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The impact of technological change on jobs and workforce structures

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ABSTRACT

Significant advancement in technologies such as artificial intelligence, machine-learning, and robotics has sparked broad debate amongst economists, futurists, and current business leaders regarding the future of jobs. The purpose of this research was to determine the impact of technological change on jobs and workforce structures. The study involved a structured collection, classification, and analysis of secondary data. It aimed to (i) determine a relationship between futures and labour economics literature, (ii) identify occupational groups with higher susceptibility to job automation, and (iii) project changes in workforce structure for various industries.

This study found that there is alignment between predicted probabilities of job automation and parameters of task routineness and task complexity from the routine-task-biased and complex-task biased technological change models. Routine-simple occupations are more susceptible to job automation, followed closely by nonroutine-simple occupations. Complex occupations are least susceptible. Stratum I occupations were more susceptible to job automation than occupations in higher strata of work. The projected change in workforce structures is highest for large hierarchical industries such as machine bureaucracies and divisionalised forms (Type 1 and 2 industries). Technological change will bring about both productivity improvements and technological anxiety. Business in affected industries must develop appropriate innovation and workforce strategies to manage this disruption.

KEYWORDS

technological change; future of jobs; automation; workforce structure

DECLARATION

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Chandon Bezuidenhout
6 November 2017

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1 INTRODUCTION TO RESEARCH PROBLEM

1.1 Technological Change, Employment and Future Workforce Structures

Significant advancement in technologies such as artificial intelligence, machine-learning, robotics, nanotechnology, 3D printing, genetics and biotechnology has sparked broad debate amongst economists, futurists and current business leaders regarding the future of jobs. Of specific interest is the extent to which technology will displace, modify or create future jobs (Arntz, Gregory, & Zierahn, 2017; Autor, 2015; Autor, Dorn, & Hanson, 2015; Frey & Osborne, 2017). A number of recent publications have predicted broad technological disruption that has the potential to completely displace specific labour, whilst others argue that technological change could bring about more high-quality creative work, promote entrepreneurship and create greater social freedom (Brynjolfsson & McAfee, 2014; Ford, 2015; Schwab, 2016; Susskind & Susskind, 2015).

In a widely cited futures paper, Frey and Osborne (2017) estimated that 47 percent of current US employment has a high probability of being automated over the next two decades. Despite being critiqued for overestimating the impacts of technological change (Arntz et al., 2017; Wajcman, 2017), this study has been used as the basis for extensive publications by research institutions, policy makers, trade journals, and consulting firms to provide government and business with insights regarding employment, skills and future workforce strategies (Deloitte, 2016; McKinsey Global Institute, 2017; Purdy & Daugherty, 2016; World Bank Group, 2016; World Economic Forum, 2016).

Academic research studying the impact of technological change in the field of labour economics has developed extensive technological change models for the United States (US) and other developed economies that explain shifts in employment and wages using historical employment data (Acemoglu & Autor, 2011; Arntz et al., 2017; Autor & Dorn, 2013; Berger & Frey, 2016; Caines, Hoffmann, & Kambourov, 2017; Goos, Manning, & Salomons, 2014; Ikenaga & Kambayashi, 2016). These models have evolved over time to explain the biases of technological change for specific occupations. Initial models highlighted technological change biases around whether workers were skilled or unskilled (Acemoglu & Autor, 2011; Vivarelli, 2014, 2015). This was subsequently refined to consider the routineness of tasks for each occupation (Autor & Dorn, 2013). More recently, these technological change models were redefined to consider the complexity of tasks at an occupational level (Caines et al., 2017).

Whilst these models contribute towards understanding historical trends in employment and wage data in response to technological change, they cannot, nor do they aim to predict changes in future occupations and workforce structures. Frey and Osborne (2017), on the other hand, intended to quantify the impact of recent technological change, such as machine learning, artificial intelligence, and mobile robotics, on the future of employment. This study made use of a task classification model from labour economics literature, but adopted a methodology from offshoring literature to predict the probability of job automation in the future.

Despite the common classification processes used in both literature bases, few attempts have been made to reconcile and assess predictions of future employment with findings and parameters established from technological change models. In other words, are the findings from futures literature consistent with the technological change biases observed from historical shifts in employment and wage data? To what extent do parameters such as task routineness and task complexity explain the probability of job automation? Is technological change biased towards jobs that are considered routine, simple, nonroutine or complex? These considerations gave rise to the first theoretical research question: what is the relationship between the probability of job automation and the routineness and complexity of tasks? (Research Question 1).

Several authors have utilised models that quantify the impact of technological change and job automation at an economic level (Acemoglu & Autor, 2011; Autor & Dorn, 2013; Michaels, Natraj, & Van Reenen, 2014; Rodrik, 2016). However, to date, these studies have been of little use to business leaders and decision-makers. This is primarily attributed to three shortcomings. Firstly, most labour economics studies involve extensive analysis of historical employment and wage data over decades. This yields significant insight into how technology has changed employment and the business landscape. However, it does little to inform business leaders on how technology may change employment and the business landscape in the future. Secondly, whilst most of the analysis is done at a task and occupational level, the results are often aggregated at an economy-level, and the implications at an industry level is not considered. Thirdly, the relative change in workforce structure within different industries is not considered. Thus, business leaders gain no insight into how technology may impact occupations across different organisational levels within their industry or firm. This hinders the development of appropriate workforce strategies and gives rise to concepts such as “technological unemployment” and “technological anxiety” (Mokyr, Vickers, & Ziebarth, 2015).

Of specific interest is the extent to which various occupations will be substituted and complemented by technology or machines. How will the work of operators, supervisors, professionals, and managers change? What impact will this have on the workforce structures of different industries? Organisational design literature in the form of stratified system theory (Jaques, 1986, 2016), together with recent theoretical frameworks for assessing the hierarchical structures of firms (Caliendo, Monte, & Rossi-Hansberg, 2015; Caliendo & Rossi-Hansberg, 2012; Mintzberg, 1980; Tåg, 2013) provide a useful lens for classifying different occupations into strata of work that represent workforce structures. This gives rise to two additional research questions: “Are specific strata of work within a workforce structure more susceptible to job automation?” (Research Question 2) and “What is the projected change in workforce structure from 2016 to 2036 at an industry level?” (Research Question 3). This study aims to address these three research questions.

1.2 Purpose of the Research

The field of this study is labour economics and technological change.

The purpose of this research is to assess the impact of technological change on jobs and future workforce structures, i.e. how is technological change such as artificial intelligence, machine learning, and robotics changing the demand for specific jobs? Is the impact of technological change biased towards jobs that are considered routine, simple, nonroutine, or complex? Is the impact of technological change biased towards specific strata of work within the organisation? How does this change the workforce structure of different industries in the future?

This study involves (i) evaluating the relationship between the probability of job automation and the routineness and complexity of tasks for various occupations; (ii) evaluating whether routine-simple, nonroutine-simple, routine-complex or nonroutine-complex occupations are more susceptible to job automation, (iii) evaluating whether specific strata of work, i.e. Stratum I, II, III, IV or V, are more susceptible to job automation, and (iv) applying the probability of job automation to employment data and industry structures using employment, industry and organisational classification systems to project changes in workforce structure from 2016 to 2036 for various industries.

By evaluating the relationship between the probability of job automation and the routineness and complexity of tasks for various occupations, it would be possible to determine the extent to which task routineness and task complexity explain variance in

the probability of job automation. A weak relationship between these parameters would highlight that the probability of job automation cannot be predicted using measures of task routineness and task complexity. This would indicate divergent findings between futures and labour economics literatures. A strong relationship between these parameters would not only demonstrate alignment between the findings of futures literature and labour economics literature, but would also provide a basic model. Such a model would allow one to predict, to a certain extent, the probability of job automation using the task routineness and task complexity for a specific occupation. Furthermore, classification of occupations as routine-simple, nonroutine-simple, routine-complex and non-routine complex, allows for the relative probabilities of job automation to be determined for each group. Thus, the findings of this study to be extrapolated and applied to other occupations. Business will gain insight into how specific occupations may be impacted by technological change.

Classification of occupations based on strata of work, could furthermore demonstrate insight as to whether technological change is biased towards specific levels within a workforce structure (i.e. Stratum I, II, III, IV or V). Provided there is a significant difference in the probability of job automation of specific strata, “stratum of work” could be introduced in the above-mentioned model.

By illustrating the projected change in workforce structures between today (2016) and the future (ca. 2036), for different industries, business will gain insight into appropriate business and workforce strategies to deal with technological change of jobs. Business will gain insight into the specific industries that will undergo significant change in workforce structure, and can thus put appropriate strategies in place to manage the change process.

1.3 Scope of the Research

The scope of the research is characterised as follows:

Firstly, whilst most studies (Acemoglu & Autor, 2011; Autor & Dorn, 2013) make use of extensive historical data to explain the impact of technological change on jobs, the scope of this study is forward-looking. Consequently, a measure of the probability of job automation from futures literature (Frey & Osborne, 2017), together with US employment data was used to estimate the impact of technological change on specific occupations.

Secondly, whilst this research has broad applicability to different geographical areas, economies and industries, the scope will be limited to industries within the US economy. Thus, the US and its industries were used as proxy for developed economies.

Thirdly, an industry consists of a multitude of jobs with different task structures and skills requirements. Literature predominantly relies on occupational descriptions in the Occupational Information Network (O*NET) database (Autor & Dorn, 2013; Caines et al., 2017; Deming, 2017; Frey & Osborne, 2017) or the Standard Occupational Classification (SOC) system. These databases have been used to develop measures of task routineness (Autor & Dorn, 2013) and task complexity (Caines et al., 2017) of various generic occupational titles. To ensure that the findings of this study are comparable and have broader applicability and reliability, the same database was used in the present study. In cases where various data sets were combined, the data was cross-referenced at an occupational level.

1.4 Research Questions

The following research questions aim to address this topic:

1. **Research Question 1:** What is the relationship between the probability of job automation and the routineness and complexity of tasks?
 - a. **Research Question 1a:** Are specific occupational groups (routine-simple, nonroutine-simple, routine-complex and nonroutine-complex) more susceptible to job automation than others?
2. **Research Question 2:** Are specific strata of work within a workforce structure more susceptible to job automation?
3. **Research Question 3:** What is the projected change in workforce structure from 2016 to 2036 at an industry level?

1.5 Theoretical and Business Implications of the Research

This research aims to contribute to the academic debate on how technological change will impact jobs and workforce structures. It aims to establish whether there is a relationship between the probability of job automation (from futures literature) and technological change model parameters such as task routineness and task complexity (from labour economics literature) for various occupations. It furthermore aims to address the theoretical question of how technological change will impact jobs and workforce structures for various industries.

By understanding the impact of technological change on jobs and workforce structures, business will be better equipped to formulate appropriate business, workforce and human resource strategies for technological change across different industries. These strategies may, for example, include investment in basic and higher education to improve local skills development; the introduction of technical and vocational education training (TVET) programmes; development of reskilling programmes of existing employees; importing of skills; outsourcing of skills; and/or promotion of lifelong learning and adult learning initiatives (World Economic Forum, 2016).

The following chapter outlines a review of recent academic literature to demonstrate the academic basis for the research. It also provides insight into the current theories, hypotheses and debates that assisted in framing the research questions.

2 LITERATURE REVIEW

2.1 Introduction

The purpose of this research is to assess the impact of technological change on jobs and workforce structures. The following literature survey aims to demonstrate the academic basis for the research and provides insight into the current theories, hypotheses and debates that assisted in framing the research questions. This literature survey is structured as follows:

Firstly, a review of recent academic literature which aimed to predict the impact of technological change on jobs is outlined. This highlights the current debates in academic literature concerning the impact of technological change on jobs. Models that aimed to predict the impact of technological change on jobs are outlined, together with factors that could affect the extent and pace of technological change.

Secondly, a review of labour economics literature describes various Classical-Neoclassical and Keynesian-Schumpeterian compensation mechanisms. This highlights how different types of technological change impact employment, how various compensation mechanisms counter-balance the effect on employment, and how these compensation mechanisms interact based on firm-level and industry-level empirical evidence.

Thirdly, a review of labour economics literature outlines three technological change models that discussed biases and shifts in historical employment and wage data. These technological change models quantified the substitutionary effect of technology on employment and wages using parameters related to occupational skills, task routineness and task complexity.

Fourthly, a review of organisational design literature provides a common framework for classifying occupations into workforce structures across various industries. A theory related to the hierarchical structure of firms, together with stratified systems theory is introduced, which allows for occupations to be classified into strata of work based on the time span of discretion, work complexity, and cognitive mechanisms that each role requires.

Lastly, an overview of the main findings leading to the research questions and research methodology is presented.

2.2 Predicting the Impact of Technological Change on Jobs

Predictions of technological change on employment can be traced to economic literature rooted in the Ricardian conceptualization and Keynesian prediction of widespread “technological unemployment” (Keynes, 1931; Ricardo, 1821). Keynes predicted that man’s ability to discover new ways to economise labour would one day exceed the rate at which new uses for labour are found, ultimately resulting in technological unemployment. Throughout economic history this process of creative destruction coupled with technological development has been demonstrated (Schumpeter, 1927).

However, significant technological advancement seldom occurs in the absence of “technological anxiety” (Mokyr et al., 2015). Two such anxieties are (i) the broad substitution of labour by machines that could lead to technological unemployment and inequality in the short run, even if the effects in the long-run are positive; and (ii) the resulting dehumanising effect, which could hold severe moral implications for human welfare. These anxieties are not new. In 1586 Queen Elizabeth I refused to grant a patent for a stocking frame knitting machine, fearing that it would deprive her subjects of employment, “...thus making them beggars” (cited in Acemoglu & Robinson, 2012, p. 182). Other famous examples include the Lancashire riots (1779) and the Luddite riots (between 1811 and 1816) in response to mechanisation in the cotton manufacturing and wool-finishing industries. However, as Amara’s law suggests, the effects of technology are often overestimated in the short-run, but underestimated in the long run.

Today’s technological advancement, particularly in the field of robotics, connectivity and cloud robotics has been likened to the “Cambrian Explosion” – a short period in history of earth that saw rapid diversification of life, most notably attributed to the evolution of vision. This Cambrian Explosion in robotics promises to improve human life considerably, but could also be a disruptive economic force when it comes to productivity and human employment (Pratt, 2015). Much like the industrial and digital revolutions, the forthcoming artificial intelligence (AI) revolution is predicted to have significant impact on societies, life, employment and business (Makridakis, 2017). Makridakis (2017) predicted that the AI revolution will aim to “substitute, supplement and amplify practically all tasks currently performed by humans, becoming in effect, for the first time, a serious competitor to them” (Makridakis, 2017, p. 47). Some authors considered the possibility of economic singularity: “The idea that rapid growth in computation and artificial intelligence will cross some boundary of Singularity after which economic growth will accelerate sharply as an ever-accelerating pace of improvement cascade through the economy” (Nordhaus,

2015, p. 1), However, Nordhaus (2015) found that this (tentatively) failed five of the seven demand-side and supply-side substitution tests.

Analysis of the historical impact of technology and robots on employment and wages in the last three centuries, together with studies that illustrate the elasticity of substitutions between human and robotic labour, concluded that advancement in artificial intelligence and robotics will have a large and robust negative effect on employment and wages (Acemoglu & Restrepo, 2016; DeCanio, 2016; Gregory, Salomons, & Zierahn, 2016). Sachs, Benzell, and LaGarda (2015) referred to this as the “paradox of robotic productivity”. Innovations that give rise to increases in productivity of robotic investment, are likely to lower both robotic and total production. This, through lowering of human wages, will result in a decline in the well-being of future generations (Sachs et al., 2015).

In a widely cited futures paper, Frey and Osborne (2017) estimated that 47 percent of current US employment has a high probability of being automated over the next two decades. These findings have sparked wide-set debate amongst economists, policy-makers, futurists and business leaders about the extent to which technology will displace, modify or create the future jobs (Autor, 2015; Autor & Dorn, 2013; Autor et al., 2015; Frey & Osborne, 2017). Despite being critiqued for overestimating the impact of technological change (Arntz et al., 2017; Autor, 2015; Wajcman, 2017), this study has been used as the basis for extensive publications and the development of models that aim to predict the impact of technological change on jobs (Deloitte, 2016; McKinsey Global Institute, 2017; Purdy & Daugherty, 2016; World Bank Group, 2016; World Economic Forum, 2016).

In response to wide-spread predictions of technological disruption of jobs, it has been argued that the substitution effect of automation on labour is often overstated, whilst the strong complementary effect between automation and labour are ignored. This complementary effect increases productivity, raises wages, and increases the demand for labour (Autor, 2015). Considering recent and future advances in artificial intelligence and robotics, Autor (2015) predicted that computers would both substitute workers that perform routine codified tasks, and complement skilled workers by enhancing problem-solving skills, adaptability and creativity.

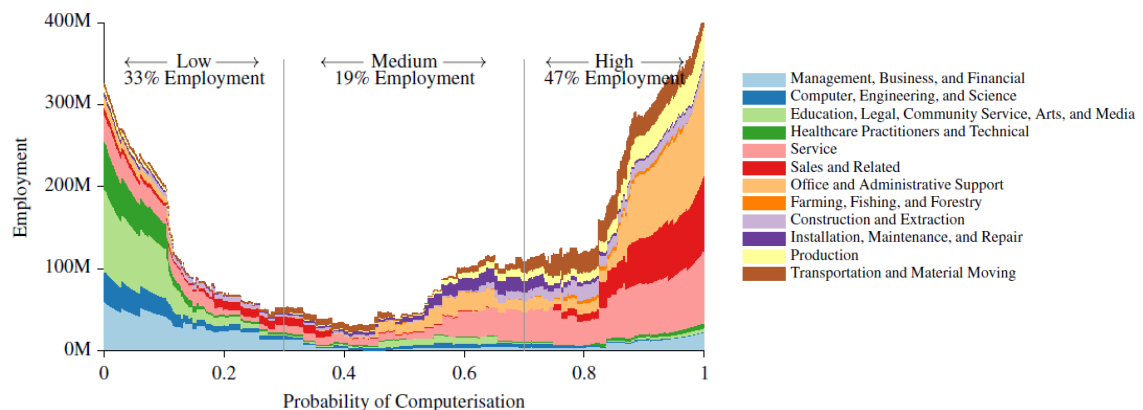
2.2.1 Models that Predict the Impact of Technological Change on Jobs

A number of models have been developed with the aim to predict the impact of technological change on jobs. These models were generally based on skills, capabilities

and traits that are likely to be automated in the future. Analysis was done at an occupational level and the results were aggregated at an economy level.

With insights from machine learning and robotics, Frey and Osborne (2017) adapted a task categorisation model from Autor, Levy and Murnane (2003), to predict the probability of job automation in the US. Their model took into consideration typical bottlenecks to job automation, namely, perception and manipulation, creative intelligence, and social intelligence. The authors used a Gaussian process classification model to calculate the probability of job automation for 702 detailed occupations in the US. This model estimated that 47 percent of current US employment has a high probability of being automated over the next two decades. Nineteen percent of US employment was found to have a medium probability of job automation ($0.3 < p < 0.7$) and 33 percent of US employment was considered to be non-automatable ($p < 0.3$). Figure 1 summarises the employment effects of job automation across 702 occupations in various industries within the US economy.

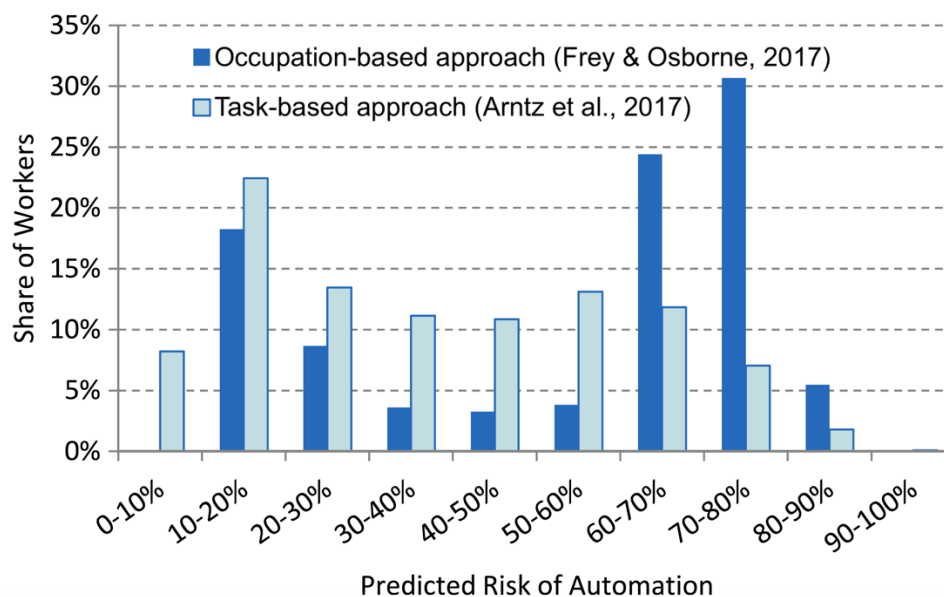
Figure 1: US employment affected by job automation (adapted from Frey & Osborne, 2017, p. 267)



Frey and Osborne's (2017) model predicted that the majority of workers in transportation and logistics, office and administrative support, production, and service occupations were highly susceptible to automation. It furthermore predicted that job automation would primarily be confined to low-skilled occupations, whilst high-skilled occupations were found to be relatively resistant to automation. These findings have sparked wide-set debate amongst economists, policy-makers, futurists, and business leaders about the extent to which technology will displace, modify or create the future jobs (Autor, 2015; Autor & Dorn, 2013; Autor et al., 2015; Frey & Osborne, 2017).

Arntz, Gregory and Zierahn (2017) disagreed with Frey and Osborne's (2017) occupation-based approach, and argued that a task-based approach was more appropriate. The authors reconstructed Frey and Osborne's (2017) model, but instead of considering job automation bottlenecks at an occupational level, they used individual-level task survey data and task structure data to estimate the probability of job automation. Using this approach, Arntz et al. (2017) predicted that approximately nine percent of US employment has a high probability of job automation, as opposed to the 47 percent cited by Frey and Osborne (2017). However, the authors failed to discuss the significantly higher percentage of US employment with a moderate probability of job automation. See Figure 2. Using the same criteria as Frey and Osborne (2017), i.e. $0.3 < p < 0.7$, the percentage of US employment with a moderate probability of job automation is estimated to be 66 percent – significantly higher than the 19 percent predicted by Frey and Osborne (2017). A total of 25 percent of US employment was estimated to be non-automatable ($p < 0.3$).

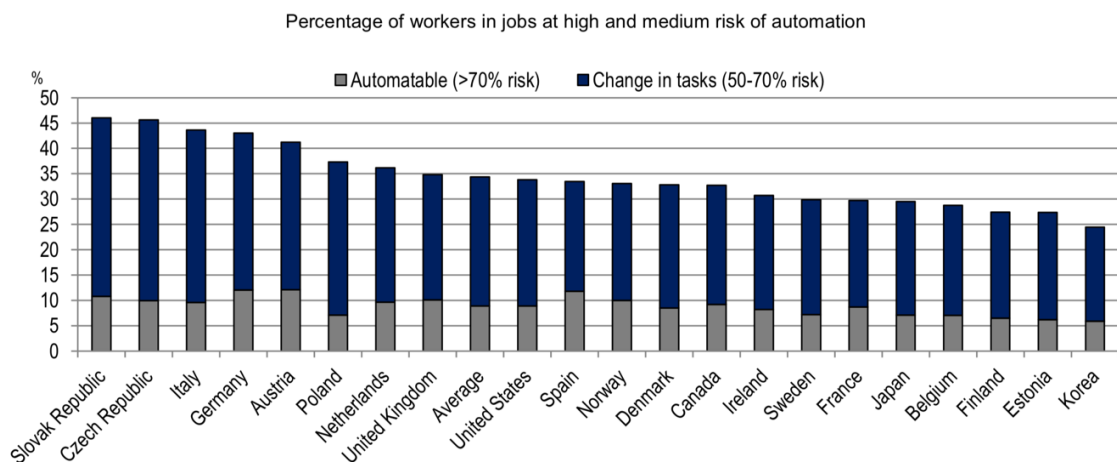
Figure 2: US employment affected by job automation: occupation-based approach vs. task-based approach (adapted from Arntz et al., 2017, p. 158)



Based on this analysis, the automation potential was found to be lower for jobs that involved presenting, training, programming, and influencing others. The automation potential was found to be higher for jobs that involve selling, using fingers and hands, and exchanging information. The authors argued that this was aligned with task-based literature that suggested routine tasks were subject to automation, whilst interactive and cognitive tasks were less susceptible to automation (Acemoglu & Autor, 2011).

Arntz, Gregory, and Zierahn (2016) used the same model to estimate the employment automation potential across 21 developed countries. It was found that the percentage of workers in occupations with a probability of job automation greater than 0.5 ranged between 25 and 46 percent across the 21 countries considered. See Figure 3. Differences across countries were attributed to different workplace organisation structures, technology investment, and educational levels (Arntz et al., 2016).

Figure 3: Percentage of workers affected by automation across 21 developed countries (Arntz et al., 2016; OECD, 2016, p. 2)

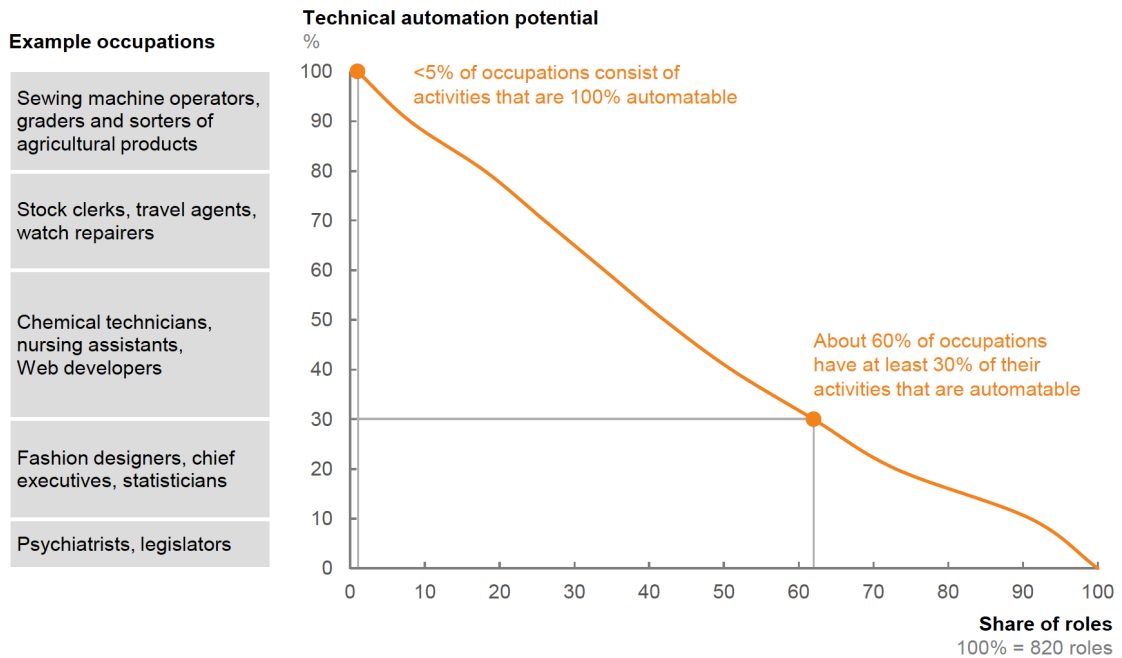


David (2017) applied a similar model to that of Frey and Osborne (2017) for the Japanese labour market to test whether the impact of technological change was more pronounced given the country's higher level of technological diffusion, and its major role in the production of innovations. Similar automation bottlenecks, namely perception and manipulation, creative intelligence, social intelligence, and appreciation were used. The author found that 56 percent of jobs in Japan are highly susceptible to job automation ($p > 0.7$). Approximately 25 percent were found to be at moderate risk of job automation and 19 percent were considered non-automatable. No significant differences were found based on gender, but temporary and part-time occupations were found to be more susceptible than regular occupations.

Building on Frey and Osborne's (2017) study, McKinsey Global Institute (2017) assessed the technical potential for automation across 2 000 work activities. The authors used five capability groups, namely sensory perception, cognitive capabilities, natural language processing, social and emotional capabilities, and physical capabilities. It was estimated that 50 percent of activities across all occupations could be automated using existing demonstrated technology. Whilst few occupations (less than five percent) were found to

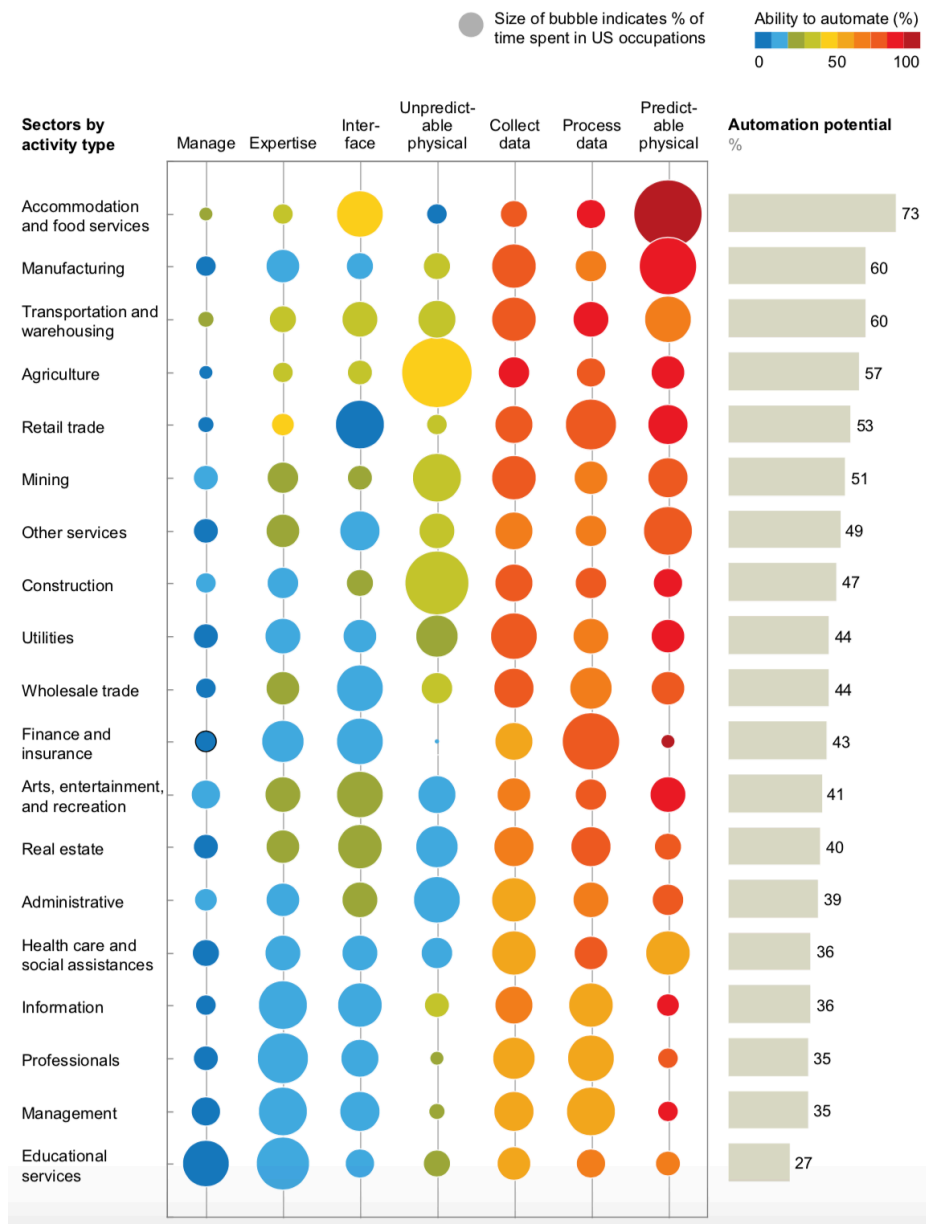
be fully automatable, approximately 60 percent of occupations comprised of at least 30 percent automatable activities. See Figure 4.

Figure 4: Technical automation potential of 820 US occupations (McKinsey Global Institute, 2017, p. 5)



Work activities that involve performing physical activities in predictable environments, processing data, and collecting data were found to have the highest technical potential (probability) for automation. Other activities such as managing and developing people, applying expertise to decision making, planning, and creative tasks, interfacing with stakeholders, and performing physical activities in unpredictable environments showed significantly lower potential for automation (McKinsey Global Institute, 2017). The automation potential for per activity type was determined for various US industries. These are given in Figure 5.

Figure 5: Technical potential for automation across US industries (McKinsey Global Institute, 2017, p. 7)



Industries where the majority of activities involve predictable physical activities, data processing, and data collection were found to have a higher automation potential. These included industries such as accommodation and food services, manufacturing, transportation and warehousing, and retail trade. Industries where the majority of activities include the managing and developing people, applying expertise to decision making, planning and creative tasks, and interfacing with stakeholders were found to have lower automation potential. These included industries such as healthcare and social assistance, professionals services, management of companies and businesses, and educational services (McKinsey Global Institute, 2017).

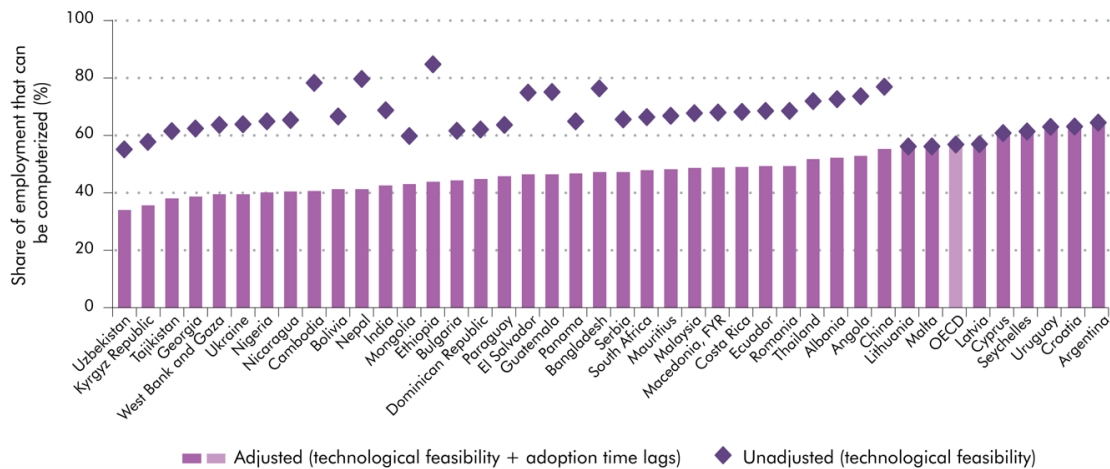
2.2.2 Factors Affecting the Extent and Pace of Technological Change

A number of studies showed that the impact of technological change on jobs is likely to be mitigated by government intervention and policy changes (David, 2017; Kim, Kim, & Lee, 2017). Using future scenario simulation techniques, Kim, Kim and Lee (2017) predicted that new technical jobs would be created. These jobs would constitute a significant portion of future employment in developed economies. Furthermore, it was anticipated that government-led initiatives and modification of education systems would prevent an employment crisis.

Conti and Sulis (2016) argued that technology adoption is a function of the workforce skills level and capacity of business to adjust to technological change. Since developed economies are characterised by advanced industries, these economies generally demonstrate faster technology adoption. Thus, these economies are more susceptible to technological change in areas where job automation is possible. Furthermore, higher wages in developed economies make job automation economically viable (World Bank Group, 2016). Emerging economies, on the other hand, have less developed industries, slower technological adoption, and lower wage structures (Ugur & Mitra, 2017). Depending on the type and relative size of industries in the country, the scope for technological change in an emerging economy is generally large. However, as a result of slow technological adoption, the impact of technological change is likely to be less, slower or significantly delayed (Conti & Sulis, 2016; World Bank Group, 2016).

Using Frey and Osborne's (2017) methodology, the World Bank (2016) estimated the share of employment susceptible to automation for a range of emerging economies. The authors adjusted for a slower pace of technology adoption and lower wages in these economies. See Figure 6.

Figure 6: Estimate share of employment susceptible to automation in the emerging economies (World Bank Group, 2016, p. 129)



The model presented by McKinsey Global Institute (2017) considered five factors that could impact the pace and extent of automation. These factors were: the technical feasibility of technology, the cost of developing and deploying technological solutions, labour market dynamics, economic benefits, and regulatory and social acceptance. This model predicted that automation would be a global force, but because of significant uncertainty around timing, the adoption of technology would take place of over decades.

Using a foresight scenario planning process, Rhisiart, Störmer and Daheim (2016) determined four probable scenarios on the future of work in the United Kingdom. These scenarios were Force Flexibility, The Great Divide, Skills Activism, and Innovation Adaptation. See Table 1. These scenarios were based on potential societal, technological, economic, environmental, resource, regulatory and political disruptions, including artificial intelligence and robotics.

Table 1: Four scenarios for the Future of Work 2030 (adapted from Rhisiart et al., 2016, p. 6)

SCENARIO	DESCRIPTION
Forced Flexibility (business-as-usual)	Greater flexibility in business, together with incremental innovation result in economic growth at the expense of low skilled jobs
The Great Divide	Robust growth in high-tech companies result in a social and economic divide between the 'haves' and 'have nots'.
Skills Activism	Technological innovation leads to job automation and large-scale job losses, followed by political pressure to create government-led skills programmes.
Innovation Adaptation	Implementation of innovative technology improved productivity in stagnant economies

2.3 The Complementary Effect for Technological Change on Jobs

In response to the wide-spread prediction regarding the technological disruption of jobs, it has been argued that the substitutionary effect of automation on labour is often overstated, whilst the strong complementary effect between automation and labour is ignored (Autor, 2015). This complementary effect increases productivity, raises wages, and alters demand for labour. Autor (2015) argued that "...the interplay between machines and humans comparative advantages allows computers to substitute for workers in performing routine, codified tasks while amplifying the comparative advantage of workers in supplying problem solving skills, adaptability, and creativity" (Autor, 2015, p. 5). The following sections outline the complementary effects of technological change together with the compensation mechanisms of employment.

Technological change can be classified as either product innovation or process innovation. Product innovation relates to the introduction of new goods and services, whilst process innovation relates to the implementation of a new or improved production or delivery methods. Various studies agreed that product innovation has a net positive impact on employment, whilst process innovation reduces either labour input or capital input within an industry (Bogliacino, Piva, & Vivarelli, 2012; Harrison, Jaumandreu, Mairesse, & Peters, 2014; Lachenmaier & Rottmann, 2011; Van Reenen, 1997). Microeconomic theory suggests that process innovation introduces either an upward shift in the short-term production function, or a downward movement of the isoquant (Vivarelli, 2013, 2014, 2015). However, compensation theory suggests that the direct impact of process innovation is often counterbalanced by economic forces that compensate for the reduction of employment. Table 2 summarises a number of Classical-Neoclassical and Keynesian-Schumpeterian compensation mechanisms (Calvino & Virgillito, 2017; Vivarelli, 2014, 2015).

Table 2: Compensation mechanism for employment as a result of technological change (adapted from Calvino & Virgillito, 2017; Vivarelli, 2014, 2015)

Economic Classification	Compensation Mechanism	Description
Classical-Neoclassical Mechanisms	<i>New machines</i>	Technological progress introduces new machines, possibly displacing labour. Labour is shifted to the machine-producing industry (sectorial shift), thus counterbalancing the initial detrimental impact on employment.
	<i>Decrease in prices</i>	New technologies enable greater productivity, displace labour and reduce production costs. In a competitive market, this results in decreased prices. Lower prices stimulate higher demand, which in-turn results in increased employment.
	<i>Decrease in wages</i>	New technology displaces labour, followed by a price adjustment in the labour market. Assuming free competition and full substitution of labour and capital (neoclassical model), a decrease in wages will increase the demand for labour.
	<i>New investments</i>	When competitive convergence is not instantaneous, entrepreneurial innovators can earn greater profit in the period between implementing new technologies and the time when prices decrease. These profits are in-turn invested to create new production and jobs.
Keynesian-Schumpeterian Mechanisms	<i>Increase in incomes</i>	Technological progress results in increased income and higher consumption for skilled staff. This increase in demand leads to a rise in employment.
	<i>New products</i>	The introduction of new products and economic branches stimulates consumption, which translates into higher demand and employment. However, new products may <i>cannibalise</i> old products, cause <i>market expansion</i> , or erode competitors' market share (<i>business stealing</i>).

The Classical-Neoclassical mechanisms explain how the introduction of new machines, a decrease in prices, a decrease in wages, and new investments can compensate for labour. Likewise, the Keynesian-Schumpeterian mechanisms outline how an increase in income, and the introduction of new products translate into an increase in employment. However, from Table 2 it is clear that the interactions of the compensation mechanism are complex, far from deterministic, and subject to limitations (Calvino & Virgillito, 2017). Furthermore, the net impact of the compensation mechanisms is a function of the institutional setting and factors such as demand elasticity, degree of competition, capital-labour substitution, and demand expectations within the specific system considered (Vivarelli, 2014, 2015).

Firm-level empirical evidence largely supported a positive relationship between technological change and employment, as measured through Research and Development intensity and patent counts. This particularly held true for high-growth firms in the high-technology sector (Bogliacino, 2014; Calvino & Virgillito, 2017; Evangelista & Vezzani, 2012; Harrison et al., 2014; Lachenmaier & Rottmann, 2011; Triguero, Córcoles, & Cuerva, 2014; Van Roy, Vertesy, & Vivarelli, 2015). A summary of the effects of product and process innovation on employment at firm level and industry level is given in Table 3 (Calvino & Virgillito, 2017).

Table 3: Effects of product and process innovation of employment at firm and industry level (adapted from Calvino & Virgillito, 2017)

	Product Innovation	Process Innovation
Firm Level	POSITIVE Product compensation mechanism	MIXED Price compensation mechanism
Industry Level	NO EFFECT - POSITIVE Business Stealing (No Effect) Market Expansion (Positive)	MIXED Sectorial Shift (Negative) Technology Diffusion (Positive)

Table 3 illustrates that product innovation at firm level generally has a positive impact on employment, whilst the impact of process innovation is mixed due to price compensation mechanisms. At industry level, product innovation has no effect on employment in the case of *business stealing*, but has a positive impact on employment in the case of *market expansion*. The impact of process innovation on employment at an industry level is mixed due to counterbalance of a *sectorial shift* (new machines) mechanism (which has a negative impact on employment) and a *technology diffusion* mechanism (which has a positive impact on employment) (Calvino & Virgillito, 2017).

2.4 Technological Change Models in Labour Economics

The impact of technological change on jobs is a function of the task that make out a specific job, and the degree to which technology will complement or substitute workers performing those tasks (Autor & Dorn, 2013). Tasks are characterised by a set of skills, i.e. cognitive, analytical, socio-emotional and manual skills (Acemoglu & Autor, 2011). The relationship between technology and skills for specific jobs is thus a function of the ease of automation and ease of complementarity (Acemoglu & Autor, 2011). See Figure 7.

Figure 7: Interaction between technology and skills (adapted from Acemoglu & Autor, 2011; World Bank Group, 2016)

		EASE OF COMPLEMENTARITY (labour-changing technology)	
		HIGH (non-manual skills)	LOW (manual skills)
EASE OF AUTOMATION (labour-saving technology)	HIGH (routine tasks)	<i>Bookkeepers Proofreaders Clerks</i>	<i>Machine operators Cashiers Typists</i>
	LOW (non-routine tasks)	<i>Researchers Teachers Manager</i>	<i>Cleaners Hairdressers Street vendors</i>

A number of technological change models were developed that aim to explain changes in employment and wage shifts over time in response to technological change. The most significant models were the skill-biased technological change model (SBTC), the routine-biased technological change model (RBTC), and the complex-task biased technological change (CBTC). The following section outlines the development and characteristics of these technological change models.

2.4.1 Skill-biased Technological Change Model

The skill-biased technological change (SBTC) hypothesis (also referred to as canonical model) was presented in the seminal work of Zvi Griliches (1969) and Finis Welch (1970). The basic premise of this model was that technological change is skill-biased (Ugur, Churchill, & Solomon, 2017; Ugur & Mitra, 2017; Vivarelli, 2013, 2014, 2015), i.e. it replaces tasks traditionally performed by unskilled workers, with new tasks that demand skilled workers. According to this model, new technologies rely on skilled workers for it to be effectively and efficiently implemented, and the demand for labour would shift in favour of more skilled workers (Acemoglu & Autor, 2011; Vivarelli, 2014, 2015). This was echoed by historical employment trends and the evolution of new jobs that call for greater socio-emotional and higher-order cognitive skills (Cunningham & Villaseñor, 2016; Deming, 2017).

A direct consequence of the SBTC hypothesis is that a “human resource constraint” may exist (Amendola & Gaffard, 1988). In other words, an insufficient number of skilled workers may limit the adoption and diffusion of new technology, and the pursuit of full

employment. Thus, technological change has the ability to generate unemployment amongst unskilled workers, unless suitable workforce strategies are in place (Vivarelli, 2014, 2015).

The SBTC model, however, failed to explain the evolution of inequality and job polarization, i.e. growth in both high-skilled and low-skilled jobs at the expense of middle-skilled jobs. This phenomenon was observed across several developed economies such as the US (Autor & Dorn, 2013; Autor, Katz, & Kearney, 2006, 2008), United Kingdom (Goos & Manning, 2007), Japan (Ikenaga & Kambayashi, 2016; Jung & Mercenier, 2014) and Europe (Goos, Manning, & Salomons, 2009; Goos et al., 2014; Michaels et al., 2014; Spitz-Oener, 2006). The SBTC also did not account for the rapid diffusion of new technologies that directly substituted capital for labour around tasks performed by moderately skilled workers (Acemoglu & Autor, 2011).

2.4.2 Routine-biased Technological Change

The shortcomings of SBTC model gave rise to the development of the routine-biased technological change (RBTC) hypothesis (Acemoglu & Autor, 2011; Autor & Dorn, 2013; Beaudry, Green, & Sand, 2016; Cortes, 2016; Goos et al., 2014; Jung & Mercenier, 2014). This model was effectively used to illustrate how the introduction of computers in the late 1980s complemented nonroutine cognitive tasks (abstract, creative, problem-solving and coordinating tasks) and substituted routine tasks, whilst little impact was observed on nonroutine manual tasks. Thus, the job polarization effect observed in developed economies was explained. In the RBTC model, jobs were classified on the basis of routineness using job task requirements from the Dictionary of Occupational Titles (DOT) database and a Routine Task Intensity (RTI) index (Autor & Dorn, 2013; Autor et al., 2015; Goos et al., 2014).

