	Home helper	0.954
477	Reflexologist	0.954
478	Housekeeper	0.954
479	Receptionist	0.954
480	Mail clerk	0.954
481	Advertiser	0.958
482	Ticket agency clerk	0.958
483	Interpreter	0.958
484	Bus Driver	0.958
485	Medical secretary	0.965
486	Secretary General	0.965
487	Shop clerk (in subway station)	0.965
488	Model	0.966
489	Translator	0.968
490	Packing worker	0.972

Table 21: Probability of Automation by Occupation

Index	Occupation	Probability
491	Truck driver	0.972
492	Hotel worker	0.974
493	Tourist Bus Driver	0.974
494	Road patrol worker	0.974
495	Computer-Assisted-Design operator	0.982
496	Data entry keyer	0.982
497	Industrial waste collection and transportation worker	0.982
498	Mail Deliverer	0.982
499	Computerized typesetting operator	0.982