Computerization and the Future of Work in Japan

Carl Benedikt Frey and Michael Osborne

In this paper, we use a novel dataset on job tasks across 601 occupations in Japan, estimating the share of employment that is susceptible to automation. Doing so, our analysis builds on a growing body of work, examining the automatability of existing jobs, following the rapidly expanding capabilities of computer-controlled technologies.

While our interest is in the future potential automatability of jobs, a growing literature shows that the diffusion of computer technologies has already significantly changed the composition of labour markets, in turn contributing to substantial shifts in income shares between workers with different skills (Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos, Manning and Salomons, 2009), as well as between labor and owners of capital (Karabarbounis and Neiman, 2014). In tandem with skill-biased technological change raising the skill premium for educated workers (Goldin and Katz, 1998), routine-biased technological change has substituted for labour performing routine rule-based activities that can easily be described in computer code and automated: as word and data processing software has spread across the workplace, for example, the jobs of bookkeepers, secretaries and tax preparers have gradually diminished (Autor et al., 2003).

Because routine tasks are typically performed by middle-income workers, labour markets across advanced economies have experienced rapid polarization as the demand for skilled workers expanded and middle-income workers have reallocated to non-automatable low income service jobs (Goos et al., 2007; 2009; 2014). The result has been a “hollowing-out” of the employment distribution across skill and income levels, with medium-skill employment declining, and employment low and highly skilled jobs expanding (Autor and Dorn, 2013; Goos, Manning and Salomons, 2009).

Although various explanations for the polarization phenomena exists, several studies show that these shifts are directly accounted for by the spread of computer technology (Autor and Dorn, 2013; Michaels et al., 2014; Graetz and Michaels, 2015), downplaying other potential explanations, including the role of offshoring, and manufacturing decline. Furthermore, an emerging literature suggests that technological change has also been capital-biased: since the 1990s, the median OECD country has experienced a 5 percentage points decline in its labor share of national income (OECD, 2012). While there is an ongoing debate about the drivers behind the falling labour share of income, recent research suggests that the decline in the price of capital goods, associated with the availability of increasingly cheap computer technologies, can account for the bulk of this decline (Karabarbounis and Neiman, 2014).

Yet the premises about the tasks computers are able to perform have recently expanded beyond routine work (Brynjolfsson and McAfee, 2014): computers are now able to perform tasks such as the translation of documents, performing medical diagnostics, driving a car, and serving customers. Examining the automatability of US employment following these trends, Frey and Osborne (2013) concluded that 47 percent of US jobs are highly susceptible to automation. While there is growing consensus that computers have had pervasive impacts on labour markets across advanced economies, the impacts of capital for labour substitution on overall employment remains contested. In a recent study, Autor et al. (2013) find that US cities that adopted computer more extensively experienced polarization, but no net negative effects on employment. Instead, they show that cities exposure to Chinese import competition is associated with an increase in unemployment. Nevertheless, as pundits have pointed out, the fact that technological change has not reduced the demand for workers in the past, does not necessarily imply that this will also hold for the future.

While we do not attempt to estimate the impact of computer technology on the overall demand for jobs, we contribute to this debate by examining the potential scope of future automation in Japan. Following Frey and Osborne (2013), using a Gaussian process classifier to estimate the susceptibility of 702 occupations to automation in the United States, we apply a similar methodology, using data on occupational characteristics for jobs in Japan. According to our estimates, 49 percent of existing jobs in Japan are susceptible to computerization over the forthcoming decades.

The remainder of this paper is structured as follows. In section 2, we describe the type of tasks that computers are able to perform and the type of tasks where human workers still hold the comparative advantage. We next turn to describing our data and methodology. In section 4, we describe our findings. Finally, in section 5, we derive some conclusions.

What computers do

While computerization in the past has been confined to routine tasks, there are numerous examples of computer-related technologies now performing non-routine tasks that were deemed non-automatable only a decade ago. Developments in autonomous vehicles provide one such example. Back in 2004, Levy and Murnane (2004) pointed at the tremendous difficulties associated with driverless cars, suggesting that: "executing a left turn against oncoming traffic involves so many factors that it is hard to imagine discovering the set of rules that can replicate a driver's behavior". It took only until 2010, when Google announced that it had successfully developed the first fully autonomous car (Brynjolfsson and McAfee, 2014).