A seminal study by Autor, Levy and Murnane (2003) investigated how automation altered job skill demand in the US over the period of 1960 to 1998. It was determined that automation reduced labour input of routine manual and cognitive tasks, whilst increasing labour input for nonroutine cognitive tasks across different industries, occupations, and educational levels. Autor and Dorn (2013) applied a similar methodology, but incorporated additional measures of abstract task intensity, creative task intensity, and routine task intensity. Using US employment and wage data from 1980 to 2005, the authors illustrated how computerisation substituted low-skilled workers performing routine tasks, and complemented highly educated workers performing abstract, creative,

problem-solving, and coordinating tasks. This highlighted how the adoption of technology within routine-centric US labour markets caused low-skill workers to reallocate into service occupations, thus resulting in polarization of the US labour market.

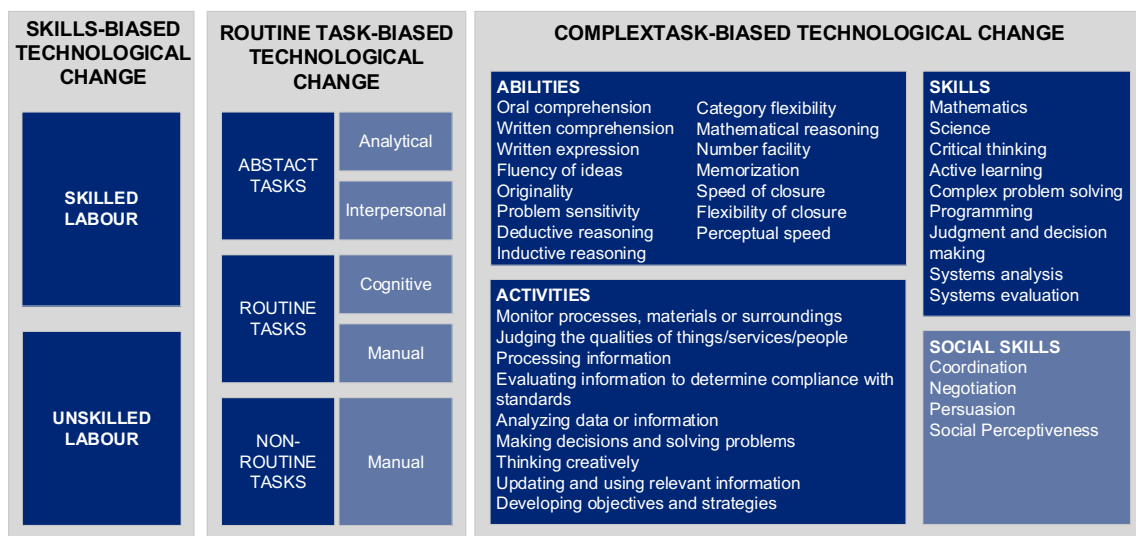
This model was subsequently used by economists to explain technological-induced job polarization across various developed economies. These included the US (Cortes, 2016; Cortes, Jaimovich, Nekarda, & Siu, 2014), the United Kingdom (Goos & Manning, 2007), Europe (Goos et al., 2014; Harrigan, Reshef, & Toubal, 2016), and Japan (Ikenaga & Kambayashi, 2016).

2.4.3 Complex-task-biased Technological Change Model

In a recent study Caines, Hoffman and Kambourov (2017) argued that classification of tasks based on complexity, as opposed to routineness, provided better insight into occupational wage structures and employment growth. This gave rise to the development of a complex-task biased technological change (CBTC) model. Using Occupational Information Network (O*NET) data, occupations were classified based on the extent to which they relied on complex tasks, i.e. tasks that required higher-order skills such as abstract problem-solving, decision-making and effective communication. Based on data from 1980 to 2005, this model illustrated that within groups of similar complexity, labour reallocated to nonroutine occupations. Furthermore, it was found that labour reallocated from occupations with lower complexity to occupations with higher complexity. This illustrated that nonroutine workers (e.g. low-skill service workers) were not shielded from the effects of technological change, and that the impact of technological change on occupations was largely a function of task complexity (Caines et al., 2017).

A summary of the SBTC, RBTC and CBTC model classifications is given in Figure 8.

Figure 8: Summary of the SBTC, RBTC and CBTC model classifications



Based on this analysis, it is evident that there is a relationship between technological change and the skills and capabilities required to perform tasks within an occupation. The evolution of technological change models highlights that factors such as task routineness and task complexity play a critical role in explaining the impact of technological change on jobs.

2.5 Organisational Design and Workforce Structure

2.5.1 The Evolution of Management Theory

Since the industrial revolution, management theory evolved significantly over time. This started with Frederick Taylor's (1911) scientific management theory that studied the relationship between people and tasks to help redesign work processes for increased efficiency. Max Weber (1946) and Henry Fayol (1949) developed administrative management theories to improve efficiency through the division of labour, the development of reporting structures, and the institutionalisation of workplace hierarchies for efficient task execution and decision making. Fayol's (1949) fourteen principles of management famously included: division of labour, authority and responsibility, unity of command, line of authority, centralization, unity of direction, equity, order, initiative, discipline, remuneration, stability of tenure, subordination of individual interests to the common interest, and esprit de corps.

The first half of the twentieth century saw the development of behavioural management theory. This involved studies related to the behaviour of managers to motivate

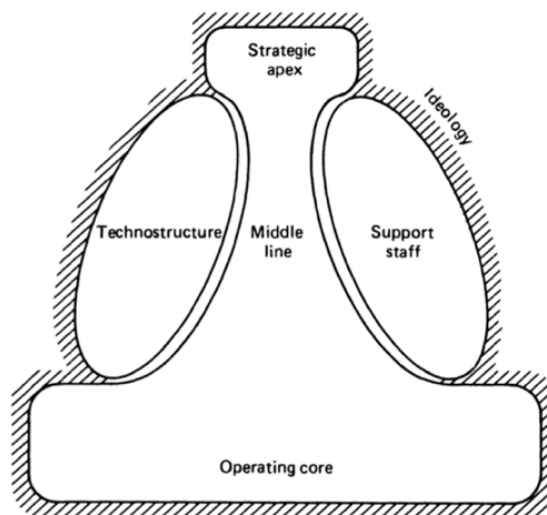
employees to perform at higher levels and gain commitment towards achieving organisational goals. Most notably, management studies lead to the development of Theory X and Theory Y (McGregor, 1960). The field of study was later expanded to management science theory that focused on providing managers with quantitative techniques to effectively manage the use of organizational resources. In later years, organisational environmental theory and contingency theory (Fiedler, 1967) was introduced.

2.5.2 Mintzberg's Five Basic Organizational Structures

Henri Mintzberg (1980) suggested that there were five key parts that make up an organisational structure. See Figure 9. These were as follows:

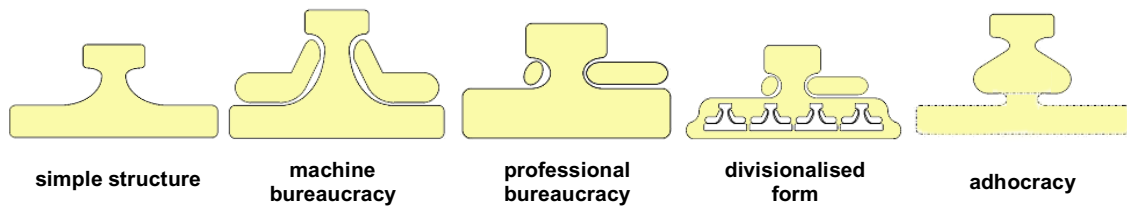
- i. strategic apex – the chief executive and top management of the organisation.
- ii. operating core – workers that complete the basic work within the organisation.
- iii. middle line – intermediate managers between the chief executive and workers.
- iv. technostructure – analysts that design systems for formal planning and control of the work, and
- v. support staff – staff that provide indirect services to the rest of the organisation.

Figure 9: Five parts that make up an organisational structure (Mintzberg, 1980, p. 324)



Mintzberg (1980) argued that not all organisations need each part. The author defined five basic organisational structures, namely, simple structure, machine bureaucracy, professional bureaucracy, divisionalised form, and adhocracy. See Figure 10.

Figure 10: Mintzberg's five basic organisational structures (adapted from Mintzberg, 1980, pp. 331–336)



Simple structures consist of a strategic apex (i.e. top managers) with a few workers in the operative core. There is no technostructure, and the proportion of middle line managers and support staff is generally small. The structure coordinates through direct supervision and there is little specialisation of jobs. This type of organisation is typically young, small, and have little planning and control systems (Mintzberg, 1980). A typical example of such a structure is an entrepreneurial firm.

Machine bureaucracies are characterised by a large technostructure that aims to design and maintain a system of standardisation. Power is concentrated at the top and hierarchies emerge in the middle line to oversee the specialisation of work. To maintain stability, large support staff complements exist (Mintzberg, 1980). A typical example is a large, mature mass-production company such as an automobile manufacturer.

Professional bureaucracies rely on standardisation of skills. Its most important component is the operating core, which consists of skilled professionals that work independently. Because of its decentralised nature, the technostructure and middle line is small. The support staff complement is large to assist with completing simple and routine tasks (Mintzberg, 1980). Examples of professional bureaucracies include hospitals, universities and accounting firms.

Divisionalised form consists of a set of independent entities (or divisions) joined by an administrative overlay. Its most important component is the middle line. Divisional managers retain most of the power, whilst the headquarters rely on performance control systems that support a coordination mechanism of standardisation of output. The headquarters maintain a small technostructure and a complement of central support staff that is common across all divisions (Mintzberg, 1980). Examples include retail outlets and food franchises.

Adhocracies consist of collaborative multi-disciplinary specialist teams that are primarily coordinated through mutual adjustment (e.g. task forces and matrix structures). Power

is dispersed throughout the structure based on the decisions that need to be made (Mintzberg, 1980). Typical examples include technology and information companies.

2.5.3 Hierarchical Structure of Firms

Building on the concept that firms are hierarchies of knowledge (Garicano, 2000; Garicano & Rossi-Hansberg, 2006), Caliendo and Rossi-Hansberg (2012) developed a theoretical model for the hierarchical structure of firms. This model was based on the premise that workers solve problems, and as problems become more complex, these problems are escalated to a higher level within the organisation, e.g. supervisors or managers. Managers, in-turn, are time-constrained, and utilise workers such that they are free to focus on solving specific problems. The author argued that this gives rise to a hierarchical structure based on the knowledge of workers. Workers that are less knowledgeable are further down the hierarchy and earn lower wages, whilst workers with more knowledge are higher up in the hierarchy and earn higher wages (Caliendo et al., 2015; Caliendo & Rossi-Hansberg, 2012; Tåg, 2013).

This theoretical model has been applied to French (Caliendo et al., 2015) and Swedish (Tåg, 2013) occupational data to illustrate the impact of hierarchy and reorganisation on firm growth. More recently, it has been used to illustrate the relationship between the hierarchical structure of a firm and entrepreneurship (Tåg, Åstebro, & Thompson, 2016). In this study, the Swedish Standard Classification of Occupations (SSYK) database were used to classify employees into four hierarchical layers at a firm-level, namely, production workers, supervisors, senior staff, and CEOs. The authors then determined the number of employees in each layer, and computed the associated span of control, i.e. the ratio of employees in each layer relative to the number of employees in the ratio above.

2.5.4 Stratified Systems Theory

In a seminal series of work, Elliott Jaques (1986) developed a theory that outlined the cognitive processes required for individuals to plan and do goal-directed activities. The author postulated that individuals change to different states of cognitive functioning (shaping, reflective articulation, extrapolation, and transformation) as they reach different points in cognitive power (measured in time horizons). This gave rise to the development of the stratified hierarchy in the organisation. Its basic premise is that the stratification of organisational structure reflects the equivalent stratification of human capability.

Jaques (1986, 2016) viewed all work as goal-directed activities that were bound by quality, time and cost, and exercised within levels of discretion that required judgment and intuition. Jaques (1986, 2016) found that the “time span of discretion” - the longest period a manager permits a subordinate to apply his or her own discretion in completing a task - was related to work complexity and human capability. This formed the basis for seven hierarchical strata of increasing complexity of work, that required greater abstractive capabilities. Table 4 summarises the seven strata of work, time span of discretion, work complexity, cognitive mechanisms, and typical positions within an organisation.

Table 4: Characteristics of each strata of work (adapted from Jaques, 2016)

Stratum	Time Span	Work Complexity	Cognitive Mechanism	Position
VII	20 – 50 years	Construct complex systems; construct versus predict future	Linear extrapolation; develop new theories	CEO, Super Corporation
VI	10 – 20 years	Oversee complex systems; group of business units; plan long term strategy	Reflective articulation between systems; higher conceptual approaches	CEO, International Corporation
V	5 – 10 years	Command one complex systems; connections to environments	Shape, reshape whole systems, boundaries; utilise theory	Group Vice President, International Corporation
IV	2 – 5 years	Oversee operating subsystems; design new methods, policies	Develop alternative systems; abstract from data; parallel processing	General Manager; Vice President
III	1 – 2 years	Direct one operating subsystem; predict need 12-18 months out	Linear extrapolation; alternate pathways	Department Manager; Senior Professional
II	3 months – 1 year	Direct an aggregate of tasks; diagnose problems	Reflective articulation; formulate new ideas; handle ambiguity	First-line Manager; Supervisor
I	1 day – 3 months	Carry out one task at a time; daily, weekly, monthly quotas	Concrete shaping; concrete thinking; linear pathways	Operators and clerks; day workers

From Table 4 it is evident that lower strata of work have shorter time span of control, lower work complexities, and require more concrete cognitive mechanisms. Typical roles include operators and clerks responsible for carrying out tasks to meet a daily, weekly and monthly quota. Higher strata of work, such as chief executives, general managers and business unit managers, have longer time spans of control (typically years), involve greater work complexity such as overseeing or commanding complex systems, and require more abstract cognitive mechanisms.

Stratified systems theory provides a framework for understanding human capability for completing different types of work. It also provides a common classification system for various occupations across different industries.

2.6 Literature Review Conclusion

In this chapter three literature bases were reviewed to provide insight into the impact of technological change on jobs and workforce structures.

A review of futures literature outlined several academic debates around how technological change will displace, modify or create future jobs. Economic concepts such as “technological unemployment” and “technological anxiety” highlighted how these debates were not new, and will remain relevant if technological advancement brings about productivity improvements. Some authors likened today’s technological advancement to a Cambrian Explosion, whilst some predicted an AI revolution that will have a significant impact on societies, life, employment and business. Others argued that the substitutionary effects of technological change were overestimated and the complementary effects of technological change were underestimated. Models that aimed to predict the impact of technological change on jobs suggested that advancement in artificial intelligence, machine learning, and robotics will significantly disrupt and automate tasks across a range of occupations. However, the degree of disruption was considered to vary across different industries, and could be influenced by factors such as technical feasibility, development costs, technological adoption rates, labour market dynamics, economic benefits, and regulatory and social acceptance.

A review of labour economics literature highlighted (i) various compensation mechanisms for employment, and (ii) three technological change models that explained biases and shifts in historical employment and wage data. The net impact of compensation mechanisms, however, was found to be complex, far from deterministic, and could be impacted by the institutional setting and factors such as demand elasticity, degree of competition, capital-labour substitution, and demand expectations. Firm-level and industry-level analysis indicated that product innovation generally had a positive impact on employment, whilst the impact of process innovation on employment was mixed. Technological change models that aimed to explain historical shifts in employment and wage data evolved over time. Initial models suggested that technological change was skills-biased. However, more recent models suggested that

technological change was biased towards task routineness, whilst others suggested that technological change was biased against task complexity.

A review of organisational design literature provided a common framework for classifying occupations into workforce structures across various industries. Mintzberg's (1980) five organisational structures provided a tool for analysing the structures within different industries. This introduced the key elements of an organisation, typical coordination mechanisms, and the different divisions of labour. The theory of hierarchical structure of firms and stratified systems theory introduced the concept of stratum of work. Each stratum represented a time span of discretion, work complexity, cognitive mechanisms, and typical positions within an organisation. Together these theories outlined mechanisms for representing workforce structures across different industries.

The above-mentioned literature sections provided a theoretical basis for determining the impact of technological change on jobs and workforce structures. However, this literature review has also highlighted a lack of integration of certain literature fields. Whilst futures literature has applied novel methodologies to predict the impact of technological change, there has been little integration of the findings from recent labour economics literature. This begs the question whether there is a misalignment between these literatures. It is recognised that the occupational structure and underlying tasks are important factors in assessing the impact of technological change on jobs. However, to date no author has considered the impact of technological change on workforce structure for different industries.

To address the above-mentioned gaps, it needs to be considered whether a relationship exists between the probability of job automation and the routineness and complexity of tasks. If such a relationship exists, it needs to be ascertained whether specific occupational groups (i.e. routine-simple, nonroutine-simple, routine-complex, and nonroutine-complex occupations) are more susceptible to job automation than others. Further consideration should be given as to whether specific strata of work are more susceptible to job automation than others. To understand the impact of technological change on workforce structure, the current workforce structure for each industry should be determined and its projected change quantified. The next chapter outlines the research questions addressed in this study.

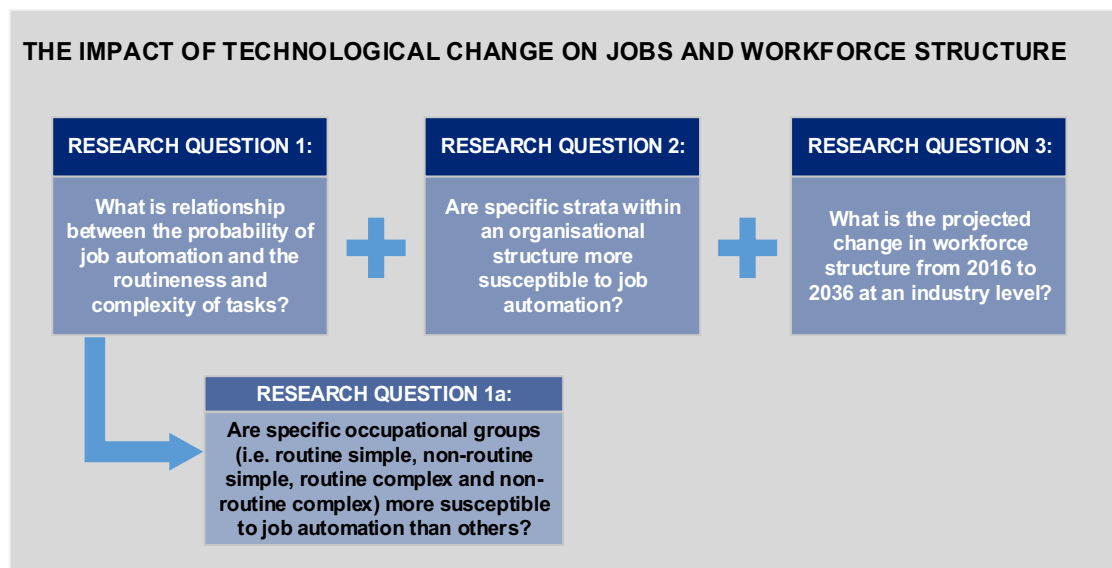
3 RESEARCH QUESTIONS

3.1 The Purpose of the Research

The purpose of this research is to assess the impact of technological change on jobs and workforce structure, i.e. how is technological change such as artificial intelligence, machine learning, and robotics changing the demand for specific jobs? Is the impact of technological change biased towards jobs that are considered routine, simple, nonroutine or complex? Is the impact of technological change biased towards specific strata of work within the organisation? How does this change the workforce structure of different industries in the future?

To achieve the purpose of the research, this study was structured around three research questions. Research Question 1 explored whether there was a relationship between the probability of job automation (established in futures literature), and the routineness and complexity of tasks (from labour economics literature). Research Question 2 explored whether specific strata of work (from organisational design literature) were more susceptible to job automation than others. Research Question 3 aimed to determine the projected change in workforce structure from 2016 to 2036 at an industry level. See Figure 11.

Figure 11: Research questions and structure



The following section outlines the outcomes and objectives of each research question.

3.2 Research Question 1

Research Question 1: What is the relationship between the probability of job automation and the routineness and complexity of tasks?

Research Question 1 aimed to establish whether there was a relationship between parameters from futures literature, i.e. the probability of job automation (Frey & Osborne, 2017), and parameters used to explain the routineness (Autor & Dorn, 2013) and complexity (Caines et al., 2017) of tasks from technological change models developed in labour economics literature. A weak relationship between these parameters would indicate that the outputs of Frey and Osborne's (2017) model (based on computerisation bottlenecks such as creative intelligence, social intelligence, perception and manipulation), were divergent from the RBTC and CBTC models (based on shifts in historical occupational and wage structures). A moderate to strong relationship would indicate that there was alignment between these models, and that future job automation could, to a certain extent, be predicted by these parameters. This model would allow for the findings of this study to be extrapolated and applied to other occupations. A moderate to strong relationship in Research Question 1 would introduce the following sub-research question:

Research Question 1a: Are specific occupational groups (routine-simple, nonroutine-simple, routine-complex and nonroutine-complex) more susceptible to job automation than others?

Research Question 1a aimed to establish whether there was a difference in the probability of job automation between routine-simple, nonroutine-simple, routine-complex, and nonroutine-complex occupations, and whether specific groups were more susceptible to job automation than others.

3.3 Research Question 2

Research Question 2: Are specific strata of work within a workforce structure more susceptible to job automation?

Research Question 2 aimed to establish whether there was a statistically significant difference in the probability of job automation of occupations classified based on stratum of work (i.e. Stratum I, II, III, IV, or V). If the probability of job automation for each group was statistically insignificant, it could be concluded that job automation is not biased towards a specific stratum of work or level within a workforce structure. However, if the

difference between groups was statistically significant, it could indicate that specific strata of work, or levels within a workforce structure, are more susceptible to job automation than others. In this event, stratum of work would be considered as an additional parameter when predicting the probability of job automation.

3.4 Research Question 3

Research Question 3: What is the projected change in workforce structure from 2016 to 2036 at an industry level?

Research Question 3 aimed to outline the implications of future job automation on the workforce structures for various industries. Workforce structure in this context was defined as the relative proportions of Stratum I, II, III, IV, and V occupations that made up an industry or economy. Similar to Frey and Osborne (2017), the projected change in workforce structure was assessed over a period of two decades, namely 2016 to 2036.

4 RESEARCH METHODOLOGY

4.1 Introduction

The purpose of this research was to assess the impact of technological change on jobs and workforce structures. In Chapter 2, a critique of recent futures literature predicted broad-scale disruption of jobs across different industries, and provided a measure of the probability of job automation for various occupations based on insights from artificial intelligence, machine learning and robotics. Labour economics literature identified various employment compensation and substitution mechanisms for technological change. The literature proposed a routine biased technological change (RBTC) model and a complex-task biased technological change (CBTC) model which provided measures of task routineness and task complexity for a range of occupations. Organisational design literature such as the theory of hierarchical structures of firms and stratified systems theory provided common frameworks for classifying occupations into workforce structures across various industries. However, to date there has been little integration of the above-mentioned literature bases to assess the impact of technological change on jobs and workforce structures. This gave rise to the development of three primary research questions.

The following section provides a description of the methodology that was used to address each research question. This section outlines the research design, a description of the population, the data collection process, the unit of analysis, and the data analysis processes for each research question.

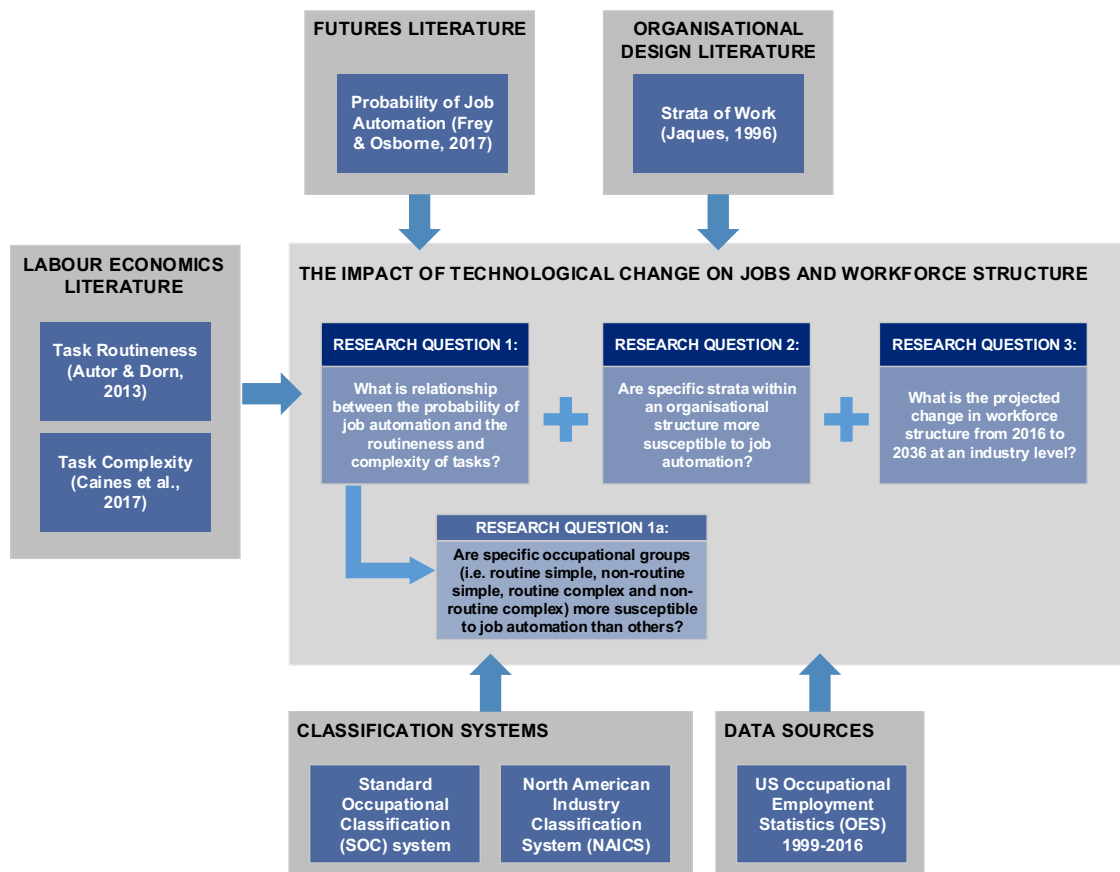
4.2 Research Design

The research design aimed to address the following research questions:

1. **Research Question 1:** What is the relationship between the probability of job automation and the routineness and complexity of tasks?
 - a. **Research Question 1a:** Are specific occupational groups (routine-simple, nonroutine-simple, routine-complex and nonroutine-complex) more susceptible to job automation than others?
2. **Research Question 2:** Are specific strata of work within a workforce structure more susceptible to job automation?
3. **Research Question 3:** What is the projected change in workforce structure from 2016 to 2036 at an industry level?

To address the above-mentioned research questions, various literature bases, classification systems and data sources were used. Figure 12 provides a schematic illustration of the integration of these literature bases, classification systems, and data sources, together with the three primary research questions.

Figure 12: Integration of literature bases, classification systems, and data sources with the research questions



This study integrated predictions of technological change and the probability of job automation (Frey & Osborne, 2017) from futures literature, with measures of task routineness (Autor & Dorn, 2013) and task complexity (Caines et al., 2017) of various occupations from labour economics literature. It furthermore used stratified systems theory (Jaques, 1986, 2016) from organisational design literature as a lens for classifying different occupations to represent workforce structures within an industry or economy.

By combining various published data sets, the relationship between the probability of job automation, and the routineness and complexity of tasks was established (Research Question 1). The same data set was used to classify occupations into routine-simple, nonroutine-simple, routine-complex, and nonroutine-complex groups to assess which were more susceptible to job automation (Research Question 1a). Likewise, occupations

were classified based on stratum of work to determine whether specific strata were more susceptible to job automation than others (Research Question 2).

Classifications systems in the form of the Standard Occupational Classification (SOC) system and the North American Industry Classification System (NAICS) were used to provide occupational and industry structures. The Standard Occupational Classification (SOC) system was developed by the US Department of Labour to classify US workers into occupational categories for the purpose of collecting and analysing employment data (U.S. Bureau of Labor Statistics, 2010). The 2010 SOC system classified 840 detailed occupations with similar job duties, skills, education and training into 461 broad occupations, 9 minor occupations and 23 major groups (U.S. Bureau of Labor Statistics, 2010). The North American Industry Classification System (NAICS) is an industry classification system that grouped organisations into industries based on similarities in production processes. It used a six-digit coding system to classify all economic activities in the US across 20 industry sectors and 1 057 detailed industries (U.S. Office of Management and Budget, 2017).

A secondary data set, namely US Occupational Employment Statistics (OES) data from 1999 to 2016, was used to determine the projected change in workforce structures from 1999 to 2016 and from 2016 to 2036 (Research Question 3). The data source contained detailed occupational descriptions and employment statistics per occupation for the US economy, broken down per industry according to the NAICS classification system.

4.3 Population

The population for this study comprised all workers participating in economic activities across various industries within a developed economy. In order to ensure that the findings of this study were comparable with Frey and Osborne (2017), Autor and Dorn (2013), and Caines et al.(2017), the US economy and its industries were identified as a subgroup of this population. Thus, this analysis focused on the workers contributing to economic activities within the US economy, spanning all industries.

4.4 Data Collection, Sampling Method and Size

The present study involved a structured collection, classification and analysis of secondary data from multiple sources.

Research Question 1 and Research Question 2 relied on secondary data from futures and labour economics literature, namely Frey and Osborne (2017), Autor and Dorn

(2013), and Caines et al. (2017). The data produced from these respective studies either originated from the US Department of Labor's *Dictionary of Occupations Titles* (DOT) classification system or the 2010 SOC system, which allowed for the respective data sets to be cross-referenced. Despite having a common data source, the authors aggregated selected occupations and omitted other occupations. For example, Frey and Osborne (2017) aggregated specific "postsecondary teaching" occupations into a single category and omitted occupations containing "all other", whilst Caines et al. (2017) omitted selected "farm and agricultural" occupations. In total, Frey and Osborne (2017) calculated the probability of job automation for 702 occupations. Autor and Dorn (2013) calculated job routineness for 330 aggregated occupations. Caines et al. (2017) calculated job complexity for 315 aggregated occupations. After combining the above-mentioned data sets, a total of 291 occupations were used in the analysis for Research Questions 1 and 2.

Research Question 3 relied on secondary employment data and industry-specific employment data from the OES database spanning 1999 to 2016. Employment data was classified according to the 2010 SOC system that contained 820 occupations. With the emergence of new roles and reclassification of the SOC system over the same duration, certain classifications needed to be cross-referenced ("crosswalked") to provide comparable figures across different years. After de-aggregating and combining this data with Frey and Osborne's (2017) data set, a total of 754 occupations could be used in this analysis. This represented between 91.5 and 96.3 percent of all workers in the US from 1999 to 2016.

4.5 Unit of Analysis

The unit of analysis for this study was detailed occupations, e.g. chief executives, human resources managers, chemical engineers, accountants, first line managers, operators, etc. See Appendix B for a detailed outline of the occupational classification system used in this study.

4.6 Data Analysis

The following section outlines the data analysis process for each research question:

4.6.1 Research Question 1

Research Question 1 aimed to establish whether there was a relationship between parameters from futures literature, i.e. the probability of job automation (Frey & Osborne,

2017) and parameters used to explain the routineness (Autor & Dorn, 2013) and complexity (Caines et al., 2017) of tasks from technological change models developed in labour economics literature.

4.6.1.1 Probability of Job Automation

Frey and Osborne (2017) calculated a “probability of computerization” for 702 occupations (referred to as the “probability of job automation” for consistency in this study). This data was published in the appendix of Frey and Osborne’s paper.

Frey and Osborne’s (2017) methodology was largely based on offshoring literature that ranked and categorised occupations on their susceptibility to offshoring. The authors aggregated detailed occupational data from the O*NET database (2010 version) with wages and employment data from the SOC database for 702 occupations. Machine learning experts classified each occupation as either “automatable” or “not automatable” in a workshop held at Oxford University Engineering Sciences Department. The authors then used 70 occupations that the experts were “highly confident” about for subsequent classification using an algorithm. A total of nine objective O*NET variables (i.e. finger dexterity; manual dexterity; cramped workspace; originality; fine arts; social perceptiveness; negotiation; persuasion; and assisting & caring for others) were identified to correspond with engineering bottlenecks to automation. The subjectively selected occupations were then classified based on these objective variables using a Gaussian process classifier. A hundred replications were done using randomly selected subsets of the data and an exponentiated quadratic classifier was found to demonstrate the best performance. This model was used in subsequent analysis to predict the probability of job automation for all 702 occupations.

Frey and Osborne’s (2017) methodology, however, was critiqued for over-estimating the technological capabilities of automation of jobs. Firstly, Arntz et al. (2017) argued that a task-based approach was more representative. Secondly, Autor (2015) noted that experts often overstate the potential of new technologies. Thirdly, the classification of occupations as binary, i.e. either “automatable” or “not automatable”, was considered to be problematic as it does not allow for the complementary interaction of automation (Green, 2012; Rohrbach-Schmidt & Tiemann, 2013). Lastly, Pratt (2015) argued that current jobs are insufficiently defined to allow for predictions to be made about the future.

Despite this critique, Frey and Osborne’s (2017) paper has been widely cited and is regarded as a seminal paper in futures literature. The probability of job automation per

occupation furthermore provided a useful measure that could be cross-referenced with other measures established in labour economics literature.

4.6.1.2 *Task Routineness*

Autor and Dorn (2013) established a measure of task routineness per occupation based on three dimensions measured in the US Department of Labor's DOT classification system, namely abstract task intensity, manual task intensity, and routine task intensity. The routine task intensity (RTI) index was calculated as follows (Autor & Dorn, 2013):

$$RTI = \ln(Routine) - \ln(Manual) - \ln(Abstract) \quad (1)$$

The RTI index corresponded to routine, manual, and abstract task inputs for each occupation as determined in 1980. This measure was used effectively as part of the RBTC model to explain employment and wage shift as a result of technological change (Autor & Dorn, 2013; Autor et al., 2015; Caines et al., 2017; Goos et al., 2014; Ikenaga & Kambayashi, 2016).

Like most labour economics studies, Autor and Dorn's (2013) study made use of historical labour and wage data combined with occupational classification data to explain the impact of technological change on jobs. The authors published RTI data for 330 aggregated occupations corresponding to the US Department of Labor's DOT classification system. This data was cross-referenced with the SOC database to determine the task routineness for corresponding occupations. See Appendix B.

4.6.1.3 *Task Complexity*

Caines et al. (2017) studied the relationship between task complexity and historical wage and employment structures. In this study, the authors developed the CBTC model that was based on the extent to which complex tasks were required in a job. Complex tasks were defined as tasks that required higher-order skills such as abstract thinking, problem solving, decision making or effective communication (See Figure 8). Using O*NET data of worker abilities, skills, and activities in a principal component analysis, the authors developed a model that calculated a complexity index for 315 aggregated occupations corresponding to the US Department of Labor's DOT classification system. This data was cross-referenced with the SOC database to determine the job complexity for the corresponding occupations. See Appendix B.

4.6.1.4 Multiple Linear Regression Analysis

Both Autor and Dorn (2013) and Caines et al. (2017) used regression analysis to demonstrate the relationship between wages as the dependent variable, and the task routineness or task complexity as independent variables (along with other parameters). To determine the relationship between the probability of job automation and the routineness and complexity of tasks, a multiple linear regression analysis (Regression Model 1) was conducted across 291 occupations. The objective of this multiple regression analysis was to determine how much of the variation in the dependent variable is explained by the independent variables. The dependent variable was “probability of job automation” and the independent variables were the “routineness” and “complexity” of tasks for corresponding occupations.

The basic requirements for a multiple linear regression analysis included testing eight assumptions. The first two assumptions are related to the choice of study design and the data, and the remaining six relate to how the data fitted the multiple regression model. These assumptions were as follows:

1. There is one dependent variable measured at a continuous level;
2. There are two or more independent variables measured either at a continuous or nominal level;
3. There is independence of observations;
4. There is a linear relationship between the predictor variables (and composite) and the dependent variable;
5. There is homoscedasticity of residuals (equal error variances);
6. There is no multicollinearity;
7. There are no significant outliers, high leverage points, or highly influential points;
8. The errors (residuals) is approximately normally distributed.

The data used in this study met both Assumptions 1 and 2. The dependent variable, “probability of job automation”, was measured at a continuous level on a scale from 0 to 1. The independent variables, “routineness” and “complexity” were also measured at a continuous level. The scale of “complexity” data ranged from 0 to 1. However, to establish a similar scale of 0 to 1 for “routineness”, percentiles of RTI index data were calculated. Independence of observations was checked statistically using a Durbin-Watson test (1950, 1951). A Durbin-Watson statistic close to 2 indicated that there was independence of observations. Tests for linearity was conducted by assessing the

linearity of (i) scatterplots of studentized residuals against (unstandardized) predicted values, and (ii) partial regression plots between each independent variable and the dependent variable. No nonlinear relationships were observed. Homoscedasticity of residuals was checked using the same scatterplots of studentized residuals against unstandardized predicted values. Multicollinearity was checked by inspecting the correlation coefficients and tolerance or variance inflation factor (VIF) value of the multiple linear regression model outputs. Correlations between independent variables were classified as strong if the correlation coefficient exceeded 0.7. Likewise, if the tolerance value for an independent parameter was less than 0.1, or if the VIF value was greater than 10, collinearity was identified. Significant outliers were identified by inspecting case wise diagnostics for any cases where the standardized residual was greater than ± 3 standard deviations. High leverage points were checked by inspecting the leverage value for each case. Values below 0.2 were not considered as highly leveraged points. Influential points were checked by inspecting Cook's distance values for each case. Values below 1 were not considered to be highly influential (Cook & Weisberg, 1982). Lastly, normality was checked by inspecting a histogram and P-P Plot of the standardized residuals.

The results of the regression analysis were interpreted by assessing whether the regression model was a good fit, and studying the coefficients of the regression model. The adjusted R^2 values was used to assess the variance explained by the model. The statistical significance of the overall model and each independent parameter was considered at a 95% confidence interval.

4.6.2 Research Question 1a

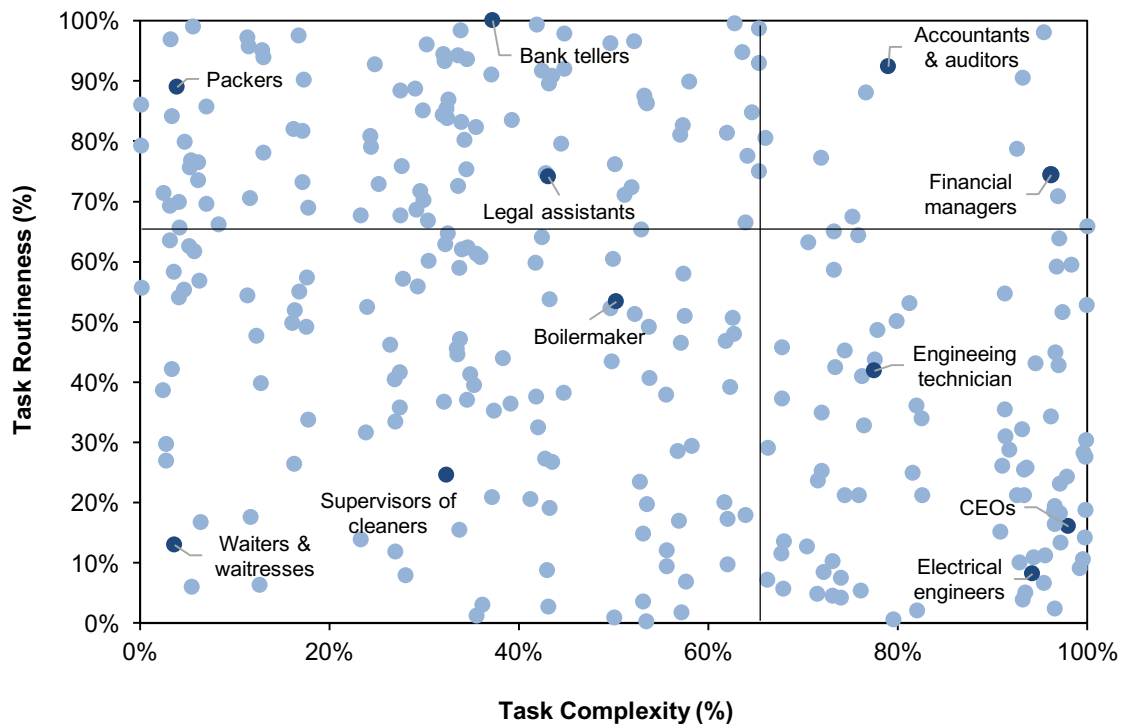
Because a moderate to strong relationship was found in Regression Model 1, a sub-research question, namely, Research Question 1a, was introduced. Research Question 1a aimed to establish whether there was a difference in the probability of job automation between routine-simple, nonroutine-simple, routine-complex and nonroutine-complex occupations, and whether specific groups were more susceptible to job automation than others.

4.6.2.1 Data Classification

Using measures of task routineness (Autor & Dorn, 2013) and task complexity (Caines et al., 2017), a total of 291 occupations were classified as either (i) routine-simple, (ii) nonroutine-simple, (iii) routine-complex, or (iv) nonroutine-complex. See Figure 13.

Following a similar approach to both Autor and Dorn (2017) and Caines et al. (2017), occupations were classified as routine if task routineness was greater than 66% and nonroutine if task routineness was less than 66%. Likewise, occupations with a task complexity of greater than 66% were classified as complex, and occupations with a task complexity of less than 66% were classified as simple. The probability of job automation (Frey & Osborne, 2017) were then cross-referenced for each occupation. See Appendix B.

Figure 13: Classification of occupations based on routineness and complexity



4.6.2.2 Kruskal-Wallis H Test

To determine whether there was a statistically significant difference in the probability of job automation (independent variable) between the four above-mentioned groups (independent variable), a one-way ANOVA was considered (Kirk, 2013). However, the data violated the assumption of normality, confirmed by visually inspecting Normal Q-Q plots, and was found to differ in shape. Thus, transformation of data was not possible. Non-parametric testing in the form of a Kruskal-Wallis H test (Kruskal & Wallis, 1952; Vargha & Delaney, 1998) coupled with case wise comparison post-hoc analysis (Dunn, 1964) was done.

The Kruskal-Wallis H test is a rank-based nonparametric test. It was used to determine if there were statistically significant differences between the distributions of “probability in automation” for the four occupational groups. The basic requirements for conducting a Kruskal-Wallis H test involved testing four assumptions. The first three are related to the choice of study design, and the fourth assumption is related to the nature of the data. These assumptions were as follows:

1. There is one dependent variable measured at a continuous or ordinal level;
2. There is one independent variable that consists of two or more categorical, independent groups;
3. There is independence of observations; and
4. The distribution of each group of independent variable must be evaluated to determine if they have the same or different shapes.

The data used in this study met both Assumptions 1 and 2. The dependent variable, “probability of job automation”, was measured at a continuous level on a scale ranging from 0 to 1. The independent variable consisted for four categorical, independent groups, namely, “routine-simple”, “nonroutine-simple”, “routine-complex”, and “nonroutine-complex”. Independence of observations was ensured through the classification process discussed in Section 4.6.2.1. Visual inspection of the histograms for each occupational group indicated that the occupational groups had different shapes. The null hypothesis (H_0) and alternative hypothesis (H_A) for the Kruskal-Wallis H test was as follows:

H_0 : the distributions of the groups are equal

H_A : the distributions of the groups are not equal

Thus, a rejection the null hypothesis indicated that there were differences in the distributions for each occupational group. To determine whether the probabilities of job automation were higher in one group relative to another, mean ranks were compared in a pairwise comparison post-hoc analysis (Dunn, 1964) with a Bonferroni correction for multiple comparisons. The adjusted significant number for each pair was considered to establish whether there was a statistically significant difference between groups. This analysis was done at a 95% confidence interval.

4.6.3 Research Question 2

4.6.3.1 Data Classification

In order to address this research question, SOC occupations were classified using Jaques' (2016) stratified system theory. A total of 752 occupations were classified as either Stratum I, II, III, IV, or V based on the time span of discretion, task complexity, and cognitive mechanisms required for each occupation. See Table 4. Occupations that involved completing tasks based on daily, weekly or monthly quotas and involved cognitive mechanisms such as concrete thinking, concrete shaping and linear pathways were classified as Stratum I. Typical examples included operators, clerks, cleaners, assistants and helpers. Occupations that involved directing of aggregated tasks and diagnosis of problems through cognitive mechanisms such as reflective articulation were classified as Stratum II occupations. Typical examples included supervisors, nurses, teachers, and technicians. Occupations that involved directing operating subsystems through cognitive mechanisms of linear extrapolation were classified as Stratum III occupations. Typical examples included professional and management occupations such as engineers, doctors, lawyers, and managers. Occupations that involved overseeing operating subsystems and designing new methods and policies through cognitive mechanisms of abstracting and parallel processing, were classified as Stratum IV. A typical example was general managers. Lastly, occupations that involved commanding of a complex subsystem through cognitive mechanisms such as shaping, was classified as Stratum V. A typical example was chief executives. The probability of job automation was cross-referenced for each occupation. See Appendix C.

4.6.3.2 Kruskal-Wallis H test

To determine whether there was a statistically significant difference in the probability of job automation (independent variable) between the five above-mentioned strata (independent variable), a one-way ANOVA was considered (Kirk, 2013). However, the data violated the assumption of normality, confirmed by visually inspecting Normal Q-Q plots, and was found to differ in shape. Thus, transformation of data was not possible. Non-parametric testing in the form of a Kruskal-Wallis H test (Kruskal & Wallis, 1952; Vargha & Delaney, 1998) coupled with case wise comparison post-hoc analysis (Dunn, 1964) was done. A similar approach as outlined in Section 4.6.2.2 was followed.

4.6.3.3 *Multiple Linear Regression*

A clear order in the susceptibility of job automation based on strata of work was observed, i.e. higher stratum of work occupations had lower probabilities of job automation. To determine the relationship between the probability of job automation and the routineness, complexity and stratum of work, a second multiple linear regression analysis (Regression Model 2) was conducted across 291 occupations. The dependent variable for this model was “probability of job automation” and the independent variables were “routineness”, “complexity”, and “stratum”. The additional independent parameter was ordinal. A similar analysis as outlined in Section 4.6.1.4 was followed.

4.6.4 **Research Question 3**

4.6.4.1 *Projected Change in Workforce Structure*

Research Question 3 aimed to illustrate how technological change would impact the workforce structures for different industries. To address this research question, the same 754 occupations classified based on stratum of work were utilised (See Section 4.6.3.1). To illustrate the changes in workforce structure over time, OES data from 1999 to 2016 was used to calculate the proportion of Stratum I, II, III, IV, and V occupations for each year. This was compared to the projected workforce structure for 2036. The projected workforce structure in 2036 was calculated by adjusting the 2016 OES data by the probability of job automation for each occupation. Where changes between the 2000 SOC and 2010 SOC systems occurred, the 2000-2010 SOC crosswalk was used to cross-reference employment data for corresponding occupations. Occupations that did not have a corresponding measure of “probability of job automation” were omitted from the analysis. After omissions, this analysis represented 91.5 - 96.4 percent of the US workforce from 1999 to 2016.

