PIER

PUEY UNGPHAKORN INSTITUTE
FOR ECONOMIC RESEARCH

Reshaping Thailand's Labor Market Structure: The Unified Forces of Technology and Trade

by

Warn N. Lekfuangfu and Voraprapa Nakavachara

January 2020

Discussion Paper

No. 123

Reshaping Thailand's Labor Market Structure: The Unified Forces of Technology and Trade*

Warn N. Lekfuangfu
Universidad Carlos III de Madrid, CReAM, & CEP

Voraprapa Nakavachara[a]
Chulalongkorn University

Version: 3 January 2020

Abstract:

Improvements in technology can have substantial impact on the labor market both directly and indirectly via changes in global trade patterns. This paper studies the potential impact of computerization and reshoring/relocating of operations by firms on Thailand's labor market. Specifically, the analysis is built upon Frey and Osborne's (2017) approach and incorporates additional measures of trade-base tasks. This is so that the revised machine-learning model can account for both the impact of technology and change in global trade patterns. Our results revealed that occupations that are mostly affected are service and sales workers, and agricultural and fishery workers. In the worst-case scenario, approximately one-third of existing jobs (12.14 million jobs) could be at risk. However, in real situations, new types of jobs may be created, workers may voluntarily adjust, or other factors could drive some overseas operations back to Thailand. Therefore, the potential outlook for Thailand's labor market may not be as severe as the model has predicted.

Keywords: Employment, Skills, Technology, International Trade, Thailand

JEL Codes: J20, O33, F16

---

* This paper received financial support from Thailand Research Fund. **Disclosure statement**: No potential conflict of interest. The authors are grateful to Nopphol Witvorapong, Doungdao Mahakitsiri, Tanapong Potipiti, Saowanee Chantapong, Lae Dilokvidhyarat, and Kornkarun Cheewatrakoolpong for their suggestions. We also thank Jumpol Goonto for his excellent research assistance.
[a] Corresponding Author: Nakavachara: Faculty of Economics, Chulalongkorn University, Thailand, email: voraprapa.n@chula.ac.th.

1. Introduction

In the past few decades, technology has changed the way we live our lives. Technology also changed the way firms operate by providing alternative ways in which goods can be manufactured. It is well-documented that firms benefited from improvement in technology since firms can be more productive and eventually can produce at lower costs. However, technological improvement could have negative impacts on workers, especially the ones that are considered substitutes of such technology.

The negative impact of technological improvement on employment has been empirically recorded. Autor, Levy, and Murnane (2003) studied the US labor market and found that computer technology had substituted workers who performed routine tasks. Consequently, Autor and Dorn (2013) recorded that medium-skilled US workers were replaced by computerization. Michaels, Natraj, and Van Reenen (2014) reported similar results for other OECD countries. Graetz and Michaels (2018) found that the use of industrial robots in OECD countries improved labor productivity growth but reduced low-skilled employment. Acemoglu and Restrepo (2017) also reported similar findings for US local employment. In addition, some economists have documented that "jobless growth" – an economic growth that no longer requires increasing employment is becoming more pervasive. (See Jaimovich and Siu, 2002; and Graetz and Michaels, 2017, for example.)

Most of the previous literature, relying on the data being readily available, examined the impact that has already happened in the past. Although it is crucial to understand what already happened, a forward-looking model should also be constructed to appropriately predict what will happen in the future. Frey and Osborne (2017) addressed this issue by estimating the impact of technology on the future employment. (The methodology proposed by Frey and Osborne, 2017, will be discussed in detailed in Sections 2 and 3.) The authors found that 47% of US labor was at high risk of being replaced by computerization in the near future. ILO (2016) followed Frey and Osborne's (2017) methodology and reported that such probability ranged from 44% to 70% for ASEAN countries.

For Thailand, Kulkolkarn (2018) documented that Thai companies have increased the use of automation in their manufacturing process in the past years. Following Frey and Osborne (2017), Leepipatpiboon and Thongsri (2018) reported that 57% of labor in agriculture sector, 55% of labor in industrial sector, and 55% of labor in retail sector were at high risk of being replaced by computerization.

Although the literature has explored the direct impact of technology on labor, it did not address another adverse impact that could also happen at the same time, namely, the possibility that firms could reshore/relocate there operations elsewhere. This paper fills the gap in the literature by combining the direct impact of technology and the reshore/relocation probability into our estimates.

In this paper, we started by following the approach suggested by Frey and Osborne (2017) in identifying the direct impact of technology on the labor demand – making adjustments in terms of occupation codes to fit the context of Thailand. For the reshoring/relocation aspect, we followed the approach suggested by Firpo, Fortin, and Lemieux (2011) and Fortin and Lemieux (2016). We combined the two approaches and estimate the impact of technology both directly and indirectly (through change global trade pattern) on Thailand's labor market. Then, we apply the probability estimation from the revised model to Thailand's Labor Force Surveys from 2011-2016 to illustrate the impact.

Specifically, we first estimate the probability of workers being at risk – either from being replaced by computerization and/or being displaced due to relocation of operations away from Thailand. Subsequently, we predict the potential impacts of these two phenomena on unemployment (extensive margin) and on working hour loss (intensive margin). We discuss policy responses to mitigate the potentially devastating impacts on skill accumulation and labor market.

The paper is organized as follow. This section introduces the subject matter and outlines the research objectives. Section 2 illustrates the conceptual framework. Section 3 explains the methodology and the data. Section 4 discusses the results. Section 5 concludes the paper and discusses policy implications.

2. Conceptual Framework

There are at least two ways that technology can have an adverse impact on the demand of labor in Thailand. First, technology can substitute labor and have a direct negative impact on the demand of labor. Second, technology can have an impact on the way firms manufacture goods in the global value chain. Up until recently, we observed global companies offshoring their operations to lower-cost countries. Thailand was one of the major targets during the period. However, the rapid improvement of technology in this twenty-first century could allow the parent countries to be able to manufacture products at lower costs elsewhere – in their home countries or near the major customer markets. Therefore, the operations previously offshored to countries like Thailand may be reshored back to the parent countries or relocated elsewhere – negatively affecting the demand for labor in Thailand. Although this paper initially focuses on reshore/relocation of operations due to change in technology, however, our proposed model can also account for relocation of operations due to other reasons such as cheaper labor in other emerging countries. Figure 1 illustrates the conceptual framework that displays the direct and indirect impacts of technology on labor demand.

Following Frey and Osborne (2017), the technology that is the main focus of this paper involves broad applications of Machine Learning (ML) and Mobile Robotics (MR). Machine Learning is branch of Artificial Intelligence (AI) that involves creating algorithms that can think/act like human without being explicitly programmed. Mobile Robotics is relating to how to make movable robots handle complicated manual tasks. One may think of the study of ML as how to make a brain smarter and the study of MR as how to make a body function better. Combining ML and MR will allow computerization not only to perform routine manual tasks but also non-routine complicated tasks.

Regarding the change in global trade pattern, this paper followed the unbundling concepts initially proposed by Baldwin (2006, 2013, 2016) and emphasized for Thailand's context by Cheewatrakoolpong et. al (2015). According to Baldwin (2006, 2013, 2016) the first unbundling of international trade started in late nineteenth century when shipping costs became rapidly cheaper due to the development of steam engine, an outcome of the First Industrial Revolution. The increasing wage gap between the industrialized countries and other countries led to the second unbundling during 1985-1990s. During the period, the advanced nations offshored their operations to emerging nations (e.g. China and other Southeast Asian countries) to take advantage of cheaper wage costs. However, a reverse trend could be happening in the third unbundling during the twenty-first century. In this period, the development of new technology could allow the operations to be performed at lower costs elsewhere – driving the operations back home or to other locations.

3. Methodology and Data

We followed the approach suggested by Frey and Osborne (2017) in identifying the computerization impact on the labor demand. In addition, we added "the potential to be reshored/relocated" feature to the Frey and Osborne's (2017) methodology. Modifying the method allows us to estimate, for each occupation, the probability to be replaced by computerization or to be displaced due to the operations being moved outside of the country. In this section, we start by describing Frey and Osborne's (2017) methodology. We then explain our proposed modification by applying reshoring/relocation related variables, proposed by Firpo, Fortin, and Lemieux (2011) and Fortin and Lemieux (2016), to the model.

3.1 Frey and Osborne (2017)

Frey and Osborne (2017) started by identifying "computerization bottlenecks" – characteristics of jobs that would still be difficult for machine to handle. Therefore, it will be hard for computerization to replace the workers who are associated with such tasks in the foreseeable future (i.e., in the next few decades). The three computerization bottlenecks proposed by Frey and Osborne (2017) were (i) Perception and Manipulation; (ii) Creative Intelligence; and (iii) Social Intelligence. They then retrieved the relevant occupation-specific information from the O*NET database (Occupational Information Network database)[1] to be used in their analysis. The O*NET database contains a list of all occupations and the relevant attributes (knowledge, skills, abilities, activities, and tasks) that each occupation requires. In the case where the attributes are measurable in terms of importance, the O*NET database also incorporates such information in the scale of 0 to 100. Specifically, Frey and Osborne (2017) identified the O*NET variables (knowledge, skills, abilities, activities, and tasks) associated with the proposed computerization bottlenecks. See Table 1 for relevant O*NET variables used by Frey and Osborne (2017).