Most recent developments in automation are a result of the growing availability of big data and advances in machine learning, allowing complex cognitive tasks to be translated in work into well-defined problems. In health-care, machine learning techniques are already taking over tasks previously performed by skilled medical professionals. IBM's Watson computer, for example, can draw upon substantially larger sets of medical data than any human doctor, giving it a comparative advantage in medical diagnostics. In a similar fashion, a growing body of digital translated text documents allows Google Translate to become a more effective translation tool, while advances in machine learning significantly has improved its accuracy over time. In the news service industry, outlets including Forbes and the LA Times, now use sophisticated machine learning techniques to generate corporate earnings reports as well as shorter news summaries. Even in cases where there is little data available for algorithms to draw upon, companies are finding approaches to collect relevant information. Work Fusion, for example, has developed software that automates routine tasks, and outsources the non-routine work to freelance workers through crowed sourcing platforms. The software then monitors the freelance workers and collects information about their working procedures, allowing the software to eventually automate even the non-routine tasks.

The expanding scope of automation further relates to improved user interfaces, allowing computers to better respond directly to human requests: advances in speech recognition, for instance, has been crucial to the development of Apple's Siri software, responding to voice commands. Such advances in natural language processing could potentially disrupt entire industries, as highlighted by the case of SmartAction, providing automated call center solutions, significantly reducing the costs associated with operating a call center. Furthermore, better and cheaper sensors constitute a key enabling technology for recent advances in robotic development: as sensors collect data about the environment in which they used, vast amounts of information become readily available to draw upon. In autonomous vehicle navigation, for example, 3D maps have been fundamental in allowing autonomous cars to improve upon human drivers.

In addition, robots are becoming increasingly flexible and mobile, meaning that a wider range of non-routine manual tasks are now automatable. A frequently cited example is Rethink Robotic's Baxter: by memorizing motions as a human worker guides the arms of the robot, Baxter can perform a wider range of tasks. Furthermore, although robots are still unable to perform more complex social interactions, as discussed in more detail below, humanoid robots are now able to substitute for receptionists, responding in different languages, and are also able to perform tasks in elderly care, such as moving patients from a bed to a wheelchair. In services, robots are further able to execute non-routine tasks, spanning from commercial cleaning to food preparation (Frey and Osborne, 2013).

Despite the expanding scope of automation, a number of tasks remain non-automatable. As noted by Frey and Osborne (2013), three key bottlenecks to automation still hinder the application of computer-controlled equipment in tasks that involve: (i) creative intelligence; (ii) complex social interactions; and (iii) the perception and manipulation of irregular objects. The challenge of automating creative tasks relates to the absence of explicit guidelines or rules. Although there is software that is able to create novel pieces of art and compose classical music, it is still extremely difficult to develop algorithms that are able to distinguish emotionally moving pieces from the rest, largely because associated distinguishing characteristics are hard to define, often resulting in disagreement even among human experts.

Second, our understanding of social interactions builds on tacit knowledge about emotive content, which is difficult to describe and specify. The state of the art of automation when it comes to complex social interactions is best highlighted by the Turing test, where chatbots try to convince judges of their human nature. So far, one chatbot has achieved this, by pretending to be a 13-year old boy, using English as his second languages. In other words, even in basic text communication, computers are still far from human levels of social skills. Because many jobs entail much more complex tasks, such as managing teams, persuading and negotiation, and require assisting or caring for others, a wide range of jobs remain safe from automation

Third, the challenges for robots to match the breadth and depth of human perception are best captured by Moravec's (1988) paradox: "it is comparatively easy to make computers exhibit adult level performance on intelligence tests or playing checkers, and difficult or impossible to give them the skills of a one-year-old when it comes to perception and mobility". While robots are good at operating and navigating in structured environments, such as a factory or a warehouse, and increasingly also while most humans can navigate unstructured environments with ease, unstructured environments still post significant challenges. While cleaning a room, for example, is a relatively easy task for most humans, the perception challenge means that robots often struggle with identifying different objects, such as distinguishing a pot that is dirty and needs to be cleaned from one that holds a plant. Against this background, we proceed to examining the susceptibility of jobs in Japan, to recent trends in technology.