4.6.4.2 *Projected Change in Workforce Structure per Industry*

To determine the projected change in workforce structure per industry, the same 754 occupations and classification of stratum of work were used. See Section 4.6.3.1. However, to illustrate the projected change in workforce structure per industry, 2016 employment data aggregated per NAICS industry was used. A total of 20 US industry sectors were studied. There were as follows: Agriculture, Forestry, Fishing and Hunting; Mining, Quarrying, Oil and Gas Extraction; Utilities; Construction; Manufacturing; Wholesale Trade; Retail Trade; Transportation and Warehousing; Information; Finance

and Insurance; Real Estate, Rental and Leasing; Professional, Scientific, and Technical Services; Management of Companies and Enterprises; Administrative, Support, Waste Management and Remediation Services; Educational Services; Health Care and Social Assistance; Arts, Entertainment, and Recreation; Accommodation and Food Services; Other Services; and Federal, State, and Local Government.

The projected workforce structure for 2036 was calculated using the “probability of job automation” at an occupational level for each industry. Occupations that did not have a corresponding measure of “probability of job automation” were omitted from the analysis. After omissions, this analysis represented 96.3 percent of the US workforce in 2016 across the 20 industry sectors.

4.6.4.3 Workforce Ratios

To illustrate the change in workforce structure at an industry level, a measure for workforce structure was introduced. This was calculated by determining the ratio of Stratum I, II, III, and IV occupations relative to the number of Stratum V occupations within an industry. This metric was used to illustrate the relative workforce structure distributions for different industries. This methodology is similar to what was used by Tåg et al. (2016) to describe span of control for different hierarchies within firms.

4.6.4.4 Type 1, 2, 3, and 4 Industries

Workforce ratios were used to construct workforce structures distributions for each industry. This allowed for industries with similar workforce structures to be compared and grouped. The 2016 workforce structure distributions were used to classify the 20 US industries as either Type 1, 2, 3 or 4 industries. The industry types were determined as follows:

- i. Type 1 industries were characterised by a pyramid-like workforce structure where the largest complement of workers was Stratum I.
- ii. Type 2 industries were characterised by a large complement of Stratum I occupations, but the Stratum III complement was either larger or equal to the Stratum II complement.
- iii. Type 3 industries were characterised by a workforce structure where the largest complement was Stratum II occupations.
- iv. Type 4 industries were characterised by a workforce structure where the largest complement was Stratum III occupations.

4.6.4.5 Projected Change in Employment

The projected change in employment was determined by calculating the percentage change in employment within each industry from 2016 to 2036.

4.6.4.6 Projected Change in Stratum I, II and III Occupations

The projected change in Stratum I, II and III occupations were determined by calculating the percentage change in the proportion of each stratum from 2016 to 2036. Changes in Stratum IV and V occupations were not considered as these occupations were not industry-specific.

4.6.4.7 Mechanisms for Workforce Structure Adjustment

By studying the projected change in Stratum I, II, and III occupations, five mechanisms for workforce structure adjustment were identified. These mechanisms explained how the workforce structure would adjust in response to job automation. For example, if a large portion of Stratum I occupations are automated, the proportion of Stratum II and III occupations within the industry would increase, thus adjusting the workforce structure. These five mechanisms were as follows:

- a. Mechanism A: Reduction in the proportion of Stratum I occupations, offset by an increase in the proportion of Stratum II occupations.
- b. Mechanism B: Reduction in the proportion of Stratum I occupations, offset by an increase in the proportion of Stratum III occupations.
- c. Mechanism C: Reduction in the proportion of Stratum I occupations, offset by an increase in the proportion of both Stratum II and III occupations.
- d. Mechanism D: Reduction in the proportion of Stratum I and Stratum II occupations, offset by an increase in the proportion of Stratum III occupations.
- e. Mechanism E: Reduction in the proportion of Stratum II occupations, offset by an increase in the proportion of Stratum I occupations.

4.7 Validity and Reliability

The research questions, research design and data analysis processes were designed to ensure content validity. This analysis was conducted at a detailed occupational level (like other authors in the field of futures and labour economics literature). This ensures that the findings of this study, when presented at an aggregate level, is representative of the change in workforce structure at an industry or company level (external validity).

The use of established occupational and industry classification systems and data, together with published datasets, ensured data reliability.

4.8 Conclusion

In conclusion, the research design followed a pragmatic, deductive approach over a longitudinal time-horizon. The most important determinants for the research design were the research questions. Research questions were defined from literature and a survey of multiple sources of secondary data was conducted. This included the structure collection, classification and analysis of secondary data over an extended period (1999 – 2016).

Quantitative data analysis techniques and procedures in the form of multiple linear regression analyses, non-parametric tests (with post-hoc analysis), and descriptive statistics were used to address the research questions (Saunders & Lewis, 2012). See Table 5 for a summary of the research design.

Table 5: Summary of the research design

Topic	Approach	Explanation
Philosophy:	Pragmatism	The most important determinants are the research questions.
Approach:	Deductive; Descriptive	Research questions defined from literature.
Strategy:	Survey of secondary data	Structure collection, classification and analysis of secondary data from various sources.
Choice:	Multi-method; Quantitative	Quantitative data analysis: Descriptive statistics, multiple linear regression analysis, non-parametric testing and pairwise comparisons post hoc analysis using secondary data from various sources.
Time horizon:	Longitudinal	Study of a topic over an extended period of time.
Techniques & procedures:	Regression; Graphs;	The data will then be analysed using both multiple regression analysis and rank-based non-parametric testing (Kruskal-Wallis H tests) followed with post-hoc analysis (RQ1 & RQ2) and descriptive statistics (RQ3).

5 RESULTS

5.1 Introduction

This chapter presents the empirical results of two regression analyses, two rank-based non-parametric tests and the results of historical and projected changes in workforce structure for the US economy and its industries.

The results are presented in five parts: Firstly, Regression Model 1 is presented. This includes the empirical results of a multiple linear regression model aimed at establishing whether a relationship exists between the probability of job automation and the routineness and complexity of tasks. Second, Non-Parametric Test 1 is presented. This includes descriptive statistics and the empirical results of a rank-based non-parametric test to determine whether routine-simple, nonroutine-simple, routine-complex or nonroutine-complex occupations were more susceptible to job automation. Thirdly, Non-Parametric Test 2 is presented. This includes descriptive statistics and the empirical results of a second rank-based non-parametric test to determine whether occupations at different strata of work were more susceptible to job automation. Fourthly, Regression Model 2 is presented. This includes the empirical results of a multiple linear regression analysis that illustrates an improved model between the probability of job automation, routineness, complexity, and stratum of work. Lastly, the historical and projected changes in workforce structure are presented at an economy level and industry level.

5.2 Regression Model 1

To determine the relationship between the probability of job automation (from futures literature), and measures of task routineness and task complexity (from labour economics literature), a multiple regression analysis was conducted. The aim of this analysis was to illustrate how much of the variation in the “probability of job automation” (dependent variable) was explained by independent variables of “routineness” and “complexity” for 291 occupations. The following sections outline the data validation and model results for Regression Model 1. Detailed results are given in Appendix C.

5.2.1 Data Validation for Multiple Regression Analysis

All independent and dependent variables, namely, “probability of job automation” and, “routineness” and “complexity”, were measured on a continuous scale of 0 to 1 for a total of 291 occupations. There was independence of residuals, as assessed by a Durbin-

Watson (1950, 1951) statistic of 1.449. Linear relationships existed between the probability of job automation and each of the independent variables. This was assessed using partial regression plots. A linear relationship existed between the probability of job automation and the collective independent variables. This was assessed using a scatterplot of the studentised residuals against the unstandardised predicted values. A visual inspection of this plot indicated that the data was homoscedastic. No multicollinearity was observed between the independent variables. As expected, the correlation between task routineness and task complexity was negative with a Pearson coefficient of -0.383.

Two significant outliers were identified where the standardised residual was greater than ± 3 standard deviations. These outliers corresponded to data for the following occupations: “Hairdressers and cosmetologists” and “Recreational facility attendants”. Despite being identified as outliers, the data points were retained as its leverage and influence was low. No data points had high leverage or was highly influential, as measured by Cook’s (1982) distance. The standardised residuals were approximately normally distributed. This was assessed by visually inspecting a histogram (with a superimposed normal curve) and a normal P-P Plot of the standardised residuals. See Appendix C for tables and figures supporting the above-mentioned analysis.

5.2.2 Job Automation, Routineness and Complexity

A multiple linear regression analysis was run to establish how much of the variation in the probability of job automation (dependent variable) is explained by the independent variables of “routineness” and “complexity” for 291 occupations. The R^2 -value for the overall model was 0.576 with an adjusted R^2 -value of 0.568. This indicated that 56.8% of the variance in the probability of job automation (adjusted for sampling bias) could be explained by measures of routineness and complexity of tasks. These variables statistically significantly predicted the probability of job automation, $F(2,95) = 191.537$, $p < 0.0005$. The ANOVA indicates that the model (p -value < 0.0005) is significant at a confidence level of 95% (p -value < 0.05). The regression equation based on this analysis was as follows:

$$P(\text{job automation}) = 0.752 + 0.341(\text{Routineness}) - 0.736(\text{Complexity})$$

A summary of the results from the multiple regression analysis for Regression Model 1 is given in Table 6.

Table 6: Summary of multiple regression analysis for Regression Model 1

Independent variable	Regression Model 1		
	B	SE _B	Beta
Constant	0.752	0.045	
Routineness	0.341	0.052	0.275*
Complexity	-0.736	0.051	-0.606*
N	291		

* $p < .05$; B = unstandardized regression coefficient; SE_B = Standard error of the coefficient; Beta = standardised coefficient.

The coefficient for complexity is -0.736 (-0.637 to -0.836, 95% CI). Thus, an increase of 10% in task complexity would decrease the probability of job automation by 7.36% (6.37% to 8.36%, 95% CI). Likewise, the coefficient for routineness is 0.341 (0.239 to 0.442, 95% CI). Thus, an increase of 10% in routineness would increase the probability of job automation by 3.41% (2.39% - 4.42%, 95% CI).

5.3 Non-Parametric Test 1

A total of 291 occupations were classified as either (i) routine-simple, (ii) nonroutine-simple, (iii) routine-complex, or (iv) nonroutine-complex. See Figure 13. To determine whether there was a statistically significant difference in the probability of job automation (dependent variable) between the four groups (independent variable) a Kruskal-Wallis H test (Kruskal & Wallis, 1952; Vargha & Delaney, 1998) coupled with case wise comparison post-hoc analysis (Dunn, 1964) was done. The following sections outline the descriptive statistics for the four occupational groups, together with data validation and model results for Non-Parametric Test 1. Detailed results are given in Appendix D.

5.3.1 Descriptive Statistics

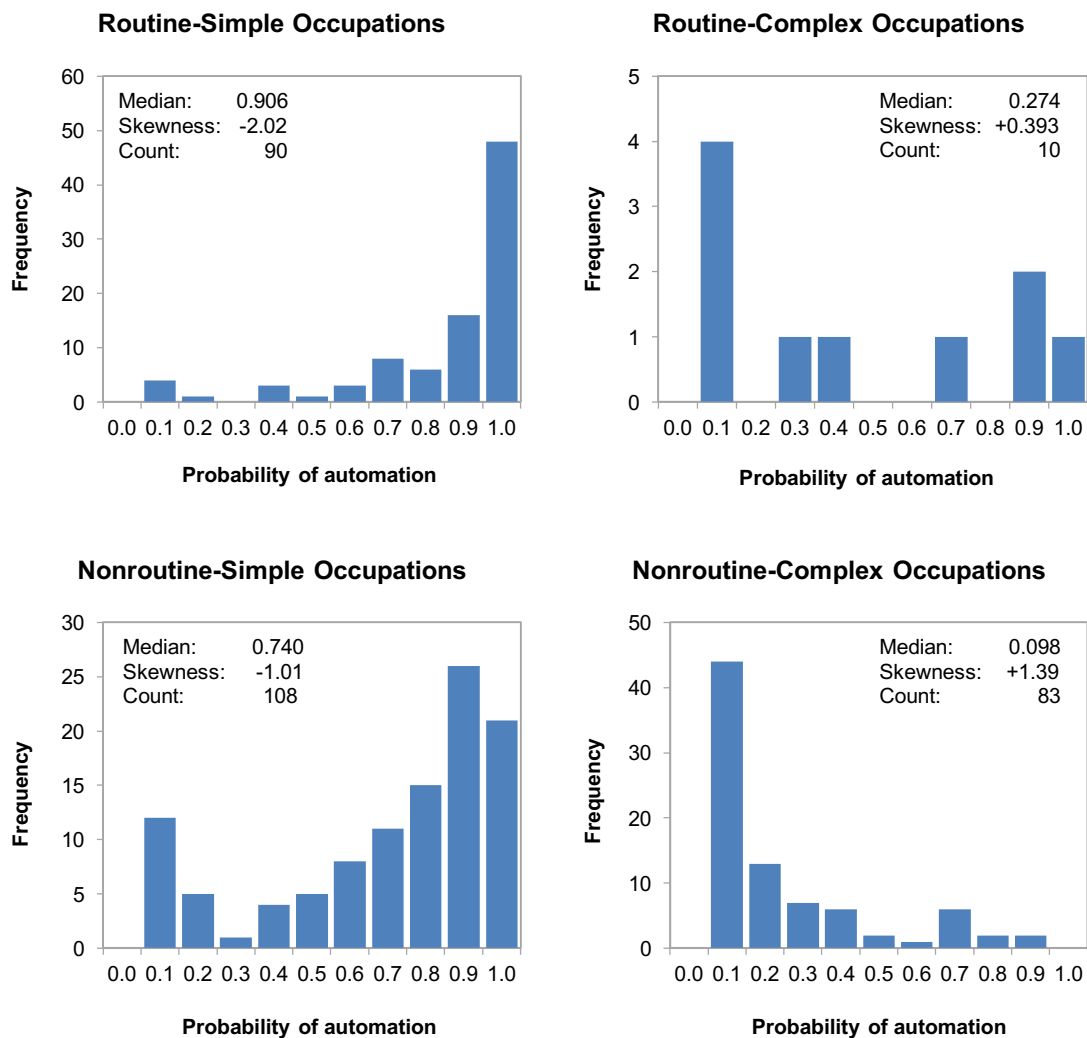
Distributions of the probability of job automation for the four occupational groups illustrate that both routine and nonroutine-simple occupations are negatively skewed, whilst both routine and nonroutine-complex tasks are positively skewed. See Figure 14.

The following results were obtained:

- Simple routine occupations have the highest probability for job automation (median = 0.902, skewness = -2.02). This is statistically significantly higher than all other occupational groups.

- ii. Nonroutine-simple occupations have a statistically significantly lower probability of job automation (median = 0.740, skewness = -1.01) than routine-simple occupations, but higher than that of nonroutine-complex occupations.
- iii. Routine-complex occupations have a lower median probability of job automation (median = 0.274, skewness = +0.393) than routine-simple occupations, but are not statistically significantly different from that of nonroutine-simple occupations or nonroutine-complex occupations.
- iv. Nonroutine-complex occupations have the lowest probability for job automation (median = 0.098, skewness = +1.39).

Figure 14: Probability of job automation for routine-simple, nonroutine-simple, routine-complex and nonroutine-complex occupations



A summary of the descriptive statistics for the above-mentioned distributions is given in Table 7.

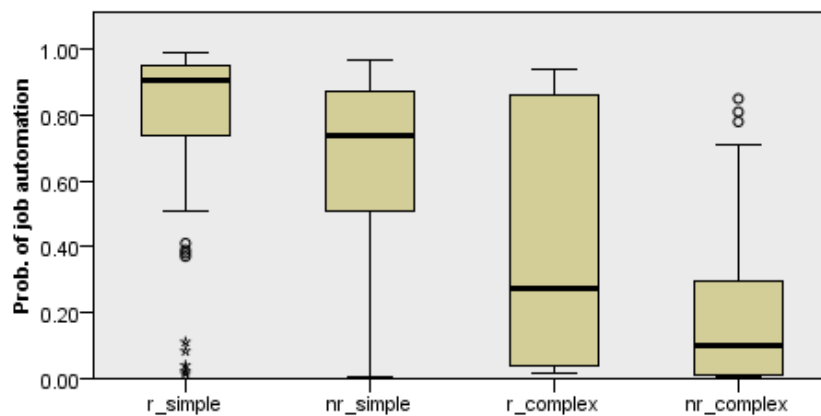
Table 7: Descriptive statistics: Probability of job automation for routine-simple, nonroutine-simple, routine-complex, and nonroutine-complex occupations.

Parameter	Routine-Simple Occupations	Nonroutine-Simple Occupations	Routine-Complex Occupations	Nonroutine-Complex Occupations
Mean	0.802	0.650	0.403	0.188
Median	0.906	0.740	0.274	0.098
Standard Deviation	0.237	0.295	0.391	0.233
Skewness	-2.016	-1.013	0.393	1.394
Minimum	0.014	0.006	0.016	0.003
Maximum	0.990	0.970	0.940	0.850
Count	90	108	10	83

5.3.2 Data Validation for Kruskal-Wallis H test

The dependent variable, namely “probability of job automation”, was measured on a continuous scale of 0 to 1 for a total of 291 occupations. The independent variable comprised four categorical, independent groups, namely “routine-simple”, nonroutine-simple”, routine-complex”, and “nonroutine-complex”. The observations were independent. Distributions of probability of job automation were not similar for all groups, as assessed by visual inspection of a boxplot. See Figure 14 and Figure 15. Because the distribution of each group had different shapes, and thus had different variability, the results of the Kruskal-Wallis H test was used to compare mean ranks. This was followed by a pairwise comparisons post-hoc analysis to establish whether the difference between the various groups were found to be statistically significant. See Appendix D for tables and figures supporting the above-mentioned analysis.

Figure 15: Box plots of the probability of job automation for routine-simple, nonroutine-simple, routine-complex and nonroutine-complex occupations



5.3.3 Routine, Nonroutine, Simple and Complex Occupations

A Kruskal-Wallis H test showed that there was a statistically significant difference in probability of job automation between the different groups, $\chi^2(3) = 132.559$, $p < 0.0005$. Pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Statistical significance was accepted at the $p < 0.005$ level. This post hoc analysis revealed statistically significant differences in the probability of job automation between the routine-simple (mean rank = 207.82) and nonroutine-simple (mean rank = 160.58) occupations ($p = 0.001$), routine-simple and routine-complex (mean rank = 115.05) occupations ($p = 0.006$), routine-simple and nonroutine-complex (mean rank = 63.72) occupations ($p < 0.0005$), nonroutine-simple and nonroutine-complex occupations ($p < 0.0005$), but not between nonroutine-simple and routine-complex occupations, or between routine-complex and nonroutine-complex occupations.

Based on this analysis, it is evident that the probability of job automation of routine-simple occupations is statistically significantly higher than all other occupational groups. The probability of job automation of nonroutine-simple occupations is statistically significantly higher than nonroutine-complex occupations. However, the probability of job automation of routine-complex occupations is not statistically significantly different from that of nonroutine-simple or nonroutine-complex occupations.

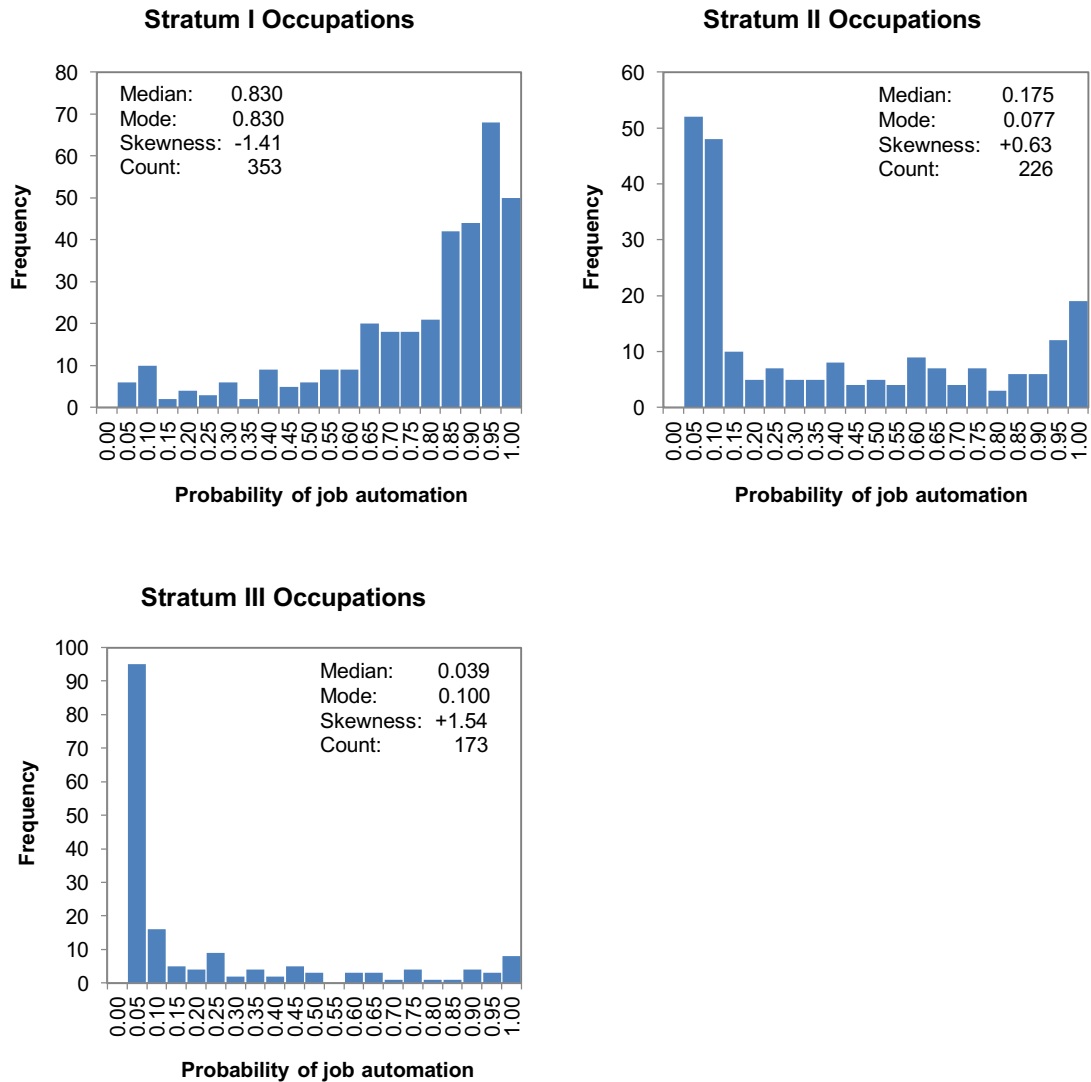
5.4 Non-Parametric Test 2

A total of 754 occupations were classified into five groups, representing stratum of work, namely, Stratum I, Stratum II, Stratum III and Stratum IV. To determine whether there was a statistically significant difference in the probability of job automation (independent variable) between the five groups of stratum of work (independent variable), a Kruskal-Wallis H test (Kruskal & Wallis, 1952; Vargha & Delaney, 1998) was performed. The following sections outline the descriptive statistics for the five occupational groups, together with data validation and model results for Non-Parametric Test 2. Detailed results are given in Appendix E.

5.4.1 Descriptive Statistics

Distributions of the probability of job automation for three occupational groups illustrate that Stratum I is negatively skewed, whilst both Stratum II and III are positively skewed. See Figure 16.

Figure 16: Probability of job automation for Stratum I, Stratum II and Stratum III occupations



The following results were obtained:

- i. Stratum I occupations have the highest probability for job automation (median = 0.830, skewness = -1.41, $n = 353$). This is statistically significantly higher than all other occupational groups.
- ii. Stratum II occupations have a statistically significantly lower probability of job automation (median = 0.175, skewness = 0.63, $n = 226$) than Stratum I occupations, but higher than Stratum III occupations.
- iii. Stratum III occupations have a statistically significantly lower probability of job automation (median = 0.039, skewness = 1.54, $n = 173$) than both Stratum I and Stratum II occupations.

- iv. Stratum IV occupations consist of a single data point, namely “general and operations managers”. The probability of job automation for this occupation is 0.160.
- v. Stratum V occupations consist of a single data point, namely “chief executives”. The probability of job automation for this occupation is 0.015.

A summary of the descriptive statistics for the above-mentioned distributions is given in Table 8.

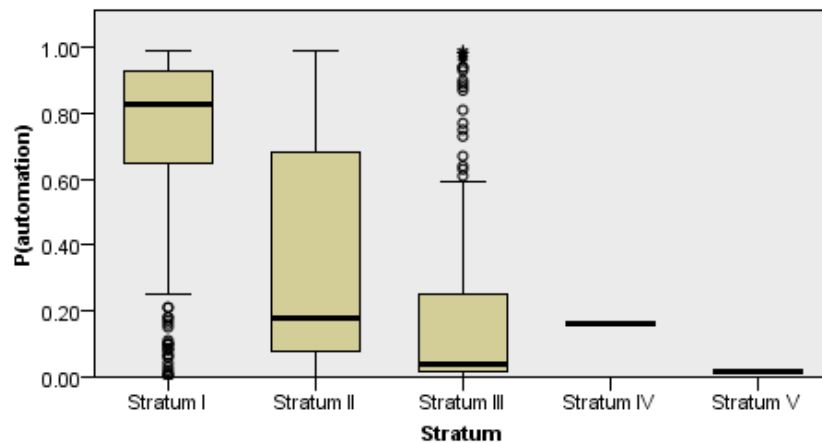
Table 8: Descriptive statistics: Probability of job automation for Stratum I, II and III occupations

Parameter	Stratum I occupations	Stratum II occupations	Stratum III occupations
Mean	0.747	0.355	0.206
Median	0.830	0.175	0.039
Mode	0.830	0.077	0.100
Standard Deviation	0.247	0.352	0.300
Skewness	-1.413	0.630	1.542
Minimum	0.005	0.003	0.003
Maximum	0.990	0.990	0.990
Count	353	226	173

5.4.2 Data Validation for Kruskal-Wallis H Test

The dependent variable, namely “probability of job automation”, was measured on a continuous scale of 0 to 1 for a total of 754 occupations. The independent variable comprised five categorical, independent groups, namely “Stratum I”, “Stratum II”, “Stratum III”, “Stratum IV” and “Stratum V”. The observations were independent. Distributions of probability of job automation were not similar for all groups, as assessed by visual inspection of a boxplot. See Figure 16 and Figure 17. Because the distribution of each group had different shapes, and thus had different variability, the results of the Kruskal-Wallis H test was used to compare mean ranks. This was followed by a pairwise comparisons post-hoc analysis to establish whether the difference between the various groups were found to be statistically significant.

Figure 17: Box plots of the probability of job automation for Stratum I, II, III, IV, and V occupations



5.4.3 Probability of Job Automation and Stratum of Work

A Kruskal-Wallis H test showed that there was a statistically significant difference in probability of job automation between the strata of work, $\chi^2(4) = 266.173$, $p < 0.0005$. Pairwise comparisons were performed using Dunn's (1964) procedure with a Bonferroni correction for multiple comparisons. Statistical significance was accepted at the $p < 0.005$ level. This post hoc analysis revealed statistically significant differences in the probability of job automation between the Stratum I (mean rank = 509.63) and Stratum II (mean rank = 305.55) occupations ($p < 0.0005$), Stratum I and Stratum III (mean rank = 204.31) occupations and Stratum II and Stratum III occupations ($p < 0.0005$), but not between Stratum IV occupations (mean rank = 250.00) and Stratum V occupations (mean rank = 87.00) or any other group combination.

Based on this analysis, it is evident that the probability of job automation of Stratum I occupations is statistically significantly higher than both Stratum II and Stratum III occupations. The probability of job automation of Stratum II occupations is also statistically significantly higher than that of Stratum III occupations.

5.5 Regression Model 2

To determine the relationship between the probability of job automation, measures of task routineness and task complexity, and stratum of work, a multiple regression analysis was conducted. The aim of this analysis was to illustrate how much of the variation in the "probability of job automation" (dependent variable) is explained by independent variables of "routineness", "complexity" and "stratum" for 291 occupations. The following

sections outline the data validation and model results for Regression Model 2. Detailed results are given in Appendix F.

5.5.1 Data Validation for Multiple Regression Analysis

The previous multiple regression analysis was expanded to include an additional independent variable, namely, “stratum”. The same 291 occupations were classified as either Stratum I, Stratum II, Stratum III or Stratum IV (based on organisation design theory) to establish a measure of ordinal data that range from 1 to 4. There was independence of residuals, as assessed by a Durbin-Watson (1950, 1951) statistic of 1.570. Linear relationships existed between (a) the probability of job automation and each of the independent variables and (b) the probability of job automation and the collective independent variables. Tests for collinearity highlighted a strong positive correlation between complexity and stratum, but collinearity tolerances were acceptable. A Spearman's (1904) rank-order correlation was run to assess the relationship between task complexity and stratum of work. Preliminary analysis showed the relationship to be monotonic, as assessed by visual inspection of a scatterplot. There was a strong positive correlation between task complexity and stratum of work, $r_s(289) = .799$, $p < .0005$. No additional significant outliers, high leverage or highly influential data points (as measured by Cook's (1982) Distance) were observed. Finally, the standardised residual was normally distributed. See Appendix F for tables and figures supporting the above-mentioned analysis.

5.5.2 Job Automation, Routineness, Complexity and Stratum

This second multiple linear regression analysis established how much of the variation in the probability of job automation (dependent variable) was explained by the independent variables of “routineness”, “complexity” and “stratum” for 291 occupations. The R^2 -value for the overall model was 0.608 with an adjusted R^2 -value of 0.604. This indicated that 60.4 percent of the variance in the probability of job automation (adjusted for sampling bias) can be explained by the measures of routineness, complexity and stratum. These variables statistically significantly predicted the probability of job automation, $F(3,95) = 148.510$, $p < 0.0005$. The ANOVA indicates that the model (p -value < 0.0005) is significant at a confidence level of 95% (p -value < 0.05). The regression equation based on this analysis is as follows:

$$P(\text{Automation}) = 0.841 + 0.315(\text{Routineness}) - 0.433(\text{Complexity}) - 0.140(\text{Stratum})$$

The coefficient for complexity in this model is -0.433 (-0.284 to -0.582, 95% CI). Thus, an increase of 10 percent in task complexity would decrease the probability of job automation by 4.33 percent (2.84 to 5.82 percent, 95% CI). The coefficient for routineness is 0.315 (0.239 to 0.442, 95% CI). Thus, an increase of 10 percent in routineness would increase the probability of job automation by 3.15 percent (2.17 to 4.13 percent, 95% CI). The coefficient for stratum is -0.140 (-0.087 to 0.193, 95% CI). Thus, an increase in stratum would result in a lower probability of job automation.

A summary of the results from the multiple regression analysis for Model 1 and Model 2 are given in Table 9.

Table 9: Summary of multiple regression analysis for Regression Model 1 and Regression Model 2

Independent variable	Regression Model 1			Regression Model 2		
	B	SE _B	Beta	B	SE _B	Beta
Constant	0.752	0.045		0.841	0.046	
Routineness	0.341	0.052	0.275*	0.315	0.050	0.254*
Complexity	-0.736	0.051	-0.606*	-0.433	0.076	-0.356*
Stratum				-0.140	0.027	-0.323*
N	291			291		

* p < .05 B = unstandardized regression coefficient; SE_B = Standard error of the coefficient; Beta = standardised coefficient

5.6 Projected Change in Workforce Structure

The following sections illustrate the results of an analysis regarding the historical change in workforce structure from 1999 to 2016. This is followed by the results of an analysis regarding the projected change in workforce structure from 2016 to 2036. Finally, the results of an analysis concerning the projected change in workforce structure from 2016 to 2036 for different industries are presented.

5.6.1 Historical Changes in Workforce Structure (1999-2016)

The historical shift in workforce structure was illustrated by firstly classifying 754 occupations according to stratum of work (See Section 5.4), and calculating the relative proportion of each stratum in each year. US employment data from 1999 to 2016 was used in this analysis. Where a change between the 2000 SOC and 2010 SOC systems occurred, the 2000-2010 SOC crosswalk was used to cross-reference employment data for corresponding occupations. Occupations which did not have a corresponding measure of “probability of job automation” were omitted from the analysis. After

omissions, this analysis represented 91.5 - 96.4 percent of the US workforce across 1990 to 2016. The change in workforce structure for the US economy from 1999 to 2016, together with the projected change in workforce structure from 2016 to 2036 are illustrated in Figure 18.

Figure 18: Workforce structure for the US economy from 1999-2016 (actual) and 2036 (projected)

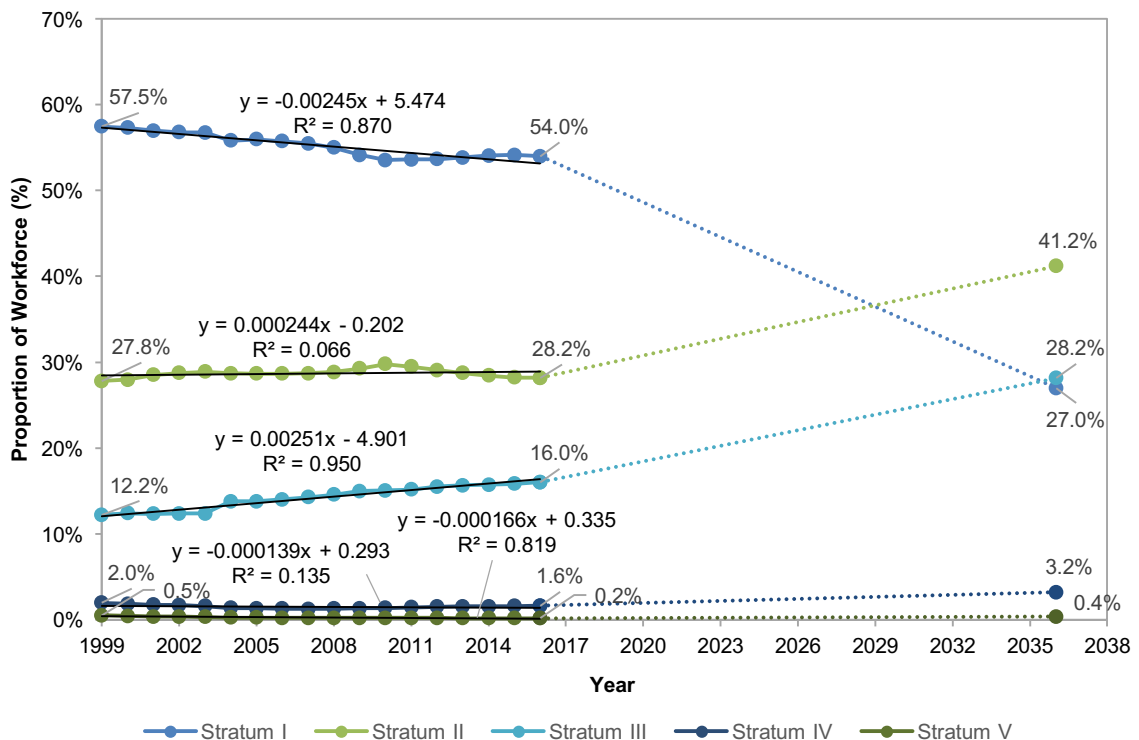


Figure 18 illustrates the following:

- The proportion of Stratum I occupations decreased linearly from 57.5 to 54.0 percent at a rate of 0.245 percent per annum ($R^2 = 0.870$).
- The proportion of Stratum II occupations increased marginally from 27.8 to 28.2 percent, but did not show a statistically significant trend over the period considered.
- The proportion of Stratum III occupations increased linearly from 12.2 to 16.0 percent at a rate of 0.251 percent per annum ($R^2 = 0.951$).
- The proportion of Stratum IV occupations decreased marginally from 2.0 to 1.6 percent, but no statistically significant trend was observed over the period considered.
- The proportion of Stratum V occupations decreased from 0.5 to 0.2 percent at a rate of 0.166 percent per annum ($R^2 = 0.819$).

5.6.2 Projected Changes in Workforce Structure (2016-2036)

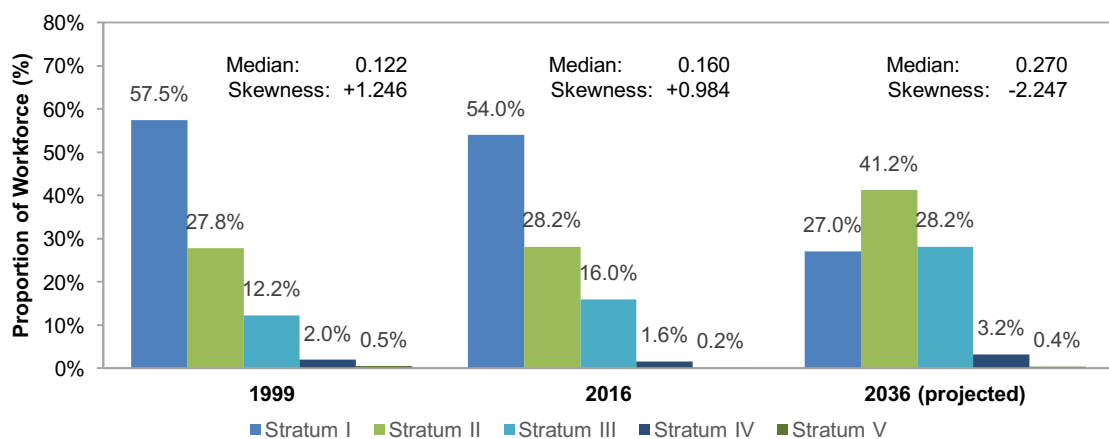
In projecting the change in workforce structure from 2016 to 2036, the 2016 employment numbers were adjusted for the “probability of job automation” at an occupational level, and aggregated to illustrate the relative change in workforce structure for the entire US economy. Occupations which did not have a corresponding measure of “probability of job automation” were omitted from the analysis. After omissions, this analysis represented 96.3 percent of the US workforce in 2016.

The projected workforce structure for the US economy in 2036 is significantly different to that of 2016 (See Figure 18 and Figure 19). The proportion of Stratum I occupations in the US economy is projected to reduce from 54.0 percent in 2016 to 27.0 percent in 2036. This significant reduction would be offset by increases in the relative proportion of all other strata of work. These are as follows:

- i. The proportion of Stratum II occupations will increase from 28.2 to 41.2 percent.
- i. The proportion of Stratum III occupations will increase from 16.0 to 28.2 percent.
- ii. The proportion of Stratum IV occupations will increase from 1.6 to 3.2 percent.
- iii. The proportion of Stratum V occupations will increase from 0.2 to 0.4 percent.

The above-mentioned figures suggest an exponential decline in Stratum I occupations, counter-balanced by an exponential increase in the proportion of Stratum II, III IV and V occupations. This shift in workforce structure over time is best illustrated by considering changes in the shape of the workforce structure distributions from 1990 to 2016 and from 2016 to 2036 (projected). Figure 19 illustrates the workforce structure distributions for 1999, 2016 and 2036.

Figure 19: Workforce structure for the US economy in 1999, 2016 and 2036 (projected).



As illustrated in Figure 19, the workforce structure distribution for 1999 is right skewed (median = 0.122; skewness = +1.246). This is attributed to the high proportion of Stratum I occupations (57.5 percent) that made up the workforce in 1999. However, between 1999 and 2016 the workforce structure distribution shifted to the left. In 2016 the shape of the workforce structure distribution is slightly less right skewed (median = 0.160; skewness = +0.984). As discussed earlier, this was attributed to a linear decrease in Stratum I occupations and an equivalent increase in Stratum III occupations.

The projected change in workforce structure from 2016 to 2036, however, yields a workforce structure distribution in 2036 that has a different shape. In 2036 the projected workforce structure distribution is left skewed (median = 0.270; skewness = -0.141). These projections suggest that the largest proportion of the workforce structure in 2036 will be Stratum II occupations, followed by Stratum III and Stratum I occupations.

Table 10 provides a summary of the descriptive statistics for the workforce structure distributions for 1999, 2016 and 2036 (projected).

Table 10: Descriptive statistics: workforce structure distributions in the US for 1999, 2016 and 2036 (projected)

Parameter	1999	2016	2036 (projected)
Mean	0.200	0.200	0.200
Median	0.122	0.160	0.270
Standard Deviation	0.236	0.222	0.176
Skewness	1.246	0.984	-0.141
Minimum	0.00513	0.00165	0.00385
Maximum	0.575	0.540	0.412
Count	5	5	5

5.6.3 Projected Change in Workforce Structure per Industry (2016-2036)

To determine the projected change in workforce structure per industry, the same 754 occupations and classification of stratum of work, as discussed in Section 5.6.2, were used. However, to illustrate the projected change in workforce structure per industry, 2016 employment data aggregated per NAICS industry was used.

The projected workforce structure for 2036 was calculated using the “probability of job automation” at an occupational level (see Section 5.6.2). However, in this case the data was aggregated at an industry level to illustrate the relative change in workforce structure

for each industry. Occupations which did not have a corresponding measure of “probability of job automation” were omitted from the analysis. After omissions, this analysis represented 96.3 percent of the US workforce in 2016 across the 20 industry sectors. Two classification metrics were developed to describe the projected change in workforce structure per industry. The first metric was workforce ratio and second metrics was the projected change in employment per industry.

5.6.3.1 Workforce Ratios per Industry

Workforce ratios were calculated by determining the ratio of Stratum I, II, III and IV occupations relative to Stratum V occupations. This gives a view of the workforce structure within the industry. For example, how many operators, supervisors, managers, professionals, and senior managers there are for every chief executive officer within a given industry. These workforce ratios were used to illustrate the relative workforce structure for different industries based on 2016 employment data and 2036 projected employment data. Table 11 and Table 12 give summaries of the workforce ratios for each industry in 2016 and 2036 (projected), respectively.

Table 11: Workforce ratios per industry in 2016

Industry Sector	I:V ratio	II:V ratio	III:V ratio	IV:V ratio	V:V ratio
Agriculture, Forestry, Fishing and Hunting	1 796	125	36	17	1
Mining, Quarrying, Oil and Gas Extraction	393	97	101	16	1
Utilities	225	121	116	11	1
Construction	512	96	56	15	1
Manufacturing	378	74	84	10	1
Wholesale Trade	191	147	51	13	1
Retail Trade	1 786	415	78	39	1
Transportation and Warehousing	1 250	201	67	18	1
Information	72	148	162	8	1
Finance and Insurance	79	120	123	7	1
Real Estate, Rental and Leasing	273	114	74	13	1
Professional, Scientific, Technical Services	47	95	185	9	1
Management of Companies and Enterprises	19	31	63	4	1
Administrative, Support, Waste Management and Remediation Services	586	192	77	14	1
Educational Services	151	521	80	3	1
Health Care and Social Assistance	363	411	120	6	1
Arts, Entertainment, and Recreation	391	117	41	12	1
Accommodation and Food Services	3 737	318	91	32	1
Other Services	285	77	52	11	1
Federal, State, and Local Government	55	35	29	2	1

Table 12: Workforce ratios per industry in 2036 (projected)

Industry Sector	I:V ratio	II:V ratio	III:V ratio	IV:V ratio	V:V ratio
Agriculture, Forestry, Fishing and Hunting	1 386	52	26	15	1
Mining, Quarrying, Oil and Gas Extraction	102	56	71	13	1
Utilities	94	71	93	9	1
Construction	154	62	40	13	1
Manufacturing	75	45	69	8	1
Wholesale Trade	42	57	37	11	1
Retail Trade	269	237	63	34	1
Transportation and Warehousing	292	124	44	15	1
Information	13	95	130	7	1
Finance and Insurance	5	59	65	6	1
Real Estate, Rental and Leasing	59	42	28	11	1
Professional, Scientific, Technical Services	7	40	143	8	1
Management of Companies and Enterprises	4	14	46	4	1
Administrative, Support, Waste Management and Remediation Services	145	95	56	12	1
Educational Services	41	451	68	3	1
Health Care and Social Assistance	194	302	111	5	1
Arts, Entertainment, and Recreation	120	77	31	10	1
Accommodation and Food Services	446	130	79	27	1
Other Services	109	46	40	10	1
Federal, State, and Local Government	25	24	22	1	1

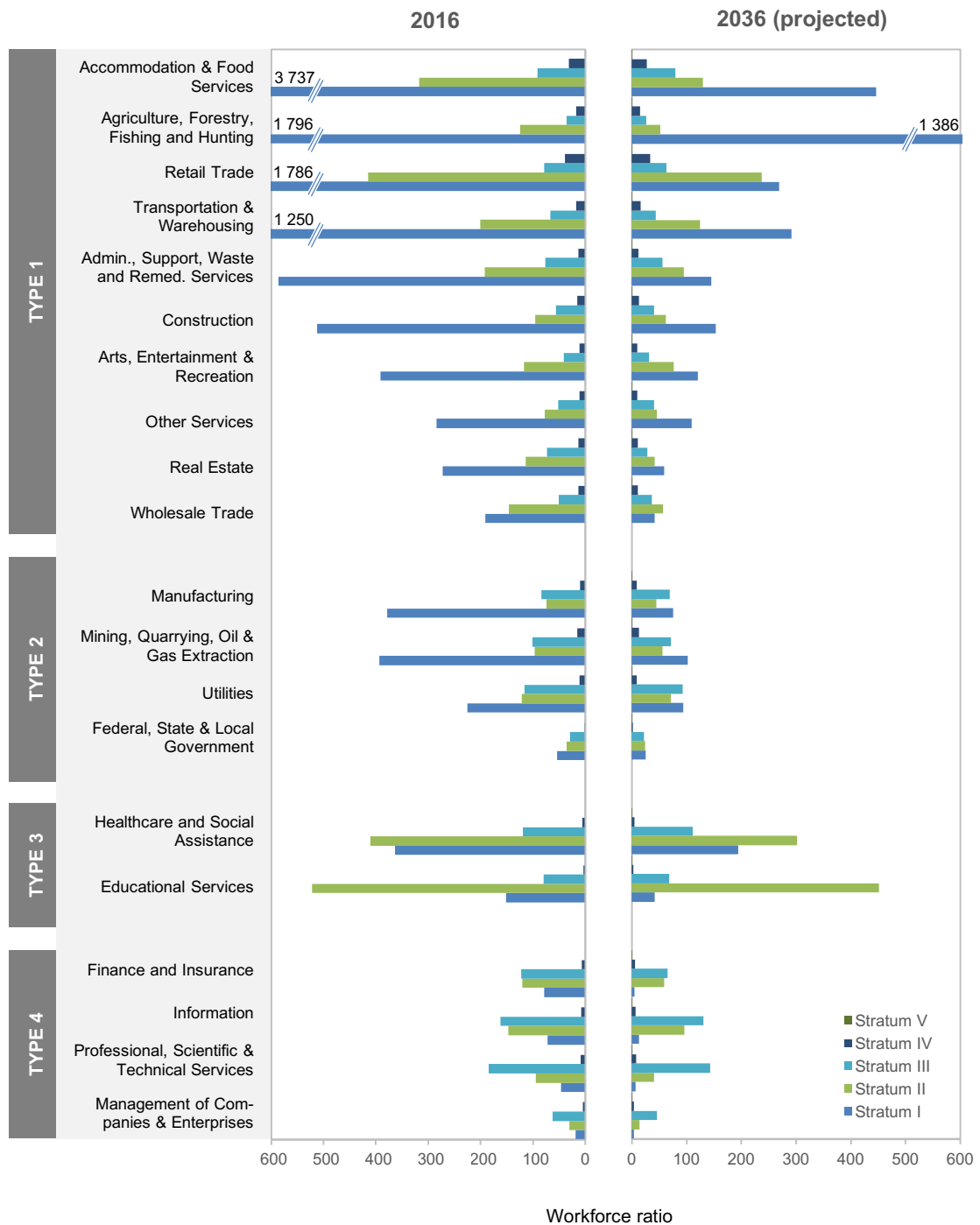
The above-mentioned workforce ratios were used to construct workforce structure distributions for each industry. Similar workforce structures were grouped as Type 1-4:

1. Industries with a pyramid workforce structure and a large complement of Stratum I occupations were classified as Type 1. This included ten industries: Accommodation and Food Services; Agriculture, Forestry, Fishing and Hunting; Retail Trade; Transportation & Warehousing; Admin., Support, Waste Management and Remediation Services; Construction; Arts, Entertainment and Recreation; Other Services; Real Estate; and Wholesale Trade.
2. Industries with a workforce structure where the largest complement was Stratum I occupations, but Stratum III occupations exceeded (or were almost equal to) the Stratum II complement, were classified as Type 2. This included four industries: Manufacturing; Mining, Quarrying, Oil and Gas Extraction; Utilities; and Federal, State and Local Government.
3. Industries with a workforce structure where the largest complement was Stratum II occupations, were classified as Type 3. This included two industries: Healthcare and Social Assistance; and Educational Services.
4. Industries with a workforce structure where the largest complement was Stratum III occupations, were classified as Type 4. This included four industries: Finance

and Insurance; Information; Professional, Scientific and Technical Services; Management of Companies and Enterprises.