Supervised machine learning techniques are applied by exploiting the expert-labelling of 70 occupations (out of 702 occupations) whether each of these occupations can be fully automatable using computerization or not (assigning 1 or 0). The model, which incorporate a set of occupational characteristics defined by the O*NET variables as attributes, is subsequently "trained" using various classification models namely linear, exponentiated quadratic, and rational quadratic.

[1] The project was developed under the sponsorship of the U.S. Department of Labor/Employment and Training (USDOL/ETA).

The least complicated model, the linear classifier model, utilized a logistic specification illustrated as $P(y=1|X)=\frac{1}{1+\exp(-(\beta' X))}$. Here, y is the vector of the outcome variables indicating whether the occupations (70 occupations) can be fully automatable using computerization or not. X is a matrix of selected attribute variables (associated with the proposed computerization bottlenecks) for each of the occupation. Alternative specifications are the exponentiated quadratic, and the rational quadratic classifier model under a Gaussian process.[2]

Using the test to validate the classifiers (by using GPML toolbox proposed by Rasmussen and Nickisch, 2010), it turned out that the exponentiated quadratic model outperformed the other models. Therefore, Frey and Osborne (2017) utilized the trained exponentiated quadratic model to predict the probability of being replaced by computerization for the remaining occupations.

In this paper, we start with the replication of Frey and Osborne (2017) methodology using Thai Labor data. Basically, we cross-walk the US's 6-digit SOC occupation codes used in their paper to the 4-digit ISCO-2008 of the Thai Labor Force Surveys. Appendix 1 outlines the full list of occupations and the corresponding probability of being at risk for each occupation per Frey and Osborne (2017) (displayed in the last column).[3]

3.2 Our Proposed Modification

In this paper, we introduce "the potential to be reshored/relocated" into the model proposed by Frey and Osborne (2017). Firpo, Fortin, and Lemieux (2011) and Fortin and Lemieux (2016) proposed "Non-Offshorability" feature of an occupation by using the O*NET variables indicating whether the job (i) needs to be performed at a specific location/space (on-site), (ii) requires face-to-face interpersonal relationship and caring for others (face-to-face), or (iii) involves decision making process (decision-making). In this paper, we follow Firpo, Fortin, and Lemieux (2011) and Fortin and Lemieux (2016)

---

[2] For the exponentiated quadratic classifier model, the function $P(y=1|f)=\frac{1}{1+\exp(-f)}$ is implemented - where f is modeled using Gaussian process. For the rational quadratic model, Frey and Osborn (2017) utilize $P(f|K)=\mathcal{N}(f;0,K)\frac{1}{\sqrt{\det 2\pi K}}\exp(-\frac{1}{2}f^T K^{-1} f)$. The covariance function $K=\mathcal{K}(X,X)$ is represented by exponentiated quadratic covariance (squared exponential) and rational quadratic covariance, respectively.

[3] Note that we were not able to map all 6-digit SOC codes to 4-digit ISCO-2008 codes. Therefore, the analysis in this paper will be based on only occupations that can be mapped, assuming that the remaining occupations are not affected.

regarding on-site variables and face-to-face variables. However, we drop decision-making variables since such tasks can be performed remotely from other locations. See Table 1 for description of O*NET variables used for Non-Offshorability.

Following Frey and Osborne (2017), we trial the three model specifications. The *X* matrix under our modified models includes both the attribute variables associated with computerization bottlenecks and the attribute variables associated with non-offshorability (on-site and face-to-face) for each of the occupation.

From the validation test validate, similar to Frey and Osborne (2017), the exponentiated quadratic model outperforms other models (as shown in Table 2). Therefore, we utilize the (modified) trained exponentiated quadratic model to predict the probability of being replaced by computerization or being reshored/relocated elsewhere for the remaining occupations.

3.3 The Data

This paper utilizes the Thailand's Labor Force Surveys of 2011 to 2016. The Thai Labor Force Survey is the national survey, compiled by the National Statistical Office since 1963. The objective of the survey is to gather necessary information about the country's labor market situations. The survey gathers information including the number of employed persons and their characteristics such as age, gender, education, occupation, industry, work status, hours of work, etc. The occupation code used in the survey followed the 4-digit ISCO-2008 format.

The main variables used in this paper are the employment status and hours of work for each occupation group (averaged over 2011 to 2016). In addition, other relevant demographic information such as age, gender, education, etc. are also incorporated to provide additional insights for the results.

3.4 Caveats of the Model

In this paper, we have proposed a novel idea of combining the probability to be replaced and probability of being reshored/relocated for each of the occupation. However, since our model is based on the model proposed by Frey and Osborne (2017), our model also inherited their shortcomings. Therefore, when interpreting the results, we need acknowledge the following limitations.

First, some of the initial inputs of the models were from human experts. Therefore, we cannot rule out the possibility that the experts' opinions were biased or prejudged. Second, the model assumed that the industry composition was fixed. In fact, workers may voluntarily move from some industries to others based on the market conditions or their own preferences. Therefore, the model provides the worst-case scenario outcomes. Third, the model could not accommodate the possibility that that new types of jobs could be created. Therefore, the actual negative impact may not be as severe as the model predicts.

4. Results

We first calculate the probability of being at risk (of being replaced by computerization or being displaced due to operations being moved outside of the country) for each occupation based on the methodology previously discussed. We will then match the probability to the data obtained from the Thai Labor Force Survey (2011 to 2016). Finally, we will estimate the potential impact of the technology on employment (extensive margin) and the potential impact on the working hours (intensive margin).

4.1 Probability of Being at Risk

Table 3 (Columns 1 to 3) revealed the probability of being at risk for each type of occupation (per 1-digit ISCO-2008 occupation code). It appears that the medium-skilled job category like clerks (secretaries, customer services, cashiers, etc.) have the highest risk (72.5%). In addition, machine operators and assemblers and elementary occupations also have high risk, approximately 68.3% and 62%, respectively. The full list of occupations and the probability of being at risk for each occupation are shown in Appendix 1 (Column 3).[4] The Appendix also includes the probably of being at risk of being replaced by computerization only (per Frey and Osborne, 2017) for comparison (last column).

[4] Note that we were not able to map all 6-digit SOC codes to 4-digit ISCO-2008 codes. Therefore, the analysis in this paper will be based on only occupations that can be mapped, assuming that the remaining occupations are not affected.

Figure 2 visualizes the probability of being displaced by 4-digit ISCO-2008 occupation codes comparing our results to those of Frey and Osborne (2017). The horizontal axis displays occupation ranked by ISCO codes. ISCO codes are designed so that higher-skilled management occupations started with lower numbers and lower-skilled manual occupations started with higher numbers. The figure reveals for lower-skilled occupations, the probability of being at risk based on our model is higher than that of Frey and Osborne (2017) whereas the reverse is true for higher-skilled occupations. The medium skilled jobs have similar risk (compared to Frey and Osborne, 2017). This could be due to the fact that including the risk of being displaced by reshoring/relocation of operations makes the high-level management jobs more vulnerable since technology allows this type of tasks to be conducted elsewhere. Whereas, in the case of lower-skilled jobs like plant or machine operators are supposed to be on-site. Incorporating the risk of being displaced by reshoring/relocation make these types of jobs less vulnerable.

4.2 Potential Impact on Employment (Extensive Margin)

We then utilize the Thai Labor Force Surveys during 2011-2016 to estimate the impact on employment.[5] Table 3 (Columns 4 to 6) reveals the potential employment at risk for each group of occupations overall and also by gender. Observing the impact on employment, it appears that service and sales workers and skilled agricultural and fishery workers are mostly affected. (This is because the current employment in these sectors is high.) In the worst-case scenario, about 12.14 million workers will be affected in the next few decades, with 6.61 million being male workers and 5.59 million being female workers. (ILO, 2016, reported 17.2 million will be at high risk whereas Leepipatpiboon and Thongsri, 2018, reported 3 million will be at high risk.) Note that the model predicts the worst-case scenario – that is no new jobs are assumed be get created by the introduction of technology and that Thailand's labor supply would remain inflexible to further structural changes. Therefore, the actual impact may not be as severe as the model has predicted.

Figure 3 illustrates the potential employment loss by occupation sorted by employment size of each occupation. The figure reveals that the occupations with large

[5] Note that the total employment of matched occupation codes is about 22.6 million which is lower than the actual employment in Thailand (2011-2016 average). Our results are calculated based on this employment number and will be conservative (assuming employment outside of these matched codes are not affected.)

proportion of employment would be heavily affected. Figure 4 visualizes the impact by gender. For most of the occupations, (rank 0 to 80), employment of male workers will be more affected compared to employment of female workers. However, for occupations with higher employment (rank 80 to 100), male and female workers are equally affected.

Table 4 reveals the potential employment loss by education. It appears that people with primary education or lower will be mostly affected (with the majority of them working in service and sales and skilled agricultural and fishery). Figure 5 demonstrates the impact by education (primary or lower, lower secondary, upper secondary, college or higher) with occupations sorted by employment level. The figure reveals that for lower-employment occupations, workers with college education or higher appear to be more highly affected. However, for higher-employment occupations, workers with primary education or lower appear to be more highly affect.