Data and methodology

Employment data

In our analysis, we draw upon data[1] characterising employment in Japan, derived by the Statistics Bureau, Ministry of Internal Affairs and Communications, Japan. Occupations were considered at the finest available level of granularity, yielding 180 different occupational titles. All occupation titles were translated to English by NRI.

Task Descriptions

In order to describe the task composition and skill requirements for Japanese occupations, we draw upon data from the Japan Institute for Labour Policy and Training (JILPT), a public entity under the Ministry of Health, Labour and Welfare. The JIPLT has produced a dataset[2] comprising 601 Japanese occupations, a more finely-grained representation than that provided by the Statistics Bureau. NRI hence split employment numbers (available at the cruder level of 180 occupations) equally amongst the many finer-grained occupations corresponding to any single more aggregate occupation. By way of comparison, 702 occupations were considered for the US in Frey and Osborne (2013).

JILPT's dataset provides a detailed quantitative description of job tasks for each of the 601 occupations. These quantitative measures form a rough equivalent to that provided by the US Department of Labor's O*NET, the basis of the analysis in Frey & Osborne (2013). The data was gathered using a web survey tool, which attracted 21,033 respondents (with more than 30 respondents for each of the 601 occupations).

For each of the 601 occupations, this data comprises thirty real numbers (normalised to have zero mean and unit standard deviation): the larger, the greater the intensity in that particular aspect. These measures are subdivided into "Occupational Interests", "Work Values", "Skills",

[1] http://www.stat.go.jp/index/seido/shokgyou
[2] http://www.jil.go.jp/institute/reports/2012/0146.html

“Knowledge” and “Working Environment”: some examples include “[Working Environment] Outdoor”, “[Occupational Interests] Persuaders” and “[Knowledge] Science & Technology”. These variables capture a diverse range of different skills that can reasonably be expected to be related to a job’s susceptibility to automation.

Training Set

We next follow the approach of Frey and Osborne (2013), using a probabilistic classifier to distinguish automatable and non-automatable occupations. This entails the identification of a training set of occupations that are most emblematically either automatable (e.g. Data Entry Keyers) or non-automatable (e.g. Clergy). Specifically, Frey and Osborne’s occupations were those for which the question: “Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment?” could be most confidently answered. A machine learning algorithm then uses this training set to identify the statistical characteristics of automatable jobs.

We identified a bespoke Japanese training set using a manual crosswalk from the US training set provided by NRI. Specifically, NRI identified the Japanese occupations matching those in the US training set: where there were multiple matches, we included all. Several US occupations in the training set did not have sufficiently close Japanese equivalents e.g. Gaming Dealers and Farm Labor Contractors, and were ignored. We made one further addition to the training set: occupation 570, Highway Toll Collection Workers (有料道路料金収受員), was included as an automatable occupation owing to this task indeed having being automated through the use of digital devices in many cities. Our final amendment was the inversion of the label for occupation 537, Waiters and Waitresses (ホールスタッフ). In Frey and Osborne (2013), waiters and waitresses were included as an example of a non-automatable occupation, owing to the expected requirement for small-talk at the tables of customers. Since 2013, technological progress has seen some restaurants, such as US chain Applebee’s, making use of Zeosk tablets on its tables, able to make recommendations, take orders, and take payments, all going some way towards automating the work of waiters and waitresses. In total, this gave us a training set containing 51 occupations, of which 24 were labelled as automatable.

Methodology

We next proceeded to use a probabilistic classification algorithm to learn the relationships between the labels of automatability and the quantitative task descriptions, which we'll henceforth refer to as features. In detail, we tested Gaussian process classifiers with both exponentiated quadratic and Matérn (with parameter $\nu = 3/2$) covariance functions, as well as logistic regression. We tested these classifiers against one another using stratified ten-folds cross-validation. That is, we randomly divided the training set into ten parts (each with automatable/non-automatable ratios roughly equal to 50%), trained the classifier on nine of the ten parts, before testing on the held-out tenth part. This process was repeated for all ten choices of the held-out part. The Matérn kernel was the best performing, with an area under the receiver operating curve (a metric often used to evaluate classifiers) of 0.99 (with perfect corresponding to 1.0).