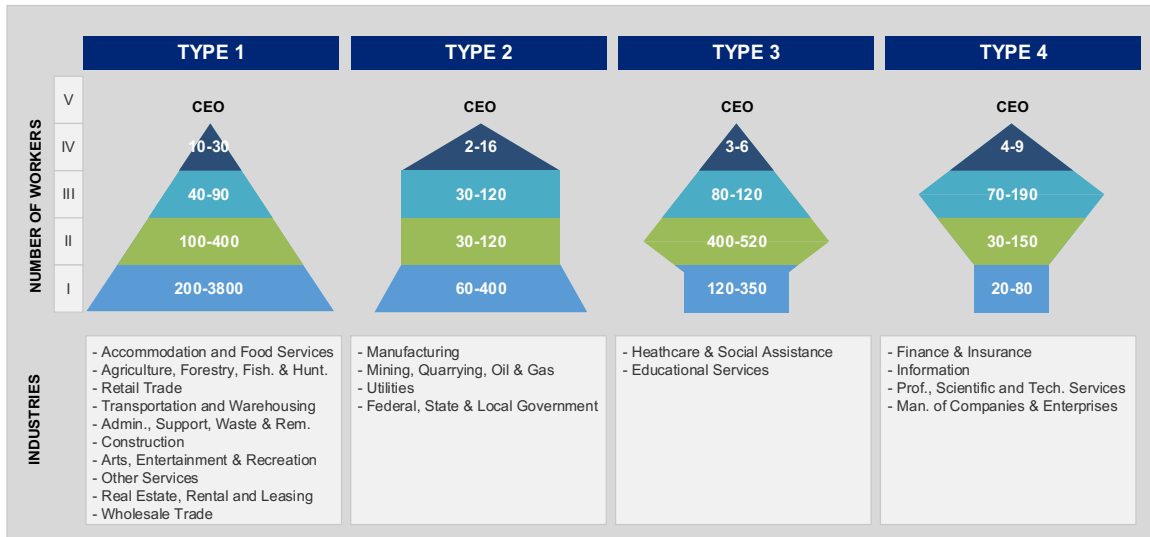
Figure 20 illustrates the 2016 and 2036 (projected) workforce structures for the above-mentioned Type 1 - 4 industries.

Figure 20: Workforce structures for Type 1-4 industries.



A summary of the four industry types, generic workforce structures, and typical workforce ratios are given in Figure 21.

Figure 21: Workforce structures for Type 1-4 Industries



5.6.3.2 Projected Change in Employment and Mechanism for Workforce Structure Adjustment

The projected change in employment was determined by calculating the percentage change in employment within each industry from 2016 to 2036. Likewise, the projected change in Stratum I, II and III occupations was determined by calculating the percentage change in the proportion of each stratum of work per industry from 2016 to 2036. Changes in Stratum IV and V occupations were not considered as these occupations were not industry-specific. By studying the projected change in Stratum I, II, and III occupations, various mechanisms for workforce structure were identified.

Figure 22, Figure 23 and Figure 24 illustrate the projected change in the proportion of Stratum I, II, and III occupations relative to the projected change in employment for each industry. The bubble size for these figures represents the size of each industry (defined by the number of workers) in 2016. See Appendix G for tables and graphs containing the supporting data.

Figure 22: Projected change in the Stratum I occupations and industry employment for various US industries

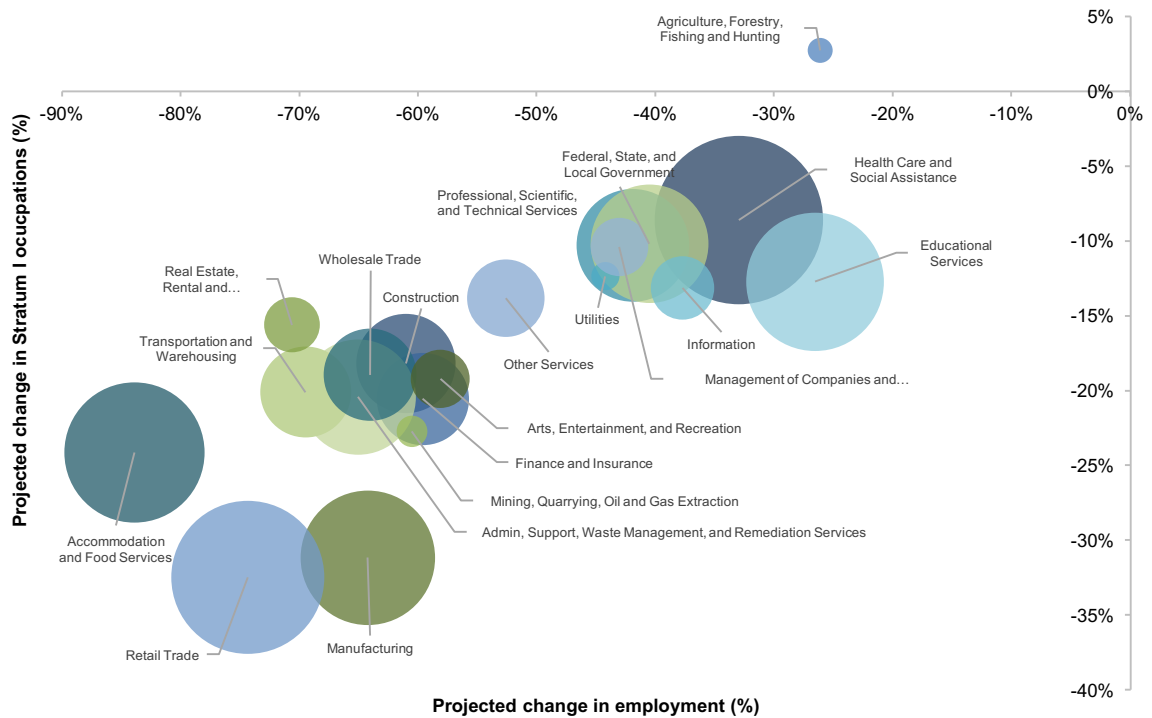


Figure 23: Projected change in the Stratum II occupations and industry employment for various US industries

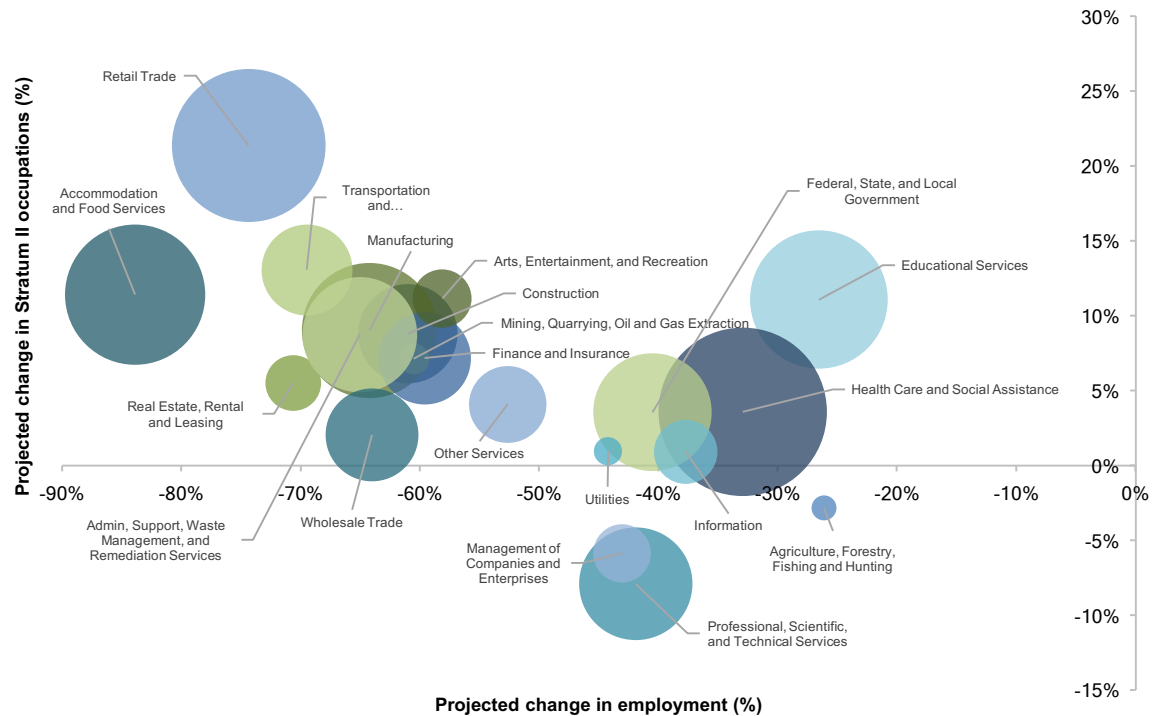
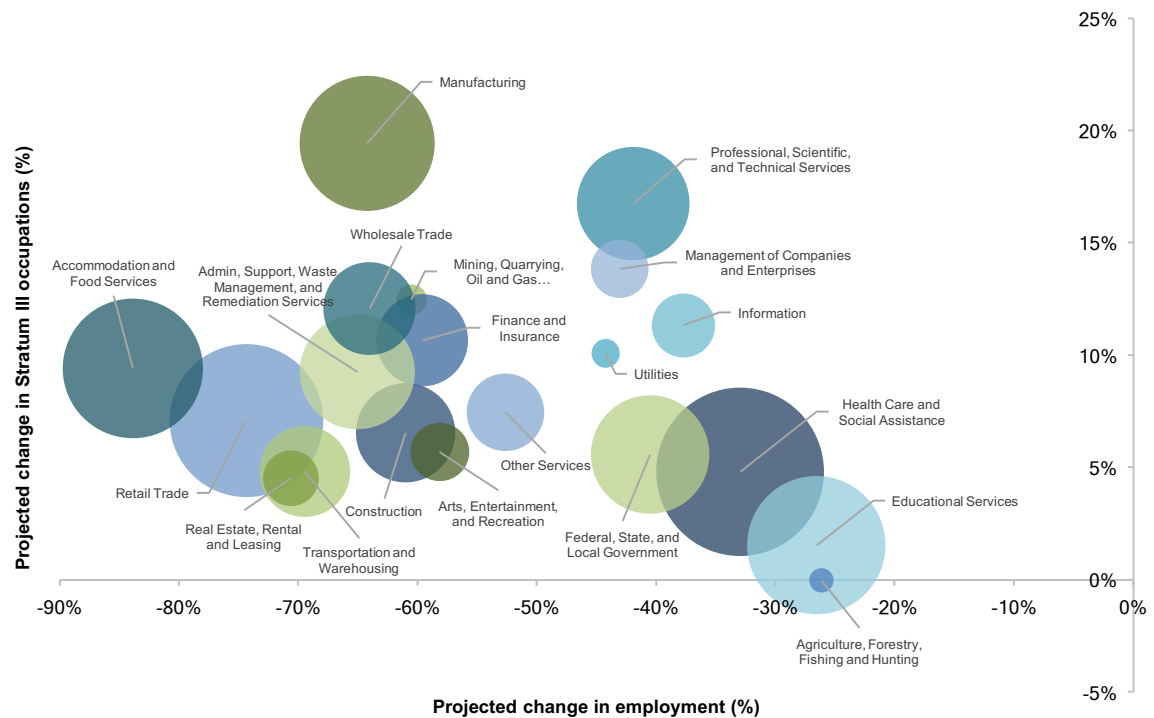


Figure 24: Projected change in Stratum III occupations and employment for various US industries



The results of this analysis indicate two industry clusters. Industries with a projected change in employment of greater than 50 percent (High), and industries with a projected change in employment of less than 50 percent (Low).

The projected change in employment for industries in the High cluster ranged from 53 to 84 percent. This cluster consisted of the following twelve industries: Retail Trade; Manufacturing; Accommodation and Food Services; Mining, Quarrying, Oil and Gas Extraction; Finance and Insurance; Administrative, Support, Waste Management and Remedial Services; Transportation and Logistics; Arts, Entertainment, and Recreation; Wholesale Trade; Construction, Real Estate, Rental and Leasing, and Other Services.

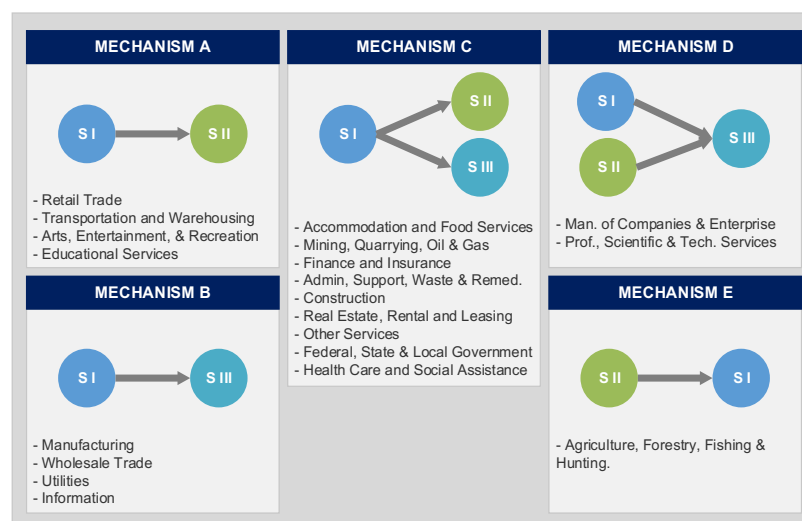
The projected change in employment for industries in the Low cluster ranged from 26 to 44 percent. This cluster consisted of the following eight industries: Utilities; Management of Companies and Enterprises; Professional, Scientific, and Technical Services; Federal, State, and Local Government; Information; Health Care and Social Assistance; Educational Services; and Agriculture, Forestry, Fishing and Hunting.

In addition to the two industry clusters, a total of five mechanisms were identified that describe different ways in which workforce structures adjust in response to technological change. These mechanisms were as follows:

- a. Mechanism A: A reduction in the proportion of Stratum I occupation was offset by a shift in predominantly Stratum II occupations. Industries which adjusted via this mechanism were: Retail Trade; Transportation and Warehousing; Arts, Entertainment, and Recreation; and Educational Services.
- b. Mechanism B: A reduction in the proportion of Stratum I occupation was offset by a shift in predominantly Stratum III occupations. Industries which adjusted via this mechanism were: Manufacturing; Wholesale Trade; Utilities; and Information.
- c. Mechanism C: A reduction in the proportion of Stratum I occupation was offset by a shift in both Stratum II and III occupations. Industries which adjusted via this mechanism were: Accommodation and Food Services; Mining, Quarrying, Oil and Gas Extraction; Finance and Insurance; Admin, Support, Waste Management, and Remediation Services; Construction; Real Estate, Rental and Leasing; Other Services; Federal, State, and Local Government; and Health Care and Social Assistance.
- d. Mechanism D: A reduction in the proportion of Stratum I and Stratum II occupation were offset by a shift in Stratum III occupations. Industries which adjusted via this mechanism were: Management of Companies and Enterprise; and Professional, Scientific, and Technical Services.
- e. Mechanism E: A reduction in the proportion of Stratum II occupations was offset by a shift in Stratum I occupations. Industries which adjusted via this mechanism were: Agriculture, Forestry, Fishing and Hunting.

A summary of the mechanisms for workforce structure adjustment is given in Figure 25.

Figure 25: Mechanisms A – E for workforce structure adjustment



A summary of the classification of the US industries based on the projected change in employment and mechanism of workforce structure adjustment is given in Table 13.

Table 13: Classification of the US industries based on the projected change of employment and mechanism of workforce structure adjustment

Cluster & Mech.		Industry	Change, employment (%)	Stratum I change (%)	Stratum II change (%)	Stratum III change (%)
HIGH	A	Retail Trade	-74.4%	-32.5%	21.4%	7.1%
		Transportation and Warehousing	-69.5%	-20.1%	13.1%	4.8%
		Arts, Entertainment, and Recreation	-58.1%	-19.2%	11.2%	5.7%
	B	Manufacturing	-64.2%	-31.2%	9.0%	19.4%
		Wholesale Trade	-64.0%	-18.9%	2.0%	12.1%
	C	Accommodation and Food Services	-83.9%	-24.1%	11.4%	9.4%
		Mining, Quarrying, Oil and Gas Extraction	-60.5%	-22.7%	7.1%	12.5%
		Finance and Insurance	-59.6%	-20.5%	7.2%	10.7%
		Admin, Support, Waste Management & Remediation Services	-65.0%	-20.4%	8.7%	9.3%
		Construction	-61.0%	-18.2%	8.8%	6.6%
		Real Estate, Rental and Leasing	-70.6%	-15.6%	5.5%	4.5%
		Other Services	-52.6%	-13.8%	4.1%	7.5%
LOW	A	Educational Services	-26.6%	-12.7%	11.1%	1.5%
	B	Utilities	-44.2%	-12.4%	1.0%	10.1%
		Information	-37.7%	-13.1%	0.9%	11.3%
	C	Federal, State, and Local Government	-40.5%	-10.2%	3.6%	5.6%
		Health Care and Social Assistance	-33.0%	-8.6%	3.6%	4.8%
	D	Management of Companies and Enterprises	-43.1%	-10.4%	-5.9%	13.8%
		Professional, Scientific, and Technical Services	-41.9%	-10.3%	-7.9%	16.8%
	E	Agriculture, Forestry, Fishing and Hunting	-26.1%	2.7%	-2.8%	0.0%

1 = Industries with a projected change in employment greater than 50 percent; 2 = Industries with a projected change in employment less than 50 percent; a = decrease in Stratum I, majority (>66 percent) increase in Stratum II; b = decrease in Stratum I, majority (>66 percent) increase in Stratum III; c = decrease in Stratum I, increase in both Stratum II and III; d = decrease in Stratum I and II, increase in Stratum III; e = decrease in Stratum II, increase in Stratum I.

6 DISCUSSION OF RESULTS

6.1 Introduction

This chapter outlines a discussion of the results in light of the research questions. It integrates concepts, theory, literature, and the results from the preceding chapters (Chapters 1 to 5) to address each research question. The results for Research Questions 1, 1a, 2, and 3 are discussed.

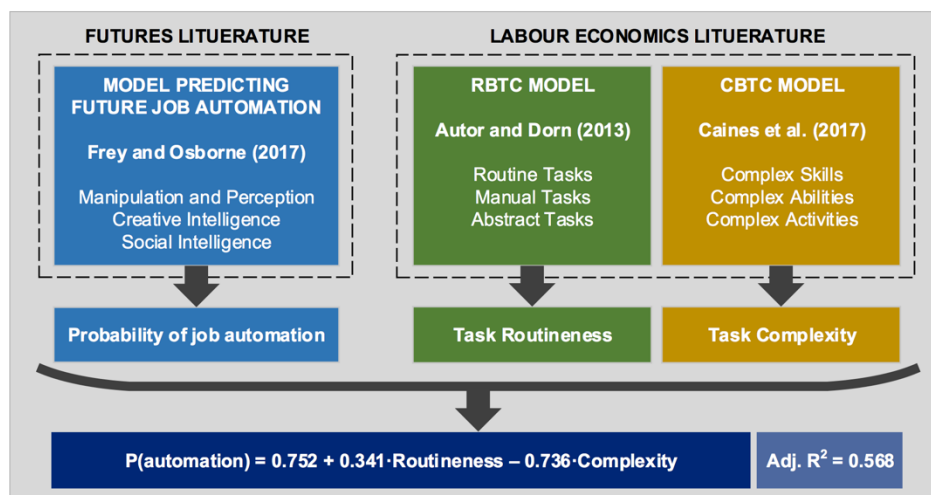
6.2 Research Question 1

What is the relationship between the probability of job automation and the routineness and complexity of tasks?

Research Question 1 aimed to establish whether there was a relationship between parameters from futures literature (probability of job automation) and parameters from technological change models (task routineness and task complexity) developed in labour economics literature.

A multiple linear regression analysis (Regression Model 1) between the probability of job automation (dependent variable) and independent variables of “routineness” and “complexity” illustrated a moderate to strong relationship between the dependent and independent variables across 219 occupations. Based on the adjusted R^2 -value, a total of 56.8 percent of the variance in the probability of job automation (adjusted for sampling bias) could be explained by the measures of routineness and complexity of tasks. See Table 6. A summary of the findings of this analysis is illustrated in Figure 26.

Figure 26: Summary of the results for Research Question 1



This analysis demonstrates alignment between predicted probabilities of job automation as determined by Frey and Osborne (2017), and the parameters from technological change models proposed by Autor and Dorn (2013) and Caines et al. (2017). As outlined in Chapter 2, these authors utilised different approaches and methodologies to assess the impact of technological change on employment. Frey and Osborne's (2017) study was forward-looking, and aimed to predict the probability of job automation at an occupational level. This was done using insights from machine learning and mobile robotics by considering three automation constraints, namely perception and manipulation, creative intelligence and social intelligence. This approach has been replicated in subsequent studies (Arntz et al., 2016, 2017; David, 2017).

The studies of Autor and Dorn (2013) and Caines et al. (2017), on the other hand, were backward-looking. These authors studied various task characteristics to quantify the task routineness and task complexity for a range of occupations. These metrics, together with historical employment and wage data, were used to illustrate technological biases with regards to changes in employment over time. This approach has been broadly used in labour economics literature (Acemoglu & Autor, 2011; Autor & Handel, 2013; Deming, 2017; Goos et al., 2014; Ikenaga & Kambayashi, 2016; Rodrik, 2016; Rohrbach-Schmidt & Tiemann, 2013).

Despite the different approaches and methodologies used in futures and labour economics literature, this analysis confirms that the findings of these studies are consistent with each other. That is, the predicted probabilities of job automation from futures literature are consistent with the technological change biases observed from historical shifts in employment and wage data.

6.2.1 Job Automation and Task Complexity

The strong negative relationship between the probability of job automation and task complexity supports findings by Autor and Dorn (2013), Deming (2017), and Caines et al. (2017) which suggest that complex tasks are less readily substituted by technology. As outlined in the CBTC model, complex tasks require higher order skills such as abstract problem-solving, decision-making, and effective communication (Caines et al., 2017). This is aligned with two of Frey and Osborne's (2017) automation constraints, namely, creative intelligence, and social intelligence. The authors noted that whilst some evidence exists that certain creative tasks and social intelligence tasks can be automated, it would be unlikely that occupations which require high degrees of creativity

and complex negotiation, persuasion, and care would be automated. Considering the various higher-order skills used by Caines et al. (2017) to determine task complexity for each occupation (See Figure 8), this strong relationship was expected.

6.2.2 Job Automation and Task Routineness

The strong positive relationship between the probability of job automation and routineness supports findings by Autor and Dorn (2013), Goos et al. (2014), Deming (2017), and Caines et al. (2017) which illustrate that tasks classified with higher routineness are more readily substituted by technology. Autor and Dorn (2013) illustrated a positive employment share differential for occupations with low routineness and a negative differential for occupations with high routineness. Likewise, Caines et al. (2017) found that routine occupations underwent a larger decline in employment share than nonroutine occupations. This is aligned with Frey and Osborne's (2017) first automation constraint, namely, perception and manipulation. The basic premise of this constraint was that robotics is unable to match human perception and the ability to perform manipulation tasks in an unstructured environment. However, as technology advances, the work environment becomes more structured, and work becomes more routine, this constraint will diminish over time. Thus, occupations that comprise a significant amount of manual, routine tasks and less abstract tasks, are more likely to be automated.

6.2.3 Findings

Based on this analysis, a moderate to strong relationship was found between the probability of job automation and the routineness and complexity of tasks. Overall the model was consistent with observations from historical employment and wage data for the US (Autor & Dorn, 2013; Caines et al., 2017; Deming, 2017; Goos et al., 2014). This analysis confirms that the findings from futures literature are consistent with the technological change biases observed from historical shifts in employment and wage data.

Given that there was a moderate to strong relationship in Research Question 1, a sub-research question, namely Research Question 1a, was posed. This is discussed in the following section.

6.3 Research Question 1a

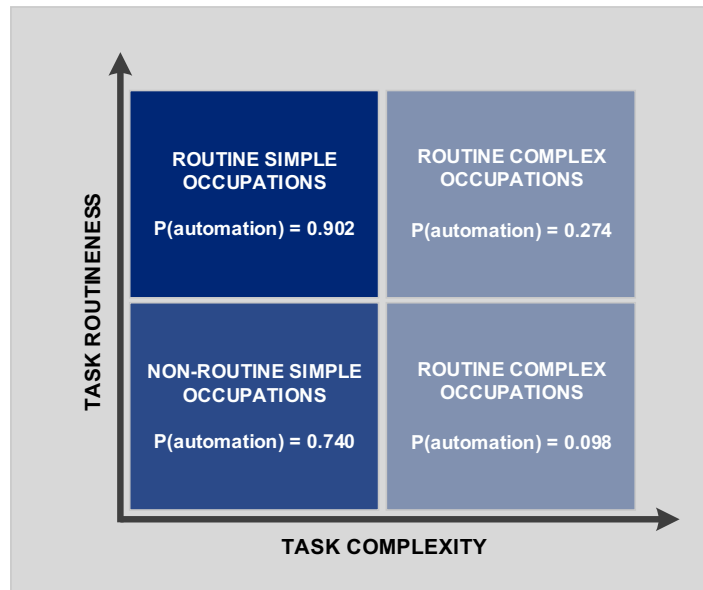
Research Question 1a: Are specific occupational groups (routine-simple, nonroutine-simple, routine-complex and nonroutine-complex) more susceptible to job automation than others?

Research Question 1a aimed to establish whether:

- i. there was a difference in the probability of job automation between routine-simple, nonroutine-simple, routine-complex and nonroutine-complex occupations, and whether,
- ii. specific occupational groups were more susceptible to job automation than others.

The relative susceptibility to automation for each group was determined by firstly, classifying occupations into four occupational groups based on routineness and complexity, and secondly, by assessing the relative probability of job automation of each group. A Kruskal-Wallis H test, followed by a pairwise comparison post-hoc analysis (Non-Parametric Test 1) was done. This illustrated statistically significant differences in the probability of job automation between all groups, except between routine-complex and nonroutine-simple occupations, and between routine-complex and nonroutine-complex occupations. Routine-simple occupations were found to have the highest probability for job automation, followed closely by nonroutine-simple occupations. Nonroutine-complex occupations have the lowest probability for job automation. The probability of job automation for routine-complex occupations was lower than routine-simple occupations, but was not found to be statistically significantly different to that of nonroutine-simple and nonroutine-complex occupations. This is consistent with the analysis by Caines et al. (2017) where routine and nonroutine occupations are collectively referred to as complex occupations. A summary of the probabilities for job automation for the four occupational groups is given in Figure 27.

Figure 27: Summary of the probability of job automation for routine-simple, nonroutine-simple, routine-complex and routine-complex occupations



Based on this analysis, it is evident that technological change in the form of automation is biased towards displacing routine-simple occupations (median = 0.902) and, to a lesser extent, nonroutine-simple occupations (median = 0.740). Nonroutine-complex occupations, on the other hand, were found to be less susceptible to automation (median = 0.098). This is consistent with observations of technological-induced job polarization described in the RBTC model (Autor & Dorn, 2013; Goos et al., 2014; Michaels et al., 2014), and the growing importance of social and complex skills outlined in the CBTC model (Beaudry et al., 2016; Caines et al., 2017; Deming, 2017).

As discussed in Chapter 2, the RBTC model explained how technological progress reduced the cost of completing routine, programmable tasks. It also explained how technological progress complemented “abstract” creative, problem-solving, and coordinating tasks that were generally performed by well-educated workers such as professionals and managers. This was evidenced by an erosion of wages paid for routine tasks in the US over the period of 1980 to 2005, which lead to the reallocation of low-skill labour to service occupations that required greater creative and social skills (Autor & Dorn, 2013). A similar phenomenon was observed across sixteen Western European countries over the period of 1993 to 2010. The net effect of technological change over this period resulted in decreased wages and employment share for routine occupations (e.g. office clerks, craft and trades workers, plant and machine operators and assemblers). Concurrently, the number of low paying service workers and high-paying managerial and professional occupations increased (Goos et al., 2014).

The CBTC model outlined higher wage levels and wage growth for complex occupations relative to simple occupations in the US from 1980 to 2005. This was coupled with a reallocation of labour from simple occupations to complex occupations over time. The CBTC model, furthermore, illustrated a larger decline in routine-simple occupations than nonroutine-simple occupations over the same period (Caines et al., 2017).

6.3.1 Routine-Simple Occupations

Analogous to the findings presented using the RBTC and CBTC models, the present study illustrates that routine-simple occupations are more susceptible to job automation. Routine-simple occupations are characterised by tasks that are manual, routine, and require less abstract, higher order skills such as problem-solving, decision-making and effective communication. Typical examples of occupations that comprise such tasks include bank tellers, packers and file clerks. As demonstrated by the RBTC and CBTC models, the employment share of simple routine occupations have declined over time with the introduction of new technology (Autor & Dorn, 2013; Goos et al., 2014). Given the high probability of job automation for this occupational group, this trend is expected to continue in years to come.

6.3.2 Nonroutine-Simple Occupations

Nonroutine-simple occupations were found to be somewhat less susceptible to job automation than routine-simple occupations, but significantly more susceptible than complex occupations. Nonroutine-simple occupations are characterised by tasks that involve less manual, less routine, and more abstract tasks, but still do not rely on the use of higher order skills. Typical examples of such occupations include repairers, machine operators, designers and writers. These occupations generally involve tasks that rely on human perception, manipulation and basic creative intelligence. As discussed, perception and manipulation tasks and tasks which involve creative intelligence currently present automation constraints (Frey & Osborne, 2017). However, given that these tasks remain simple and could possibly be substituted by emerging technologies in the next two decades, this occupational group is expected to remain highly susceptible to job automation.

6.3.3 Complex Occupations

Complex occupations, as opposed to simple occupations, were found to be significantly less susceptible to automation. This is attributed to the need for higher order skills such

as abstract problem-solving, decision-making, and effective communication. These occupations furthermore rely on tasks that involve creative intelligence and social intelligence - two factors considered to be both current and future automation constraints (Frey & Osborne, 2017).

Probabilities of job automation for routine-complex occupations varied greatly, but were nevertheless found to be lower than that of simple routine occupations. Typical examples of routine-complex occupations include financial managers, lawyers, and accountants. Whilst evidence suggests that some routine tasks which make up these occupations could be automated in the future, it is more likely that technology will have a compensatory effect, as opposed to a substitutionary effect on these occupations.

As expected, the probability of job automation for nonroutine-complex occupations were found to be the lowest of all occupational groups considered. Typical examples of nonroutine-complex occupations include chief executives, engineers, physicians, and specialists. As illustrated by historical employment and wage trends, technological advancement is likely to increase the employment share of nonroutine-complex occupations over time. Much like nonroutine-complex tasks, technological change is expected to have a compensatory effect on these occupations.

6.3.4 Findings

The RBTC and CBTC models are useful in explaining historical shifts in employment and wage data in response to technological change. The present study, however, has illustrated that parameters of task routineness and task complexity are also important in assessing probable job automation for the future. By classifying occupations into four occupational groups based on routineness and complexity, and assessing the relative probability of job automation of each group, the relative susceptibility to automation for each group could be determined. Based on this analysis, it is evident that routine-simple occupations are most susceptible to automation, followed by nonroutine-simple occupations. Complex occupations, particularly nonroutine-complex occupations, were found to be less susceptible to automation.

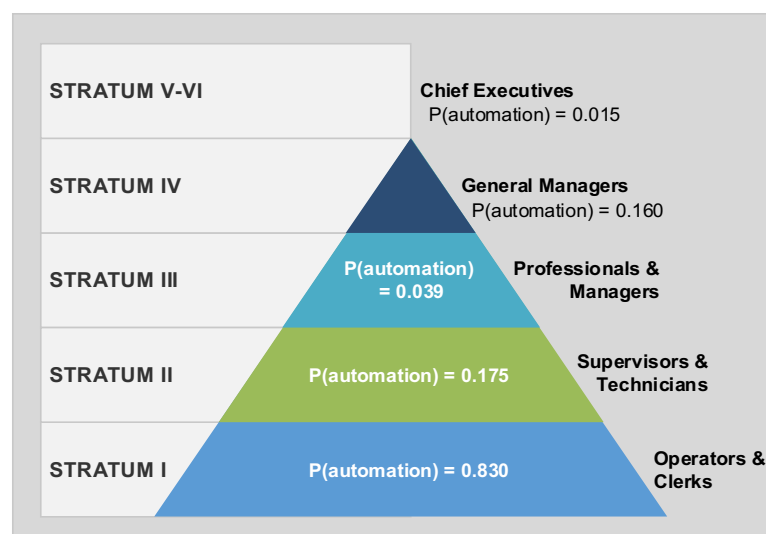
6.4 Research Question 2

Research Question 2: Are specific strata of work within a workforce structure more susceptible to job automation?

Thus far, this analysis has focused on establishing the relationship between futures literature and labour economics literature to explain the future impact of technological change on jobs. However, to determine the impact of technological change on workforce structures, concepts from organisational design literature were introduced. This was in the form of stratified systems theory (Jaques, 1986, 2016). Research Question 2 aimed to establish whether there was a statistically significant difference in the probability of job automation of occupations classified based on stratum of work (i.e. Stratum I, II, III, IV, or V).

By classifying occupations into five occupational groups based on stratum of work, and assessing the relative probability of job automation of each group, the relative susceptibility to automation for each group could be determined. A Kruskal-Wallis H test, followed by a pairwise comparison post-hoc analysis (Non-Parametric Test 2) was done. This illustrated statistically significant differences in the probability of job automation between Stratum I, II and III occupations. Stratum I occupations had the highest probability for job automation. The probabilities of job automation were significantly lower for Stratum II and III occupations. The data sets for Stratum IV and V occupations consisted of a single data point. A summary of the probabilities of job automation of each strata of work is given in Figure 28.

Figure 28: Summary of the probabilities of job automation of Stratum I, II, III, IV, and V occupations



Based on this analysis, it is evident that job automation is biased towards displacing Stratum I (median = 0.830) occupations. Stratum II occupations (median = 0.175) were less susceptible to automation than Stratum I occupations. Stratum III occupations (median = 0.039) were less susceptible to automation than both Stratum I and Stratum II occupations. Since Stratum IV and Stratum V occupations only comprised a single data point each, no statistical conclusion could be drawn regarding the susceptibility of automation of these groups relative to Stratum I, II and III occupations. However, based on the relative probability of job automation for “general and operations managers” and “chief executives”, there is sufficient evidence to suggest that Stratum IV occupations were more susceptible to automation than Stratum V occupations.

6.4.1 Stratum of Work

The above-mentioned results suggest that stratum of work does have an impact on the probability of job automation. More specifically, the higher the stratum of work, the lower the probability of job automation. This, to a certain extent, can be explained by the parallels in Jaques’ definitions of stratum of work (1986, 2016), and the higher order, abstract skills required for more complex occupations such as managers and professionals (Autor & Dorn, 2013; Caines et al., 2017; Deming, 2017; Goos et al., 2014). A strong positive correlation was found between “stratum of work” ($r_s = .799$) and “task complexity” across the 291 occupations considered in Research Question 1.

As discussed in Chapter 2, Jaques’ seven strata of work corresponded with increasing work complexity. Higher strata of work were characterised by longer time spans of discretion and require greater abstractive capabilities (Jaques, 1986, 2016). By way of example, “operators” were classified as Stratum I occupations. The time span of discretion for these occupations range from one day to three months. The work complexity involves carrying out single tasks at a time. This requires cognitive mechanisms such as concrete thinking and concrete shaping by means of linear pathways. “General managers”, on the other hand were classified as Stratum IV occupations. The time span of discretion ranges from two to five years. The work complexity involves overseeing operating subsystems, and designing new methods and policies. These occupations rely on more abstract cognitive mechanisms such as parallel processing, abstracting from data, and developing alternative systems.

Autor and Dorn (2013) illustrated that technological change complemented abstract creative problem-solving, and coordinating tasks performed by managers and

professionals. This has been confirmed by analysis by Beaudry et al. (2016), Deming (2017), and Caines et al. (2017) over the last three decades. Beaudry et al. (2016) illustrated growth in both employment and wages for occupations that require higher cognitive skills. Deming (2017) attributed employment and wage growth to occupations that require greater social skills, particularly when combined with cognitive skills. Similarly, Caines et al. (2017) attributed this growth to occupations with greater task complexity.

6.4.2 Regression Model 2

The results from the present study suggest that there is a relationship between strata of work and the probability of job automation. To validate this relationship, Regression Model 1 was expanded to include stratum of work as an additional independent parameter.

This second multiple linear regression analysis (Regression Model 2) between the probability of job automation (dependent variable) and independent variables of “routineness”, “complexity”, and “stratum” illustrated a moderate to strong relationship between the dependent and independent variables across 219 occupations. Based on the adjusted R^2 -value, a total of 60.4 percent of the variance in the probability of job automation (adjusted for sampling bias) could be explained by measures of task routineness, task complexity, and stratum of work. See Table 9. Thus, by including stratum of work as an additional independent variable, the model could explain an additional 3.60 percent of the variance in the probability of job automation.

A negative relationship between the probability of job automation and stratum of work ($B_{\text{stratum}} = -0.140$), confirms that the probability of job automation decreases with increasing stratum of work.

This analysis illustrates that lower strata of work within a workforce structure are more susceptible to job automation. Given the significant projections around job automation over the next two decades, this is likely to have a major impact on workforce structure in the future. However, the impact will differ across industries. Different industries consist of a different mix of occupations spanning different strata of work. Most industries have chief executives (Stratum V and above), but the relative ratios of Stratum I, II, III and IV occupations vary. This is attributed to two factors. Firstly, many industries consist of industry-specific occupations for which the tasks differ vastly in routineness and complexity. Secondly, industries employ different workforce structures. For example,

firms in the manufacturing industry generally have large hierarchical organisational structures, consistent with Mintzberg's classification of a machine bureaucracy (1980). These structures generally consist of a large complement of operators (Stratum I), supervisors and technicians (Stratum II) and professionals, managers and engineers (Stratum III). Technology firms, on the other hand, are consistent with Mintzberg's classification of an adhocracy (1980). These firms generally consist of a network of managers and professionals (Stratum III occupations) with very little Stratum I and Stratum II occupations.

6.4.3 Findings

This analysis illustrates that Stratum I occupations were most susceptible of job automation. Higher strata of work within a workforce structure were found to be less susceptible to job automation. Higher strata of work are characterised by longer time spans of discretion and require greater abstractive capabilities. This aligns with findings that technological progress complements abstract, creative problem-solving and coordinating tasks performed by managers and professionals (Autor & Dorn, 2013; Beaudry et al., 2016; Caines et al., 2017; Deming, 2017). By including stratum of work as an additional independent variable, the model for probability of job automation (See Research Question 1) was improved.

6.5 Research Question 3

Research Question 3: What is the projected change in workforce structure from 2016 to 2036 at an industry level?

Research Question 3 aimed to illustrate how technological change will impact future workforce structures at an industry level.

6.5.1 Projected Change in Workforce Structure

An analysis of the workforce structure within the US economy from 1999 to 2016 highlighted a linear decrease in the proportion of Stratum I occupations. This decrease was associated with an equivalent linear increase in Stratum III occupations. See Figure 18. That is, the reduction in Stratum I occupations over the last two decades was adjusted by an increase in Stratum III occupations. This migration of labour from low-skilled occupations to high-skilled professional occupations over the last two decades has largely been attributed to technological change. Rapid advancement coupled with the declining cost of technology, has led to both substitution of simple-routine tasks and

the complementing of nonroutine-complex tasks. This has led to a reduction in low-skilled occupations (Autor & Dorn, 2013; Goos et al., 2014; Michaels et al., 2014) and an increase in high-skilled cognitive and abstract occupations over the last two decades (Beaudry et al., 2016; Caines et al., 2017; Deming, 2017).

Assuming this shift from Stratum I to Stratum III occupations continues at a linear rate of 0.25 percent per annum over the next two decades, the proportion of Stratum I occupations is estimated to decrease from 54.0 percent in 2016 to 38.4 percent in 2036. Likewise, the proportion of Stratum III occupations is estimated to increase from 16.0 to 18.9 percent. This scenario firstly assumes that the US economy can facilitate the required growth in professional occupations without being constrained by the requirements for a minimum number of unskilled occupations. Secondly, it assumes that workers, at an aggregated level (e.g. across the US economy), have the capability to shift from unskilled to professional occupations and that they have access to suitable education or experience. Thirdly, it assumes that technological change and automation of unskilled occupations take place linearly over time.

However, futures literature suggests that technological progress in the fields of artificial intelligence, robotics and machine learning will have a significant impact on societies, life, employment and business in the next two decades (Frey & Osborne, 2017; Makridakis, 2017; Pratt, 2015). The introduction of robotics and artificial intelligence in the workplace is thought to have a large and robust negative effect on employment and wages (Acemoglu & Restrepo, 2016; DeCanio, 2016; Gregory et al., 2016; Sachs et al., 2015). All indications are thus that technological change in the forthcoming AI revolution will follow Amara's law, and technological change will be exponential.

Projections of workforce structure changes for the US economy from 2016 to 2036 suggest an exponential decrease in the proportion of Stratum I occupations, accompanied by an exponential structural adjustment in Stratum II and III occupations. See Figure 18 and Figure 19. These projections take into account the probability of job automation within the US economy (Frey & Osborne, 2017), but are most notably influenced by the technological biases toward substitution of (i) routine and nonroutine-simple occupations, and (ii) Stratum I occupations (See Research Questions 1 and 2). The proportion of Stratum I occupations in the US economy are projected to reduce from 54.0 percent in 2016 to 27.0 percent in 2036. Stratum III occupations are projected to increase from 16.0 to 28.2 percent over the same period. Unlike what was observed from 1999 to 2016, the projected figures also illustrate an increase in the proportion of Stratum

II occupations from 28.2 to 41.2 percent. Thus, technological bias towards job automation of Stratum I occupations is likely to result in a concentration of the workforce structure, i.e. future organisations will have less employees in Stratum I occupations and generally more (or the same amount of) employees in Stratum II and Stratum III occupations.

This structural adjustment in Stratum II and III occupations could be interpreted in two different ways:

- i. There is a decrease in the number of Stratum I occupations, but the number of Stratum II and III occupations remains unchanged. Thus, the net effect is that there will be fewer total occupations, and the current Stratum II and III occupations will make up a larger portion of the workforce. This assumes that technological change will have a purely substitutive effect on employment, and no new higher-order complex occupations will be created because of its complementary effect. It also assumes that the demand for Stratum II and III occupations does not increase.
- ii. There is a decrease in the number of Stratum I occupations and an increase in the number of Stratum II and/or III occupations due to the introduction of new higher-order complex occupations. This assumes that technological change will have both a substitutionary and complementary effect on future employment (Autor, 2015). As outlined in Chapter 2, there are a number of compensation effects that can increase, or create new demand for labour (Calvino & Virgillito, 2017; Vivarelli, 2014, 2015).

Irrespective of how this structural adjustment is interpreted, such a drastic change in workforce structure would have a significant impact on the business environment. Of interest would be the workforce and human resource strategies that businesses across different industries develop in response to this technological disruption.