Table 5 shows the potential employment loss by age group. The age group 35-44 appears to be mostly affected. However, looking at older workers (45 or older), almost 4 million workers could be affected. Note that, in general, older workers take longer to adjust and learn new skills. Therefore, re-skilling is needed to help these workers to transition themselves into new job functions.

4.3 Potential Impact on Working Hours (Intensive Margin)

Table 6 outlines the impact on weekly hours estimated from the model. In the worst-case scenario, up to 720 million working hours would be loss per week. Most of the hours are from skilled agricultural and fishery sectors. The impact on weekly hours for male workers is slightly higher than that of female workers.

The impact on weekly hours by occupation sorted by employment size of each occupation is shown in Figure 6. The occupations with large proportion of employment appear to be heavily affected. Figure 7 visualizes the impact by gender. For most of the occupations, (rank 0 to 80), the impact on hours for male workers is higher than that of female workers. However, for occupations with higher employment (rank 80 to 100), male and female workers are equally affected.

By education, the estimated impact on weekly hours is the most dominating among workers with primary education or lower (see Table 7). Figure 8 visualizes the impact by education (primary or lower, lower secondary, upper secondary, college or higher) with occupations sorted by employment level. The figure reveals that for lower-employment occupations, workers with college education or higher appear to be more highly affected. However, for higher-employment occupations, workers with primary education or lower appear to be more highly affect.

Table 8 revealed the potential weekly hour loss by age group. Most of the hours are from the workers with age group 35-44 years old. This age group is those who are at their prime potential in the labor force, and still far away from their retirement. Loss of human capital due to the reduction in their work hours can also be substantial.

5. Conclusion and Policy Implications

This paper studies the potential impact of computerization and reshoring/relocating of operations by firms on Thailand's labor market. Specifically, the authors followed the approach suggested by Frey and Osborne (2017) in identifying the computerization impact on the labor demand. In addition, the authors added "the potential to be reshored/relocated" feature to the Frey and Osborne's (2017) methodology. Modifying the method allows us to estimate, for each occupation, the probability to be replaced by computerization or to be displaced due to the operations being moved outside of the country.

Our results reveal that occupations that are mostly affected are service and sales workers, and agricultural and fishery workers. In the worst-case scenario, approximately 12.14 million jobs could be at risk – account for almost one-third of Thailand's current labor force. However, the workers may voluntarily adjust or new jobs can be created or workers can earn additional income from part-time jobs. In addition, situations like the current trade war could result in operations being relocated from disputed countries to a country like Thailand. Therefore, the potential outlook for Thailand's labor market may not be as severe as the model has predicted.

Regarding policy implications, the authors believe that certain measures must be put in place to help the existing workers deal with the technological disruption. Upskilling and re-skilling programs could be offered by the government so that the workers affected by computerization can find new job functions. Private sector can also help by trying to retain and re-train the workers instead of terminating them. Moreover, the government could provide some incentives for firms that try to re-train their workers and help them find new roles when machines are put in place to perform the workers' previous roles.

For future workforce (i.e., students), schools and universities could offer courses that will equip them with necessary skills for the future. World Economic Forum (2018) indicated that the skills of the future are analytical thinking and innovation, active learning, creativity, technology design and programing, critical thinking and analysis. Not only that schools and universities can offer appropriate courses for students, they can also provide continuous learning programs for adult workers so that they can sharpen their skills.

Lastly, the workers themselves should have the growth mindset. They need to accept the fact that they will have to continue learning new things for the rest of their lives. With the fast-changing technological improvement, it is undeniable that workers will have to adapt and learn fast in order for them to remain relevant. Moreover, the workers should find ways for them to utilize the technology for their own benefits and/or to augment their capabilities. In other words, workers should adapt so that they are the complements of the technology and not the substitutes.

6. References

Acemoglu, D., and Restrepo, P. (2017). *Robots and Jobs: Evidence from US Labor Markets* (No. w23285). National Bureau of Economic Research.

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., 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.

Baldwin, R. (2006). Globalisation: the great unbundling (s). *Economic Council of Finland*, *20*(3), 5-47.

Baldwin, R. (2013). Trade and industrialization after globalization's second unbundling: how building and joining a supply chain are different and why it matters. In *Globalization in an age of crisis: Multilateral economic cooperation in the twenty-first century* (pp. 165-212). University of Chicago Press.

Baldwin, R. (2016). *The great convergence*. Harvard University Press.

Blinder, A. S. (2009). How many US jobs might be offshorable? *World Economics*, *10*(2), 41.

Cheewatrakoolpong, K., Potipiti, T., Satchachai, P., Bunditwattanawong, N. and Nopparattayaporn, A. (2015). The New Normal of Global Trade: The Impact on Thailand's Export Structure and Structural Changes, Bank of Thailand Symposium.

De Backer, K., Menon, C., Desnoyers-James, I., and Moussiegt, L. (2016). Reshoring: Myth or reality?. *OECD Science, Technology and Industry Policy Papers*, No. 27, OECD Publishing, Paris.

Firpo, S., Fortin, N., and Lemieux, T. (2011). Occupational Tasks and Changes in the Wage Structure. *IZA Discussion Paper*, No. 5542.

Fortin, N., and Lemieux, T. (2016). Inequality and Changes in Task Prices: Within and between Occupation Effects. In *Inequality: Causes and consequences* (pp. 195-226). Emerald Group Publishing Limited.

Frey, C. B., and Osborne, M. A. (2017). The future of employment: how susceptible are jobs to computerisation?. *Technological forecasting and social change, 114*, 254-280.

Graetz, G., and Michaels, G. (2017). Is modern technology responsible for jobless recoveries? *American Economic Review*, *107*(5), 168-73.

Graetz, G., and Michaels, G. (2018). Robots at Work. *The Review of Economics and Statistics*, Forthcoming.

International Federation of Robotics (2017). *World Robotics 2017 Industrial Robots*.

International Labor Organization (2016). *ASEAN in Transformation: The Future of Jobs at Risk of Automation*.

Jaimovich, N., and Siu, H. E. (2012). *The trend is the cycle: Job polarization and jobless recoveries* (No. w18334). National Bureau of Economic Research.

Jensen, J. B., and Kletzer, L. G. (2010). Measuring the task content of offshorable services jobs, tradable services and job loss. *Labor in the new economy*, 309-335.

Kulkolkarn, K. (2018). Thailand's Human Capital Management under the 4.0 Era. Ministry of Labor, Thailand.

Leepipatpiboon, P., Thongsri, N. (2018). Industrial Robots and its Impact on Labor Market, Bank of Thailand.

Lekfuangfu, W.N. (2017) Intensive and Extensive Margins of Labour Supply in Thailand: Decomposing the Pattern of Work Behaviours, PIER Discussion Paper No. 59

Michaels, G., Natraj, A., and Van Reenen, J. (2014). Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. *Review of Economics and Statistics*, *96*(1), 60-77.

Oldenski, L. (2015). Reshoring by US firms: What do the data say? *Peterson Institute for International Economics Policy Brief*, Number PB15-14, 1-11.

Rasmussen, C. E., & Nickisch, H. (2010). Gaussian processes for machine learning (GPML) toolbox. *Journal of machine learning research*, *11*(Nov), 3011-3015.

Rattanakhamfu, S., Tangkitvanich, S., Sukphisan, W. and Thammapiranan, P. (2014). Relocating labor-intensive industries from Thailand to neighboring countries: possibility and policy implications. *TDRI Quarterly Review*, Vol.29, No.1, 4-17.

Turing, A. (1950). Computing Machinery and Intelligence. *Mind*, 49, 433-460.

World Economic Forum (2018). The Future of Jobs Report.

Figures and Tables

Figure 1: Conceptual Framework

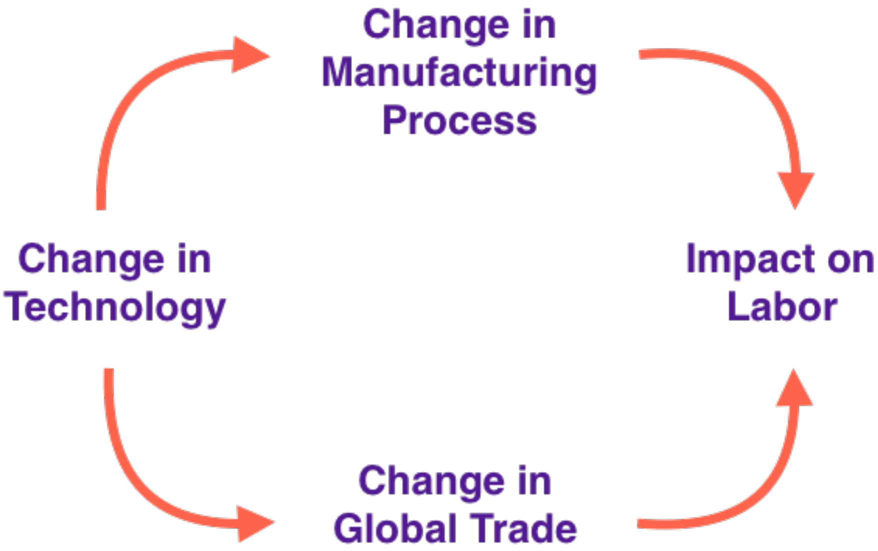


Figure 2: Risk by Occupation
Comparison between the Modified Model (Tech and Trade)
and the Original Model (Frey & Osborne, 2017)