We additionally perform feature selection to select the variables that were most informative in predicting the labels. Those features that were chosen can be thought of as those that are most strongly correlated with automatability: high scores on these variables are likely to render an occupation secure from automation. Crucially, a variable's significance cannot be assessed in isolation: even if poor individually, it may contribute in conjunction with another. Our non-linear Gaussian process classifier is able to benefit from these correlations. In detail, we performed greedy forward feature selection, using model evidence as an objective function, to select the ten best features. This means simply that we pick the best single feature, then, holding it fixed, select an additional feature from those remaining. The three most significant features were, in order, "[Knowledge] Arts & Humanities", "[Skills] Human Skills" and "[Occupational Interests] C: Organizers (Conventional)". This exercise provides evidence that supports the conclusions of Frey and Osborne (2013) – that social intelligence and creativity are significant bottlenecks to automation – for the case of the workforce of Japan.

We can, finally, use the entire training set to assign probabilities of automation for all 601 Japanese occupations. In the next section, we will discuss our findings in detail.

Results

Figure 1 reports the share of employment in Japan that is susceptible to computerization over the forthcoming decades, distinguishing between high, medium and low risk occupations, depending on their probability of automation (thresholding at probabilities of 0.7 and 0.3). Our findings suggest that 49 percent of total employment in Japan is at high risk of automation, meaning that they are employed in occupations that will be technologically possible to automate over the next decades. In terms of interpretation, we note that the probability axis provides a rough timeline, with high risk jobs being more likely to be automated relatively soon.

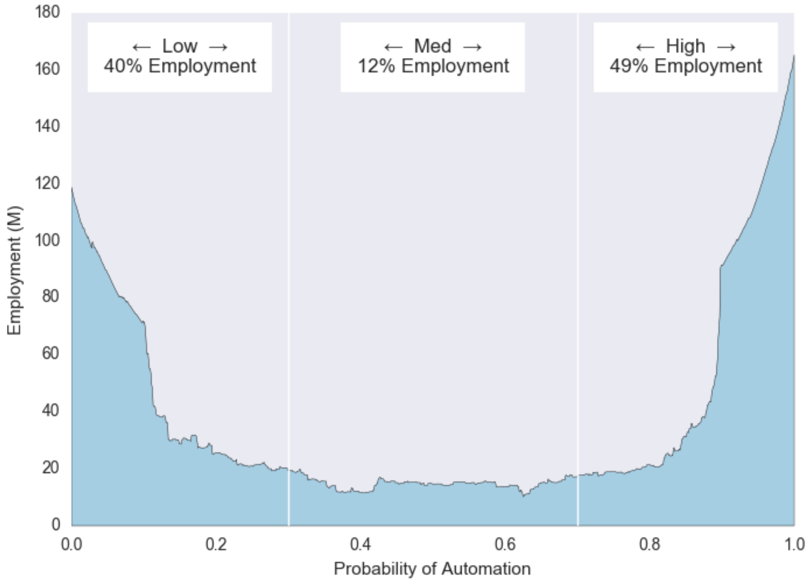

Figure 1: The automatability of Jobs in Japan

Our findings speak to general trends we observe in technology. Among the most susceptible jobs to automation, we find occupations that are intensive in tasks associated with the storing and processing of information, something that computers are relatively good at: general office clerks as well as data entry device operators provide such examples (see Tables 1 and 2). Nevertheless, while such work is typically routine, and has been automatable for quite some time, there is also evidence to suggest that the potential scope of automation has expanded beyond routine work. Warehouse workers, for example, are now equally susceptible to automation, as highlighted by anecdotal evidence, including the Amazon.com acquisition of Kiva Systems: using bar-code stickers on the floor, informing robots of their precise location, the problem of warehouse navigation, Amazon.com warehouses are now fully automated.

Occupation Titles		Probability of Automatability
電車運転士	Train Drivers	99.8%
経理事務員	Accounting Clerks	99.8%
検針員	Meter Reading Workers	99.7%
一般事務員	General Administrative Clerks	99.7%

包装作業員	Packaging Workers	99.7%
路線バス運転者	Route Bus Drivers	99.7%
積卸作業員	Loading and Unloading Workers	99.7%
こん包工	Balers	99.7%
レジ係	Cashiers	99.7%
製本作業員	Binding Workers	99.7%