6.5.2 Projected Change in Workforce Structure per Industry

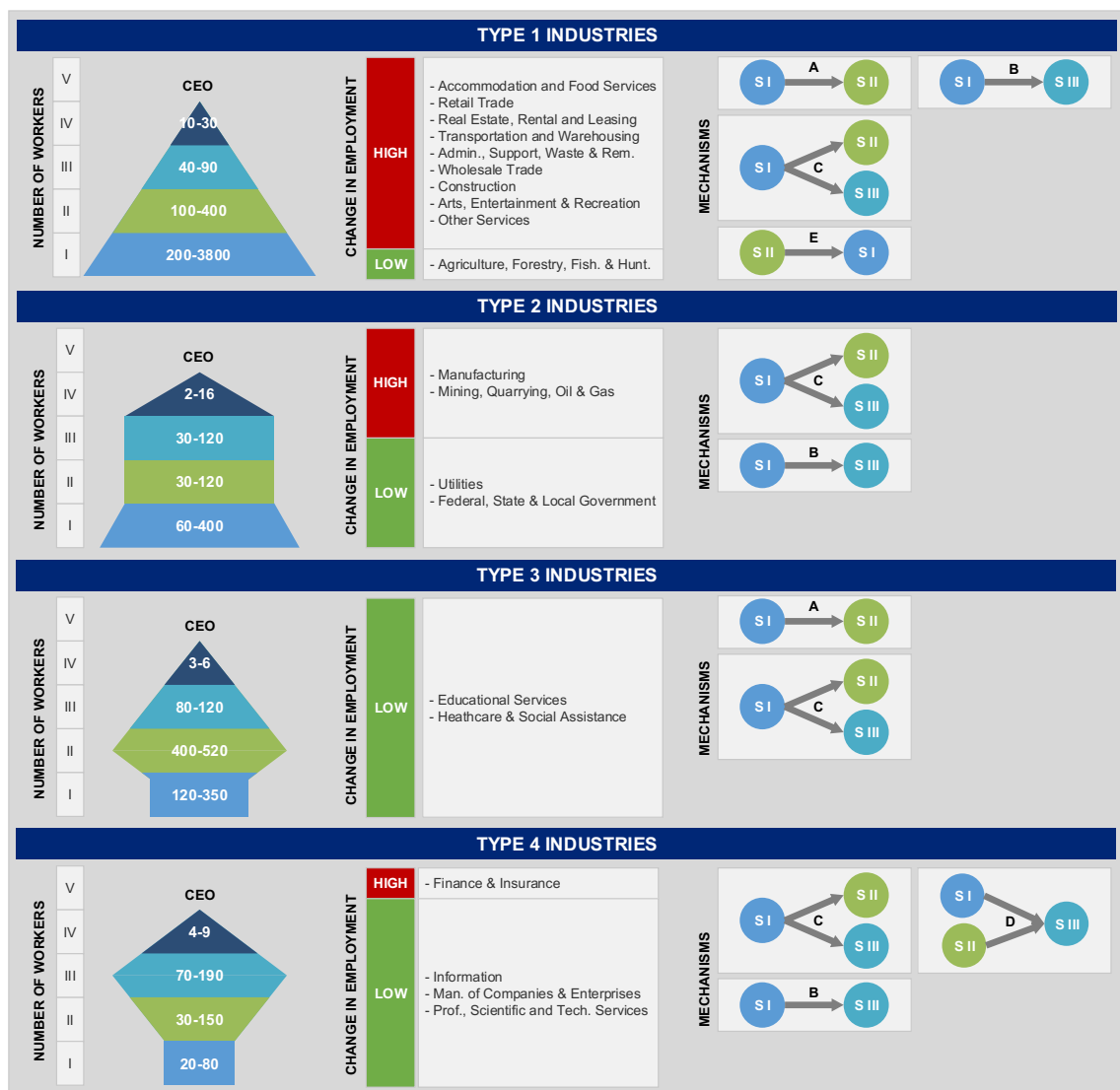
The analysis thus far has focused on aggregated data for the US economy. However, as discussed in Research Question 2, the impact of technological change will differ across industries. This is attributed to the different occupational structures (that include industry-specific occupations), and different workforce structures across industries. To represent the workforce structure of different industries, a novel measure, namely the workforce

ratio for an industry was established. This gave rise to four industry types with similar workforce structures based on 2016 employment data. See Figure 21.

In addition to defining workforce ratios for each industry, the projected change in employment from 2016 to 2036 for each industry was classified as either Low or High. Mechanisms A to E for workforce structure adjustment were also identified. See Figure 25.

Figure 29 gives a summary of the projected change in workforce structure and mechanisms of workforce structure adjustment for each industry type. The following sections discuss the projected change in workforce structure per industry type.

Figure 29: Summary of the change in workforce structure and mechanisms of workforce structure adjustment for Industry Types 1 - 4



6.5.2.1 *Type 1 Industries*

Type 1 industries were characterised by a workforce structure in a typical pyramid configuration with its largest complement being Stratum I occupations. That is, for every chief executive within this industry there were 10 – 30 general managers, 40 – 90 professionals, 100 – 400 supervisors, and 200 – 3800 operators or clerks. The workforce structures of these industries closely represent a divisionalised form. The key coordinating mechanism for organisations within these industries is standardisation of outputs (Mintzberg, 1980). Thus, these organisations generally have large middle lines (e.g. supervisors and managers), and smaller technostructures (e.g. analysts and professionals). Division of labour is high, leading to both vertical and horizontal job specialisation. This results in a large bureaucratic pyramid-like workforce structure with a large complement of Stratum I occupations.

The impact of technological change on Type 1 industries is high, except in the case of the Agriculture, Forestry, Fishing and Hunting industry. Type 1 industries are projected to undergo workforce structure adjustment via Mechanism A, B, and C. However, in the case of the Agriculture, Forestry, Fishing and Hunting industry, a reduction in Stratum II occupations is projected with a workforce structure adjustment via Mechanism E.

6.5.2.2 *Type 2 Industries*

Type 2 industries were characterised by a workforce structure where the largest complement was Stratum I occupations, but the complement of Stratum III occupations was either larger or equal to the Stratum II complement. That is, for every chief executive within this industry there were 2 – 16 general managers, 30 – 120 professionals, 30 – 120 supervisors, and 60 – 400 operators or clerks. The workforce structures of these industries closely represent machine bureaucracies. The key coordination mechanism for organisations within these industries is standardisation of work (Mintzberg, 1980). Thus, these organisations generally have large technostructures that consist of analysts, planners, and professionals which are classified as Stratum II and III occupations. Division of labour is high, leading to both vertical and horizontal job specialisation. Thus, the organisation has a large complement of Stratum I occupations.

The impact of technological change on Type 2 industries ranges from moderate to high. The Manufacturing, and Mining, Quarrying, Oil and Gas industries will be severely impacted, whilst the Utilities and Federal, State and Local Government industries will see

a moderate impact. Because of the high complement of Stratum II and III occupations, the reduction in Stratum I occupations was adjusted via Mechanisms B or C.

6.5.2.3 *Type 3 Industries*

Type 3 industries were characterised by a workforce structure comprising the largest complement of Stratum II occupations. That is, for every chief executive within this industry there were 3 – 6 general managers, 80 – 120 professionals, 400 – 520 supervisors, and 150 – 350 operators or clerks. The workforce structures of these industries closely represent professional bureaucracies. The key coordination mechanism for organisations within these industries is standardisation of skills (Mintzberg, 1980). Thus, these organisations have a large complement of skilled professionals (Stratum II and III occupations) in the operating core, together with a large complement of support staff that perform simple routine tasks (Stratum I and II occupations). Horizontal job specialisation is high, whilst vertical specialisation is low. The organisation, thus, has a large complement of Stratum II and III occupations, with a smaller complement of Stratum I occupations.

The impact of technological change on Type 3 industries is low. The decrease in Stratum I occupations is adjusted via Mechanisms A and C.

6.5.2.4 *Type 4 Industries*

Type 4 industries were characterised by a workforce structure where the largest complement was Stratum III occupations. That is, for every chief executive within this industry there were 4 – 9 general managers, 70 – 190 professionals, 30 – 150 supervisors, and 20 – 80 operators or clerks. The workforce structures of these industries closely represent adhocracies. The key coordination mechanism for organisations within these industries is mutual adjustment (Mintzberg, 1980). Thus, these organisations have a large complement of skilled professionals (Stratum III occupations) that work in multi-disciplinary specialist teams. These teams are supported by a smaller complement of support staff (Stratum I and II occupations). Horizontal job specialisation is high, whilst vertical specialisation is low.

The impact of technological change on Type 4 industries is low, except in the case of the Finance and Insurance industry. The decrease in Stratum I and II occupations is adjusted via Mechanisms B, C, and D.

6.5.3 Findings

In this section, it was illustrated using both historical and projected employment data that the workforce structure within the US economy is concentrating over time, i.e. future organisations will have less employees in Stratum I occupations and generally more (or the same amount of) employees in Stratum II and Stratum III occupations. Whilst historical data indicated that technological change had a linear impact on the workforce structure over the last two decades, the impact of technological change in the next two decades is projected to have an exponential impact. Four different industry types were identified within the US economy based on similar workforce structures. The projected change in workforce structures was found to be different across the four industry types. Technological change will have the greatest impact on Type 1 and Type 2 industries. Furthermore, a total of five mechanisms for workforce structure adjustment were identified. These mechanisms give insight into how the workforce structure may change for organisations operating in different industries.

7 CONCLUSION

In the previous chapter, the results of this study were discussed in terms of the research questions, theory and literature. This chapter sets out the principal findings of the research. Based on these findings, recommendations are made to business and managers. The limitations of the research are discussed, and suggestions for future research are made.

7.1 Principal Findings

There are four principal findings from this study. These are as follow:

1. There is alignment between predicted probabilities of job automation and parameters from technological change models based on historical employment and wage data.
2. Routine-simple occupations are more susceptible to job automation than nonroutine-simple and complex occupations.
3. Stratum I occupations are more susceptible to job automation than higher strata of work occupations.
4. Technological change will have the greatest impact on Type 1 and Type 2 industries.

Each of these findings are discussed in the following sections.

7.1.1 Alignment between Predicted Probabilities of Job Automation and Parameters from Technological Change Models

A moderate to strong relationship exists between the probability of job automation and the routineness and complexity of tasks. Approximately 57 percent of the variance in probability of job automation can be explained by task routineness and task complexity for the occupations considered. The positive relationship between probability of job automation and task routineness, and the negative relationship between probability of job automation and task complexity supports findings by Autor and Dorn (2013), Goos et al. (2014), Deming (2017), and Caines et al. (2017). Tasks classified with higher routineness are more susceptible to substitution by technology. Whereas tasks which require higher order skills are more susceptible to being complemented by technology. This is aligned with Frey and Osborne's (2017) three automation constraints, namely, perception and manipulation, creative intelligence and social intelligence.

This analysis demonstrates alignment between predicted probabilities of job automation as determined by Frey and Osborne (2017), and the parameters from the RBTC (Autor & Dorn, 2013) and CBTC (Caines et al., 2017) models. Whilst the RBTC and CBTC models are useful in explaining historical shifts in employment and wage data in response to technological change, the present study illustrates that parameters of task routineness and task complexity are also important in assessing probable job automation for the future.

7.1.2 Routine-Simple Occupations are More Susceptible to Job Automation than Nonroutine-Simple and Complex Occupations

By classifying occupations into four occupational groups based on routineness and complexity, namely, routine-simple, nonroutine-simple, routine-complex, and nonroutine-complex occupations, the relative probability of job automation for each group can be determined. Routine-simple occupations are the most susceptible to automation, followed by nonroutine-simple occupations. Complex occupations, particularly nonroutine-complex occupations, are less susceptible to automation. This is consistent with observations of technological-induced job polarization described in the RBTC model (Autor & Dorn, 2013; Goos et al., 2014; Michaels et al., 2014), and the growing importance of social and complex skills outlined in the CBTC model (Beaudry, et al., 2016; Caines et al., 2017; Deming, 2017).

Routine-simple occupations are characterised by tasks that are manual, routine, and require less abstract higher order skills. The employment share of simple-routine occupations have declined over time with the introduction of new technology (Autor & Dorn, 2013; Goos et al., 2014). Given the high probability of job automation for this occupational group, this trend is expected to continue over in years to come. Nonroutine-simple occupations involve less manual, less routine, and more abstract tasks, but still do not rely on the use of higher order skills. Despite being subject to automation constraints such as manipulation and perception, and basic creative skills, these tasks remain simple; and there is evidence that suggests that these tasks can be substituted by new and emerging technologies in the next two decades (Frey & Osborne, 2017). Thus, this occupational group is expected to remain highly susceptible to job automation.

Complex occupations, on the other hand, are significantly less susceptible to automation. This is attributed to the need for higher orders skills. These occupations furthermore rely on tasks that involve creative intelligence and social intelligence - two factors considered

to be both current and future automation constraints (Frey & Osborne, 2017). Thus, the susceptibility to job automation for complex occupations is significantly lower.

7.1.3 Stratum I Occupations are More Susceptible to Job Automation than Higher Strata of Work Occupations

By classifying occupations based on stratum of work, the relative probability of job automation for different levels within a workforce structure can be determined. Stratum I occupations are the most susceptible to job automation. Higher strata of work, characterised by longer time spans of discretion and the use of greater abstractive capabilities (Jaques, 1986, 2016) are less susceptible to job automation. This aligns with findings that technological progress complements abstract creative problem-solving and coordinating tasks performed by managers and professionals (Autor & Dorn, 2013; Beaudry et al., 2016; Caines et al., 2017; Deming, 2017). Given the significant projections around job automation over the next two decades, this is likely to have a major impact on workforce structures in the future. However, the impact will differ across industries as a result of different occupational and workforce structures (Mintzberg, 1980).

By including stratum of work as an additional independent variable, the model for probability of job automation is improved. In the expanded model, approximately 60 percent of the variance in probability of job automation is explained by task routineness, task complexity, and stratum of work.

7.1.4 Technological Change Will Have the Greatest Impact on Type 1 and Type 2 Industries

Historical change in workforce structure over the last two decades illustrated a linear decrease in Stratum I occupations, and a corresponding linear increase in Stratum III occupations. However, future projections as a result of technological change suggest that the changes in workforce structure will be exponential over the next two decades (Acemoglu & Restrepo, 2016; DeCanio, 2016; Gregory et al., 2016; Makridakis, 2017; Pratt, 2015; Sachs et al., 2015). This is consistent with Amara's law that suggests that technological change is overestimated in the short run and underestimated in the long run.

Four different industry types are identified within the US economy based on similar workforce structures. Industry Types 1 and 2 have the highest projected change in

employment as a result of job automation. Type 1 industries are characterised as divisionalised forms with large middle lines and small technostructures (Mintzberg, 1980). Type 2 industries are characterised as machine bureaucracies with a large technostructure and high division of labour through vertical and horizontal job specialisation (Mintzberg, 1980). In both these cases, a large portion of Stratum I occupations is projected to be substituted by technology. The workforce structure is expected to adjust via Mechanism A, B, or C, resulting in a greater proportion of Stratum II and III occupations. Other industry types, such as Types 3 and 4, resemble professional bureaucracies and adhocracies (Mintzberg, 1980). These industries are not expected to undergo major workforce structure changes in the next two decades as a result of job automation.

7.2 Implications for Business

Technology-induced changes to employment and workforce structure will have a direct and lasting impact on business. Two of the most significant factors are outlined and recommendations for business are made.

7.2.1 Productivity Improvement

Much like in the industrial and digital revolution, technological advancement will bring about significant productivity improvements for business (Makridakis, 2017). Automation is estimated to result in an annual global productivity growth of 0.8 to 1.4 percent (McKinsey Global Institute, 2017). It reduces labour costs, increases throughput and reliability, and improves quality. It has the potential to facilitate healthy GDP per capita growth for advance economies, and can help emerging economies “leapfrog” to greater economic success. However, it also has the potential to create a greater divide between economies, industries and firms that embrace technological change, and those which do not (Conti & Sulis, 2016; Rhisiart et al., 2016; World Bank Group, 2016). This study illustrates that Type 1 and Type 2 industries have the greatest potential for job automation. Thus, businesses operating in these industries are faced with the greatest opportunity for productivity gains. However, these businesses are also most vulnerable to technological innovation from their direct competitors and emerging businesses with drastically different business models. It should also be noted that it is not only Type 1 and Type 2 industries that will be disrupted by technological change, as evident from the high projected change in employment in the Finance and Insurance industry. Again, this

highlights an opportunity for both productivity improvement or disruption by competitors or new entrants.

Based on these considerations, it is recommended that businesses with high projected change in employment identify innovation opportunities where emerging technologies could introduce greater productivity gains. These productivity gains are likely to result in either a competitive advantage or a powerful disruptive force for existing businesses operating in a traditional manner.

7.2.2 Technological Anxiety and Technological Unemployment

Automation of jobs will increase technological anxiety and concerns of technological unemployment (Mokyr et al., 2015). These concerns will not be limited to internal business dynamics such as lower employee engagement, reduced productivity, and labour unrest, but may also impact business by changes in government policy or industry regulations (Kim et al., 2017). As illustrated in this study, specific occupational groups, levels within an organisation, and industries with specific structures are more susceptible to job automation than others. Industries with large bureaucratic, hierarchical structures (Type 1 and 2) will experience the greatest impact of technological change, and thus are most susceptible to the manifestations of technological anxiety and technological unemployment.

Based on these considerations, it is recommended that business with high projected change in employment develop appropriate strategies for managing technology-induced change within their firms. These strategies may include educating staff on how technology is likely to impact different occupations, reskilling workers, implementing lifelong learning programmes, developing appropriate policies and engagement mechanism with government and regulatory bodies, and equipping supervisors and managers to deal with the imminent disruption appropriately.

7.3 Limitations of the Research

The impact of forthcoming technological change on jobs and the resulting impact on workforce structures cannot be measured directly. However, it can be approximated by integrating the findings from futures, labour economics and organisational design literature. This presented certain limitations:

Firstly, this study is limited by the data published by Frey and Osborne (2017), Autor and Dorn (2013), and Caines et al. (2017). It assumes that the probability of job automation

was primarily associated with the routineness and complexity of tasks, and introduces stratum of work as a third independent variable. Whilst, is a valid assumption given the academic literature presented (See RBTC and CBTC models in Section 2.4), it does not account for all the factors that may impact job automation in the future.

Secondly, the study is limited by the classification systems and available data sources. Whilst care was taken to provide the most recent and relevant level of data required to present meaningful results, the study is constrained by the current definitions, task descriptions, occupational classification, and workforce structures. Technological change and the emergence of the AI revolution is likely to disrupt economies at an industry-level – old industries will be redefined and new industries will be created. Likewise, existing occupations will be redefined and new occupations will emerge. Depending on the definition and relationships of these occupations with others, the workforce structure of the future may be significantly different.

Thirdly, the use of Jaques' (1986, 2016) stratified systems theory for classifying different jobs to represent workforce structure presents a further limitation. Despite being applied to a broad range of industries and organisations, the requisite organisation principles and theories have been critiqued for being “practitioner” theory and not supported by academic rigour. It furthermore portrays the organisation as hierarchical with a “command and control”-type leadership philosophy, which may be contrary to organisational design theory and leadership principles employed in future organisations.

Fourthly, a further limitation of this study is that it does not consider factors such as government policy, institutional strength, infrastructure, education, healthcare, international openness, innovation and technology adoption rates. These factors may have a significant impact on the extent of change in workforce structures in a given economic setting (Kim et al., 2017; Ugur et al., 2017; Vivarelli, 2014). The rate of technological change at a company level could furthermore be impacted by industry composition, the competitive landscape and other organisational factors. Whilst these factors are recognised as important contributors, they are not considered in the analysis of this study.

7.4 Suggestions for Future Research

There are three suggestions for future research to build on the findings of this study.

7.4.1 Substitutionary and Complementary Effects of Technological Change

Future research aimed at understanding the impact of technological change on employment should focus on both the substitutionary and complementary effects of technological change. Substitutionary effects should include the factors considered in this study and other studies cited, namely, task routineness, task complexity, stratum of work, and automation bottlenecks such as manipulation, perception, creative intelligence, and social intelligence. Complementary effects should include factors such as: the productivity improvements new technologies introduced at an occupational level, the rate and type of new occupations created because of technological progress, the rate and magnitude of new industries created because of technological progress, and the creation of entrepreneurial jobs and independent or freelance jobs facilitated by technological progress. Modifying factors such as government policy, institutional strength, infrastructure, education, healthcare, international openness, innovation, technology adoption rates, industry composition, the competitive landscape, and organisational factors should also be considered. These factors should be combined in a comprehensive model that projects the impact of technological progress based on both historical trends and projections based on a set of validated assumptions.

7.4.2 The Impact of Technological Change on Management and Leadership

This study illustrates that technological change has the capacity to completely transform the business environment. The impact of this technological disruption is a function of the occupational and workforce structures. However, technology-induced change to employment and workforce structure does not occur in isolation (as shown by the evolution of management theory (See Section 2.5.1)). Changes in workforce structure through the replacement and addition of occupations invariably impact the role of supervision, management, and the dominant leadership characteristics required within specific businesses and industries. Future research should study how technological progress is changing the role of supervision and management. These studies should aim to identify the management and leadership characteristics that would be most valuable in firms and industries that are undergoing technological disruption.

7.4.3 Managing Technological Change through Effective Strategies

This study identifies the need for the development of business, workforce, and human resources strategies to manage the exponential nature of technological change over the next two decades. This is particularly true for Type 1 and Type 2 industries. These

strategies may include investment in education and skills development, investment in technical and vocational training, importing or outsourcing of skills, and the development of lifelong learning programmes. Future research should focus on determining effective strategies for firms operating in various industries subject to technological disruption.

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APPENDIX A: CONSISTENCY MATRIX

TITLE: The impact of technological change on jobs and workforce structure

RESEARCH QUESTION	LITERATURE REVIEW	DATA COLLECTION TOOL	ANALYSIS
Research Question 1: What is the relationship between the probability of job automation and the routineness and complexity of tasks? Research Question 1a: Are specific occupational groups (routine-simple, nonroutine-simple, routine-complex and nonroutine-complex) more susceptible to job automation than others?	(Makridakis, 2017) (Pratt, 2015) (Nordhaus, 2015) (Frey & Osborne, 2017) (David, 2017) (Arntz et al., 2017) (Autor, 2015) (Calvino & Virgillito, 2017) (Vivarelli, 2013, 2014, 2015) (Acemoglu & Autor, 2011) (Autor & Dorn, 2013) (Deming, 2017) (Caines et al., 2017)	<u>Secondary data:</u> Probability of job automation (Frey & Osborne, 2017) Task routineness (Autor & Dorn, 2013) Task complexity (Caines et al., 2017)	Descriptive statistics Regression Analysis Descriptive statistics Kruskal-Wallis H test Post-hoc Analysis
Research Question 2: Are specific strata of work within a workforce structure more susceptible to job automation?	(Frey & Osborne, 2017) (Caliendo et al., 2015) (Tåg, 2013) (Tåg et al., 2016) (Jaques, 1986, 2016)	<u>Secondary data:</u> Probability of job automation (Frey & Osborne, 2017)	Descriptive statistics Kruskal-Wallis H test Post-hoc Analysis Regression analysis
Research Question 3: What is the projected change in workforce structure from 2016 to 2036 at an industry level?	(Frey & Osborne, 2017) (Caliendo et al., 2015) (Tåg, 2013) (Tåg et al., 2016) (Jaques, 1986, 2016)	<u>Secondary data:</u> Probability of job automation (Frey & Osborne, 2017) US Occupational Employment Statistics data (1999-2016)	Descriptive statistics

APPENDIX B: DATA

No.	Occupation	P(Auto)	Routineness	Complexity	Stratum
1	Chief executives, public administrators, and legislators	0.015	0.161	0.979	5
2	Financial managers	0.069	0.744	0.961	3
3	Human resources and labor relations managers	0.006	0.355	0.913	3
4	Managers and specialists in marketing, advert., PR	0.023	0.531	0.813	3
5	Managers in education and related fields	0.006	0.340	0.825	3
6	Managers of medicine and health occupations	0.007	0.255	0.933	3
7	Managers of properties and real estate	0.810	0.072	0.662	3
8	Funeral directors	0.200	0.018	0.572	3
9	Managers and administrators, n.e.c.	0.250	0.151	0.908	3
10	Accountants and auditors	0.940	0.924	0.790	3
11	Insurance underwriters	0.990	0.930	0.653	3
12	Other financial specialists	0.330	0.674	0.753	3
13	Management analysts	0.130	0.261	0.910	3
14	Personnel, HR, training, and labor rel. specialists	0.310	0.361	0.820	3
15	Purchasing agents and buyers of farm products	0.870	0.987	0.654	3
16	Buyers, wholesale and retail trade	0.290	0.632	0.706	3
17	Purchasing managers, agents, and buyers, n.e.c.	0.030	0.501	0.799	3
18	Business and promotion agents	0.240	0.094	0.556	3
19	Construction inspectors	0.630	0.136	0.680	3
20	Inspectors and compliance officers, outside	0.080	0.322	0.931	3
21	Architects	0.018	0.708	0.969	3
22	Aerospace engineers	0.017	0.142	0.998	3
23	Metallurgical and materials engineers	0.021	0.282	0.996	3
24	Petroleum, mining, and geological engineers	0.150	0.428	0.970	3
25	Chemical engineers	0.017	0.528	1.000	3
26	Civil engineers	0.019	0.106	0.996	3
27	Electrical engineers	0.100	0.082	0.941	3
28	Industrial engineers	0.029	0.185	0.965	3
29	Mechanical engineers	0.011	0.595	0.983	3
30	Engineers and other professionals, n.e.c.	0.014	0.243	0.979	3
31	Computer systems analysts and computer scientists	0.011	0.100	0.929	3
32	Operations and systems researchers and analysts	0.035	0.112	0.956	3
33	Actuaries	0.210	0.188	0.998	3
34	Mathematicians and statisticians	0.134	0.547	0.913	3
35	Physicists and astronomers	0.071	0.659	1.000	3
36	Chemists	0.100	0.516	0.973	3
37	Atmospheric and space scientists	0.670	0.024	0.966	3
38	Geologists	0.630	0.133	0.972	3
39	Physical scientists, n.e.c.	0.430	0.194	0.966	3
40	Agricultural and food scientists	0.053	0.231	0.971	3
41	Biological scientists	0.113	0.303	0.999	3
42	Foresters and conservation scientists	0.012	0.021	0.821	3
43	Medical scientists	0.005	0.276	0.998	3
44	Physicians	0.004	0.091	0.992	3
45	Dentists	0.004	0.109	0.943	3
46	Veterinarians	0.038	0.787	0.926	3
47	Optometrists	0.140	0.164	0.966	3
48	Podiatrists	0.005	0.449	0.966	3
49	Registered nurses	0.009	0.258	0.936	3
50	Pharmacists	0.012	0.431	0.946	3
51	Dieticians and nutritionists	0.004	0.039	0.932	3
52	Respiratory therapists	0.066	0.212	0.759	3
53	Occupational therapists	0.004	0.212	0.744	3
54	Physical therapists	0.021	0.212	0.826	3
55	Speech therapists	0.006	0.212	0.926	3
56	Physicians' assistants	0.300	0.212	0.933	2
57	Kindergarten and earlier school teachers	0.150	0.036	0.531	2
58	Primary school teachers	0.170	0.048	0.715	2
59	Secondary school teachers	0.008	0.075	0.740	2
60	Special education teachers	0.012	0.103	0.731	2
61	Teachers, n.e.c.	0.010	0.085	0.722	2
62	Vocational and educational counselors	0.134	0.410	0.762	2
63	Librarians	0.650	0.373	0.678	2
64	Archivists and curators	0.383	0.042	0.740	2
65	Economists, market and survey researchers	0.330	0.592	0.967	3

No.	Occupation	P(Auto)	Routineness	Complexity	Stratum
66	Psychologists	0.007	0.638	0.971	3
67	Social scientists and sociologists, n.e.c.	0.059	0.066	0.954	3
68	Urban and regional planners	0.130	0.182	0.971	3
69	Social workers	0.012	0.486	0.778	2
70	Clergy and religious workers	0.008	0.644	0.759	3
71	Welfare service workers	0.028	0.097	0.620	2
72	Lawyers and judges	0.218	0.981	0.954	3
73	Writers and authors	0.038	0.179	0.639	2
74	Technical writers	0.890	0.197	0.535	3
75	Designers	0.042	0.507	0.626	2
76	Musicians and composers	0.045	0.088	0.430	2
77	Actors, directors, and producers	0.196	0.057	0.679	3
78	Painters, sculptors, craft-artists, and print-makers	0.039	0.811	0.571	3
79	Photographers	0.021	0.875	0.533	2
80	Dancers	0.130	0.209	0.372	2
81	Editors and reporters	0.083	0.775	0.641	3
82	Announcers	0.720	0.513	0.522	2
83	Athletes, sports instructors, and officials	0.147	0.003	0.534	2
84	Clinical laboratory technologies and technicians	0.685	0.650	0.732	2
85	Dental hygienists	0.680	0.863	0.535	2
86	Health record technologists and technicians	0.910	0.370	0.346	2
87	Radiologic technologists and technicians	0.230	0.291	0.663	2
88	Licensed practical nurses	0.058	0.349	0.719	2
89	Health technologists and technicians, n.e.c.	0.400	0.425	0.734	2
90	Engineering technicians	0.240	0.419	0.775	2
91	Drafters	0.670	0.848	0.646	2
92	Surveyors, cartographers, mapping scientists/techs	0.630	0.054	0.761	2
93	Biological technicians	0.300	0.586	0.733	2
94	Chemical technicians	0.570	0.437	0.776	2
95	Other science technicians	0.610	0.480	0.627	2
96	Airplane pilots and navigators	0.180	0.051	0.935	2
97	Air traffic controllers	0.110	0.310	0.914	2
98	Broadcast equipment operators	0.740	0.580	0.574	2
99	Computer software developers	0.086	0.288	0.918	2
100	Programmers of numerically controlled machine tools	0.360	0.458	0.678	2
101	Legal assistants and paralegals	0.940	0.741	0.431	2
102	Sales supervisors and proprietors	0.178	0.127	0.704	2
103	Insurance sales occupations	0.920	0.948	0.636	2
104	Real estate sales occupations	0.860	0.805	0.660	2
105	Financial service sales occupations	0.016	0.881	0.766	2
106	Advertising and related sales jobs	0.540	0.996	0.628	2
107	Sales engineers	0.004	0.343	0.962	2
108	Retail salespersons and sales clerks	0.920	0.522	0.497	2
109	Cashiers	0.970	0.975	0.168	1
110	Door-to-door sales, street sales, and news vendors	0.940	0.167	0.064	1
111	Sales demonstrators, promoters, and models	0.745	0.422	0.034	1
112	Office supervisors	0.014	0.750	0.653	2
113	Computer and peripheral equipment operators	0.780	0.452	0.744	1
114	Secretaries and stenographers	0.903	0.993	0.419	1
115	Typists	0.810	0.972	0.114	1
116	Interviewers, enumerators, and surveyors	0.940	0.911	0.371	1
117	Hotel clerks	0.940	0.668	0.304	1
118	Transportation ticket and reservation agents	0.610	0.762	0.502	1
119	Receptionists and other information clerks	0.960	0.942	0.336	1
120	Correspondence and order clerks	0.860	0.753	0.345	1
121	Human resources clerks, excl payroll and timekeeping	0.900	0.908	0.435	1
122	Library assistants	0.950	0.589	0.338	1
123	File clerks	0.970	0.984	0.339	1
124	Bookkeepers and accounting and auditing clerks	0.980	0.966	0.522	1
125	Payroll and timekeeping clerks	0.970	0.620	0.340	1
126	Billing clerks and related financial records processing	0.950	0.936	0.346	1
127	Mail and paper handlers	0.940	0.756	0.053	1
128	Office machine operators, n.e.c.	0.920	0.854	0.324	1
129	Telephone operators	0.970	0.951	0.130	1
130	Postal clerks, excludng mail carriers	0.950	0.960	0.303	1
131	Mail carriers for postal service	0.680	0.626	0.052	1

No.	Occupation	P(Auto)	Routineness	Complexity	Stratum
132	Mail clerks, outside of post office	0.940	0.957	0.115	1
133	Messengers	0.940	0.781	0.130	1
134	Dispatchers	0.960	0.826	0.573	1
135	Shipping and receiving clerks	0.980	0.796	0.445	1
136	Stock and inventory clerks	0.640	0.696	0.071	1
137	Meter readers	0.850	0.647	0.325	1
138	Weighers, measurers, and checkers	0.950	0.869	0.326	1
139	Material recording, sched., prod., plan., expediting cl.	0.880	0.772	0.719	1
140	Insurance adjusters, examiners, and investigators	0.980	0.866	0.534	1
141	Customer service reps, invest., adjusters, excl. insur.	0.550	0.814	0.620	1
142	Eligibility clerks for government prog., social welfare	0.700	0.920	0.448	1
143	Bill and account collectors	0.950	0.978	0.448	1
144	General office clerks	0.960	0.927	0.249	1
145	Bank tellers	0.980	1.000	0.372	1
146	Proofreaders	0.840	0.817	0.172	1
147	Data entry keyers	0.990	0.838	0.324	1
148	Statistical clerks	0.660	0.905	0.932	1
149	Teacher's aides	0.560	0.471	0.338	1
150	Housekeepers, maids, butlers, and cleaners	0.675	0.270	0.028	1
151	Laundry and dry cleaning workers	0.710	0.841	0.034	1
152	Fire fighting, fire prevention, and fire inspection occs	0.325	0.006	0.795	1
153	Police and detectives, public service	0.098	0.045	0.731	1
154	Sheriffs, bailiffs, correctional institution officers	0.480	0.267	0.435	1
155	Crossing guards	0.490	0.297	0.028	1
156	Guards and police, except public service	0.840	0.723	0.519	1
157	Protective service, n.e.c.	0.670	0.191	0.433	1
158	Bartenders	0.770	0.802	0.343	1
159	Waiters and waitresses	0.940	0.130	0.036	1
160	Cooks	0.768	0.887	0.291	1
161	Food preparation workers	0.870	0.556	0.002	1
162	Miscellaneous food preparation and service workers	0.895	0.553	0.047	1
163	Dental Assistants	0.510	0.963	0.497	1
164	Health and nursing aides	0.390	0.273	0.428	1
165	Supervisors of cleaning and building service	0.940	0.246	0.324	2
166	Superv. of landscaping, lawn service, groundskeeping	0.570	0.121	0.556	2
167	Gardeners and groundskeepers	0.950	0.316	0.239	1
168	Janitors	0.660	0.386	0.025	1
169	Pest control occupations	0.660	0.376	0.418	1
170	Barbers	0.800	0.990	0.056	1
171	Hairdressers and cosmetologists	0.110	0.820	0.162	1
172	Recreation facility attendants	0.006	0.176	0.117	1
173	Guides	0.484	0.446	0.335	1
174	Ushers	0.960	0.583	0.036	1
175	Baggage porters, bellhops and concierges	0.520	0.118	0.270	1
176	Recreation and fitness workers	0.046	0.012	0.356	1
177	Motion picture projectionists	0.970	0.735	0.062	1
178	Child care workers	0.084	0.537	0.433	1
179	Supervisors of personal service jobs, n.e.c	0.076	0.173	0.620	2
180	Public transportation attendants and inspectors	0.825	0.027	0.431	1
181	Animal caretakers, except farm	0.820	0.629	0.322	1
182	Supervisors of mechanics and repairers	0.003	0.249	0.816	1
183	Automobile mechanics and repairers	0.590	0.379	0.555	1
184	Bus, truck, and stationary engine mechanics	0.730	0.382	0.448	1
185	Aircraft mechanics	0.710	0.328	0.764	1
186	Small engine repairers	0.930	0.613	0.355	1
187	Auto body repairers	0.910	0.808	0.244	1
188	Heavy equipment and farm equipment mechanics	0.575	0.395	0.353	1
189	Industrial machinery repairers	0.860	0.455	0.335	1
190	Machinery maintenance occupations	0.860	0.945	0.320	1
191	Repairers of industrial electrical equipment	0.410	0.665	0.639	1
192	Repairers of data processing equipment	0.740	0.747	0.429	1
193	Repairers of household appliances and power tools	0.720	0.604	0.500	1
194	Telecom and line installers and repairers	0.425	0.234	0.528	1
195	Repairers of electrical equipment, n.e.c.	0.650	0.468	0.618	1
196	Heating, air conditioning, and refrigeration mechanics	0.650	0.392	0.623	1
197	Precision makers, repairers, and smiths	0.785	0.896	0.432	1

No.	Occupation	P(Auto)	Routineness	Complexity	Stratum
198	Locksmiths and safe repairers	0.770	0.598	0.418	1
199	Repairers of mechanical controls and valves	0.630	0.601	0.305	1
200	Elevator installers and repairers	0.390	0.407	0.538	1
201	Millwrights	0.590	0.294	0.583	1
202	Mechanics and repairers, n.e.c.	0.500	0.440	0.383	1
203	Supervisors of construction work	0.170	0.115	0.678	2
204	Masons, tilers, and carpet installers	0.847	0.404	0.269	1
205	Carpenters	0.720	0.206	0.412	1
206	Drywall installers	0.790	0.544	0.114	1
207	Electricians	0.150	0.285	0.568	1
208	Electric power installers and repairers	0.097	0.148	0.531	1
209	Painters, construction and maintenance	0.750	0.477	0.123	1
210	Paperhangers	0.870	0.541	0.041	1
211	Plasterers	0.840	0.334	0.270	1
212	Plumbers, pipe fitters, and steamfitters	0.350	0.364	0.392	1
213	Concrete and cement workers	0.940	0.519	0.164	1
214	Glaziers	0.730	0.550	0.169	1
215	Insulation workers	0.735	0.367	0.321	1
216	Paving, surfacing, and tamping equipment operators	0.830	0.525	0.240	1
217	Roofers and slaters	0.900	0.352	0.374	1
218	Structural metal workers	0.830	0.337	0.178	1
219	Drillers of earth	0.850	0.358	0.275	1
220	Misc. construction and related occupations	0.710	0.413	0.349	1
221	Drillers of oil wells	0.530	0.434	0.498	1
222	Explosives workers	0.480	0.252	0.720	1
223	Miners	0.565	0.559	0.293	1
224	Other mining occupations	0.930	0.568	0.063	1
225	Production supervisors or foremen	0.016	0.200	0.617	2
226	Tool and die makers and die setters	0.840	0.899	0.580	1
227	Machinists	0.910	0.711	0.512	1
228	Boilermakers	0.680	0.534	0.502	1
229	Patternmakers and model makers	0.915	0.933	0.322	1
230	Engravers	0.980	0.790	0.244	1
231	Cabinetmakers and bench carpeters	0.920	0.325	0.420	1
232	Furniture/wood finishers, other prec. wood workers	0.870	0.939	0.131	1
233	Dressmakers, seamstresses, and tailors	0.840	0.574	0.177	1
234	Upholsterers	0.390	0.835	0.393	1
235	Hand molders and shapers, except jewelers	0.900	0.686	0.292	1
236	Bookbinders	0.950	0.607	0.360	1
237	Butchers and meat cutters	0.930	0.635	0.032	1
238	Bakers	0.890	0.902	0.173	1
239	Batch food makers	0.700	0.677	0.275	1
240	Water and sewage treatment plant operators	0.610	0.465	0.571	1
241	Power plant operators	0.850	0.237	0.716	1
242	Plant and system operators, stationary engineers	0.870	0.492	0.537	1
243	Other plant and system operators	0.860	0.510	0.575	1
244	Lathe, milling, and turning machine operatives	0.840	0.729	0.252	1
245	Rollers, roll hands, and finishers of metal	0.830	0.641	0.425	1
246	Drilling and boring machine operators	0.940	0.832	0.340	1
247	Grinding, abrading, buffing, and polishing workers	0.950	0.917	0.424	1
248	Molders and casting machine operators	0.950	0.699	0.041	1
249	Heat treating equipment operators	0.910	0.623	0.346	1
250	Sawing machine operators and sawyers	0.860	0.617	0.058	1
251	Nail, tacking, shaping and joining mach ops (wood)	0.960	0.689	0.178	1
252	Winding and twisting textile and apparel operatives	0.960	0.884	0.275	1
253	Knitters, loopers, and toppers textile operatives	0.730	0.969	0.033	1
254	Textile cutting and dyeing machine operators	0.960	0.726	0.336	1
255	Textile sewing machine operators	0.890	0.656	0.042	1
256	Shoemaking machine operators	0.970	0.714	0.025	1
257	Clothing pressing machine operators	0.810	0.860	0.002	1
258	Packers, fillers, and wrappers	0.980	0.759	0.276	1
259	Extruding and forming machine operators	0.930	0.702	0.300	1
260	Mixing and blending machine operators	0.830	0.823	0.355	1
261	Separating, filtering, and clarifying machine operators	0.880	0.653	0.529	1
262	Food roasting and baking machine operators	0.910	0.857	0.071	1
263	Washing, cleaning, and pickling machine operators	0.810	0.693	0.032	1

No.	Occupation	P(Auto)	Routineness	Complexity	Stratum
264	Paper folding machine operators	0.670	0.677	0.233	1
265	Furnace, kiln, and oven operators, apart from food	0.370	0.492	0.176	1
266	Slicing, cutting, crushing and grinding machine	0.860	0.732	0.172	1
267	Photographic process workers	0.990	0.851	0.299	1
268	Welders, solderers, and metal cutters	0.940	0.662	0.084	1
269	Assemblers of electrical equipment	0.950	0.844	0.320	1
270	Painting and decoration occupations	0.920	0.264	0.163	1
271	Supervisors of motor vehicle transportation	0.029	0.170	0.569	2
272	Truck, delivery, and tractor drivers	0.740	0.139	0.233	1
273	Bus drivers	0.780	0.063	0.127	1
274	Taxi cab drivers and chauffeurs	0.890	0.079	0.281	1
275	Parking lot attendants	0.870	0.060	0.055	1
276	Railroad conductors and yardmasters	0.830	0.009	0.501	1
277	Locomotive operators: engineers and firemen	0.945	0.030	0.362	1
278	Railroad brake, coupler, and switch operators	0.830	0.155	0.337	1
279	Ship crews and marine engineers	0.010	0.069	0.576	1
280	Operating engineers of construction equipment	0.950	0.416	0.274	1
281	Crane, derrick, winch, hoist, longshore operators	0.823	0.717	0.296	1
282	Excavating and loading machine operators	0.940	0.398	0.128	1
283	Helpers, constructions	0.787	0.571	0.278	1
284	Construction laborers	0.880	0.462	0.264	1
285	Production helpers	0.660	0.768	0.054	1
286	Garbage and recyclable material collectors	0.930	0.799	0.048	1
287	Machine feeders and offbearers	0.930	0.705	0.117	1
288	Garage and service station related occupations	0.910	0.765	0.062	1
289	Vehicle washers and equipment cleaners	0.370	0.793	0.002	1
290	Packers and packagers by hand	0.380	0.890	0.039	1
291	Laborers, freight, stock, and material handlers, n.e.c.	0.850	0.498	0.161	1

Major Group	Minor Group	Occupational Title	QCC code	Stratum	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Interim 2017	
Business and Financial Occupations	Top Executives	11-1001 Chief Executive Officers	11-1001	5	597 060	521 890	455 920	452 400	389 880	334 960	321 300	299 520	299 160	1 603 810	1 664 280	1 655 410	1 697 680	1 689 680	1 708 080	1 805 030	1 899 460	1 889 460	1 889 460	
		11-1002 General and Operations Managers	11-1002	4	2 305 610	2 221 510	2 064 120	1 990 310	1 482 970	1 704 110	1 668 810	1 663 280	1 555 410	1 697 680	1 689 680	1 708 080	1 805 030	1 899 460	1 889 460	1 889 460	1 889 460	1 889 460	1 889 460	
		11-1003 Advertising, Marketing, Promotions, Public Relations, and Sales Managers	11-1003	5	409 330	422 800	475 850	61 690	61 690	61 690	61 690	61 690	61 690	61 690	61 690	61 690	61 690	61 690	61 690	61 690	61 690	61 690	61 690	
		11-2001 Administration and Operations Managers	11-2001	3	100 600	93 420	85 950	81 090	71 100	49 120	41 710	38 130	36 160	36 160	36 160	36 160	36 160	36 160	36 160	36 160	36 160	36 160	36 160	
		11-2002 Sales Managers	11-2002	3	207 710	202 100	189 140	190 080	182 600	172 300	166 470	159 950	165 240	166 790	169 330	164 590	168 410	171 430	174 010	184 490	192 590	205 900	205 900	
		11-3001 Administration and Operations Managers	11-3001	3	397 640	344 880	317 410	329 680	314 380	317 970	317 970	309 980	322 170	313 910	329 980	334 720	358 920	344 720	358 920	364 750	365 230	365 230	365 230	
		11-3002 Administration and Operations Managers	11-3002	3	365 330	344 440	311 600	306 370	278 360	248 860	239 410	232 410	239 360	246 920	249 580	260 320	269 600	264 000	269 520	268 720	270 980	266 260	266 260	
		11-3003 Computer and Information Systems Managers	11-3003	3	280 820	283 480	267 310	264 790	265 020	248 960	239 330	232 410	239 360	246 920	249 580	260 320	269 600	264 000	269 520	268 720	270 980	266 260	266 260	
		11-3004 Financial Managers	11-3004	3	644 050	622 800	570 110	560 020	521 750	489 170	471 950	468 270	484 390	500 590	499 180	478 940	477 650	484 910	469 320	489 320	531 120	544 300	544 300	
		11-3005 Purchasing Managers	11-3005	3	213 510	205 370	188 050	179 960	166 350	156 720	153 950	152 810	152 810	154 030	149 250	151 430	151 430	150 550	165 340	167 000	169 340	168 400	168 400	
Operations and Support Occupations	Operations Specialists	11-3006 Human Resources Managers	11-3006	3	137 950	126 030	107 130	91 060	91 060	72 120	69 300	66 490	65 080	67 150	65 080	65 080	65 080	65 080	65 080	65 080	65 080	65 080	65 080	
		11-3007 Training and Development Managers	11-3007	3	123 450	116 680	108 390	107 400	97 450	83 120	78 640	76 460	74 760	76 460	74 760	76 460	74 760	76 460	74 760	76 460	74 760	76 460	76 460	
		11-3008 Human Resources Managers	11-3008	3	227 810	227 810	227 810	227 810	227 810	227 810	227 810	227 810	227 810	227 810	227 810	227 810	227 810	227 810	227 810	227 810	227 810	227 810	227 810	
		11-3009 Farming, Forestry, and Other Agricultural Managers	11-3009	3	5 450	5 370	5 270	5 630	5 420	4 660	4 070	3 380	3 480	3 480	3 480	3 480	3 480	3 480	3 480	3 480	3 480	3 480	3 480	
		11-3010 Construction Managers	11-3010	3	240 490	229 200	213 960	208 360	196 110	188 750	192 610	207 630	216 120	203 590	209 760	191 430	195 000	207 580	217 710	239 640	249 650	249 650	249 650	
		11-3011 Education Administrators, Postsecondary	11-3011	3	186 320	186 320	186 320	186 320	186 320	186 320	186 320	186 320	186 320	186 320	186 320	186 320	186 320	186 320	186 320	186 320	186 320	186 320	186 320	186 320
		11-3012 Education Administrators, Postsecondary	11-3012	3	95 690	92 280	94 120	96 910	98 160	102 880	105 360	103 330	101 160	97 410	109 900	110 860	113 620	125 910	126 340	131 070	135 690	138 430	138 430	
		11-3013 Education Administrators, All Other	11-3013	3	248 210	242 280	214 760	205 390	194 940	188 820	187 410	183 960	184 410	182 300	178 110	174 720	184 530	187 640	183 430	179 720	178 390	178 390	178 390	
		11-3014 Architectural and Engineering Managers	11-3014	3	287 940	282 290	260 880	249 710	229 960	205 400	191 420	189 050	191 460	196 080	199 250	186 830	183 940	189 510	191 030	198 610	201 370	201 470	201 470	
		11-3015 Food Service Managers	11-3015	3	4 590	4 720	4 670	3 760	3 460	3 180	3 110	3 110	3 110	3 110	3 110	3 110	3 110	3 110	3 110	3 110	3 110	3 110	3 110	
Business and Financial Occupations	Other Management Occupations	11-3016 Medical and Health Services Managers	11-3016	3	230 640	230 640	230 640	230 640	230 640	230 640	230 640	230 640	230 640	230 640	230 640	230 640	230 640	230 640	230 640	230 640	230 640	230 640	230 640	
		11-3017 Natural Sciences Managers	11-3017	3	36 920	36 920	42 450	42 470	41 810	40 250	40 250	38 660	39 370	41 960	41 960	41 960	41 960	41 960	41 960	41 960	41 960	41 960	41 960	
		11-3018 Property, Real Estate, and Community Association Managers	11-3018	3	26 930	26 850	26 850	26 470	26 460	26 610	26 120	25 980	25 980	25 980	25 980	25 980	25 980	25 980	25 980	25 980	25 980	25 980	25 980	
		11-3019 Insurance Agents, Brokers, and Service Managers	11-3019	3	143 040	145 340	156 380	156 120	156 120	152 590	154 230	156 880	159 660	159 660	159 660	159 660	159 660	159 660	159 660	159 660	159 660	159 660	159 660	
		11-3020 Insurance Agents, Brokers, and Service Managers	11-3020	3	88 490	91 460	100 810	111 480	116 020	113 760	112 910	112 910	113 760	117 150	117 150	113 760	116 480	115 360	113 760	116 480	119 720	126 390	126 390	
		11-3021 Insurance Agents, Brokers, and Service Managers	11-3021	3	11 390	10 790	10 790	10 790	9 760	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	
		11-3022 Insurance Agents, Brokers, and Service Managers	11-3022	3	11 390	10 790	10 790	10 790	9 760	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	
		11-3023 Insurance Agents, Brokers, and Service Managers	11-3023	3	7 260	6 600	10 270	11 550	12 380	10 030	10 640	11 110	11 680	12 110	11 680	12 110	11 680	12 110	11 680	12 110	11 680	12 110	11 680	
		11-3024 Buyers and Purchasing Agents, Farm Products	11-3024	3	21 550	17 910	17 640	16 570	15 550	13 180	12 970	13 110	13 930	11 690	10 120	10 560	10 820	10 560	10 820	10 560	10 820	10 560	10 820	
		11-3025 Wholesale and Retail Buyers, Except Farm Products	11-3025	3	133 070	137 040	138 880	138 880	138 880	138 880	138 880	138 880	138 880	138 880	138 880	138 880	138 880	138 880	138 880	138 880	138 880	138 880	138 880	138 880
Business and Financial Occupations	Business Operations Specialists	11-3026 Purchasing Agents, Except Wholesale, Retail, and Farm Products	11-3026	3	24 110	238 940	228 860	231 490	237 210	263 140	267 410	273 510	281 950	286 980	288 940	286 980	288 940	286 980	288 940	286 980	288 940	286 980	288 940	
		11-3027 Claims Adjusters, Examiners, and Investigators	11-3027	3	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	
		11-3028 Insurance Claims Adjusters, Examiners, and Investigators	11-3028	3	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	121 450	
		11-3029 Compliance Officers	11-3029	3	123 260	126 840	136 860	146 670	154 600	158 890	161 810	220 080	231 910	242 270	249 000	204 000	204 000	204 000	204 000	204 000	204 000	204 000	204 000	
		11-3030 Cost Estimators	11-3030	3	201 500	196 420	188 840	185 080	186 620	195 270	204 330	216 900	213 070	218 400	199 130	183 790	199 130	183 790	199 130	183 790	199 130	183 790	199 130	
		11-3031 Human Resources Specialists	11-3031	3	181 710	188 060	178 940	168 550	164 020	173 160	181 260	186 620	186 620	205 800	198 130	198 130	205 800	198 130	198 130	205 800	198 130	198 130	205 800	
		11-3032 Farm Labor Contractors	11-3032	3	11 390	10 790	10 790	10 790	9 760	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	
		11-3033 Labor Relations Specialists	11-3033	3	11 390	10 790	10 790	10 790	9 760	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	10 860	
		11-3034 Management Analysts	11-3034	3	300 600	337 610	363 860	392 070	423 880	427 470	441 000	476 070	499 460	535 850	527 770	534 130	56 950	64 020	70 480	73 290	77 940	81 400	81 400	
		11-3035 Meeting, Convention, and Event Planners	11-3035	3	32 020	32 000	31 960	32 380	32 380	32 380	32 380	32 380	32 380	32 380	32 380	32 380	32 380	32 380	32 380	32 380	32 380	32 380	32 380	
Business and Financial Occupations	Financial Specialists	11-3036 Financial Specialists	11-3036	3	78 310	81 400	81 400	81 400	81 400	81 400	81 400	81 400	81 400	81 400	81 400	81 400	81 400	81 400	81 400	81 400	81 400</			