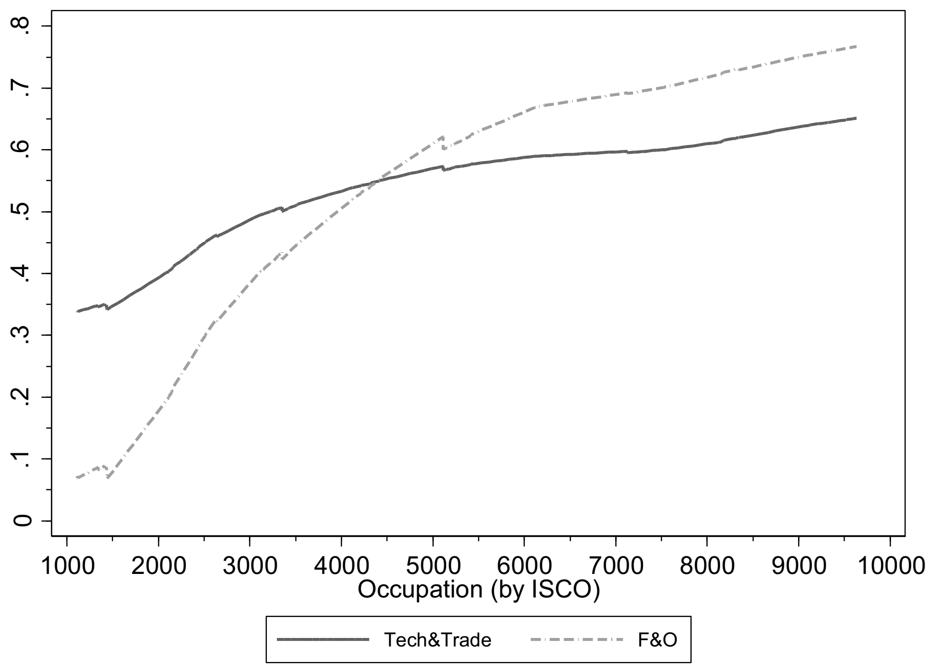
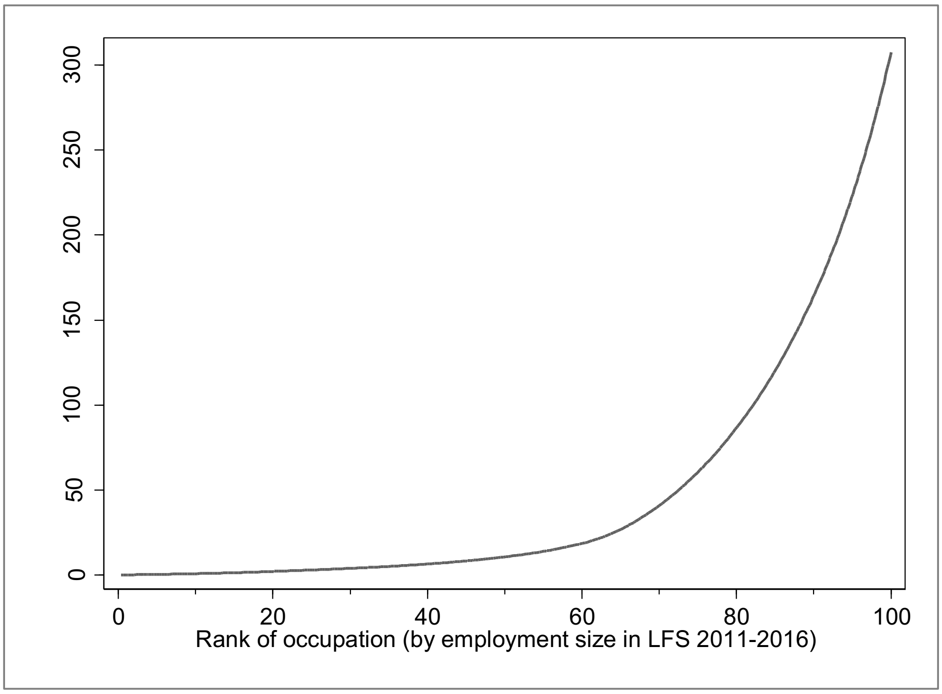
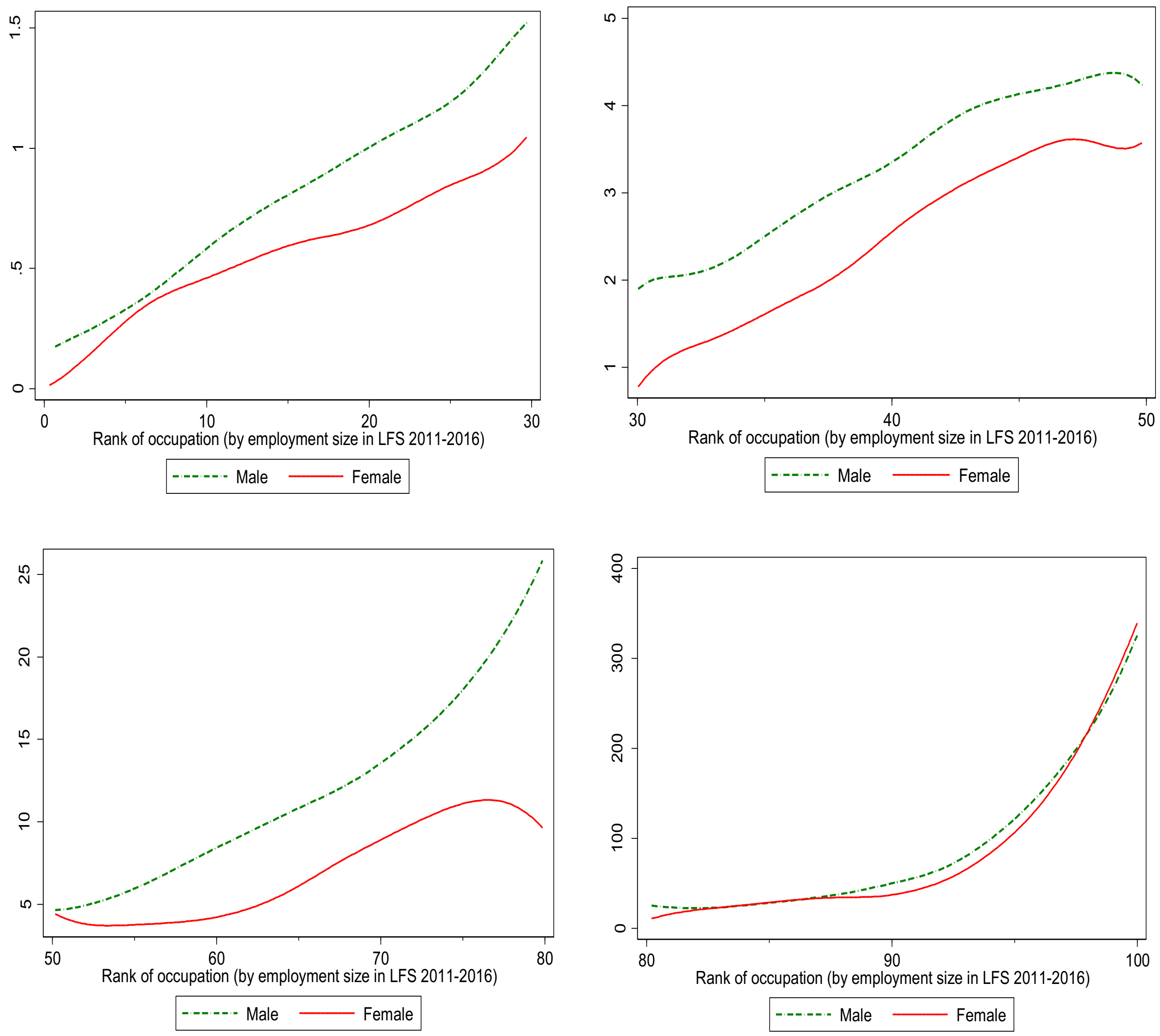


Figure 3: Potential Employment Loss by Occupation
(Sorted by Employment Size)