Table 1: Occupations at highest susceptibility to automation

Occupation Titles		Probability of Automatability
精神科医	Psychiatrists	0.1%
国際協力専門家	International Cooperation Experts	0.1%
作業療法士	Occupational Therapists	0.1%
言語聴覚士	Speech Therapists	0.1%
産業カウンセラー	Industrial Counselors	0.2%
外科医	Surgeons	0.2%
はり師・きゅう師	Acupuncturists and Moxibutionists	0.2%
盲・ろう・養護学校教員	Special Education Teachers	0.2%
メイクアップアーティスト	Make-up Artists	0.2%
小児科医	Pediatricians	0.2%

Table 2: Occupations at lowest susceptibility to automation

Similarly, we find automobile drivers in the high risk category, speaking to recent developments in autonomous vehicles, such as the Google driverless car. The high automatability of tax accountants is further in line with the emergence of tax preparation software: most workers can now file their taxes without a tax accountant, using software like TurboTax. We also find receptionists and attendants among the most susceptible jobs to automation: in Japan, the Bank of Tokyo Mitsubishi UFJ employs a receptionist robot speaking 19 languages, and one recently opened hotel in Nagasaki has a receptionist robot.

A large share of jobs in Japan are however equally at low risk of automation: around 40 percent of Japanese workers are employed in occupations that our analysis deem non-automatable. As highlighted by Frey and Osborne (2013), most jobs that are difficult to automate involve tasks that require complex social interactions. Our estimates seemingly largely confirm this intuition. The jobs of therapists, kindergarten teachers as well as university lectures, are all among the least susceptible to automation. Similarly, physicists, architectural engineers, sculptures, and dancers, are in the low risk category, further speaking to the intuition that jobs involving creative tasks remain among the most difficult ones to automate.

Conclusions

A large literature shows that computer technologies have shifted the composition of labour markets across advanced economies. While workers with skills that are complementary to these technologies have benefited as a result, computers have equally substituted for human workers in a wide range of routine tasks. The potential scope of automation has however recently expanded beyond routine work. In particular, plenty of anecdotal evidence suggests that computers are now able to perform tasks including, medical diagnostics, driving a car, operating a call center, and performing translation work. Against this background, we estimate the potential future impacts of the expanding scope of automation on jobs in Japan. Doing so, we find that some 49 percent of Japanese jobs are susceptible to automation over the forthcoming decades. While our findings suggest that the arrival of increasingly sophisticated computer technologies might constitute a watershed to the Japanese labour market, we emphasizes that these findings do not necessarily imply an overall reduction in the demand for jobs.

References

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. The Journal of Economic Perspectives, 29(3), 3-30.

Autor, D. H. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the us labor market. American Economic Review, 103(5), 1553–97.

Autor, D. H. and Dorn, D. Hanson, G. (2015). Untangling Trade and Technology: Evidence from Local Labour Markets, Economic Journal, Royal Economic Society, vol. 0(584), pages 621-646, 05.

Autor, D., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. The Quarterly Journal of Economics, 118(4), 1279–1333.

Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. WW Norton & Company.

Frey, C. B., & Osborne, M. A. (2013). The Future of Employment: How Susceptible are Jobs to Computerisation?. Oxford Martin School Working Paper.

Goldin, C. and Katz, L.F. (1998). The origins of technology-skill complementarity. The Quarterly Journal of Economics, vol. 113, no. 3, pp. 693–732.

Goos, M. and Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in Britain. The Review of Economics and Statistics, vol. 89, no. 1, pp. 118–133.

Goos, M., Manning, A. and Salomons, A. (2009). Job Polarization in Europe. The American Economic Review, vol. 99, no. 2, pp. 58–63.

Goos, Maarten, Alan Manning, and Anna Salomons. (2014). Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. American Economic Review, 104 (8), 2509–2526.

Graetz, G., & Michaels, G. (2015). Robots at work. CEP Discussion Paper No 1335.

Karabarbounis, L., and Neiman, B. (2014a) The Global Decline of the Labor Share. The Quarterly Journal of Economics, Oxford University Press, vol. 129(1),pages 61-103.

Levy, F. and Murnane, R.J. (2004). The new division of labor: How computers are creating the next job market. Princeton University Press.

Michaels, Guy, Ashwini Natraj, and John Van Reenen. 2014. “Has ICT Polarized Skill Demand? Evidence from Eleven Countries over 25 Years.” Review of Economics and Statistics, 96(1): 60-77.

OECD (2012) OECD Employment Outlook 2012. OECD Publishing, Paris.