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Major Group	Minor Group	OCC code	Occupational Title	Stratum	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	(last column)	
Community and Social Service Occupations	Counselors, Social Workers, and Other Community and Social Service Specialists	21-1011	Substance Abuse and Behavioral Disorder Counselors	2	57 290	56 080	61 500	63 310	65 170	70 400	72 210	75 940	76 830	79 180	78 170	77 940	76 600	80 130	83 120	85 180	87 090	91 040	0.033	
		21-1012	Educational, Guidance, School, and Vocational Counselors	2	19 390	18 000	20 500	21 340	21 450	24 350	24 160	28 720	23 470	24 160	23 150	24 690	24 690	24 690	24 870	24 870	24 870	24 870	0.029	
		21-1013	Marriage and Family Therapists	2	18 530	19 420	20 380	21 130	22 150	20 060	18 500	21 330	23 240	24 520	26 430	33 990	34 350	33 990	34 270	29 160	31 570	36 960	0.014	
		21-1014	Mental Health Counselors	2	62 210	65 780	67 590	81 090	89 260	87 220	91 880	95 970	104 650	106 220	110 300	114 180	115 080	115 590	120 010	120 200	130 820	139 820	0.005	
		21-1015	Rehabilitation Counselors	2	93 130	104 850	106 450	110 590	115 690	116 560	117 330	121 380	123 890	125 090	127 440	112 690	114 690	104 070	103 890	103 890	101 630	103 030	0.009	
		21-1021	Child, Family, and School Social Workers	2	262 570	266 570	257 080	259 990	256 160	255 300	256 430	262 830	263 830	262 830	274 140	277 670	276 100	276 510	279 920	276 760	286 520	294 080	298 840	0.028
		21-1022	Healthcare Social Workers	2	101 680	103 390	103 490	103 180	103 270	108 290	112 220	116 750	120 060	131 730	133 510	143 080	138 890	140 000	141 830	145 920	155 590	159 310	0.004	
		21-1023	Mental Health and Substance Abuse Social Workers	2	72 730	79 740	85 550	91 240	96 990	115 810	120 140	114 820	118 690	131 010	127 440	119 960	115 390	109 920	110 010	109 460	110 070	110 070	114 040	0.003
		21-1029	Social Workers, All Other	2	41 620	43 670	43 890	43 240	42 780	62 120	60 940	61 270	64 990	68 230	73 250	69 920	63 110	58 430	62 640	64 410	59 570	59 570	59 540	0.045
		21-1091	Health Educators	2	48 930	50 500	50 500	50 500	50 500	51 970	51 970	57 900	61 290	62 120	62 120	63 220	58 150	56 610	55 270	56 720	57 020	57 570	57 570	0.050
Legal Occupations	Lawyers, Judges, and Related Workers	21-1092	Probation Officers and Correctional Treatment Specialists	2	78 930	80 500	78 640	78 990	86 810	91 960	90 600	88 650	94 120	97 330	92 910	89 500	88 820	86 780	85 810	86 800	87 950	87 500	0.250	
		21-1093	Parole Officers and Probation Officers	2	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	0.130
		21-1094	Community Health Workers	2	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	0.045
		21-1099	Community and Social Service Specialists, All Other	2	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	24 230	0.005
		21-2011	Clergy	3	26 000	30 980	32 940	36 450	38 170	35 120	36 590	37 820	40 960	42 900	42 900	42 900	42 900	42 900	42 900	42 900	42 900	42 900	42 900	0.008
		21-2021	Directors, Religious Activities and Education	3	14 960	13 610	12 120	13 120	11 840	13 360	13 610	14 750	14 790	14 790	15 060	16 840	17 560	18 110	18 600	18 850	20 280	20 590	20 590	0.025
		21-2099	Religious Workers, All Other	3	464 250	489 530	490 000	504 370	516 220	528 270	529 190	547 710	555 770	553 690	556 790	561 350	570 950	584 920	592 670	603 310	609 930	619 530	0.035	
		23-1012	Judicial Law Clerks	3	25 050	25 190	40 340	41 760	41 550	41 940	40 620	41 860	41 860	41 860	41 860	41 860	41 860	41 860	41 860	41 860	41 860	41 860	41 860	0.030
		23-1021	Administrative Law Judges, Adjudicators, and Hearing Officers	3	27 250	12 560	30 520	16 700	16 850	15 530	14 470	14 100	13 370	13 140	14 300	14 680	14 550	14 700	14 140	14 500	14 540	14 540	14 540	0.640
		23-1022	Administrators, Mediators, and Conciliators	3	6 260	4 850	5 060	5 090	4 640	5 150	5 780	8 110	8 810	9 570	8 110	6 920	6 880	6 520	6 830	6 710	6 880	6 900	6 800	0.640
Legal Support Workers	23-1023	Judges, Magistrate Judges, and Magistrates	3	23 150	25 190	27 890	25 100	24 640	25 000	25 330	25 870	25 870	25 870	25 870	25 870	25 870	25 870	25 870	25 870	25 870	25 870	25 870	0.940	
	23-2011	Paralegals and Legal Assistants	2	17 570	17 930	18 530	19 300	20 670	21 520	22 700	23 940	24 120	23 040	24 810	24 600	24 790	25 250	26 030	27 130	27 580	27 710	27 710	0.900	
	23-2091	Court Reporters	2	17 460	18 630	19 000	20 770	21 570	22 860	23 980	24 940	26 100	26 980	28 180	28 480	28 590	28 480	28 590	29 000	29 300	29 600	29 600	0.900	
	23-2099	Title Examiners, Abstractors, and Searchers	2	38 730	40 000	42 720	48 060	47 840	69 220	71 060	38 910	39 670	39 310	39 590	42 160	44 720	47 000	45 700	45 120	45 570	44 960	0.900		

Major Group	Minor Group	QCC code	Occupational title	Stratum	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Performance	
Education, Training and Library Occupations	Postsecondary Teachers	25-1011	Business Teachers, Postsecondary	2	63 110	61 660	65 050	66 520	68 760	67 420	67 390	67 390	69 690	73 790	79 070	82 090	82 460	85 220	85 030	84 890	83 030	0.077		
		25-1021	Computer Science Teachers, Postsecondary	2	30 760	27 770	29 690	33 990	34 470	37 800	38 520	38 520	38 520	32 520	32 520	34 520	35 510	35 510	35 510	37 760	37 760	37 760	0.077	
		25-1022	Mathematical Science Teachers, Postsecondary	2	38 850	37 660	38 480	41 140	41 880	45 820	44 570	44 570	44 570	45 710	48 100	51 980	53 590	53 970	54 010	53 850	52 000	0.077		
		25-1031	Architectural Science Teachers, Postsecondary	2	7 730	6 600	7 960	8 260	8 260	8 260	8 260	8 260	8 260	8 260	8 260	8 260	8 260	8 260	8 260	8 260	8 260	8 260	0.077	
		25-1041	Art, Drama, and Music Teachers, Postsecondary	2	38 850	37 660	38 480	41 140	41 880	45 820	44 570	44 570	44 570	45 710	48 100	51 980	53 590	53 970	54 010	53 850	52 000	0.077		
		25-1042	Biological Sciences Teachers, Postsecondary	2	8 190	10 720	11 590	11 760	11 590	11 590	11 460	11 460	11 460	11 460	10 000	10 720	10 000	10 720	10 000	10 720	9 860	10 340	0.077	
		25-1043	Forestry and Conservation Science Teachers, Postsecondary	2	33 790	36 910	38 590	47 150	51 590	59 540	51 590	52 560	51 590	52 560	51 590	54 540	54 540	50 540	50 540	50 540	51 640	50 820	0.077	
		25-1043	Forestry and Conservation Science Teachers, Postsecondary	2	1 830	1 980	1 950	2 350	2 660	2 980	2 980	2 980	2 980	2 980	2 450	2 380	2 410	2 520	2 490	2 440	1 850	1 660	1 750	0.077
		25-1051	Atmospheric, Earth, Marine, and Space Sciences Teachers, Postsecondary	2	7 930	8 000	7 630	8 270	8 420	8 830	8 810	8 810	8 810	9 030	9 900	10 080	10 660	10 930	10 690	10 890	10 850	10 850	0.077	
		25-1052	Chemistry Teachers, Postsecondary	2	17 860	16 020	16 610	17 670	17 100	19 380	19 380	19 380	19 380	19 380	19 950	20 370	21 150	20 830	20 430	20 820	21 470	21 460	21 250	0.077
		25-1053	Environmental Sciences Teachers, Postsecondary	2	5 790	5 350	5 480	5 860	5 860	6 470	6 470	6 470	6 470	6 470	4 710	4 710	4 710	4 990	4 990	5 110	5 300	5 510	0.077	
		25-1054	Physics Teachers, Postsecondary	2	11 230	11 880	11 880	12 480	12 480	13 660	13 660	13 660	13 660	13 660	12 810	13 660	13 660	14 000	14 000	14 000	14 310	14 310	0.077	
		25-1055	Health Sciences Teachers, Postsecondary	2	3 000	4 070	5 070	6 040	7 980	7 980	7 980	7 980	7 980	7 980	7 980	8 710	8 710	9 710	9 710	9 710	9 710	9 710	0.077	
		25-1063	Economics Teachers, Postsecondary	2	11 100	11 530	11 600	11 600	11 420	12 460	12 460	12 460	12 460	12 460	12 460	13 020	13 020	13 020	13 020	13 020	13 020	13 020	0.077	
		25-1064	Geography Teachers, Postsecondary	2	3 330	3 570	3 600	3 920	3 910	4 220	4 250	4 250	4 250	4 050	4 330	4 330	4 440	4 440	4 440	4 440	4 350	4 140	0.077	
		25-1065	Political Science Teachers, Postsecondary	2	10 480	10 820	11 230	11 910	12 320	13 530	13 530	13 530	13 530	13 530	14 360	15 380	17 360	16 770	17 660	17 050	17 460	16 720	0.077	
		25-1066	Psychology Teachers, Postsecondary	2	24 690	24 000	24 850	25 790	29 860	30 240	29 860	30 240	29 860	30 240	31 420	33 450	34 350	37 540	38 680	40 380	37 930	38 360	0.077	
		25-1067	Sociology Teachers, Postsecondary	2	12 490	13 760	12 890	13 590	13 990	15 920	15 920	15 920	15 920	16 110	16 330	17 320	17 320	16 880	17 200	15 900	16 160	14 540	0.077	
		25-1069	Social Science Teachers, Postsecondary	2	25 130	26 680	26 320	28 770	28 770	30 830	30 830	30 830	30 830	30 830	31 570	32 310	32 310	30 430	30 430	31 080	31 080	31 220	31 220	0.077
		25-1071	Health Sciences Teachers, Postsecondary	2	25 130	26 680	26 320	28 770	28 770	30 830	30 830	30 830	30 830	30 830	31 570	32 310	32 310	30 430	30 430	31 080	31 080	31 220	31 220	0.077
		25-1072	Health Sciences Teachers, Postsecondary	2	25 130	26 680	26 320	28 770	28 770	30 830	30 830	30 830	30 830	30 830	31 570	32 310	32 310	30 430	30 430	31 080	31 080	31 220	31 220	0.077
		25-1081	Education Teachers, Postsecondary	2	30 030	41 190	40 480	42 300	44 880	48 670	51 320	53 470	54 420	55 860	56 860	61 450	63 360	62 920	61 190	59 980	60 260	58 850	0.077	
		25-1082	Library Science Teachers, Postsecondary	2	3 870	4 160	4 040	3 760	4 110	3 760	3 960	3 890	3 890	3 890	3 940	4 370	4 410	4 510	4 510	4 510	4 910	4 870	0.077	
		25-1111	Criminal Justice and Law Enforcement Teachers, Postsecondary	2	7 830	8 480	8 060	8 870	9 610	9 770	9 860	10 430	11 110	11 530	12 010	13 860	14 630	14 030	14 030	14 870	14 890	14 560	14 620	0.077
		25-1112	Home Economics Teachers, Postsecondary	2	4 970	4 380	4 350	4 490	4 500	4 060	4 060	4 330	4 770	4 820	4 800	5 910	5 910	5 490	4 700	3 870	3 650	2 970	0.077	
25-1113	Recreation and Fitness Studies Teachers, Postsecondary	2	14 970	14 050	14 700	14 650	14 780	16 150	16 150	16 150	17 110	17 500	17 410	16 850	17 720	18 660	19 410	18 820	18 650	17 980	0.077			
25-1193	Vocational Education Teachers, Postsecondary	2	129 780	115 080	116 890	119 350	121 090	108 540	105 960	109 860	112 300	112 840	112 840	114 420	120 290	125 160	121 550	121 360	121 200	119 800	114 390	0.077		
25-1199	Postsecondary Teachers, All Other	2	338 310	357 230	371 640	367 300	368 870	368 870	368 870	368 870	368 870	368 870	368 870	368 870	368 870	368 870	368 870	368 870	368 870	368 870	368 870	0.077		
25-2012	Primary School Teachers, Except Special Education	2	159 250	155 520	161 610	163 660	164 900	171 290	165 900	171 290	165 900	171 290	170 880	173 430	173 430	164 900	162 370	157 660	154 240	151 380	151 380	0.077		
25-2021	Primary School Teachers, Except Special Education	2	1 357 340	1 409 140	1 453 160	1 443 160	1 432 800	1 431 360	1 486 650	1 509 180	1 538 030	1 544 270	1 544 270	1 544 270	1 485 000	1 415 590	1 360 380	1 344 240	1 335 020	1 384 430	1 395 660	0.004		
Preschool, Primary, Secondary, and Special Education/School Teachers	Preschool, Primary, Secondary, and Special Education/School Teachers	25-2022	Education	2	570 010	561 200	571 100	583 620	604 370	626 110	637 340	652 700	662 960	661 820	665 420	655 090	642 820	620 900	621 970	630 620	637 760	626 310	0.170	
		25-2023	Secondary School Teachers, Except Special and Career/Technical Education	2	17 450	19 010	18 530	17 730	17 430	16 020	15 380	15 740	15 740	15 740	14 960	14 960	18 870	18 150	18 150	14 000	13 090	12 730	0.260	
		25-2031	Career/Technical Education Teachers, Secondary School	2	947 010	938 800	980 730	984 600	1 011 240	1 026 050	1 015 740	1 010 780	1 008 870	1 009 490	1 091 710	1 033 140	1 004 850	959 770	946 710	960 380	962 820	1 003 250	0.008	
		25-2032	Special Education Teachers, Secondary School	2	107 310	103 200	107 680	106 920	101 190	100 200	96 600	95 400	97 550	99 860	92 980	91 660	87 780	85 020	81 560	77 430	86 100	80 100	0.029	
		25-2033	Special Education Teachers, Middle School	2	208 690	208 970	211 240	211 530	205 830	214 060	215 930	219 890	219 890	219 890	226 150	228 860	230 220	230 220	230 220	208 820	208 820	208 820	208 820	0.004
		25-2034	Special Education Teachers, Middle School	2	88 850	87 790	87 330	89 330	91 790	103 480	103 480	103 480	103 480	103 480	103 480	103 480	103 480	100 510	100 510	96 380	96 380	94 800	90 250	0.008
		25-2035	Special Education Teachers, Secondary School	2	119 870	116 760	123 570	134 870	131 930	135 260	136 260	136 260	136 260	141 320	146 240	141 320	137 960	133 080	133 450	129 770	134 490	131 490	131 490	0.008
		25-2039	Special Education Teachers, All Other	2																			0.004	
		25-3011	Adult Basic and Secondary Education and Literacy Teachers and Instructors	2	56 880	53 250	58 310	61 440	62 510	66 560	66 070	71 740	72 240	73 050	68 430	68 430	67 770	66 400	69 880	65 990	65 110	58 810	0.130	
		25-3021	Self-Enrichment Education Teachers	2	125 650	125 960	130 440	134 780	136 680	141 750	141 650	149 700	156 960	163 190	162 310	160 990	160 990	169 200	179 650	187 180	202 360	217 530	229 840	0.130
		25-3022	Teachers and Instructors, All Other, Except Substitute Teachers	2																			0.000	
		25-3023	Substitute Teachers	2																			0.000	
		25-4011	Archivists	2	167 760	167 760	167 760	167 760	167 760	167 760	167 760	167 760	167 760	167 760	167 760	167 760	167 760	167 760	167 760	167 760	167 760	167 760	167 760	0.000
		25-4012	Curators	2																			0.000	
		25-4013	Museum Technicians and Conservators	2	137 760	139 460	150 280	156 920	153 330	145 140	146 740	148 610	148 800	151 170	150 520	148 240	145 710	140 230	136 510	133 150	129 350	123 550	0.050	
25-4021	Librarians	2	9 690	8 740	10 320	9 040	8 970	6 810	6 910	6 520	6 350	6 160	6 800	7 740	8 000	8 690	8 840	8 960	10 170	10 340	0.990			
25-4022	Audio-Visual and Multimedia Collections Specialists	2	9 690																					

Major Group	Minor Group	OCC code	Occupational Title	Stratum	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Pl (automation)
Arts, Design, Entertainment, Sports, and Media Occupations	Art and Design Workers	27-1011	Art Directors	3	19 130	20 560	20 880	23 200	24 000	28 310	29 350	31 000	32 290	33 670	31 660	29 700	30 680	31 570	32 250	33 140	34 590	36 210	0.023
		27-1012	Craft Artists	3	4 830	5 190	5 410	5 710	5 910	6 410	6 730	7 050	7 370	7 690	7 910	8 410	8 730	9 050	9 370	9 690	10 010	10 330	0.023
		27-1013	Fine Artists, including Printers, Sculptors, and Illustrators	3	13 240	11 930	9 710	10 380	9 690	10 320	10 390	11 260	11 260	11 260	8 980	9 380	10 320	11 260	11 880	12 000	12 400	12 400	0.042
		27-1014	Graphic Designers	3	30 530	31 120	30 530	34 150	32 310	35 820	36 530	37 820	38 530	39 820	40 530	41 820	42 530	43 820	44 530	45 820	46 530	47 820	0.042
		27-1015	Illustrators	3	30 530	31 120	30 530	34 150	32 310	35 820	36 530	37 820	38 530	39 820	40 530	41 820	42 530	43 820	44 530	45 820	46 530	47 820	0.042
		27-1016	Interior Designers	3	38 350	33 910	33 600	35 710	33 900	29 770	31 650	33 540	34 480	32 940	29 170	28 710	28 630	28 540	29 410	29 410	31 860	31 860	N/A
		27-1017	Commercial and Industrial Designers	3	38 350	33 910	33 600	35 710	33 900	29 770	31 650	33 540	34 480	32 940	29 170	28 710	28 630	28 540	29 410	29 410	31 860	31 860	0.037
		27-1018	Fashion Designers	2	9 600	10 460	8 800	10 710	11 770	13 190	12 860	15 760	16 490	16 920	15 780	15 060	16 010	16 560	17 370	17 840	19 040	19 230	0.021
		27-1019	Visual Designers	2	59 410	71 280	69 660	66 860	69 730	64 780	63 920	61 320	59 530	57 530	51 470	47 850	47 180	47 110	46 690	45 050	44 350	43 990	0.047
		27-1020	Graphic Designers	2	119 820	133 630	136 470	141 830	151 950	168 060	178 530	190 880	201 080	209 290	200 870	192 240	193 550	194 440	194 360	197 540	204 850	210 710	0.047
	Performers, Sports and Related Workers	27-1021	Interfer Designers	2	29 690	30 680	39 340	40 670	46 240	46 950	50 020	52 440	52 620	53 290	52 290	40 120	40 950	40 750	43 710	45 010	51 050	53 160	0.022
		27-1022	Merchandise Designers and Window Trimmers	2	51 530	51 240	49 520	53 550	59 150	63 590	64 320	62 580	68 660	63 320	61 280	64 330	67 290	73 390	72 590	93 000	100 540	114 690	0.082
		27-1023	Set and Exhibit Designers	2	8 290	8 470	7 840	8 380	8 060	8 760	8 380	8 320	8 620	7 940	7 940	8 120	8 510	8 680	9 750	10 460	11 930	12 060	0.006
		27-1024	Designers, All Other	2						12 550	12 410	11 390	11 890	11 890	11 160	10 510	8 070	7 560	7 330	6 890	6 990	7 230	N/A
		27-2011	Actors	3	84 790	63 500	94 470	52 560	51 840	62 640	59 590	51 880	44 860	44 360	39 880	54 740	60 830	70 540	63 230	59 210	50 570	48 620	0.370
		27-2012	Producers and Directors	3	39 200	46 750	52 130	50 780	54 370	58 180	59 070	63 840	72 390	70 060	79 780	83 520	82 880	87 010	92 510	97 300	104 650	114 510	0.022
		27-2013	Athletes and Sports Competitors	2	10 620	9 920	10 520	10 400	11 840	11 780	12 230	12 500	12 670	13 660	13 660	12 670	12 670	12 670	13 880	11 520	11 710	10 260	0.080
		27-2014	Cosplay Artists	2	6 820	6 820	6 820	6 820	6 820	6 820	6 820	6 820	6 820	6 820	6 820	6 820	6 820	6 820	6 820	6 820	6 820	6 820	0.023
		27-2015	Cosplay Artists, and Other Sports Officials	2	15 820	15 820	15 820	15 820	15 820	15 820	15 820	15 820	15 820	15 820	15 820	15 820	15 820	15 820	15 820	15 820	15 820	15 820	0.023
		27-2016	Photographers, and Other Sports Officials	2	14 910	20 900	17 010	16 800	15 900	16 490	16 240	16 010	12 530	11 370	10 700	11 200	11 240	11 390	11 440	11 340	10 930	10 060	0.130
	Media and Communication Equipment Workers	27-2017	Choreographers	2	11 170	10 860	12 660	15 820	14 810	15 360	16 150	16 340	15 250	13 860	14 700	14 700	12 390	10 870	7 400	6 030	5 130	5 160	0.004
		27-2018	Music Directors and Composers	2	6 310	6 660	7 020	8 980	9 000	9 470	8 610	9 470	9 110	9 110	14 330	20 640	25 290	24 940	23 390	21 880	21 540	18 380	0.015
		27-2019	Musicians and Singers	2	46 440	52 180	55 100	53 940	50 000	52 350	50 410	46 600	47 520	47 030	47 260	43 350	42 100	39 360	38 900	37 090	40 110	40 110	0.074
		27-2020	Entertainers and Performers, Sports and Related Workers, All	2						65 100	68 540	59 450	32 040	36 190	23 500	23 510	17 930	16 360	16 440	15 780	14 570	13 150	N/A
		27-3011	Radio and Television Announcers	2	50 410	49 770	50 420	49 790	50 410	41 140	41 090	40 020	39 500	37 290	35 130	32 520	31 680	31 340	30 320	30 320	30 320	29 210	0.100
		27-3012	Public Address System and Other Announcers	2	8 480	8 150	8 300	8 490	8 300	8 480	8 150	8 300	8 490	8 280	7 280	7 580	7 770	8 120	7 450	7 450	8 000	8 020	0.067
		27-3021	Broadcast News Analysts	2	64 590	64 590	64 590	64 590	64 590	52 730	52 920	53 060	51 620	50 690	46 130	45 130	45 270	46 570	43 830	42 380	41 050	40 090	0.130
		27-3022	Reporters and Correspondents	2	118 280	128 570	132 390	136 360	147 570	180 200	191 430	209 560	225 880	240 610	242 670	225 590	215 510	201 280	202 590	208 030	218 910	226 940	0.180
		27-3031	Editors	3	95 210	104 210	105 130	106 520	108 990	97 380	96 270	100 170	105 920	110 010	105 040	99 160	98 990	99 040	98 790	97 350	96 980	97 370	0.055
		27-3032	Technical Writers	3	46 680	50 700	46 900	44 200	44 690	45 380	46 250	45 330	46 740	47 460	48 270	48 990	48 120	48 120	47 800	48 210	49 710	49 710	0.050
	Media and Communication Equipment Workers	27-3033	Printers and Press Operators	2	13 640	15 780	18 900	18 800	21 510	26 320	29 240	30 910	33 680	36 610	40 000	44 200	47 960	50 320	49 860	49 460	49 850	51 350	0.380
		27-3034	Interpret and Translation	2						25 970	25 660	22 970	24 420	24 470	25 460	23 740	23 610	23 030	26 940	25 530	22 240	23 310	N/A
		27-3035	Media and Communication Workers, All Other	2	38 090	34 110	38 960	35 770	37 370	39 860	40 360	40 360	45 200	46 070	47 510	49 180	54 310	56 440	60 200	62 460	69 670	69 670	0.550
		27-4011	Broadcast Technicians	2	25 570	33 560	31 100	31 520	32 750	30 670	30 730	32 070	34 250	31 220	33 550	31 220	30 360	31 680	27 800	26 600	28 270	30 330	0.740
		27-4012	Radio Operators	2	3 290	3 060	3 360	2 510	2 960	1 400	1 190	1 220	1 110	820	870	1 200	1 280	1 280	1 160	1 100	940	870	0.980
		27-4013	Sound Engineering Technicians	2	9 380	10 380	9 350	11 110	11 860	12 070	12 680	14 080	15 490	16 600	15 560	15 650	14 980	14 280	13 880	13 750	13 840	15 210	0.300
		27-4014	Photographers	2	66 070	65 360	61 250	63 440	57 740	55 450	58 260	60 300	62 370	61 670	57 560	54 550	54 410	56 140	54 830	52 250	50 070	48 660	0.021
		27-4031	Camera Operators, Television, Video, and Motion Picture	2	17 330	20 970	22 040	21 270	21 830	22 410	22 530	22 230	19 990	19 270	17 760	17 560	16 760	16 270	16 110	16 860	18 310	20 060	0.000
		27-4032	Film and Video Editors	2	12 770	10 990	13 750	15 180	15 100	14 890	15 200	17 360	17 410	18 720	17 550	19 930	20 730	21 500	21 920	24 460	27 660	29 880	0.310
		27-4099	Media and Communication Equipment Workers, All Other	2						18 180	17 200	17 740	18 580	19 770	17 610	16 820	14 090	16 090	17 650	17 650	17 650	18 620	N/A

Major Group	Minor Group	OS Code	Occupational Title	1998	2000	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Projected				
Healthcare Practitioners and Technical Occupations	Health Diagnosing and Treating Practitioners	29-1011	Occupational Health Technicians	3	11,540	16,740	18,000	20,610	22,710	24,290	25,470	27,190	27,050	26,250	26,310	27,510	27,740	28,850	29,810	32,080	32,960	34,000			
		29-1021	Dentists, General	3	69,300	69,300	69,300	69,300	69,300	69,300	69,300	69,300	69,300	69,300	69,300	69,300	69,300	69,300	69,300	69,300	69,300	69,300	69,300		
		29-1022	Oral and Maxillofacial Surgeons	3																					
		29-1023	Orthodontists	3																					
		29-1024	Prosthodontists	3																					
		29-1025	Dentists, All Other Specialists	3																					
		29-1031	Dietitians and Nutritionists	3	41,320	43,030	43,200	45,150	46,190	47,820	48,850	51,230	52,800	53,630	53,220	53,510	56,130	58,240	59,590	59,740	61,810	63,800	65,800		
		29-1041	Ophthalmologists	3	21,400	23,880	24,230	25,940	27,740	29,130	30,220	32,720	34,220	34,900	35,340	35,340	37,980	39,480	40,810	41,140	43,540	45,040	46,540		
		29-1051	Pharmacists	3	226,300	212,600	223,620	219,390	226,200	229,470	239,320	253,110	266,410	267,860	265,030	272,320	281,560	287,420	297,780	295,620	305,510	305,510	310,010		
		29-1061	Anesthesiologists	3	25,910	24,350	24,700	24,780	23,790	26,140	27,970	29,860	31,030	34,210	34,900	34,820	33,310	29,930	30,260	30,660	29,720	30,390	30,000		
		29-1062	Family and General Practitioners	3	134,490	124,620	135,250	119,020	119,900	108,800	112,150	109,400	113,250	106,210	97,820	101,800	120,860	124,810	127,430	127,790	132,770	132,770	137,750		
		29-1063	Physicians, General	3	134,490	124,620	135,250	119,020	119,900	108,800	112,150	109,400	113,250	106,210	97,820	101,800	120,860	124,810	127,430	127,790	132,770	132,770	137,750		
		29-1064	Physicians, General	3	18,790	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300		
		29-1065	Pediatricians, General	3	18,790	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300		
		29-1066	Pediatricians, General	3	18,790	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300	19,300		
		29-1067	Psychiatrists	3	17,870	21,280	21,620	19,750	19,530	22,500	23,860	24,730	22,140	22,210	22,690	23,100	22,640	23,080	23,100	23,660	24,660	24,800	25,000		
		29-1067	Psychiatrists	3	48,420	48,770	48,920	51,580	49,710	55,390	52,830	54,900	50,760	47,070	44,160	43,240	42,410	42,410	41,000	41,000	41,000	41,000	41,000		
		29-1069	Physicians and Surgeons, All Other	3	56,750	52,490	56,200	61,910	60,030	74,720	180,210	208,960	237,400	262,850	274,160	293,740	302,720	311,320	307,120	311,320	327,740	338,620	348,620		
		29-1071	Physician Assistants	3	4,470	7,870	7,780	7,490	7,800	8,790	9,020	9,960	9,940	9,780	9,940	9,940	9,940	9,940	9,940	9,940	9,940	9,940	9,940		
		Healthcare Practitioners and Technical Occupations	Health Diagnosing and Treating Practitioners, All Other	29-1081	Podiatrists	3	78,950	75,150	77,080	78,580	81,380	87,710	88,570	91,920	94,800	97,840	97,840	100,570	105,540	108,400	110,520	114,660	118,070	120,000	
29-1122	Occupational Therapists			3	131,050	120,410	126,450	130,290	134,970	145,210	151,180	156,100	161,850	167,300	174,490	180,280	185,440	190,560	195,670	200,670	209,690	216,920	220,000		
29-1124	Rehabilitation Therapists			3	12,340	13,100	13,460	13,510	13,990	14,040	14,120	14,290	14,620	14,850	15,570	16,590	18,380	18,230	18,950	16,380	16,930	17,450	17,340		
29-1225	Recreational Therapists			3	30,190	28,930	28,130	22,860	23,350	23,260	24,120	23,240	22,510	21,960	20,830	20,370	19,650	19,180	18,640	17,950	17,880	18,700	18,000		
29-1226	Respiratory Therapists			3	80,230	82,670	85,930	87,380	94,500	95,320	99,300	101,380	103,870	107,420	110,770	113,980	118,640	119,410	120,330	126,780	127,880	130,760	130,000		
29-1227	Speech-Language Pathologists			3	85,920	81,850	83,110	87,030	86,640	93,200	94,660	98,600	103,810	107,340	111,640	117,520	121,690	125,500	128,500	131,450	135,980	138,000	140,000		
29-1228	Exercise Physiologists			3																					
29-1229	Complementary Health Practitioners, All Other			3																					
29-1311	Registered Nurses			3	30,250	40,270	41,240	43,900	43,800	48,700	49,750	50,780	53,110	54,130	54,480	57,920	58,420	60,920	61,420	63,920	64,420	66,920	67,420		
29-1311	Registered Nurses			2	2,205,430	2,389,670	2,217,990	2,246,430	2,338,530	2,368,070	2,417,150	2,468,340	2,442,760	2,583,770	2,655,020	2,724,570	2,613,900	2,663,980	2,667,310	2,745,910	2,857,380	2,867,600	2,909,000		
29-1351	Nurse Anesthetists			2																					
29-1361	Nurse Midwives			2																					
29-1371	Nurse Practitioners			2																					
29-1381	Audiologists			2																					
29-1391	Health Diagnosing and Treating Practitioners, All Other			2																					
Healthcare Practitioners and Technical Occupations	Health Diagnosing and Treating Practitioners, All Other			29-2011	Medical and Clinical Laboratory Technologists	2	145,750	144,530	145,400	146,480	146,900	154,180	155,250	160,760	163,270	166,510	166,860	164,430	162,220	160,700	160,700	162,550	166,780	167,900	
				29-2012	Dental and Clinical Laboratory Technicians	2	90,050	146,060	146,920	144,120	143,610	142,330	144,710	145,800	148,670	152,400	156,480	156,860	157,080	157,080	160,460	157,610	160,150	160,150	160,150
				29-2021	Medical Hygienists	2	50,090	146,460	146,920	146,920	146,920	146,920	146,920	146,920	146,920	146,920	146,920	146,920	146,920	146,920	146,920	146,920	146,920	146,920	146,920
				29-2031	Cardiovascular Technologists and Technicians	2	41,490	40,080	40,990	42,870	43,300	43,320	43,460	43,870	44,000	44,000	44,000	44,000	44,000	44,000	44,000	44,000	44,000	44,000	44,000
				29-2032	Diagnostic Medical Sonographers	2	29,280	31,760	32,990	35,510	37,240	42,500	43,490	44,760	46,780	48,920	51,000	53,080	51,080	51,080	51,080	51,080	51,080	51,080	51,080
		29-2033	Nuclear Medicine Technologists	2	17,880	18,030	17,160	17,690	17,550	18,280	19,270	20,100	21,000	21,670	22,160	22,160	22,160	22,160	22,160	22,160	22,160	22,160	22,160		
		29-2034	Health Information Technicians	2	17,880	18,030	17,160	17,690	17,550	18,280	19,270	20,100	21,000	21,670	22,160	22,160	22,160	22,160	22,160	22,160	22,160	22,160	22,160		
		29-2035	Diagnostic Medical Sonographers	2	17,880	18,030	17,160	17,690	17,550	18,280	19,270	20,100	21,000	21,670	22,160	22,160	22,160	22,160	22,160	22,160	22,160	22,160	22,160		
		29-2036	Diagnostic Medical Sonographers	2	17,880	18,030	17,160	17,690	17,550	18,280	19,270	20,100	21,000	21,670	22,160	22,160	22,160	22,160	22,160	22,160	22,160	22,160	22,160		
		29-2037	Diagnostic Medical Sonographers	2	17,880	18,030	17,160	17,690	17,550	18,280	19,270	20,100	21,000	21,670	22,160	22,160	22,160	22,160	22,160	22,160	22,160	22,160	22,160		
		29-2038	Diagnostic Medical Sonographers	2	17,880	18,030	17,160	17,690	17,550	18,280	19,270	20,100	21,000	21,670	22,160	22,160	22,160	22,160	22,160	22,160	22,160	22,160	22,160		
		29-2039	Diagnostic Medical Sonographers	2	17,880	18,030	17,160	17,690	17,550	18,280	19,270	20,100	21,000	21,670	22,160	22,160	22,160	22,160	22,160	22,160	22,160	22,160	22,160		
		29-2041	Diagnostic Medical Technicians and Paramedics	2	172,360	165,530	170,690	178,700	181,790	191,070	196,880	196,190	201,200	207,610	217,910	221,760	229,340	232,860	237,660	241,800	244,860	248,860	250,000		
		29-2051	Diagnostic Medical Technicians and Paramedics	2	29,190	28,010	28,940	28,910	28,620	29,410	29,780	24,450	24,450	24,450	23,890	23,890	23,890	23,890	23,890	23,890	23,890	23,890	23,890		
		29-2052	Pharmacy Technicians	2	196,430	190,940	207,140	207,380	211,270	205,390	266,790	282,450	301,950	324,110	331,880	333,500	343,550	353,340	367,660	368,700	379,830	398,390	402,000		
		29-2053	Psychiatric Technicians	2	54,560	53,350	59,750	58,600	56,000	62,960	62,960	58,940	60,690	60,690	60,690	60,690	60,690	60,690	60,690	60,690	60,690	60,690	60,690		
		29-2054	Respiratory Therapy Technicians	2	33,990	28,290	28,290	25,470	21,970	22,660	18,710	18,710	18,710	18,710	15,100	13,940	13,940	10,700	10,610	10,000	10,600	10,000	10,000		
		29-2055	Surgical Technicians	2	64,810	68,590	67,460	72,040	73,250	82,070	83,880	84,330	86,000	87,610	92,260	94,490	97,930	98,450	100,720	100,720	105,700	105,700	105,700		
		29-2056	Veterinary Technicians and Technicians	2	47,400	50,370	51,790	54,040	53,730	61,110	63,860	69,700	73,740	78,920	79,200	78,920	83,330	87,870	91,300	95,790	99,390	102,990	102,990		
		29-2057	Ophthalmic Medical Technicians and Technicians	2	34,590	36,980	34,450	39,320	36,340	39,320	39,320	39,320	39,320	39,320	39,320	39,320	39,320	39,320	39,320	39,320	39,320	39,320	39,320		
Healthcare Practitioners and Technical Occupations	Health Diagnosing and Treating Practitioners, All Other	29-2061	Licensed Practical and Licensed Vocational Nurses	2	685,510	679,470	683,790	692,290	706,860	710,020	720,380	719,240	730,500	728,670	730,290	730,290	718,800	705,200	695,610	697,250	702,400	705,800			
		29-2071	Medical Records and Health Information Technicians</																						