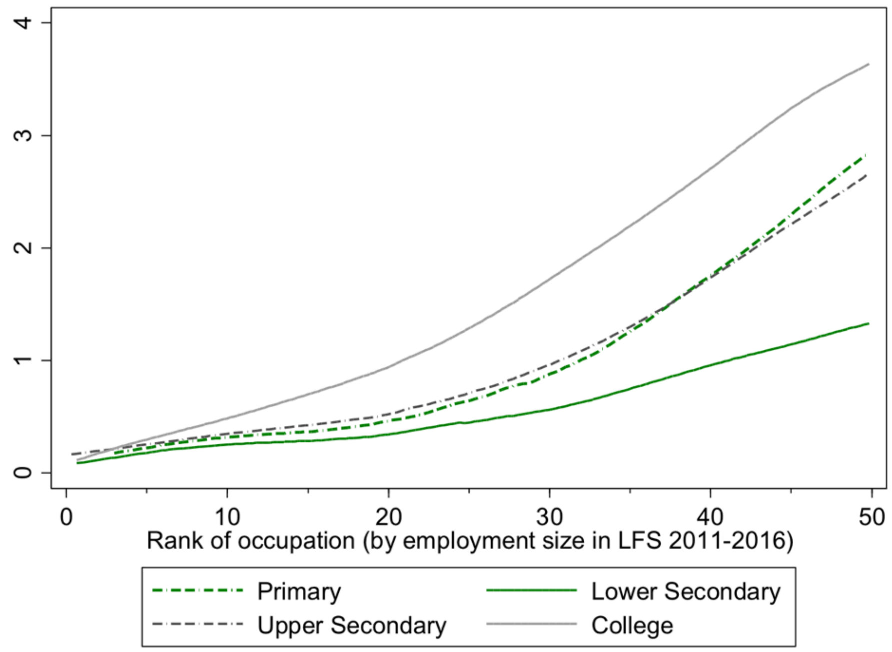
Unit: Thousand workers

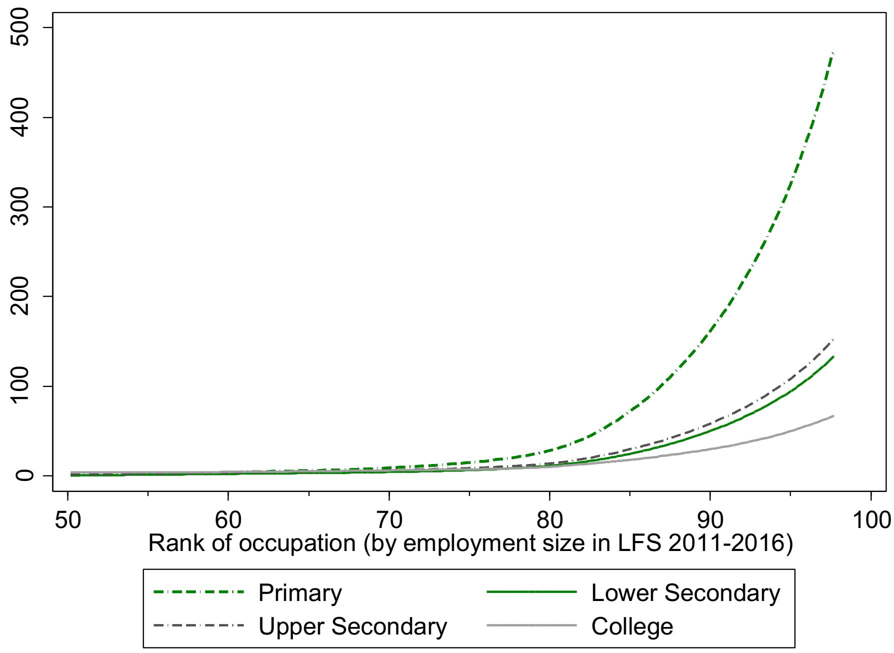
Figure 4: Potential Employment Loss Segregated by Gender
(Sorted by Occupation Employment Size)



Unit: Thousand workers

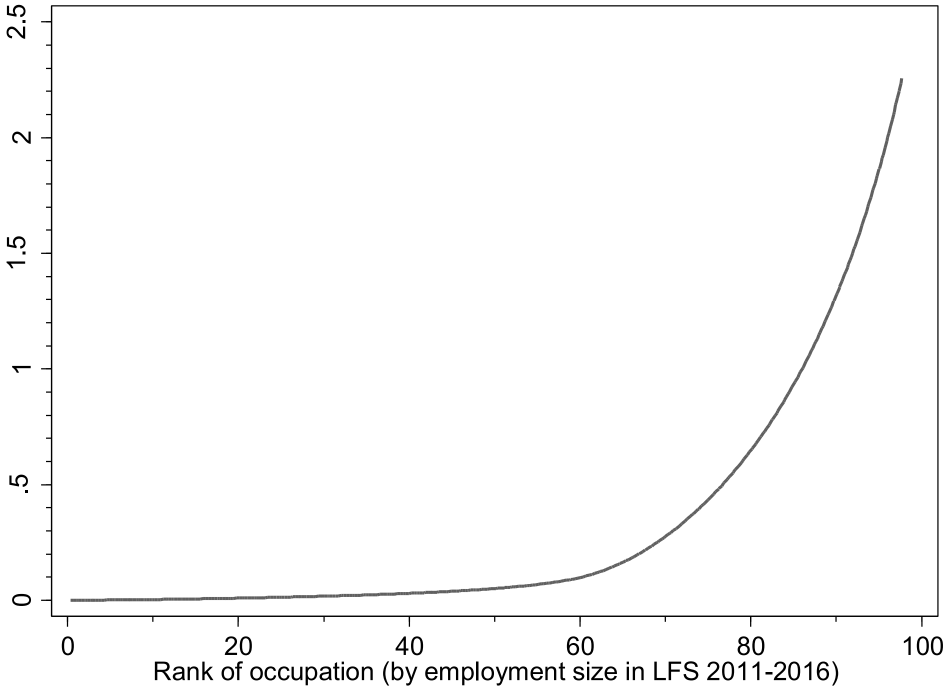
Figure 5: Potential Employment Loss Segregated by Education
(Sorted by Occupation Employment Size)





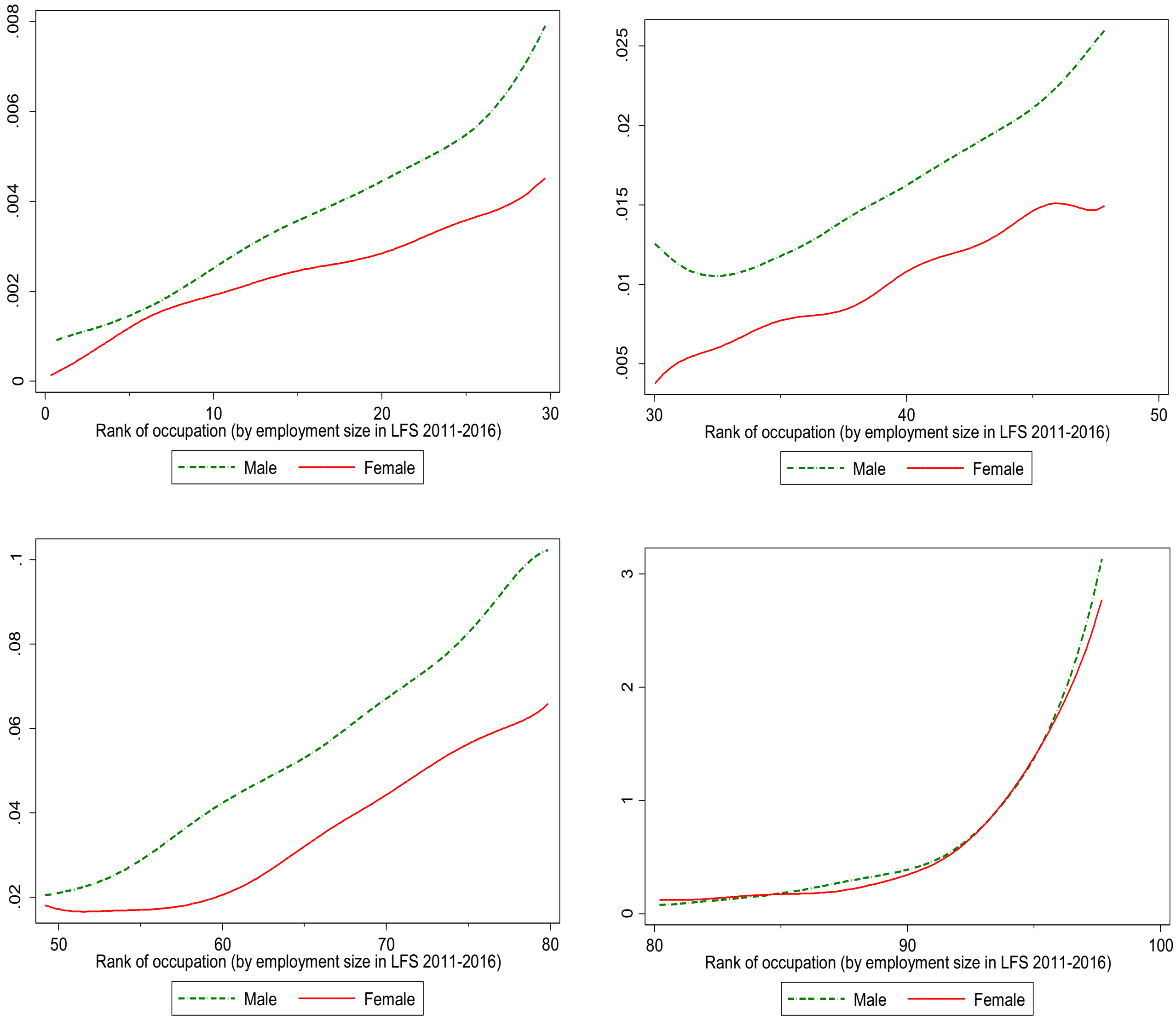
Unit: Thousand workers

Figure 6: Potential Weekly Hour Loss by Occupation
(Sorted by Employment Size)



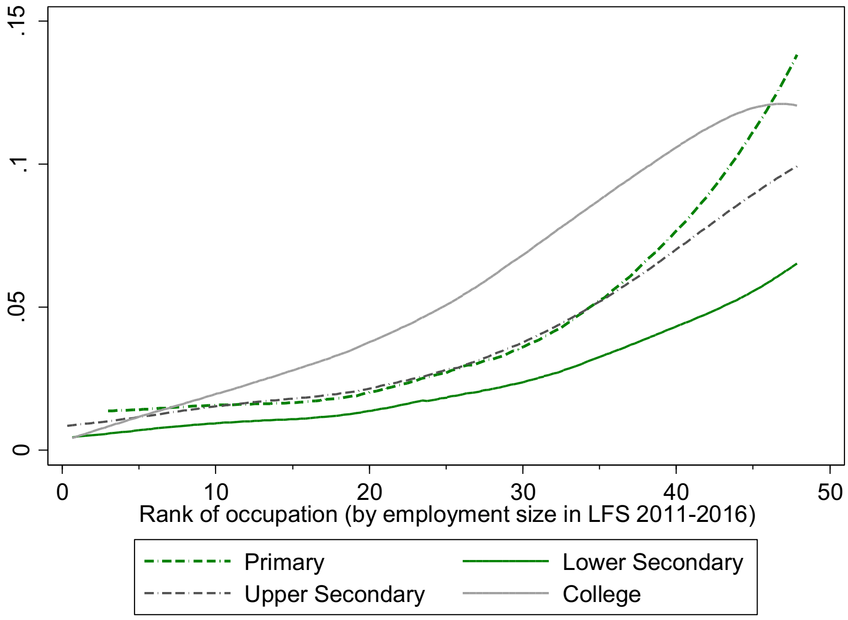
Unit: Million Hours

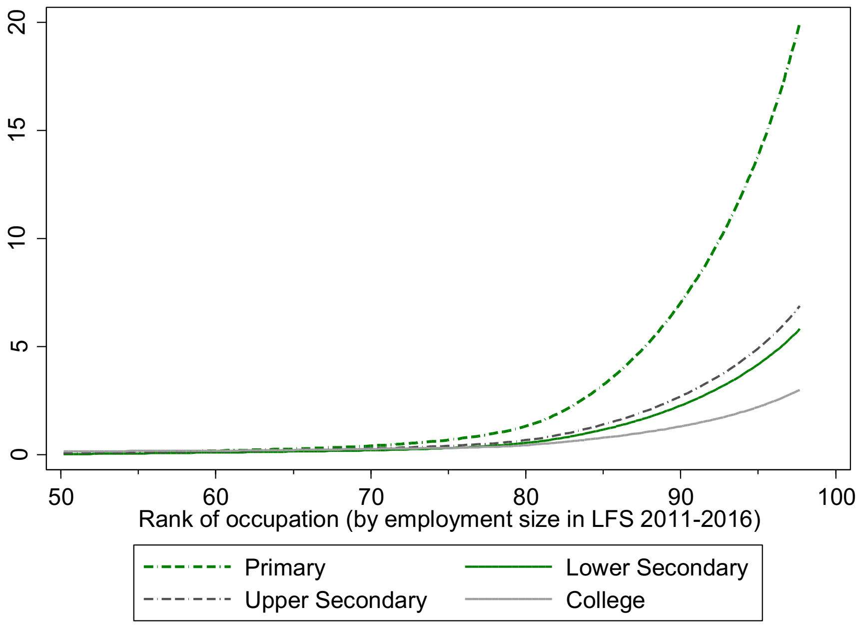
Figure 7: Potential Weekly Hour Loss Segregated by Gender
(Sorted by Occupation Employment Size)



Unit: Million Hours

Figure 8: Potential Weekly Hour Loss Segregated by Education
(Sorted by Occupation Employment Size)





Unit: Million Hours

Table 1: O*NET Variables Used in Our Model

Computerization Bottleneck	O*NET Variable	Description	Citation
Perception and Manipulation	Finger Dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.	Frey & Osborne (2017)
	Manual Dexterity	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.	
	Cramped Work Space, Awkward Positions	How often does this job require working in cramped work spaces that requires getting into awkward positions?	
Creative Intelligence	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.	
	Fine Arts	Knowledge of theory and techniques required to compose, produce, and perform works of music, dance, visual arts, drama, and sculpture.	
Social Intelligence	Social Perceptiveness	Being aware of others' reactions and understanding why they react as they do.	
	Negotiation	Bringing others together and trying to reconcile differences.	
	Persuasion	Persuading others to change their minds or behaviour.	
	Assisting and Caring for Others	Providing personal assistance, medical attention, emotional support, or other personal care to others such as coworkers, customers, or patients.	
Non-Offshorability	On-Site	The job must be performed at a specific location/space.	Firpo, Fortin, and Lemieux (2011); Fortin and Lemieux (2016)
	Face-to-Face	the job requires face-to-face personal communication and/or contact with end users of the service.	

Table 2: Model Performance Comparison (Best Performances in Bold)

	Variables	**Model Specification**	**Log Likelihood**	**Average AUC (SD)**
I.	9 O*NET variables	Linear (Logistic Regression)	-54.81	0.6788 (0.0643)
II.		**Exponentiated Quadratic**	**-34.17**	**0.8220 (0.0566)**
III.		Rational Quadratic	-34.20	0.8216 (0.0557)
IV.	9 O*NET variables + On-Site index + Face-to-Face index	Linear (Logistic Regression)	-59.02	0.6925 (0.0696)
V.		**Exponentiated Quadratic**	**-35.17**	**0.8159 (0.0554)**
VI.		Rational Quadratic	-35.18	0.8154 (0.0561)

Table 3: Potential Employment Loss (by Gender)

1-Digit ISCO	Occupation	Probabiity at Risk	Potential Employment Loss		
			Total	Male	Female
1	Legislators, Senior Officials, and Managers	38.2%	486,162	320,231	167,205
2	Professionals	41.8%	551,996	224,623	330,373
3	Technicians and Associate Professionals	53.9%	587,276	256,669	335,277
4	Clerks	72.5%	685,410	216,213	469,935
5	Service Workers and Shop and Market Sales Workers	57.0%	3,285,656	1,397,460	1,888,296
6	Skilled Argicultural and Fishery Workers	57.3%	2,755,300	1,627,920	1,127,528
7	Craft and Related Trades Workers	57.9%	1,468,133	1,115,333	354,727
8	Plant and Machine Operators and Assemblers	68.3%	1,589,534	1,193,064	396,919
9	Elementary Occupations	62.0%	1,581,264	705,758	876,039
Total		**53.7%**	**12,140,010**	**6,607,174**	**5,586,553**

Table 4: Potential Employment Loss (by Education)

1-Digit ISCO	Occupation	Potential Employment Loss (by Education)			
		Primary	**Lower-Secondary**	**Upper-Secondary**	**College or Higher**
1	Legislators, Senior Officials, and Managers	102,370	43,604	114,967	227,838
2	Professionals	13,448	12,474	47,315	488,251
3	Technicians and Associate Professionals	34,407	30,356	197,365	338,467
4	Clerks	35,114	65,728	269,989	316,284
5	Service Workers and Shop and Market Sales Workers	1,359,205	605,064	913,611	408,924
6	Skilled Argicultural and Fishery Workers	1,843,816	426,524	405,621	79,854
7	Craft and Related Trades Workers	809,413	300,802	310,965	54,263
8	Plant and Machine Operators and Assemblers	578,510	456,863	509,619	46,880
9	Elementary Occupations	1,015,172	327,316	218,211	22,177
Total		**5,315,523**	**2,047,990**	**2,738,330**	**2,086,463**

Table 5: Potential Employment Loss (by Age)

1-Digit ISCO	Occupation	Potential Employment Loss (by Age)				
		15-24	25-34	35-44	45-54	55-64
1	Legislators, Senior Officials, and Managers	13,720	89,355	156,774	154,816	63,526
2	Professionals	48,134	183,620	136,769	134,522	58,742
3	Technicians and Associate Professionals	72,987	225,816	168,720	102,457	30,333
4	Clerks	125,161	306,346	155,503	81,429	17,992
5	Service Workers and Shop and Market Sales Workers	424,332	745,426	831,843	747,634	406,208
6	Skilled Argicultural and Fishery Workers	342,393	480,924	633,115	645,832	469,265
7	Craft and Related Trades Workers	220,606	364,885	416,049	309,675	136,287
8	Plant and Machine Operators and Assemblers	268,544	511,104	443,968	268,290	92,228
9	Elementary Occupations	314,279	371,309	419,793	323,879	129,018
Total		**1,655,486**	**3,028,877**	**3,155,549**	**2,641,673**	**1,341,653**