Major Group	Minor Group	Occupational Title	Stratum	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037	2038	2039	2040	2041	2042	2043	2044	2045	2046	2047	2048	2049	2050	2051	2052	2053	2054	2055	2056	2057	2058	2059	2060	2061	2062	2063	2064	2065	2066	2067	2068	2069	2070	2071	2072	2073	2074	2075	2076	2077	2078	2079	2080	2081	2082	2083	2084	2085	2086	2087	2088	2089	2090	2091	2092	2093	2094	2095	2096	2097	2098	2099	2100	2101	2102	2103	2104	2105	2106	2107	2108	2109	2110	2111	2112	2113	2114	2115	2116	2117	2118	2119	2120	2121	2122	2123	2124	2125	2126	2127	2128	2129	2130	2131	2132	2133	2134	2135	2136	2137	2138	2139	2140	2141	2142	2143	2144	2145	2146	2147	2148	2149	2150	2151	2152	2153	2154	2155	2156	2157	2158	2159	2160	2161	2162	2163	2164	2165	2166	2167	2168	2169	2170	2171	2172	2173	2174	2175	2176	2177	2178	2179	2180	2181	2182	2183	2184	2185	2186	2187	2188	2189	2190	2191	2192	2193	2194	2195	2196	2197	2198	2199	2200	2201	2202	2203	2204	2205	2206	2207	2208	2209	2210	2211	2212	2213	2214	2215	2216	2217	2218	2219	2220	2221	2222	2223	2224	2225	2226	2227	2228	2229	2230	2231	2232	2233	2234	2235	2236	2237	2238	2239	2240	2241	2242	2243	2244	2245	2246	2247	2248	2249	2250	2251	2252	2253	2254	2255	2256	2257	2258	2259	2260	2261	2262	2263	2264	2265	2266	2267	2268	2269	2270	2271	2272	2273	2274	2275	2276	2277	2278	2279	2280	2281	2282	2283	2284	2285	2286	2287	2288	2289	2290	2291	2292	2293	2294	2295	2296	2297	2298	2299	2300	2301	2302	2303	2304	2305	2306	2307	2308	2309	2310	2311	2312	2313	2314	2315	2316	2317	2318	2319	2320	2321	2322	2323	2324	2325	2326	2327	2328	2329	2330	2331	2332	2333	2334	2335	2336	2337	2338	2339	2340	2341	2342	2343	2344	2345	2346	2347	2348	2349	2350	2351	2352	2353	2354	2355	2356	2357	2358	2359	2360	2361	2362	2363	2364	2365	2366	2367	2368	2369	2370	2371	2372	2373	2374	2375	2376	2377	2378	2379	2380	2381	2382	2383	2384	2385	2386	2387	2388	2389	2390	2391	2392	2393	2394	2395	2396	2397	2398	2399	2400	2401	2402	2403	2404	2405	2406	2407	2408	2409	2410	2411	2412	2413	2414	2415	2416	2417	2418	2419	2420	2421	2422	2423	2424	2425	2426	2427	2428	2429	2430	2431	2432	2433	2434	2435	2436	2437	2438	2439	2440	2441	2442	2443	2444	2445	2446	2447	2448	2449	2450	2451	2452	2453	2454	2455	2456	2457	2458	2459	2460	2461	2462	2463	2464	2465	2466	2467	2468	2469	2470	2471	2472	2473	2474	2475	2476	2477	2478	2479	2480	2481	2482	2483	2484	2485	2486	2487	2488	2489	2490	2491	2492	2493	2494	2495	2496	2497	2498	2499	2500	2501	2502	2503	2504	2505	2506	2507	2508	2509	2510	2511	2512	2513	2514	2515	2516	2517	2518	2519	2520	2521	2522	2523	2524	2525	2526	2527	2528	2529	2530	2531	2532	2533	2534	2535	2536	2537	2538	2539	2540	2541	2542	2543	2544	2545	2546	2547	2548	2549	2550	2551	2552	2553	2554	2555	2556	2557	2558	2559	2560	2561	2562	2563	2564	2565	2566	2567	2568	2569	2570	2571	2572	2573	2574	2575	2576	2577	2578	2579	2580	2581	2582	2583	2584	2585	2586	2587	2588	2589	2590	2591	2592	2593	2594	2595	2596	2597	2598	2599	2600	2601	2602	2603	2604	2605	2606	2607	2608	2609	2610	2611	2612	2613	2614	2615	2616	2617	2618	2619	2620	2621	2622	2623	2624	2625	2626	2627	2628	2629	2630	2631	2632	2633	2634	2635	2636	2637	2638	2639	2640	2641	2642	2643	2644	2645	2646	2647	2648	2649	2650	2651	2652	2653	2654	2655	2656	2657	2658	2659	2660	2661	2662	2663	2664	2665	2666	2667	2668	2669	2670	2671	2672	2673	2674	2675	2676	2677	2678	2679	2680	2681	2682	2683	2684	2685	2686	2687	2688	2689	2690	2691	2692	2693	2694	2695	2696	2697	2698	2699	2700	2701	2702	2703	2704	2705	2706	2707	2708	2709	2710	2711	2712	2713	2714	2715	2716	2717	2718	2719	2720	2721	2722	2723	2724	2725	2726	2727	2728	2729	2730	2731	2732	2733	2734	2735	2736	2737	2738	2739	2740	2741	2742	2743	2744	2745	2746	2747	2748	2749	2750	2751	2752	2753	2754	2755	2756	2757	2758	2759	2760	2761	2762	2763	2764	2765	2766	2767	2768	2769	2770	2771	2772	2773	2774	2775	2776	2777	2778	2779	2780	2781	2782	2783	2784	2785	2786	2787	2788	2789	2790	2791	2792	2793	2794	2795	2796	2797	2798	2799	2800	2801	2802	2803	2804	2805	2806	2807	2808	2809	2810	2811	2812	2813	2814	2815	2816	2817	2818	2819	2820	2821	2822	2823	2824	2825	2826	2827	2828	2829	2830	2831	2832	2833	2834	2835	2836	2837	2838	2839	2840	2841	2842	2843	2844	2845	2846	2847	2848	2849	2850	2851	2852	2853	2854	2855	2856	2857	2858	2859	2860	2861	2862	2863	2864	2865	2866	2867	2868	2869	2870	2871	2872	2873	2874	2875	2876	2877	2878	2879	2880	2881	2882	2883	2884	2885	2886	2887	2888	2889	2890	2891	2892	2893	2894	2895	2896	2897	2898	2899	2900	2901	2902	2903	2904	2905	2906	2907	2908	2909	2910	2911	2912	2913	2914	2915	2916	2917	2918	2919	2920	2921	2922	2923	2924	2925	2926	2927	2928	2929	2930	2931	2932	2933	2934	2935	2936	2937	2938	2939	2940	2941	2942	2943	2944	2945	2946	2947	2948	2949	2950	2951	2952	2953	2954	2955	2956	2957	2958	2959	2960	2961	2962	2963	2964	2965	2966	2967	2968	2969	2970	2971	2972	2973	2974	2975	2976	2977	2978	2979	2980	2981	2982	2983	2984	2985	2986	2987	2988	2989	2990	2991	2992	2993	2994	2995	2996	2997	2998	2999	3000	3001	3002	3003	3004	3005	3006	3007	3008	3009	3010	3011	3012	3013	3014	3015	3016	3017	3018	3019	3020	3021	3022	3023	3024	3025	3026	3027	3028	3029	3030	3031	3032	3033	3034	3035	3036	3037	3038	3039	3040	3041	3042	3043	3044	3045	3046	3047	3048	3049	3050	3051	3052	3053	3054	3055	3056	3057	3058	3059	3060	3061	3062	3063	3064	3065	3066	3067	3068	3069	3070	3071	3072	3073	3074	3075	3076	3077	3078	3079	3080	3081	3082	3083	3084	3085	3086	3087	3088	3089	3090	3091	3092	3093	3094	3095	3096	3097	3098	3099	3100	3101	3102	3103	3104	3105	3106	3107	3108	3109	3110	3111	3112	3113	3114	3115	3116	3117	3118	3119	3120	3121	3122	3123	3124	3125	3126	3127	3128	3129	3130	3131	3132	3133	3134	3135	3136	3137	3138	3139	3140	3141	3142	3143	3144	3145	3146	3147	3148	3149	3150	3151	3152	3153	3154	3155	3156	3157	3158	3159	3160	3161	3162	3163	3164	3165	3166	3167	3168	3169	3170	3171	3172	3173	3174	3175	3176	3177	3178	3179	3180	3181	3182	3183	3184	3185	3186	3187	3188	3189	3190	3191	3192	3193	3194	3195	3196	3197	3198	3199	3200	3201	3202	3203	3204	3205	3206	3207	3208	3209	3210	3211	3212	3213	3214	3215	3216	3217	3218	3219	3220	3221	3222	3223	3224	3225	3226	3227	3228	3229	3230	3231	3232	3233	3234	3235	3236	3237	3238	3239	3240	3241	3242	3243	3244	3245	3246	3247	3248	3249	3250	3251	3252	3253	3254	3255	3256	3257	3258	3259	3260	3261	3262	3263	3264	3265	3266	3267	3268	3269	3270	3271	3272	3273	3274	3275	3276	3277	3278	3279	3280	3281	3282	3283	3284	3285	3286	3287	3288	3289	3290	3291	3292	3293	3294	3295	3296	3297	3298	3299	3300	3301	3302	3303	3304	3305	3306	3307	3308	3309	3310	3311	3312	3313	3314	3315	3316	3317	3318	3319	3320	3321	3322	3323	3324	3325	3326	3327	3328	3329	3330	3331	3332	3333	3334	3335	3336	3337	3338	3339	3340	3341	3342	3343	3344	3345	3346	3347	3348	3349	3350	3351	3352	3353	3354	3355	3356	3357	3358
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Major Group	Minor Group	Occupational Title	Spectrum	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Platform
Farming, Fishing, and Forestry Occupations	Supervisors of Farming, Fishing, and Forestry Workers	45-1011 First-Line Supervisors of Farming, Fishing, and Forestry Workers	2	20 360	21 350	22 180	20 910	20 620	19 740	19 750	19 670	20 060	20 000	20 700	19 940	18 920	18 340	18 540	18 530	19 060	19 550	0.720
		45-2011 Agricultural Inspectors	2	10 520	12 210	13 980	13 760	13 670	12 020	11 740	14 290	14 760	14 340	14 000	13 360	13 780	13 740	13 740	13 800	14 070	14 170	0.940
		45-2021 Animal Breeders	1	1 420	1 680	1 690	1 390	1 750	1 530	1 860	2 060	2 310	2 800	1 700	1 460	1 460	1 240	1 110	1 170	1 370	1 010	0.950
		45-2041 Graders and Sorters, Agricultural Products	1	62 380	56 210	54 110	54 500	51 210	47 290	45 010	45 890	40 770	37 300	37 500	38 950	40 970	39 060	38 120	36 100	33 920	34 870	0.410
		45-2090 Miscellaneous Agricultural Workers	1	17 630	23 230	26 580	21 820	21 330	18 490	19 940	21 140	22 480	22 480	22 480	22 480	22 480	22 480	22 480	22 480	22 480	22 480	0.700
	Agriculture Workers	45-2091 Agricultural Equipment Operators	1	215 080	215 550	215 020	218 020	234 450	231 210	227 750	230 780	239 380	244 390	243 360	233 650	228 620	253 670	261 720	269 650	272 170	273 450	n/a
		45-2092 Farmworkers and Laborers, Crop, Nursery, and Greenhouse	1	34 510	38 270	34 590	38 260	42 890	44 810	49 740	47 870	44 780	38 110	35 000	31 880	29 750	31 000	31 000	31 530	35 670	35 670	n/a
		45-2093 Farmworkers, Farm, Ranch, and Aquacultural Animals	1	34 510	38 270	34 590	38 260	42 890	44 810	49 740	47 870	44 780	38 110	35 000	31 880	29 750	31 000	31 000	31 530	35 670	35 670	n/a
		45-2099 Agricultural Workers, All Other	1	34 510	38 270	34 590	38 260	42 890	44 810	49 740	47 870	44 780	38 110	35 000	31 880	29 750	31 000	31 000	31 530	35 670	35 670	n/a
		45-3011 Fishers and Related Fishing Workers	1							890	770	880	960	1 110	670	700	640	570	480	400	540	520
	Forest, Conservation, and Logging Workers	45-4011 Forest and Conservation Workers	1	11 780	9 990	12 750	9 140	9 170	8 980	8 700	8 330	8 770	8 330	5 840	7 040	8 250	7 910	6 940	6 870	6 870	7 170	0.970
		45-4021 Fallers	1	9 420	9 910	9 790	10 180	9 620	9 780	8 790	8 790	7 790	7 120	6 480	6 360	5 020	5 150	5 790	6 090	5 840	5 370	0.760
		45-4022 Logging Equipment Operators	1	33 230	34 180	30 930	29 060	28 190	27 650	26 880	28 300	27 700	27 010	23 800	22 880	22 470	23 240	24 480	26 010	27 290	27 250	0.790
		45-4023 Log Graders and Skidders	1	5 500	5 470	4 950	4 730	4 900	4 570	4 520	4 810	4 430	4 310	2 840	2 880	2 810	2 770	2 780	2 740	2 740	3 010	0.970
		45-4029 Logging Workers, All Other	1							5 790		5 880	5 740	5 180	4 010	3 130	2 760	2 890	2 810	2 730	2 880	3 010
Construction and Extraction Occupations	Supervisors of Construction and Extraction Workers	47-1011 First-Line Supervisors of Construction Trades and Extraction Workers	2	476 770	502 010	514 750	506 620	516 540	549 130	555 380	574 870	577 130	577 980	531 840	474 510	459 830	456 640	467 130	496 630	517 560	538 220	0.170
		47-2011 Boilermakers	1	291 660	25 280	24 390	24 560	20 270	17 640	17 760	17 240	18 650	20 400	22 400	20 930	18 850	17 660	15 950	17 210	16 350	16 660	0.680
		47-2021 Brickmasons and Blockmasons	1	98 530	108 590	109 840	109 900	114 400	115 950	118 080	116 390	106 270	87 780	68 520	62 560	57 090	58 730	59 340	59 340	61 360	64 370	0.520
		47-2022 Stonemasons	1	8 640	10 100	11 880	12 870	13 710	15 450	17 030	18 210	18 760	18 310	14 080	11 950	11 330	10 410	11 290	13 120	13 190	13 190	0.890
		47-2031 Carpenters	1	771 030	858 890	851 610	857 590	852 080	913 130	935 920	985 970	969 670	899 920	743 760	620 410	578 910	567 820	580 570	617 060	639 190	676 980	0.720
	Construction Trades Workers	47-2041 Carpet Installers	1	37 750	38 010	36 340	38 320	37 720	40 400	37 050	36 940	34 390	29 080	25 580	24 670	25 350	24 640	26 050	25 810	25 660	25 660	0.790
		47-2042 Floor Layers, Except Carpet, Wood, and Hard Tiles	1	11 310	12 300	13 560	14 840	15 070	15 250	14 510	14 070	14 070	14 070	14 070	14 070	14 070	14 070	14 070	14 070	14 070	14 070	0.790
		47-2043 Floor Finishers and Finishers	1	7 600	7 610	8 230	7 740	6 700	6 060	5 590	7 480	8 220	7 480	8 220	7 480	8 220	7 480	8 220	7 480	8 220	7 480	0.790
		47-2044 Tile and Marble Setters	1	21 330	22 750	26 380	27 350	26 900	25 000	24 710	25 190	24 610	23 200	21 330	20 000	18 850	17 660	16 000	14 850	13 400	12 400	0.700
		47-2051 Cement Masons and Concrete Finishers	1	151 760	169 550	176 590	177 930	180 540	195 020	204 710	218 170	213 860	201 710	165 700	140 950	133 130	133 200	141 910	152 570	161 360	173 920	0.840
	Construction Workers	47-2053 Terrazzo Workers and Finishers	1	4 570	4 510	5 800	6 130	6 460	6 960	5 440	6 550	5 910	5 550	4 290	3 640	3 500	3 350	3 220	3 250	3 420	0.800	
		47-2061 Construction Laborers	1	769 450	821 210	823 390	830 860	837 650	893 940	934 000	1 016 510	1 063 690	1 020 390	856 440	777 700	779 370	814 470	824 970	852 870	887 580	912 110	0.880
		47-2071 Paving, Surfacing, and Tamping Equipment Operators	1	58 410	56 330	57 880	58 760	57 980	62 400	63 220	63 680	61 320	54 850	51 320	54 460	55 720	54 940	53 100	51 880	51 880	53 880	0.830
		47-2072 Pile-Driver Operators	1	4 940	4 320	4 950	4 670	4 390	4 550	4 410	5 280	5 050	4 790	4 440	4 230	3 830	3 800	3 620	3 470	3 670	3 570	0.520
		47-2073 Operating Engineers and Other Construction Equipment Operators	1	324 350	333 200	335 650	341 710	341 640	369 280	378 720	393 990	403 620	398 910	368 200	344 730	335 410	335 160	340 950	344 510	353 140	357 570	0.950
Construction and Extraction Occupations	Construction Trades Workers	47-2081 Drywall and Ceiling Tile Installers	1	118 300	118 280	121 450	111 970	112 240	126 810	140 610	137 570	128 440	128 880	82 320	75 320	75 820	75 820	85 020	88 490	95 180	95 180	0.790
		47-2082 Plaster and Stucco Workers	1	619 350	619 350	619 350	619 350	619 350	619 350	619 350	619 350	619 350	619 350	619 350	619 350	619 350	619 350	619 350	619 350	619 350	619 350	0.790
		47-2083 Glaziers	1	486 350	481 160	469 960	469 960	46 230	45 930	46 500	46 500	46 500	46 500	46 500	46 500	46 500	46 500	46 500	46 500	46 500	46 500	0.790
		47-2121 Installation Workers, Floor, Ceiling, and Wall	1	56 650	54 710	54 720	51 740	52 170	56 330	61 340	51 450	29 660	28 390	26 500	23 360	21 740	22 540	43 350	44 050	43 820	44 230	0.730
		47-2132 Installation Workers, Mechanical	1	260 880	261 040	256 220	257 140	247 880	148 940	224 800	219 440	27 900	29 110	30 150	29 620	28 100	28 600	28 220	27 740	28 660	29 330	0.720
	Construction Trades Workers	47-2141 Painters, Construction and Maintenance	1	47 210	47 210	47 210	47 210	47 210	47 210	47 210	47 210	47 210	47 210	47 210	47 210	47 210	47 210	47 210	47 210	47 210	47 210	0.720
		47-2142 Paperhangers	1	10 070	10 090	9 320	9 450	9 190	7 330	7 710	6 160	5 910	5 680	5 440	4 450	4 320	4 360	3 460	3 460	3 570	3 020	0.970
		47-2151 Plumbers, Pipefitters, and Steamfitters	1	53 530	59 560	56 190	52 380	51 940	54 120	56 260	58 300	56 860	54 440	49 190	45 440	44 240	43 590	41 000	41 000	40 710	39 620	0.620
		47-2152 Plumbers, Pipefitters, and Steamfitters	1	413 370	437 140	438 290	431 660	423 260	420 770	415 960	415 010	415 010	415 010	415 010	415 010	415 010	415 010	415 010	415 010	415 010	415 010	0.550
		47-2161 Roofers, Flat and Gable	1	27 760	27 010	29 610	29 540	30 250	31 000	30 720	30 180	28 720	28 620	28 620	28 620	28 620	28 620	28 620	28 620	28 620	28 620	0.700
	Construction Trades Workers	47-2211 Roofers, Hip and Gable	1	115 260	114 410	118 160	117 140	118 990	117 860	120 070	125 010	123 180	123 180	108 890	99 380	95 840	97 650	99 060	103 650	109 720	116 410	0.900
		47-2212 Sheet Metal Workers	1	231 690	218 020	207 960	197 110	185 590	181 720	174 550	177 540	167 710	163 000	146 690	131 600	130 670	134 110	132 530	135 570	134 450	134 450	0.920
		47-2221 Structural Iron and Steel Workers	1	85 520	81 710	78 700	70 700	70 420	71 310	68 900	67 560	65 100	68 070	65 130	58 460	56 320	57 070	57 480	60 010	64 280	69 440	0.830
		47-2222 Solar Photovoltaic Installers	1																			n/a
		47-2231 Helpers—Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters	1	56 660	58 090	64 730	60 740	59 890	59 790	58 690	62 290	57 870	53 300	40 770	31 160	26 750	24 310	24 280	23 570	23 950	23 950	0.830
	Helpers, Construction Trades	47-3012 Helpers—Carpenters	1	1																		

Major Group	Minor Group	Occupational Title	Stratum	1998	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Information	
Supervisors of Installation, Maintenance, and Repair Occupations	Electrical and Electronic Equipment Mechanics, Installers, and Repairers	49-2011 First-Line Supervisors of Mechanics, Installers, and Repairers	2	386 170	421 740	441 700	433 640	445 520	455 600	455 600	457 710	443 790	443 840	427 560	415 900	418 330	428 620	434 810	445 510	453 390	463 190	0.310	
		49-2012 Computer, Automated Teller, and Office Machine Repairers	2	130 090	142 390	148 810	135 380	144 370	139 770	139 770	139 770	139 770	139 770	139 770	139 770	139 770	139 770	139 770	139 770	139 770	139 770	139 770	0.740
		49-2021 Radio, Cellular, and Tower Equipment Installers and Repairers	2	4 570	7 110	6 990	6 990	6 990	6 990	6 990	6 990	6 990	6 990	6 990	6 990	6 990	6 990	6 990	6 990	6 990	6 990	6 990	0.910
		49-2022 Telecommunications Equipment Installers and Repairers, Except Line Installers	2	172 700	192 470	210 650	195 680	195 500	198 450	198 350	190 130	189 390	195 170	188 850	190 100	199 240	208 220	209 350	213 620	219 100	228 430	0.360	
		49-2023 Airlines Technicians	2	15 560	15 360	16 340	21 710	21 420	22 450	22 450	15 360	16 300	18 860	17 960	18 320	17 070	16 810	17 310	17 150	17 330	17 300	0.760	
		49-2024 Electrical and Electronic Equipment Mechanics, Installers, and Repairers, Transportation Equipment	2	35 270	36 620	29 240	28 720	26 070	19 880	20 070	22 100	22 150	23 400	20 660	18 740	18 710	19 020	18 490	17 380	17 920	17 050	0.760	
		49-2025 Electrical and Electronics Installers and Repairers, Transportation Equipment	2	14 700	15 950	16 650	17 320	17 370	19 920	20 560	20 480	18 160	15 860	13 900	12 850	14 410	15 530	15 540	14 160	14 210	13 960	0.910	
		49-2026 Electrical and Electronics Repairers, Commercial and Industrial Equipment	2	71 530	81 760	77 780	82 820	83 820	69 320	69 620	78 570	79 510	77 770	72 520	67 550	67 720	66 440	67 410	65 900	69 290	67 390	0.410	
		49-2027 Electrical and Electronics Repairers, Powerhouse, Substation, and Relay	2	20 980	19 300	19 680	20 040	20 700	21 140	21 250	22 090	23 310	23 180	22 970	23 220	23 860	23 920	23 210	22 120	23 070	21 760	0.380	
		49-2028 Electronic Equipment Installers and Repairers, Motor Vehicles	2	14 250	12 480	13 210	15 200	14 590	16 840	17 650	19 150	19 130	19 980	17 090	15 630	13 610	12 590	11 900	11 460	12 470	11 500	0.610	
Installation, Maintenance, and Repair Occupations	Vehicle and Mobile Equipment Mechanics, Installers, and Repairers	49-2029 Electronic Home Entertainment Equipment Installers and Repairers	1	26 090	29 550	29 770	30 600	33 340	33 200	35 360	35 310	38 170	38 680	34 200	30 840	27 580	27 050	26 960	26 890	25 550	0.650		
		49-2030 Security and Fire Alarm Systems Installers	1	38 350	38 810	42 050	41 310	46 850	46 340	49 470	51 740	60 700	62 720	63 690	57 390	56 330	53 960	55 300	60 160	64 710	67 700	0.920	
		49-2031 Aircraft Mechanics and Service Technicians	1	125 970	135 730	125 250	125 850	117 360	114 240	115 120	118 210	118 780	116 130	112 530	117 530	117 830	115 410	118 830	124 000	128 570	128 570	0.710	
		49-2032 Automotive Body and Related Repairers	1	179 960	168 170	168 320	175 590	169 850	158 160	155 500	158 160	155 500	179 740	147 200	133 290	129 730	131 040	135 610	143 940	143 940	143 940	0.910	
		49-2033 Automotive Service Technicians and Mechanics	1	20 520	21 240	21 550	19 710	18 550	16 810	17 760	18 650	18 340	18 330	15 920	14 020	13 690	14 780	15 910	15 670	17 160	18 610	0.550	
		49-2034 Automotive Gas Installers and Repairers	1	587 320	692 570	701 150	687 380	660 780	662 840	664 800	642 360	650 780	649 660	606 960	587 510	589 730	598 830	604 990	633 390	638 080	647 380	0.590	
		49-2035 Bus and Truck Mechanics and Diesel Engine Specialists	1	273 320	258 800	254 420	248 450	248 890	248 890	248 890	248 890	248 890	248 890	248 890	248 890	248 890	248 890	248 890	248 890	248 890	248 890	248 890	0.720
		49-2036 Farm Equipment Mechanics and Service Technicians	1	40 490	37 010	35 420	33 310	29 030	30 800	29 560	29 560	30 800	30 800	30 800	30 800	30 800	30 800	30 800	30 800	30 800	30 800	0.750	
		49-2037 Mobile Heavy Equipment Mechanics, Except Engines	1	113 540	118 300	116 260	113 340	115 090	114 920	117 500	119 060	124 180	125 390	120 560	108 940	109 810	110 200	116 590	119 280	121 900	123 570	0.400	
		49-2038 Rail Car Repairers	1	7 230	10 620	11 860	13 520	15 810	22 520	24 270	23 810	23 190	20 780	20 510	19 380	19 480	19 140	19 250	20 080	21 410	22 090	0.880	
Production Occupations	Food Processing Workers	49-2039 Motorboat Mechanics and Service Technicians	1	18 450	19 040	18 370	18 550	18 890	18 220	18 190	18 550	18 550	19 640	18 650	16 770	18 380	19 650	20 210	20 440	20 260	20 660	0.660	
		49-2040 Motorcycle Mechanics	1	11 390	11 720	13 290	13 030	13 690	16 270	16 400	16 700	16 800	16 650	16 070	14 550	15 010	14 950	15 400	15 850	16 000	16 500	0.790	
		49-2041 Outdoor Power Equipment and Other Small Engine Mechanics	1	26 550	25 760	27 250	25 170	24 740	24 680	25 560	27 560	26 440	26 010	25 010	26 610	26 010	26 610	27 350	28 250	29 220	31 560	33 020	0.930
		49-2042 Bicycle Repairers	1	8 080	7 940	7 790	7 400	6 670	7 480	7 980	8 360	9 130	9 690	9 390	9 590	9 390	9 590	10 490	10 450	10 520	12 560	0.940	
		49-2043 Recreational Vehicle Service Technicians	1	13 100	12 200	11 830	12 400	12 810	11 830	13 540	13 560	14 010	13 600	9 940	10 110	10 970	11 200	10 990	11 370	13 520	13 520	0.590	
		49-2044 Tire Repairers and Changers	1	99 880	88 530	86 200	81 560	82 840	85 930	100 860	103 120	100 510	98 520	92 440	94 120	94 740	96 880	99 370	100 510	107 500	109 350	0.700	
		49-2045 Mechanical Door Repairers	1	9 620	10 460	10 510	10 730	10 860	12 920	13 400	15 130	18 380	17 930	17 930	13 400	14 620	15 750	17 050	17 220	17 930	19 840	0.910	
		49-2046 Control and Valve Installers and Repairers, Except Mechanical Door	1	31 040	34 910	37 740	36 720	37 840	37 840	38 640	42 270	43 160	43 900	42 180	43 430	42 450	40 310	40 940	41 290	42 510	45 740	0.630	
		49-2047 Heating, Air Conditioning, and Refrigeration Mechanics and	1	187 850	197 950	201 850	206 870	212 200	232 050	241 380	259 970	262 570	261 610	244 100	224 320	221 160	240 480	251 700	261 390	274 680	294 780	0.650	
		49-2048 Air-Conditioning and Refrigeration Mechanics and	1	175 070	185 070	189 070	194 070	200 070	210 070	215 070	220 070	225 070	225 070	225 070	225 070	225 070	225 070	225 070	225 070	225 070	225 070	225 070	0.720
Supervisors of Production Workers	Food Processing Workers	49-2049 Maintenance Workers, Machinery	1	107 180	107 500	98 280	90 500	89 360	83 890	83 890	81 860	78 760	73 650	66 880	69 880	69 880	88 450	89 510	93 730	92 520	89 630	0.860	
		49-2050 Millwrights	1	80 390	75 940	67 900	55 280	53 320	49 860	46 510	41 640	36 670	37 730	38 050	38 680	39 290	38 680	39 290	40 030	39 670	40 030	0.590	
		49-2051 Electrical Power-Line Installers and Repairers	1	99 090	98 200	99 140	96 040	95 190	100 160	106 060	110 520	109 990	111 580	108 990	105 540	105 570	112 450	111 360	114 420	115 380	117 670	0.920	
		49-2052 Telecommunications Line Installers and Repairers	1	158 990	168 480	168 260	156 160	148 060	148 740	142 560	156 440	160 250	168 050	162 400	156 390	148 930	133 040	120 050	114 420	111 360	117 670	0.920	
		49-2053 Camera and Photographic Equipment Repairers	1	5 330	5 080	5 580	5 220	4 640	3 440	3 160	3 470	3 870	3 820	3 290	2 810	2 650	2 590	3 180	3 150	3 360	3 360	0.490	
		49-2054 Medical Equipment Repairers	1	19 640	22 020	22 070	21 770	21 500	24 970	27 940	32 100	34 880	34 650	34 550	32 980	34 710	37 740	40 090	41 400	41 860	43 770	0.270	
		49-2055 Precision Instrument Repairers and Tuners	1	3 870	4 000	3 680	3 770	3 390	3 390	3 390	3 390	3 390	3 390	3 390	3 390	3 390	3 390	3 390	3 390	3 390	3 390	3 390	0.930
		49-2056 Precision Instrument and Equipment Repairers, All Other	1	1 201 690	1 212 260	1 232 260	1 232 620	1 230 880	1 291 090	1 307 620	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	0.640
		49-2057 Maintenance and Repair Workers, General	1	1 201 690	1 212 260	1 232 260	1 232 620	1 230 880	1 291 090	1 307 620	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	1 310 940	0.640
		49-2058 Wind Turbine Service Technicians	1	35 500	35 480	33 100	33 520	33 370	38 840	39 570	39 940	42 150	41 280	38 770	36 240	36 940	36 940	36 940	36 940	36 940	36 940	36 940	0.640
Production Occupations	Food Processing Workers	49-2059 Commercial Divers	1	2 400	2 920	3 050	2 990	2 690	1 840	2 310	2 680	1 980	2 270	3 030	3 720	3 760	3 680	3 620	3 450	3 370	0.340		
		49-2060 Fabric Menders, Except Garment	1	2 980	2 990	2 090	2 090	1 720	2 070	2 400	1 280	990	960	840	690	760	770	800	710	620	550	0.960	
		49-2061 Locksmiths and Safe Repairers	1	11 360	13 150	13 450	13 970	13 940	12 440	12 560	12 560	12 560	12 560	12 560	12 560	12 560	12 560	12 560	12 560	12 560	12 560	0.960	
		49-2062 Manufactured Building and Mobile Home Installers	1	13 8																			

Major Group	Minor Group	Occupational title	DOC code	Stratum	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Retention rate	
Production Occupations	Metal Workers and Plastic Workers	Computer-Controlled Machine Tool Operators, Metal and Plastic	51-4011	1	168 170	162 360	140 540	128 400	126 150	130 600	136 490	139 380	178 800	169 900	154 480	123 600	128 870	138 870	139 930	148 040	146 600	146 190	0,650	
		Computer Numerically Controlled Machine Tool Programmers, Metal and Plastic	51-4012	1	24 180	22 460	20 800	18 910	17 820	16 840	17 860	17 800	17 800	17 800	16 990	15 480	16 380	20 370	23 990	24 340	24 960	25 660	25 180	0,350
		Extending and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	51-4021	1	108 570	114 210	102 320	96 620	93 600	90 060	87 290	93 810	95 330	92 160	81 610	76 260	75 170	74 490	73 140	72 520	72 390	71 960	0,910	
		Forging Machine Setters, Operators, and Tenders, Metal and Plastic	51-4022	1	609 700	53 950	49 760	44 920	41 230	35 850	31 650	30 130	28 800	24 580	22 110	21 790	22 270	23 570	21 940	19 650	19 160	19 650	0,930	
		Rolling Machine Setters, Operators, and Tenders, Metal and Plastic	51-4023	1	47 590	49 710	45 090	42 270	42 090	39 150	37 500	34 710	37 500	34 710	32 880	31 900	35 180	36 040	32 550	33 370	31 740	29 060	0,830	
		Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	51-4031	1	353 300	351 050	296 070	277 410	260 560	257 500	265 480	269 640	254 160	242 970	209 730	182 170	181 160	182 570	187 640	190 250	194 670	192 800	0,780	
		Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic	51-4032	1	75 140	71 490	58 060	51 730	48 730	42 830	43 180	42 480	42 480	42 480	33 550	28 140	21 560	20 660	19 880	17 470	14 840	12 290	0,940	
		Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	51-4033	1	127 920	124 080	107 300	99 580	97 660	100 640	101 530	100 010	96 710	91 990	87 140	70 120	70 450	69 510	70 910	70 130	73 570	74 600	0,950	
		Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic	51-4034	1	83 940	84 020	75 650	72 720	70 300	71 480	71 410	65 840	61 140	56 500	51 260	40 970	39 930	37 920	41 730	43 570	40 140	33 850	0,840	
		Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic	51-4035	1	35 830	35 610	32 680	30 340	28 580	29 820	29 140	29 040	26 610	26 220	23 770	20 520	21 700	22 840	22 110	19 750	17 560	17 560	0,980	
Production Occupations	Metal Workers and Plastic Workers	Mechanics	51-4041	1	419 800	420 320	390 090	368 740	368 740	364 130	368 380	385 690	410 970	380 720	352 650	368 510	388 370	391 130	392 700	399 040	391 120	391 120	0,650	
		Metal-Refining Furnace Operators and Tenders	51-4042	1	19 950	15 660	14 580	12 900	12 770	14 120	14 340	14 880	15 070	15 320	13 900	11 190	10 620	10 320	9 690	9 690	9 690	9 690	0,870	
		Pourers and Casters, Metal	51-4052	1	15 600	15 660	14 580	12 900	12 770	14 120	14 340	14 880	15 070	15 320	13 900	11 190	10 620	10 320	9 690	9 690	9 690	9 690	0,870	
		Mold Makers, Metal and Plastic	51-4061	1	12 520	10 540	8 990	8 360	7 990	8 360	7 990	8 360	8 360	7 710	6 000	5 700	6 200	6 140	6 360	6 250	6 250	6 250	0,930	
		Patternmakers, Metal and Plastic	51-4062	1	8 840	8 290	6 840	6 300	6 090	7 010	6 800	7 070	7 250	6 220	5 220	4 380	4 290	4 130	4 100	3 770	4 020	3 420	0,900	
		Multiple Tool and Core Machine Setters, Operators, and Tenders, Metal and Plastic	51-4071	1	34 840	34 130	28 270	21 360	20 710	23 960	15 890	14 460	15 600	13 540	13 540	10 040	11 860	12 910	13 100	11 870	12 860	12 810	0,670	
		Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	51-4072	1	179 640	158 280	140 000	147 060	144 140	157 310	157 080	155 070	147 850	145 760	126 840	114 760	118 300	124 440	124 810	128 540	135 550	145 560	0,950	
		Plastic	51-4081	1	103 620	109 950	101 500	96 560	100 320	99 930	98 120	96 480	91 090	87 800	76 130	69 330	77 290	85 110	93 100	98 160	105 570	117 300	0,910	
		Tool and Die Makers	51-4111	1	132 350	131 080	112 960	105 210	104 210	99 820	96 860	92 640	85 610	76 630	70 320	76 430	78 700	75 950	74 510	72 210	70 510	72 210	0,840	
		Welders, Cutters, Solderers, and Braisers	51-4121	1	410 040	413 720	382 400	361 970	354 300	351 710	358 050	376 530	385 740	392 520	357 740	314 260	316 290	329 710	352 250	369 610	386 240	382 730	0,940	
Production Occupations	Textile, Apparel, and Furnishings Workers	Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders	51-4132	1	68 680	69 670	60 810	56 280	53 750	44 670	45 420	48 770	45 420	48 770	50 620	51 840	38 530	40 930	49 430	50 860	55 360	53 080	46 920	0,610
		Textile Milling Machine Setters, Operators, and Tenders, Metal and Plastic	51-4131	1	36 370	35 840	32 490	28 410	27 290	26 380	26 510	27 650	25 500	23 630	20 420	18 300	20 770	21 760	21 500	20 980	20 570	19 760	0,810	
		Laying and Coating Machine Setters, Operators, and Tenders	51-4132	1	17 990	16 770	14 100	12 490	12 540	11 110	10 970	9 960	9 190	8 340	9 020	8 770	9 600	12 380	13 420	13 070	10 660	9 070	0,840	
		Plating and Coating Machine Setters, Operators, and Tenders	51-4133	1	58 350	45 540	41 580	40 800	39 630	39 930	40 550	41 900	41 720	40 300	34 310	30 580	31 150	34 420	36 120	35 900	35 640	35 570	0,920	
		Tool Grinders, Filers, and Sharpeners	51-4134	1	28 150	28 360	25 410	22 700	22 320	19 930	18 180	17 620	17 620	17 620	16 410	13 740	11 930	11 860	11 950	11 540	10 860	10 220	0,890	
		Metal Workers and Plastic Workers, All Other	51-4199	1	109 350	104 920	96 580	89 370	82 970	73 120	72 050	70 890	65 540	61 170	53 710	48 070	44 340	41 420	38 020	22 270	22 100	22 910	N/A	
		Printers, Bookbinding and Finishing Workers	51-5111	1	109 350	104 920	96 580	89 370	82 970	73 120	72 050	70 890	65 540	61 170	53 710	48 070	44 340	41 420	38 020	22 270	22 100	22 910	N/A	
		Textile Bleaching and Finishing Workers	51-5113	1	116 220	111 100	100 740	95 910	93 890	88 390	83 960	76 960	70 820	71 960	66 220	66 710	60 900	54 230	53 980	52 000	51 430	52 380	52 710	0,950
		Laundry and Dry-Cleaning Workers	51-6011	1	217 350	216 690	214 520	217 800	215 800	215 800	218 360	217 800	218 360	217 800	211 400	204 820	201 180	198 720	197 690	199 330	201 620	207 710	207 710	0,710
		Pressers, Textile, Garment, and Related Materials	51-6021	1	93 320	100 190	92 730	87 130	87 500	79 500	78 620	75 150	69 260	67 500	60 440	56 600	52 850	51 520	50 150	48 340	45 150	43 450	0,810	
Production Occupations	Textile, Apparel, and Furnishings Workers	Sewing Machine Operators	51-6031	1	403 770	362 010	308 380	277 800	265 200	244 300	233 130	219 080	200 340	190 440	166 080	147 000	142 380	143 370	142 070	141 520	139 500	139 500	0,890	
		Shoe and Leather Workers and Repairers	51-6041	1	11 560	12 210	9 970	9 860	8 090	8 000	7 680	7 450	7 880	8 170	7 190	6 010	5 360	5 790	6 460	7 710	8 180	7 760	0,520	
		Shoe Machine Operators and Repairers	51-6042	1	11 450	8 070	6 440	6 320	6 020	4 550	3 850	4 080	4 130	3 990	3 380	3 510	3 420	4 300	3 550	3 230	3 500	3 500	0,970	
		Sewers, Hand	51-6051	1	23 910	24 240	22 550	19 180	18 790	11 870	11 090	9 750	8 350	7 050	6 020	5 770	5 460	5 500	5 700	5 960	6 920	6 540	0,990	
		Textile, Apparel, and Custom Sewers	51-6052	1	32 310	32 840	31 580	29 560	31 580	27 490	30 000	31 550	31 700	26 450	26 250	25 530	24 870	21 400	20 200	19 880	21 660	21 660	0,940	
		Textile Bleaching and Dyeing Machine Operators and Tenders	51-6061	1	44 450	38 350	31 650	25 950	24 260	22 720	21 660	20 070	18 650	16 800	12 880	12 700	11 870	11 350	11 680	11 510	11 680	10 860	0,970	
		Textile Bleaching and Dyeing Machine Setters, Operators, and Tenders	51-6062	1	39 870	37 320	37 250	33 970	33 970	31 420	29 160	20 710	21 680	20 710	17 890	15 960	15 960	15 960	14 370	14 680	15 040	15 040	0,950	
		Textile Knitting and Weaving Machine Setters, Operators, and Tenders	51-6063	1	79 440	69 110	57 830	49 410	47 720	44 880	42 760	38 900	33 400	33 400	30 250	24 530	21 190	21 160	21 110	22 200	22 760	21 550	0,730	
		Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	51-6064	1	83 360	83 320	68 530	62 600	60 550	50 380	47 670	44 110	40 650	36 540	30 530	27 840	27 400	27 400	26 020	25 740	27 760	30 340	0,960	
		Production Occupations	Textile, Apparel, and Furnishings Workers	Extending and Forming Machine Setters, Operators, and Tenders	51-6091	1	35 810	36 350	30 370	26 620	26 700	24 200	23 040	17 860	15 240	14 440	13 680	14 670	16 050	17 620	18 890	19 770	19 810	19 340
Synthetic and Glass Fibers	51-6092			1	16 920	14 890	12 580	10 310	10 070	10 070	9 650	8 840	8 270	7 500	6 640	6 060	5 400	5 500	6 000	5 400	5 140	5 310	0,005	
Fabric and Apparel Patternmakers	51-6093			1	45 180	42 410	37 960	34 960	31 660	40 980	41 040	40 480	40 480	39 900	38 810	30 210	28 260	27 840	28 790	29 770	30 180	32 520	0,930	
Apparel Patternmakers	51-6093			1	45 180	42 410	37 960	34 960	31 660	40 980	41 040	4												

Major Group	Minor Group	Occupational title	QCC code	Stratum	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Phantom		
Production Occupations	Other Production Occupations	51-9011 Chemical and Allied Equipment Operators and Tenders	51-9011	1	33 470	36 110	35 380	35 550	37 360	40 730	41 250	43 660	44 310	41 260	37 490	38 050	39 660	41 430	42 510	43 310	47 760	73 840	0.760		
		51-9012 Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders	51-9012	1	33 470	36 110	35 380	35 550	37 360	40 730	41 250	43 660	44 310	41 260	37 490	38 050	39 660	41 430	42 510	43 310	47 760	73 840	0.760		
		51-9021 Grinding and Polishing Workers, Hand	51-9021	1	49 690	48 010	46 470	44 370	43 320	41 320	41 480	41 510	42 360	41 270	38 360	33 140	31 540	29 320	30 580	29 980	31 140	29 830	0.970		
		51-9022 Grinding and Polishing Workers, Machine	51-9022	1	49 530	48 610	44 050	43 370	43 910	42 980	44 890	43 980	42 750	40 280	32 550	27 420	27 630	30 170	31 200	29 320	28 110	26 670	0.970		
		51-9023 Mixing and Blending Machine Setters, Operators, and Tenders	51-9023	1	114 540	111 480	111 610	103 940	106 610	122 390	129 440	140 710	139 370	140 120	129 250	123 840	117 170	117 390	122 670	129 270	130 480	0.830			
		51-9024 Cutters and Trimmers, Hand	51-9024	1	33 590	34 340	30 910	28 360	28 360	30 110	28 360	28 360	28 360	28 360	28 360	28 360	28 360	28 360	28 360	28 360	28 360	28 360	0.640		
		51-9025 Cutting and Slicing Machine Setters, Operators, and Tenders	51-9025	1	85 060	82 450	76 670	75 130	70 960	76 810	78 030	77 860	80 260	76 500	70 700	61 300	59 430	55 560	59 460	62 570	63 330	61 330	0.860		
		51-9026 Extending, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	51-9026	1	74 100	76 370	76 640	71 500	73 990	76 900	80 420	81 000	88 600	85 130	72 770	61 300	66 330	68 980	69 740	71 430	71 260	0.930			
		51-9028 Operators, and Tenders	51-9028	1	29 640	31 800	30 020	29 400	30 320	29 700	28 140	27 000	28 140	29 500	27 900	19 900	18 470	18 940	19 940	20 590	19 550	20 070	0.770		
		51-9029 Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	51-9029	1	29 640	31 800	30 020	29 400	30 320	29 700	28 140	27 000	28 140	29 500	27 900	19 900	18 470	18 940	19 940	20 590	19 550	20 070	0.770		
		51-9030 Inspectors, Sorters, Samplers, and Weighers	51-9030	1	28 500	31 700	30 500	29 500	30 500	29 500	28 500	27 500	28 500	29 500	27 500	20 500	21 500	21 500	22 500	21 500	20 500	21 500	0.850		
		51-9031 Dental Laboratory Technicians	51-9031	1	42 940	40 580	39 750	40 480	41 860	44 310	45 600	45 840	44 530	40 480	38 360	37 600	36 700	36 700	35 320	37 520	37 110	37 070	0.970		
		51-9032 Medical Appliance Technicians	51-9032	1	13 610	11 490	12 410	11 970	11 870	10 810	10 610	10 610	11 900	12 900	13 360	13 360	12 390	13 290	14 280	13 290	14 460	14 570	0.450		
		51-9033 On-machine Laboratory Technicians	51-9033	1	34 590	36 980	34 490	32 020	30 320	26 030	26 740	29 130	30 900	32 900	30 360	27 880	27 680	27 680	29 280	27 610	27 990	28 570	0.970		
		51-9111 Packaging and Filling Machine Operators and Tenders	51-9111	1	379 760	370 080	377 750	390 380	400 680	412 360	398 270	384 160	368 320	357 480	338 320	342 280	354 810	367 720	372 210	381 760	378 540	386 520	0.980		
		51-9112 Packaging, Filling, and Sealing Machine Setters, Operators, and Tenders	51-9112	1	101 610	103 650	94 050	91 960	93 110	99 430	100 830	102 120	103 600	103 310	89 340	77 870	77 090	79 970	87 070	90 590	88 760	86 750	0.910		
		51-9121 Painters, Transportation Equipment	51-9121	1	45 520	43 270	40 090	45 670	46 600	50 720	52 650	52 370	51 260	50 310	28 460	23 970	24 730	46 390	46 770	49 950	51 760	54 860	0.690		
		51-9122 Painting, Coating, and Decorating Workers	51-9122	1	34 780	33 940	31 770	30 830	29 590	29 400	27 830	29 950	31 740	31 200	28 460	23 970	19 370	16 310	15 900	16 280	16 020	15 450	0.920		
		51-9141 Semiconductor Processors	51-9141	1	76 140	67 000	51 060	43 830	50 160	43 420	44 720	41 520	36 690	32 250	25 750	20 930	22 070	21 380	27 250	23 580	24 230	24 430	0.880		
		51-9151 Photographic Process Workers and Processing Machine Operators	51-9151	1	76 140	67 000	51 060	43 830	50 160	43 420	44 720	41 520	36 690	32 250	25 750	20 930	22 070	21 380	27 250	23 580	24 230	24 430	0.880		
		51-9152 Machine Tooling Machine Operators and Tenders	51-9152	1	32 440	34 220	29 190	26 880	25 690	25 030	25 650	23 340	21 670	19 460	16 190	15 660	16 940	16 800	18 260	18 120	17 400	16 940	0.950		
		51-9153 Machine Tooling Machine Operators and Tenders	51-9153	1	18 850	18 440	18 070	18 010	17 590	16 080	15 250	15 500	16 850	18 870	19 550	18 320	16 430	16 050	16 460	17 360	17 420	17 860	0.810		
		Transportation and Material Moving Occupations	Supervisors of Transportation and Material Moving Workers	53-1011 First-Line Supervisors of Supervisors	53-1011	2	138 210	146 790	147 490	147 180	154 750	173 640	176 030	178 820	184 000	186 230	174 440	166 360	166 560	168 210	167 190	171 720	176 930	182 620	0.420
				53-1021 First-Line Supervisors of Transportation and Material Moving	53-1021	2	125 060	134 720	137 430	137 840	147 180	164 750	166 030	168 820	173 640	178 820	184 000	186 230	174 440	166 360	166 560	168 210	167 190	171 720	176 930
53-2011 Air Traffic Controllers	53-2011			2	88 540	94 820	88 540	78 810	79 770	78 430	72 520	70 570	72 520	71 840	70 570	68 430	68 580	66 770	69 100	69 700	70 570	71 840	0.520		
53-2021 Air Traffic Controllers	53-2021			2	88 540	94 820	88 540	78 810	79 770	78 430	72 520	70 570	72 520	71 840	70 570	68 430	68 580	66 770	69 100	69 700	70 570	71 840	0.520		
53-2022 Air Traffic Controllers	53-2022			2	22 020	24 340	23 990	23 410	23 040	21 680	21 590	23 240	24 180	24 240	24 240	23 970	23 580	23 660	23 060	22 860	23 240	23 240	0.110		
53-2023 Flight Attendants	53-2023			2	4 510	4 580	5 360	5 560	4 540	4 510	4 760	5 210	8 050	9 710	9 710	8 050	6 900	6 990	7 250	7 050	7 320	8 760	0.710		
53-3011 Motor Vehicle Operators, Except Emergency Medical Technicians	53-3011			1	123 110	126 380	115 750	104 380	107 120	101 730	95 390	96 760	97 010	99 480	95 390	88 020	87 150	84 960	95 500	98 510	108 510	113 390	0.520		
53-3012 Bus Drivers, Transit and Intercity	53-3012			1	13 520	15 700	17 620	16 650	18 320	18 320	21 100	21 500	18 870	18 870	19 550	18 320	18 080	18 540	18 380	19 350	19 350	17 300	0.250		
53-3021 Bus Drivers, School or Special Client	53-3021			1	160 210	175 470	170 320	176 600	180 170	183 450	191 120	189 050	184 160	177 510	179 700	176 150	162 840	157 830	158 050	168 620	169 680	169 680	0.970		
53-3022 Bus Drivers, School or Special Client	53-3022			1	383 160	457 050	469 120	468 790	467 840	475 700	465 880	456 570	461 590	460 100	469 400	467 610	487 950	496 110	499 480	495 410	499 480	515 020	0.880		
53-3031 Heavy and Tractor-Trailer Truck Drivers	53-3031			1	385 210	371 660	368 730	368 730	368 730	400 560	400 560	383 360	372 720	363 590	371 660	387 950	394 110	409 480	409 480	417 660	417 660	417 660	0.980		
53-3032 Heavy and Tractor-Trailer Truck Drivers	53-3032			1	1 538 400	1 577 070	1 548 480	1 548 480	1 548 480	1 548 480	1 548 480	1 548 480	1 548 480	1 548 480	1 548 480	1 548 480	1 548 480	1 548 480	1 548 480	1 548 480	1 548 480	1 548 480	0.790		
53-3041 Taxi Drivers and Chauffeurs	53-3041			1	1 119 630	1 130 220	1 125 860	1 125 860	1 125 860	1 125 860	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	0.890		
53-3042 Motor Vehicle Operators, All Other	53-3042			1	1 119 630	1 130 220	1 125 860	1 125 860	1 125 860	1 125 860	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	1 141 470	0.890		
53-3099 Motor Vehicle Operators, All Other	53-3099			1	109 340	116 930	109 930	108 460	108 460	108 460	124 250	124 250	124 250	124 250	124 250	124 250	124 250	124 250	124 250	124 250	124 250	124 250	0.970		
53-4011 Locomotive Engineers	53-4011			1	29 940	29 390	30 730	28 250	30 450	33 990	37 390	36 670	41 760	42 760	42 760	43 560	40 730	38 790	36 800	38 470	37 490	39 900	0.960		
53-4012 Locomotive Engineers	53-4012			1	890	1 040	730	710	680	590	540	560	580	590	590	590	590	590	590	590	590	590	0.960		
53-4013 Railroad Conductors and Yardmasters	53-4013			1	5 070	4 020	4 840	4 840	4 840	4 840	4 840	4 840	4 840	4 840	4 840	4 840	4 840	4 840	4 840	4 840	4 840	4 840	0.930		
53-4031 Railroad Conductors and Yardmasters	53-4031			1	36 680	40 380	40 910	38 070	34 720	34 690	38 330	37 110	37 540	39 360	41 540	42 700	42 760	42 760	42 760	42 760	42 760	42 760	0.720		
53-4041 Subway and Streetcar Operators	53-4041			1	3 100	3 100	3 100	3 100	3 100	3 100	3 100	3 100	3 100	3 100	3 100	3 100									