Table 6: Potential Weekly Hour Loss (by Gender)
Unit: Million Hours

1-Digit ISCO	Occupation	Potential Weekly Hour Loss			
		Hour Loss	**% of Total**	**Male**	**Female**
1	Legislators, Senior Officials, and Managers	21.06	36.82%	14.03	7.09
2	Professionals	19.87	36.65%	8.41	11.55
3	Technicians and Associate Professionals	31.73	64.36%	11.01	20.90
4	Clerks	17.99	77.87%	4.61	13.41
5	Service Workers and Shop and Market Sales Workers	177.29	59.90%	73.61	103.69
6	Skilled Argicultural and Fishery Workers	197.38	48.62%	115.77	81.63
7	Craft and Related Trades Workers	109.30	62.10%	81.71	27.67
8	Plant and Machine Operators and Assemblers	72.13	55.48%	48.57	23.58
9	Elementary Occupations	73.34	58.20%	33.78	39.58
Total		**720.08**	**54.55%**	**391.50**	**329.11**

Table 7: Potential Weekly Hour Loss (by Education)
Unit: Million Hours

1-Digit ISCO	Occupation	Potential Weekly Hour Loss (by Education)			
		Primary	**Lower-Secondary**	**Upper-Secondary**	**College or Higher**
1	Legislators, Senior Officials, and Managers	4.70	1.86	4.85	9.78
2	Professionals	0.49	0.53	2.07	17.21
3	Technicians and Associate Professionals	1.74	1.52	10.25	18.78
4	Clerks	0.77	1.28	7.14	8.88
5	Service Workers and Shop and Market Sales Workers	74.19	33.67	49.01	20.47
6	Skilled Argicultural and Fishery Workers	142.68	27.73	23.71	3.27
7	Craft and Related Trades Workers	55.88	22.95	26.70	4.15
8	Plant and Machine Operators and Assemblers	24.57	21.65	24.22	1.85
9	Elementary Occupations	46.82	14.99	10.51	1.10
Total		**351.85**	**126.18**	**158.46**	**85.50**

Table 8: Potential Weekly Hour Loss (by Age)
Unit: Million Hours

1-Digit ISCO	Occupation	Potential Weekly Hour Loss (by Age)				
		15-24	**25-34**	**35-44**	**45-54**	**55-64**
1	Legislators, Senior Officials, and Managers	0.60	3.86	6.80	6.73	2.76
2	Professionals	1.81	6.95	5.28	4.45	1.80
3	Technicians and Associate Professionals	4.14	12.83	8.98	4.97	1.31
4	Clerks	3.43	8.06	4.09	2.07	0.41
5	Service Workers and Shop and Market Sales Workers	24.33	41.74	44.76	39.33	20.75
6	Skilled Argicultural and Fishery Workers	21.29	31.32	44.90	51.46	36.85
7	Craft and Related Trades Workers	18.17	28.36	30.57	21.41	9.27
8	Plant and Machine Operators and Assemblers	13.28	25.69	19.74	10.12	3.19
9	Elementary Occupations	13.95	17.44	19.59	15.25	6.08
Total		**101.00**	**176.25**	**184.71**	**155.79**	**82.42**

Appendix 1: Risk by Occupation Comparison between the Modified Model (Tech and Trade) and the Original Model (Frey & Osborne, 2017)

Occupation (SOC-2010)	Rank (Tech&Trade)	Probability (Tech&Trade)	Probability (F&O)
First-Line Supervisors of Mechanics, Installers, and Repairers	1	0.182	0.003
First-Line Supervisors of Fire Fighting and Prevention Workers	2	0.183	0.004
Electrical Power-Line Installers and Repairers	4	0.216	0.097
Police and Sheriff's Patrol Officers	5	0.239	0.098
Industrial Production Managers	12	0.256	0.030
Captains, Mates, and Pilots of Water Vessels	13	0.257	0.270
First-Line Supervisors of Police and Detectives	15	0.261	0.004
Commercial Divers	16	0.270	0.180
Childcare Workers	18	0.271	0.084
Meeting, Convention, and Event Planners	22	0.280	0.037
Career/Technical Education Teachers, Secondary School	23	0.280	0.009
Industrial Engineering Technicians	37	0.303	0.030
First-Line Supervisors of Construction Trades and Extraction Workers	39	0.312	0.170
Farmers, Ranchers, and Other Agricultural Managers	43	0.315	0.047
First-Line Supervisors of Farming, Fishing, and Forestry Workers	46	0.320	0.570
Dentists, General	48	0.322	0.004
Athletic Trainers	49	0.324	0.007
Licensed Practical and Licensed Vocational Nurses	58	0.335	0.058
Diagnostic Medical Sonographers	60	0.337	0.350
Audiologists	65	0.340	0.003
Physical Therapists	68	0.343	0.021
Curators	72	0.349	0.007
Physician Assistants	74	0.354	0.140
Social and Community Service Managers	75	0.354	0.007
Photographers	80	0.360	0.021
Lodging Managers	81	0.360	0.004
Veterinarians	84	0.364	0.038
Architects, Except Landscape and Naval	88	0.366	0.018
Chief Executives	91	0.369	0.015
Dental Assistants	98	0.372	0.510
Medical Assistants	101	0.377	0.300
Instructional Coordinators	105	0.379	0.004
Pharmacists	110	0.385	0.012
Ship Engineers	112	0.388	0.041
Mechanical Engineering Technicians	119	0.394	0.380
Plant and System Operators, All Other	120	0.397	0.860
Sailors and Marine Oilers	124	0.400	0.830
Education Administrators, Elementary and Secondary School	126	0.400	0.005
Materials Engineers	127	0.401	0.021
Choreographers	128	0.401	0.004
First-Line Supervisors of Transportation and Material-Moving Machine and Vehicle Operators	136	0.408	0.029
Landscape Architects	137	0.408	0.045
Anthropologists and Archeologists	138	0.409	0.008
Music Directors and Composers	141	0.411	0.015
Optometrists	146	0.416	0.140
First-Line Supervisors of Retail Sales Workers	152	0.425	0.280
Dietitians and Nutritionists	161	0.431	0.004
Explosives Workers, Ordnance Handling Experts, and Blasters	168	0.433	0.480
Fine Artists, Including Painters, Sculptors, and Illustrators	171	0.434	0.042
Kindergarten Teachers, Except Special Education	179	0.438	0.150
Forest and Conservation Technicians	180	0.438	0.420
Actors	183	0.440	0.370
Musical Instrument Repairers and Tuners	186	0.442	0.910
First-Line Supervisors of Food Preparation and Serving Workers	189	0.442	0.630
Secondary School Teachers, Except Special and Career/Technical Education	190	0.443	0.008
Reservation and Transportation Ticket Agents and Travel Clerks	191	0.443	0.610
First-line Supervisor of Landscaping, Lawn Service, and Groundskeeping Workers	193	0.444	0.570
Graphic Designers	196	0.447	0.082
Writers and Authors	197	0.447	0.038
Sales Engineers	198	0.448	0.004
Self-Enrichment Education Teachers	199	0.448	0.130
Social and Human Service Assistants	203	0.453	0.130
Soil and Plant Scientists	204	0.453	0.021
Excavating and Loading Machine and Dragline Operators	205	0.456	0.940
Food Service Managers	206	0.457	0.083
Photographic Process Workers and Processing Machine Operators	208	0.457	0.990
Radio, Cellular, and Tower Equipment Installers and Repairs	209	0.457	0.930
Business Operations Specialists, All Other	212	0.461	0.230
Marketing Managers	214	0.462	0.014
Transportation, Storage, and Distribution Managers	216	0.463	0.590
Special Education Teachers, Secondary School	217	0.464	0.008
Public Relations and Fundraising Managers	218	0.464	0.015
Health Educators	220	0.466	0.045
Natural Sciences Managers	222	0.466	0.018

Occupation (SOC-2010)	Rank (Tech&Trade)	Probability (Tech&Trade)	Probability (F&O)
Network and Computer Systems Administrators	224	0.468	0.030
Middle School Teachers, Except Special and Career/Technical Education	225	0.468	0.170
Historians	228	0.470	0.440
Carpenters	232	0.475	0.720
Construction Managers	233	0.477	0.071
Education Administrators, Preschool and Childcare Center/Program	237	0.479	0.015
Urban and Regional Planners	238	0.480	0.130
Engineering Technicians, Except Drafters, All Other	239	0.481	0.240
Environmental Engineers	243	0.485	0.018
Lawyers	245	0.487	0.035
Mathematicians	248	0.489	0.047
Arbitrators, Mediators, and Conciliators	249	0.490	0.060
Correctional Officers and Jailers	251	0.492	0.600
Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	255	0.494	0.250
Insulation Workers, Mechanical	256	0.496	0.640
Medical and Clinical Laboratory Technicians	259	0.498	0.470
Geoscientists, Except Hydrologists and Geographers	260	0.498	0.630
Adult Basic and Secondary Education and Literacy Teachers and Instructors	267	0.503	0.190
Chemical Engineers	269	0.504	0.017
Industrial-Organizational Psychologists	270	0.507	0.012
Management Analysts	271	0.508	0.130
General and Operations Managers	274	0.512	0.160
Tank Car, Truck, and Ship Loaders	279	0.515	0.720
Bus Drivers, Transit and Intercity	282	0.518	0.670
Railroad Conductors and Yardmasters	286	0.520	0.830
Rolling Machine Setters, Operators, and Tenders, Metal and Plastic	287	0.520	0.830
Computer and Information Systems Managers	291	0.522	0.035
Medical and Health Services Managers	294	0.523	0.007
Electrical and Electronics Engineering Technicians	297	0.526	0.840
Bartenders	298	0.527	0.770
Broadcast News Analysts	300	0.527	0.067
Administrative Services Managers	303	0.534	0.730
Pipelayers	306	0.538	0.620
Interpreters and Translators	307	0.539	0.380
Electronics Engineers, Except Computer	309	0.542	0.025
Managers, All Other	311	0.546	0.250
Electrical and Electronics Installers and Repairers, Transportation Equipment	316	0.550	0.910
Real Estate Sales Agents	317	0.550	0.860
Automotive Glass Installers and Repairers	318	0.552	0.550
Librarians	319	0.553	0.650
First-Line Supervisors of Non-Retail Sales Workers	320	0.553	0.075
Surveyors	322	0.554	0.380
Judges, Magistrate Judges, and Magistrates	323	0.554	0.400
Printing Press Operators	329	0.561	0.830
Athletes and Sports Competitors	333	0.565	0.280
Brickmasons and Blockmasons	334	0.566	0.820
Fishers and Related Fishing Workers	336	0.571	0.830
Mining and Geological Engineers, Including Mining Safety Engineers	339	0.573	0.140
Veterinary Assistants and Laboratory Animal Caretakers	340	0.573	0.860
Financial Managers	342	0.574	0.069
Riggers	343	0.574	0.890
Jewelers and Precious Stone and Metal Workers	344	0.574	0.950
Stonemasons	349	0.577	0.890
Chemical Plant and System Operators	350	0.578	0.850
Gaming Managers	351	0.578	0.091
Opticians, Dispensing	353	0.580	0.710
Architectural and Civil Drafters	354	0.581	0.520
Executive Secretaries and Executive Administrative Assistants	358	0.582	0.860
Septic Tank Servicers and Sewer Pipe Cleaners	359	0.582	0.830
Zoologists and Wildlife Biologists	362	0.586	0.300
Painters, Construction and Maintenance	365	0.588	0.750
Coin, Vending, and Amusement Machine Servicers and Repairers	367	0.588	0.940
Paper Goods Machine Setters, Operators, and Tenders	369	0.591	0.670
Etchers and Engravers	371	0.594	0.980
Tour Guides and Escorts	373	0.594	0.910
Parts Salespersons	375	0.595	0.980
Industrial Engineers	376	0.596	0.029
Database Administrators	379	0.598	0.030
Electrical Engineers	380	0.600	0.100
Rail-Track Laying and Maintenance Equipment Operators	382	0.602	0.890
Hunters and Trappers	385	0.604	0.770
Chemists	386	0.604	0.100
Compensation and Benefits Managers	387	0.605	0.960
Astronomers	391	0.612	0.041
Agricultural Inspectors	394	0.613	0.940
Financial Examiners	400	0.618	0.170

Occupation (SOC-2010)	Rank (Tech&Trade)	Probability (Tech&Trade)	Probability (F&O)
Chemical Technicians	401	0.618	0.570
Upholsterers	403	0.619	0.390
Sheet Metal Workers	404	0.619	0.820
Fence Erectors	407	0.625	0.920
Pharmacy Technicians	410	0.627	0.920
Agricultural and Food Science Technicians	412	0.629	0.970
Stationary Engineers and Boiler Operators	416	0.634	0.890
Mathematical Technicians	423	0.639	0.990
Floor Sanders and Finishers	424	0.639	0.870
Eligibility Interviewers, Government Programs	429	0.646	0.700
Buyers and Purchasing Agents, Farm Products	437	0.650	0.870
Computer Systems Analysts	439	0.651	0.007
Door-to-Door Sales Workers, News and Street Vendors, and Related Workers	440	0.651	0.940
Computer Programmers	446	0.653	0.480
Painters, Transportation Equipment	451	0.658	0.690
Nuclear Power Reactor Operators	453	0.663	0.950
Receptionists and Information Clerks	456	0.665	0.960
Woodworking Machine Setters, Operators, and Tenders, Except Sawing	458	0.667	0.970
Refuse and Recyclable Material Collectors	462	0.671	0.930
Pump Operators, Except Wellhead Pumpers	467	0.674	0.900
Insurance Sales Agents	469	0.676	0.920
Glaziers	472	0.678	0.730
Barbers	473	0.678	0.800
Atmospheric and Space Scientists	475	0.680	0.670
Taxi Drivers and Chauffeurs	478	0.683	0.890
Models	480	0.685	0.980
Cooling and Freezing Equipment Operators and Tenders	481	0.685	0.930
Private Detectives and Investigators	487	0.687	0.310
Transportation Attendants, Except Flight Attendants	488	0.687	0.750
Engine and Other Machine Assemblers	490	0.688	0.820
Logging Equipment Operators	491	0.689	0.790
Software Developers, Systems Software	494	0.690	0.130
Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders	495	0.693	0.880
Shoe and Leather Workers and Repairers	496	0.694	0.520
Bill and Account Collectors	497	0.695	0.950
Adhesive Bonding Machine Operators and Tenders	499	0.699	0.950
Economists	500	0.701	0.430
Wellhead Pumpers	501	0.702	0.840
Print Binding and Finishing Workers	502	0.703	0.950
Cleaners of Vehicles and Equipment	505	0.707	0.370
Computer Numerically Controlled Machine Tool Programmers, Metal and Plastic	507	0.708	0.360
Hotel, Motel, and Resort Desk Clerks	509	0.711	0.940
Tapers	511	0.712	0.620
Financial Specialists, All Other	512	0.713	0.330
Tax Examiners and Collectors, and Revenue Agents	513	0.713	0.930
Tailors, Dressmakers, and Custom Sewers	519	0.722	0.840
Reinforcing Iron and Rebar Workers	521	0.724	0.900
Textile Knitting and Weaving Machine Setters, Operators, and Tenders	523	0.726	0.730
Customer Service Representatives	526	0.727	0.550
Packers and Packagers, Hand	528	0.728	0.380
Subway and Streetcar Operators	530	0.728	0.860
Combined Food Preparation and Serving Workers, Including Fast Food	536	0.739	0.920
Landscaping and Groundskeeping Workers	537	0.739	0.950
Dispatchers, Except Police, Fire, and Ambulance	539	0.741	0.960
Terrazzo Workers and Finishers	540	0.743	0.880
Baggage Porters and Bellhops	542	0.745	0.830
Financial Analysts	556	0.758	0.230
Computer Operators	558	0.758	0.780
Metal-Refining Furnace Operators and Tenders	563	0.760	0.880
Laborers and Freight, Stock, and Material Movers, Hand	564	0.760	0.850
Telemarketers	567	0.764	0.990
Grinding and Polishing Workers, Hand	569	0.765	0.970
Cutters and Trimmers, Hand	574	0.771	0.640
Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	575	0.771	0.960
Geological and Petroleum Technicians	577	0.772	0.910
Packaging and Filling Machine Operators and Tenders	583	0.775	0.980
Foundry Mold and Coremakers	595	0.785	0.670
Tax Preparers	596	0.785	0.990
Cooks, Fast Food	597	0.787	0.810
Butchers and Meat Cutters	604	0.793	0.930
Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	606	0.794	0.910
Cooks, Restaurant	610	0.796	0.960
Word Processors and Typists	612	0.800	0.810
Sawing Machine Setters, Operators, and Tenders, Wood	614	0.801	0.860
Proofreaders and Copy Markers	615	0.802	0.840
Food Cooking Machine Operators and Tenders	618	0.804	0.610

Occupation (SOC-2010)	Rank (Tech&Trade)	Probability (Tech&Trade)	Probability (F&O)
Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic	619	0.806	0.920
Fabric Menders, Except Garment	621	0.807	0.960
Food Batchmakers	622	0.807	0.700
Shampooers	623	0.809	0.790
Brokerage Clerks	625	0.812	0.980
Legal Secretaries	627	0.812	0.980
Couriers and Messengers	629	0.814	0.940
Payroll and Timekeeping Clerks	630	0.815	0.970
Animal Breeders	631	0.816	0.950
Graders and Sorters, Agricultural Products	632	0.817	0.410
Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	633	0.817	0.950
Janitors and Cleaners, Except Maids and Housekeeping Cleaners	634	0.818	0.660
Maids and Housekeeping Cleaners	636	0.819	0.690
Shoe Machine Operators and Tenders	637	0.819	0.970
Court, Municipal, and License Clerks	640	0.824	0.460
Appraisers and Assessors of Real Estate	641	0.825	0.900
Bakers	642	0.825	0.890
Umpires, Referees, and Other Sports Officials	643	0.826	0.980
Mixing and Blending Machine Setters, Operators, and Tenders	644	0.827	0.830
Team Assemblers	647	0.829	0.970
Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	652	0.834	0.960
Bookkeeping, Accounting, and Auditing Clerks	657	0.839	0.980
Medical Transcriptionists	658	0.839	0.890
Machine Feeders and Offbearers	676	0.868	0.930
Textile Bleaching and Dyeing Machine Operators and Tenders	679	0.874	0.970
Data Entry Keyers	680	0.876	0.990
Pressers, Textile, Garment, and Related Materials	682	0.880	0.810
Laundry and Dry-Cleaning Workers	684	0.891	0.710