APPENDIX C: REGRESSION MODEL 1

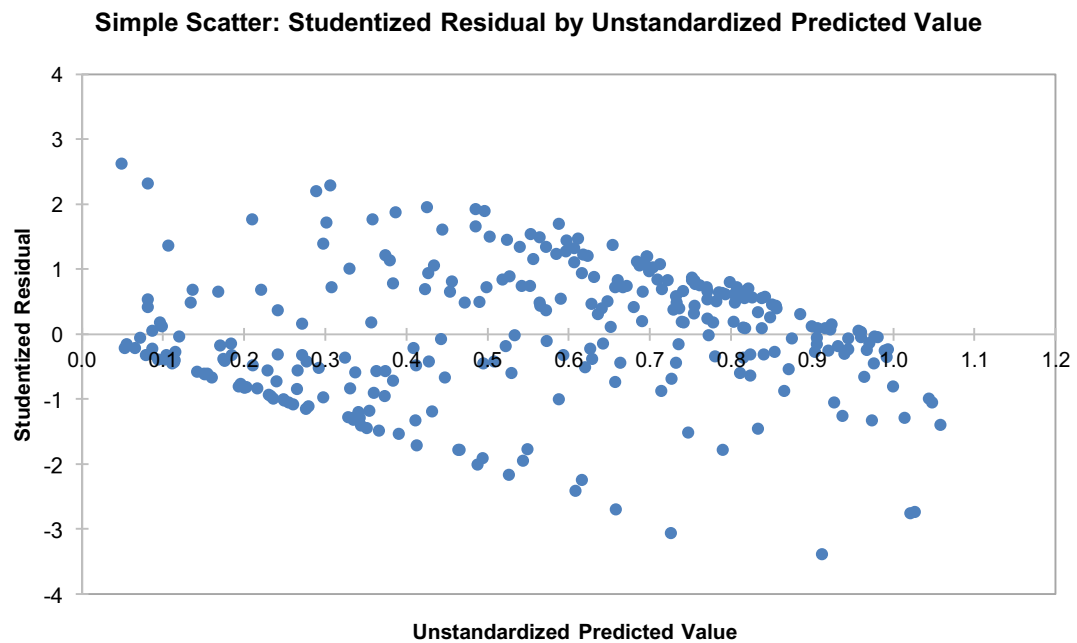
Test for Independence of Observations

Model Summary ^b					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.756 ^a	.571	.568	.2380733	1.449

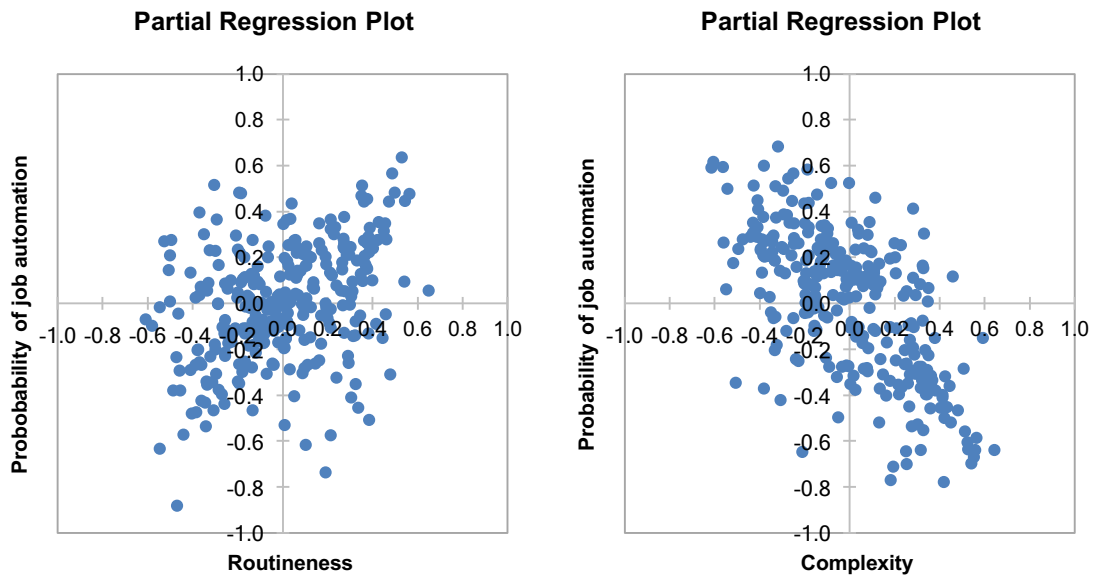
a. Predictors: (Constant), Complexity, Routineness

b. Dependent Variable: Prob_automation

Test for Linearity between the Dependent and Independent Variables Collectively and Test for Homoscedasticity



Test for Linearity between the Dependent Variable and Each Independent Variable



Test for Multicollinearity

Correlations

		Prob_automation	Routineness	Complexity
Pearson Correlation	Prob_automation	1.000	.507	-.712
	Routineness	.507	1.000	-.383
	Complexity	-.712	-.383	1.000
Sig. (1-tailed)	Prob_automation	.	.000	.000
	Routineness	.000	.	.000
	Complexity	.000	.000	.
N	Prob_automation	291	291	291
	Routineness	291	291	291
	Complexity	291	291	291

Coefficients^a

Model		Correlations			Collinearity Statistics	
		Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)					
	Routineness	.507	.362	.254	.854	1.172
	Complexity	-.712	-.650	-.560	.854	1.172

a. Dependent Variable: Prob_automation

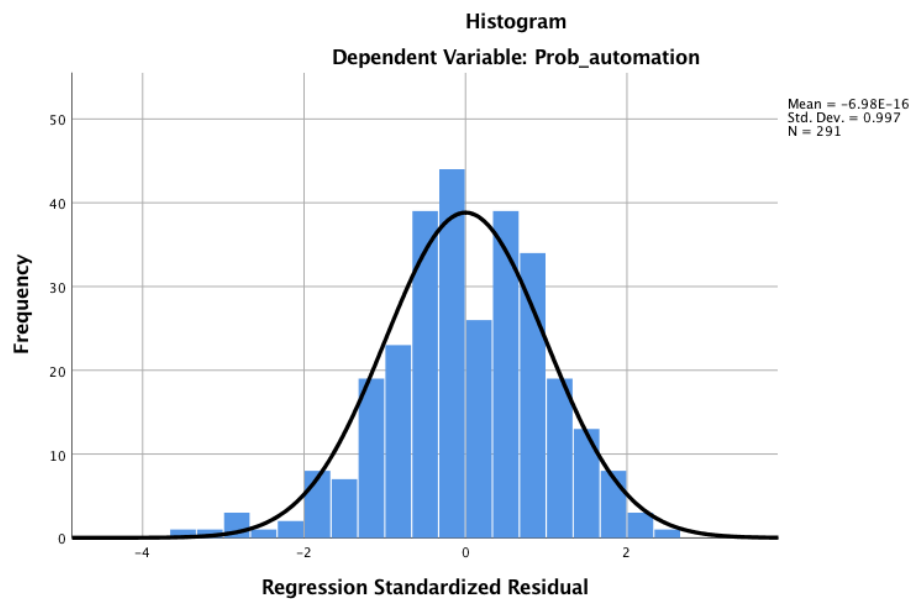
Test for Unusual Points

Casewise Diagnostics^a

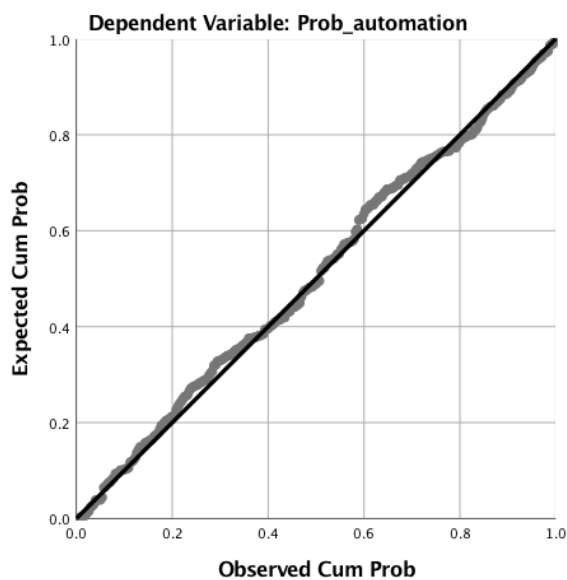
Case Number	Std. Residual	Prob_automation	Predicted Value	Residual
171	-3.368	.1100	.911788	-.8017883
172	-3.023	.0060	.725611	-.7196110

a. Dependent Variable: Prob_automation

Test for Normality



Normal P-P Plot of Regression Standardized Residual



Regression Results

Variables Entered/Removed ^a			
Model	Variables Entered	Variables Removed	Method
1	Complexity, Routineness ^b	.	Enter

a. Dependent Variable: Prob_automation

b. All requested variables entered.

Model Summary ^b					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.756 ^a	.571	.568	.2380733	1.449

a. Predictors: (Constant), Complexity, Routineness

b. Dependent Variable: Prob_automation

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	21.712	2	10.856	191.537	.000 ^b
	Residual	16.324	288	.057		
	Total	38.036	290			

a. Dependent Variable: Prob_automation

b. Predictors: (Constant), Complexity, Routineness

Coefficients ^a								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.752	.045		16.767	.000	.664	.840
	Routineness	.341	.052	.275	6.583	.000	.239	.442
	Complexity	-.736	.051	-.606	-14.509	.000	-.836	-.637

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.049079	1.057969	.556622	.2736235	291
Std. Predicted Value	-1.855	1.832	.000	1.000	291
Standard Error of Predicted Value	.014	.042	.024	.005	291
Adjusted Predicted Value	.038815	1.063250	.556759	.2737399	291
Residual	-.8017883	.6209212	.0000000	.2372509	291
Std. Residual	-3.368	2.608	.000	.997	291
Stud. Residual	-3.384	2.630	.000	1.002	291
Deleted Residual	-.8095058	.6311848	-.0001372	.2398635	291
Stud. Deleted Residual	-3.447	2.657	-.001	1.006	291
Mahal. Distance	.005	8.125	1.993	1.327	291
Cook's Distance	.000	.062	.004	.007	291
Centered Leverage Value	.000	.028	.007	.005	291

a. Dependent Variable: Prob_automation

APPENDIX D: NON-PARAMETRIC TEST 1

Kruskal-Wallis H Test Results

Probability of job automation

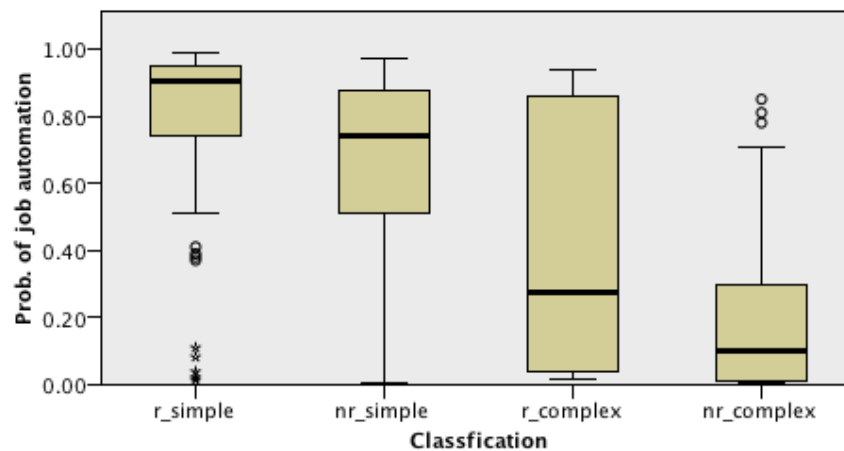
Classification	Median	N
r_simple	0.906	90
nr_simple	0.740	108
r_complex	0.274	10
nr_complex	0.098	83
Total	0.675	291

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of P(automation) is the same across categories of Classification.	Independent-Samples Kruskal-Wallis H Test	.000	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Independent-Samples Kruskal-Wallis Test

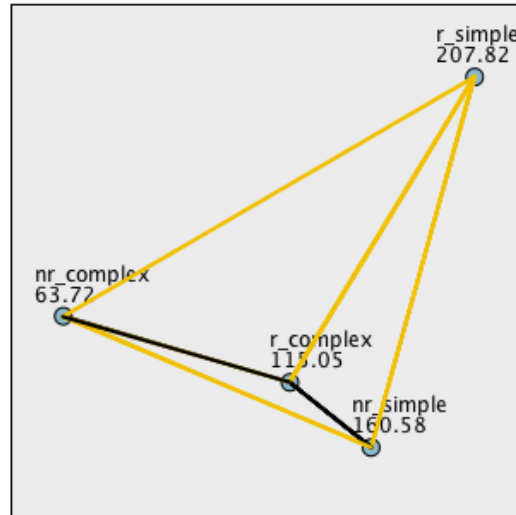


Total N	291
Test Statistic	132.559
Degrees of Freedom	3
Asymptotic Sig. (2-sided test)	.000

1. The test statistic is adjusted for ties.

Pairwise Comparisons

Pairwise Comparisons of Classification



Each node shows the sample average rank of Classification.

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
nr_complex-r_complex	51.327	28.164	1.822	.068	.410
nr_complex-nr_simple	96.856	12.281	7.886	.000	.000
nr_complex-r_simple	144.099	12.804	11.254	.000	.000
r_complex-nr_simple	45.529	27.811	1.637	.102	.610
r_complex-r_simple	92.772	28.046	3.308	.001	.006
nr_simple-r_simple	47.244	12.008	3.934	.000	.001

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same. Asymptotic significances (2-sided tests) are displayed. The significance level is .05. Significance values have been adjusted by the Bonferroni correction for multiple tests.

APPENDIX E: NON-PARAMETRIC TEST 2

Kruskal-Wallis H Test Results

Probability of job automation

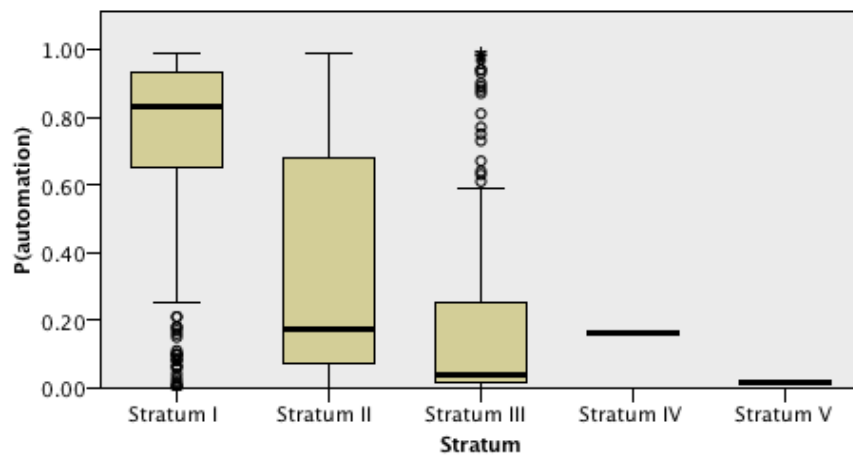
Stratum	Median	N
Stratum I	0.830	353
Stratum II	0.175	226
Stratum III	0.038	173
Stratum IV	0.160	1
Stratum V	0.015	1
Total	0.585	754

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
2	The distribution of P(automation) is the same across categories of Stratum.	Independent-Samples Kruskal-Wallis H Test	.000	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Independent-Samples Kruskal-Wallis Test

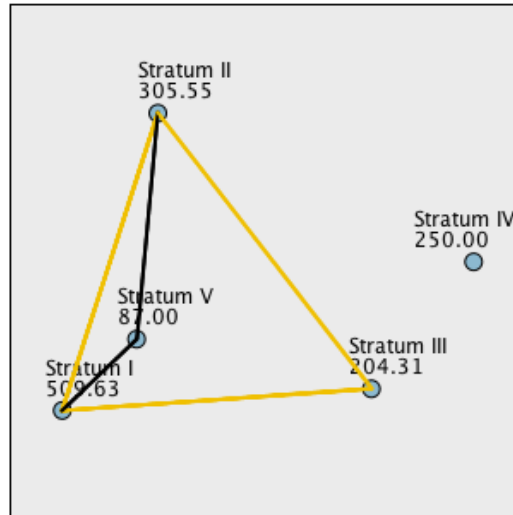


Total N	754
Test Statistic	266.173
Degrees of Freedom	4
Asymptotic Sig. (2-sided test)	.000

1. The test statistic is adjusted for ties.

Pairwise Comparisons

Pairwise Comparisons of Stratum



Each node shows the sample average rank of Stratum.

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
Stratum V-Stratum III	117.306	218.398	.537	.591	1.000
Stratum V-Stratum IV	163.000	307.972	.529	.597	1.000
Stratum V-Stratum II	218.546	218.251	1.001	.317	1.000
Stratum V-Stratum I	422.630	218.077	1.938	.053	.526
Stratum III-Stratum IV	-45.694	218.398	-.209	.834	1.000
Stratum III-Stratum II	101.240	21.999	4.602	.000	.000
Stratum III-Stratum I	305.324	20.211	15.107	.000	.000
Stratum IV-Stratum II	55.546	218.251	.255	.799	1.000
Stratum IV-Stratum I	259.630	218.077	1.191	.234	1.000
Stratum II-Stratum I	204.084	18.552	11.001	.000	.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .05.
Significance values have been adjusted by the Bonferroni correction for multiple tests.

APPENDIX F: REGRESSION MODEL 2

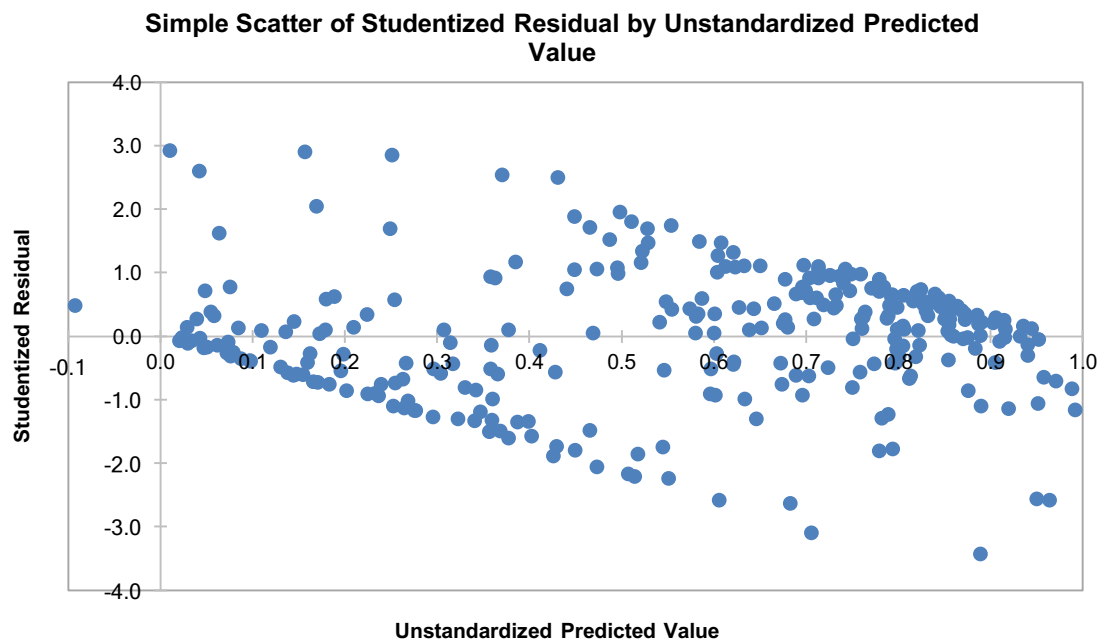
Test for Independence of Observations

Model Summary ^b					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
2	.780 ^a	0.608	0.604	0.2278682	1.570

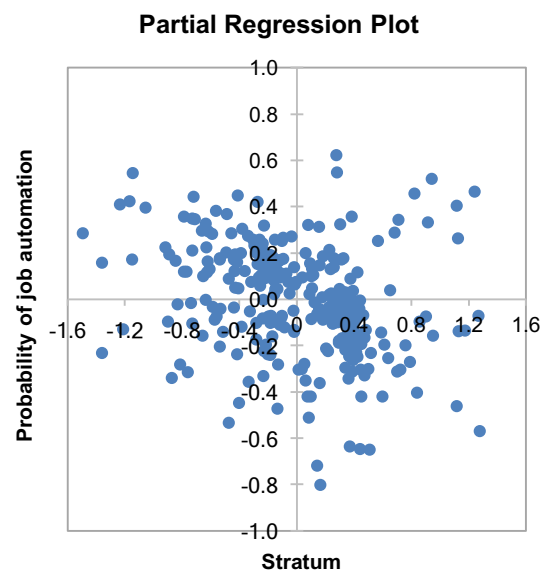
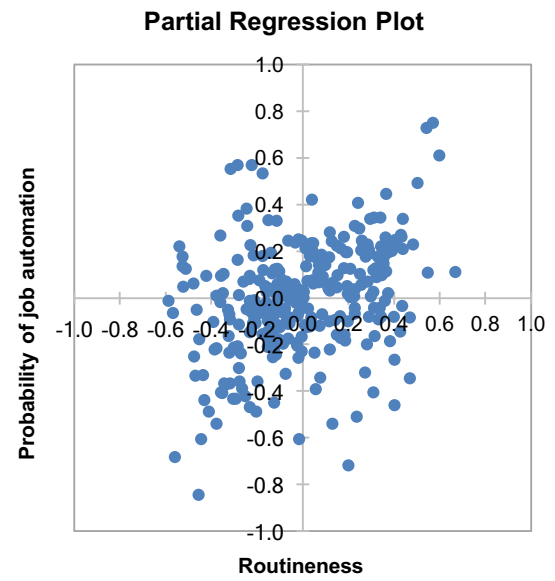
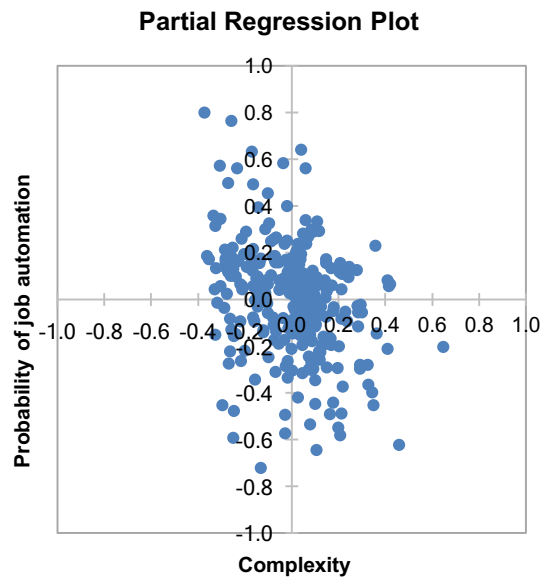
a. Predictors: (Constant), Stratum, Complexity, Routineness

b. Dependent Variable: Prob_automation

Test for Linearity between the Dependent and Independent Variables Collectively and Test for Homoscedasticity



Test for Linearity between the Dependent Variable and each Independent Variable



Test for Multicollinearity

Correlations					
		Prob_automation	Routineness	Complexity	Stratum
Pearson Correlation	Prob_automation	1.000	0.507	-0.712	-0.699
	Routineness	0.507	1.000	-0.383	-0.360
	Complexity	-0.712	-0.383	1.000	0.799
	Stratum	-0.699	-0.360	0.799	1.000
Sig. (1-tailed)	Prob_automation		0.000	0.000	0.000
	Routineness	0.000		0.000	0.000
	Complexity	0.000	0.000		0.000
	Stratum	0.000	0.000	0.000	
N	Prob_automation	291	291	291	291
	Routineness	291	291	291	291
	Complexity	291	291	291	291
	Stratum	291	291	291	291

Coefficients ^a					
Model	Correlations			Collinearity Statistics	
	Zero-order	Partial	Part	Tolerance	VIF
(Constant)					
2 Routineness	0.507	0.350	0.234	0.845	1.183
Complexity	-0.712	-0.320	-0.211	0.351	2.846
Stratum	-0.699	-0.295	-0.193	0.358	2.791

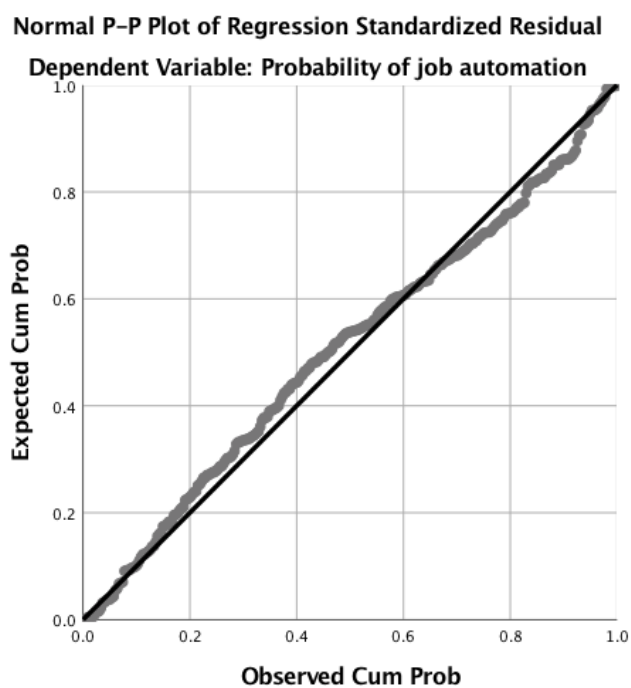
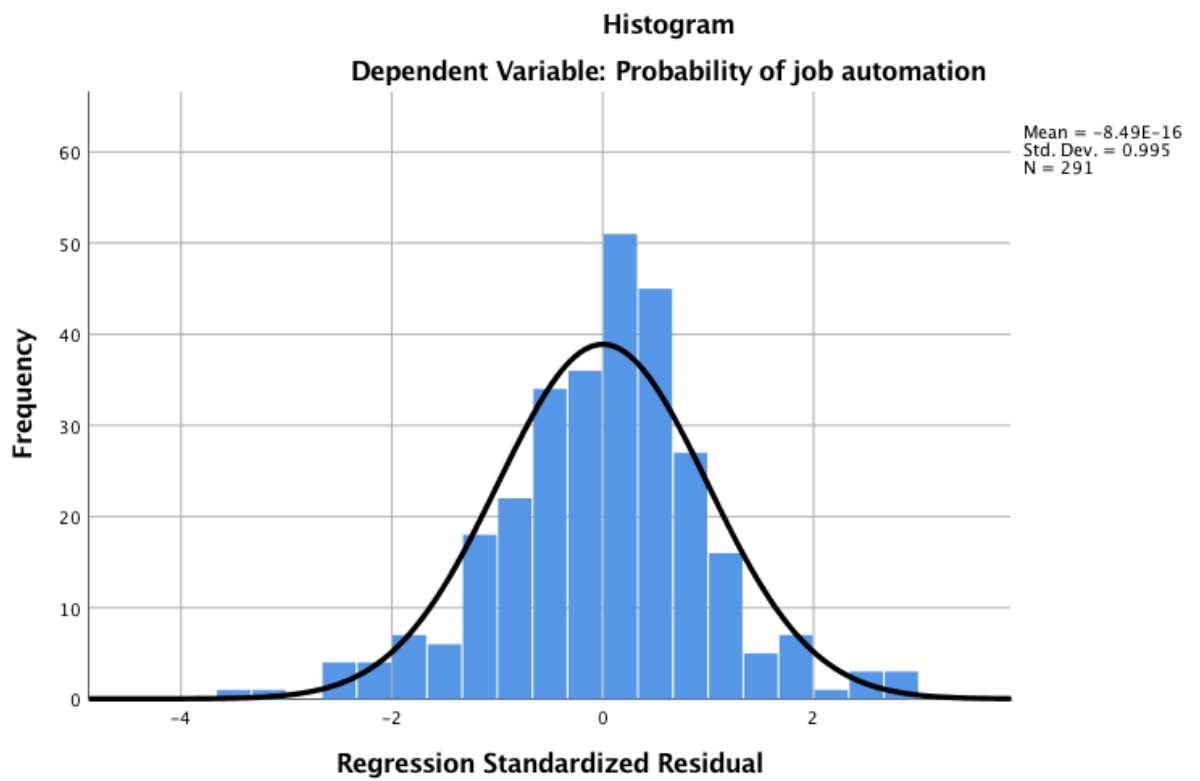
a. Dependent Variable: Prob_automation

Test for Unusual Points

Casewise Diagnostics ^a				
Case Number	Std. Residual	Prob_automation	Predicted Value	Residual
171	-3.418	0.1100	0.888836	-0.7788365
172	-3.069	0.0060	0.705406	-0.6994058

a. Dependent Variable: Prob_automation

Test for Normality



Regression Results

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
2	Stratum, Complexity, Routineness ^b	.	Enter

a. Dependent Variable: Prob_automation

b. All requested variables entered.

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
2	.780 ^a	0.608	0.604	0.2278682	1.570

a. Predictors: (Constant), Stratum, Routineness, Complexity

b. Dependent Variable: Prob_automation

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
2	Regression	23.134	3	7.711	148.510	.000 ^b
	Residual	14.902	287	0.052		
	Total	38.036	290			

a. Dependent Variable: Prob_automation

b. Predictors: (Constant), Stratum, Routineness, Complexity

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
2	(Constant)	0.841	0.046		18.216	0.000	0.750	0.932
	Routineness	0.315	0.050	0.254	6.332	0.000	0.217	0.413
	Complexity	-0.433	0.076	-0.356	-5.714	0.000	-0.582	-0.284
	Stratum	-0.140	0.027	-0.323	-5.232	0.000	-0.193	-0.087

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-0.09214	0.991843	0.556622	0.2824377	291
Std. Predicted Value	-2.297	1.541	0.000	1.000	291
Standard Error of Predicted Value	0.015	0.054	0.026	0.006	291
Adjusted Predicted Value	-0.09614	0.996894	0.556555	0.2826700	291
Residual	-0.77884	0.6594736	0.0000000	0.2266865	291
Std. Residual	-3.418	2.894	0.000	0.995	291
Stud. Residual	-3.435	2.919	0.000	1.003	291
Deleted Residual	-0.78663	0.6710878	0.0000665	0.2303917	291
Stud. Deleted Residual	-3.502	2.959	0.000	1.008	291
Mahal. Distance	0.232	15.376	2.990	1.997	291
Cook's Distance	0.000	0.060	0.004	0.009	291
Centered Leverage Value	0.001	0.053	0.010	0.007	291

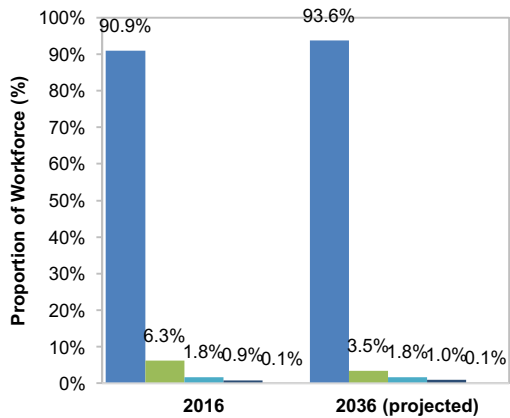
a. Dependent Variable: Prob_automation

APPENDIX G: CHANGE IN WORKFORCE STRUCTURE DATA

Industry	Industry, size, 2016 (workers, '000)	Change in employment (%)	Change in Stratum I (%)	Change in Stratum II (%)	Change in Stratum III (%)
Agriculture, Forestry, Fishing and Hunting	414 710	2.7%	-2.8%	0.0%	0.1%
Mining, Quarrying, Oil and Gas Extraction	644 100	-22.7%	7.1%	12.5%	2.9%
Utilities	545 710	-12.4%	1.0%	10.1%	1.2%
Construction	6 680 940	-18.2%	8.8%	6.6%	2.6%
Manufacturing	12 319 530	-31.2%	9.0%	19.4%	2.4%
Wholesale Trade	5 823 610	-18.9%	2.0%	12.1%	4.4%
Retail Trade	15 963 310	-32.5%	21.4%	7.1%	3.9%
Transportation and Warehousing	5 595 450	-20.1%	13.1%	4.8%	2.1%
Information	2 734 800	-13.1%	0.9%	11.3%	0.7%
Finance and Insurance	5 756 260	-20.5%	7.2%	10.7%	2.3%
Real Estate, Rental and Leasing	2 097 640	-15.6%	5.5%	4.5%	5.1%
Professional, Scientific, and Technical Services	8 663 310	-10.3%	-7.9%	16.8%	1.2%
Management of Companies and Enterprises	2 273 990	-10.4%	-5.9%	13.8%	1.8%
Admin, Support, Waste Management, and Remediation Services	8 974 570	-20.4%	8.7%	9.3%	2.2%
Educational Services	12 956 380	-12.7%	11.1%	1.5%	0.1%
Health Care and Social Assistance	19 231 860	-8.6%	3.6%	4.8%	0.2%
Arts, Entertainment, and Recreation	2 312 690	-19.2%	11.2%	5.7%	2.1%
Accommodation and Food Services	13 332 360	-24.1%	11.4%	9.4%	3.2%
Other Services	4 066 380	-13.8%	4.1%	7.5%	2.1%
Federal, State, and Local Government	9 491 390	-10.2%	3.6%	5.6%	0.5%

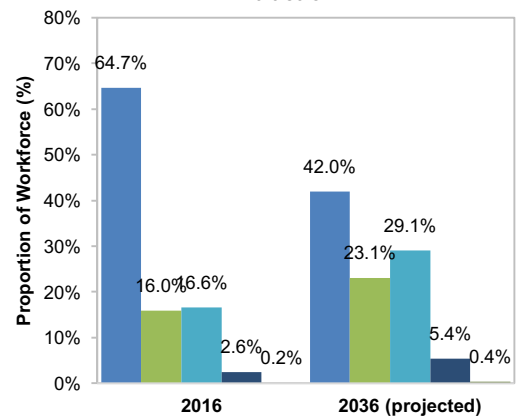
Cluster	Industry	Change Employment (%)	Change, Stratum I (%)	Change, Stratum II (%)	Change, Stratum III (%)
1	Accommodation and Food Services	-83.9%	-24.1%	11.4%	9.4%
	Retail Trade	-74.4%	-32.5%	21.4%	7.1%
	Real Estate, Rental and Leasing	-70.6%	-15.6%	5.5%	4.5%
	Transportation and Warehousing	-69.5%	-20.1%	13.1%	4.8%
	Admin, Support, Waste Management, and Remediation Services	-65.0%	-20.4%	8.7%	9.3%
	Manufacturing	-64.2%	-31.2%	9.0%	19.4%
	Wholesale Trade	-64.0%	-18.9%	2.0%	12.1%
	Construction	-61.0%	-18.2%	8.8%	6.6%
	Mining, Quarrying, Oil and Gas Extraction	-60.5%	-22.7%	7.1%	12.5%
	Finance and Insurance	-59.6%	-20.5%	7.2%	10.7%
	Arts, Entertainment, and Recreation	-58.1%	-19.2%	11.2%	5.7%
	Other Services	-52.6%	-13.8%	4.1%	7.5%
2	Utilities	-44.2%	-12.4%	1.0%	10.1%
	Management of Companies and Enterprises	-43.1%	-10.4%	-5.9%	13.8%
	Professional, Scientific, and Technical Services	-41.9%	-10.3%	-7.9%	16.8%
	Federal, State, and Local Government	-40.5%	-10.2%	3.6%	5.6%
	Information	-37.7%	-13.1%	0.9%	11.3%
	Health Care and Social Assistance	-33.0%	-8.6%	3.6%	4.8%
	Educational Services	-26.6%	-12.7%	11.1%	1.5%
	Agriculture, Forestry, Fishing and Hunting	-26.1%	2.7%	-2.8%	0.0%

Agriculture, Forestry, Fishing, Hunting



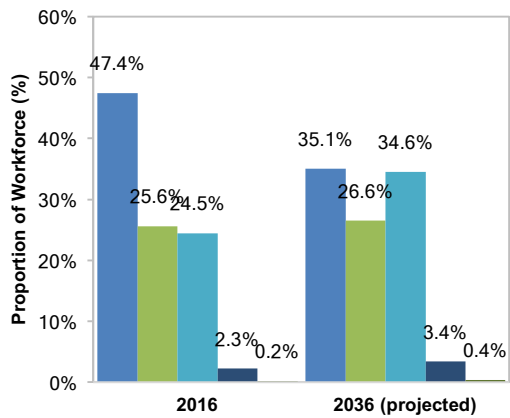
■ Stratum I ■ Stratum II ■ Stratum III ■ Stratum IV ■ Stratum V

Mining, Quarrying, Oil and Gas Extraction



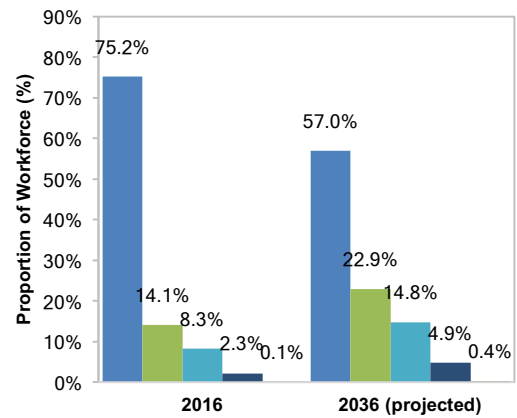
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Utilities



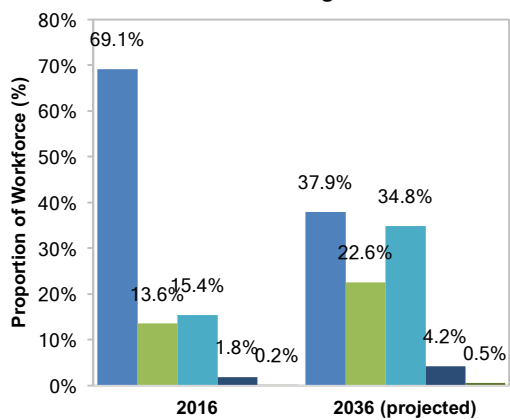
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Construction



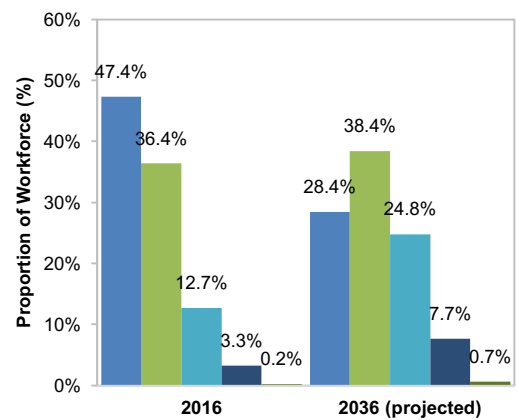
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Manufacturing



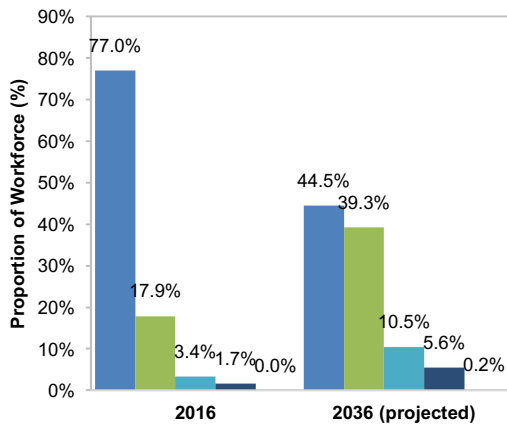
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Wholesale Trade



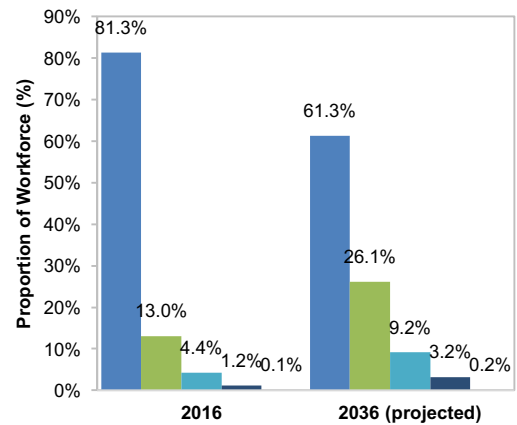
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Retail Trade



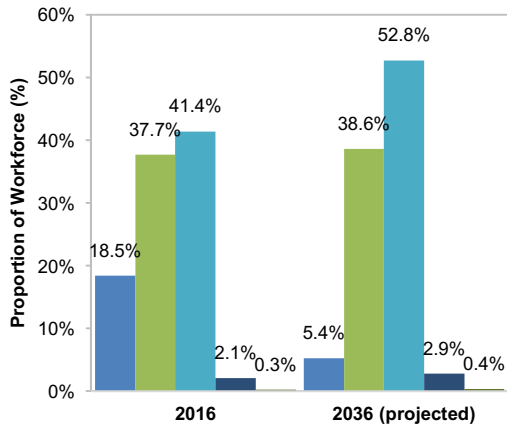
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Transportation and Warehousing



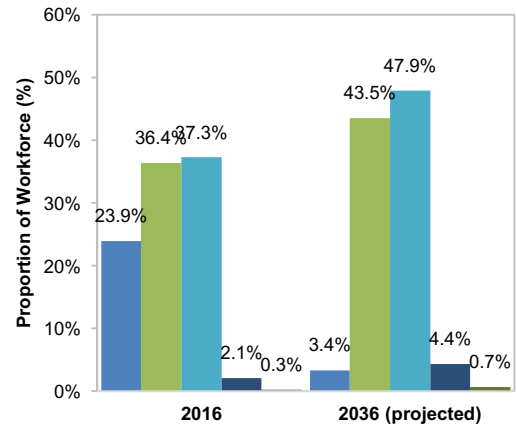
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Information



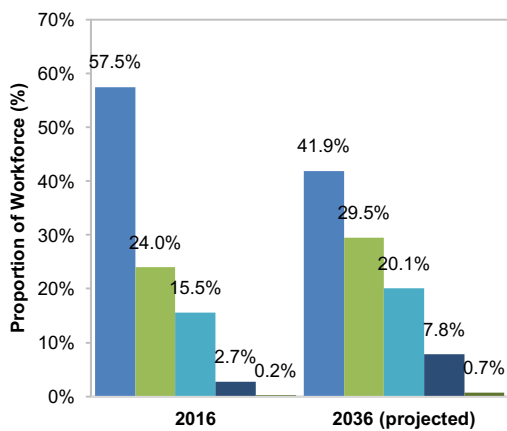
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Finance and Insurance



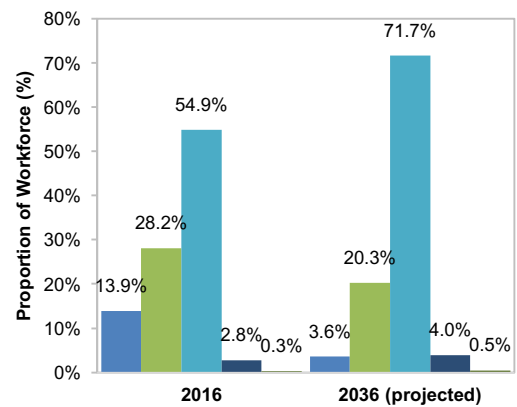
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Real Estate, Rental and Leasing



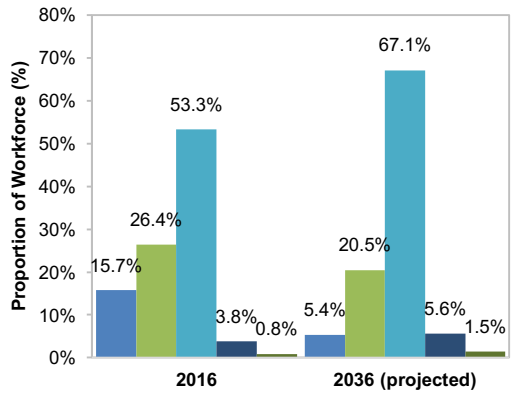
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Professional, Scientific, and Technical Services



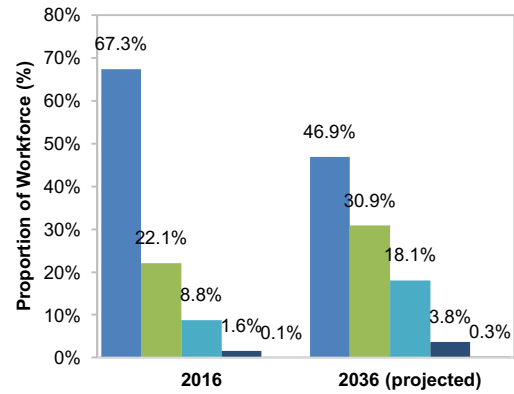
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Management of Companies and Enterprises



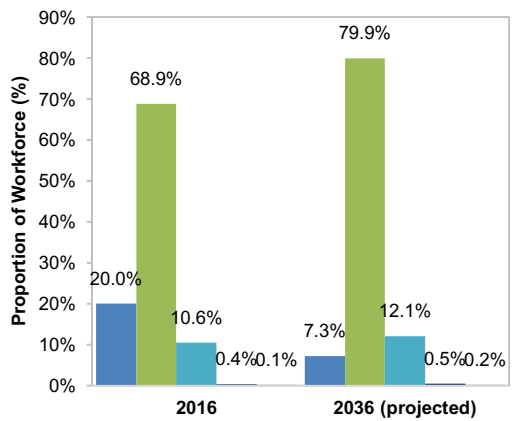
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Administrative and Support and Waste Management and Remediation Services



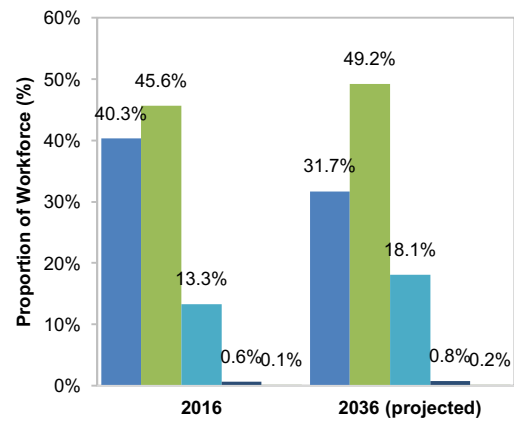
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Educational Services



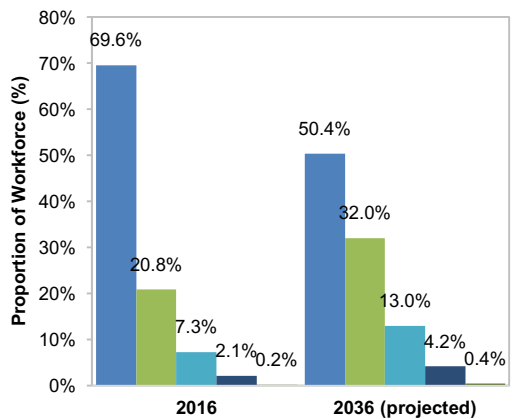
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Health Care and Social Assistance



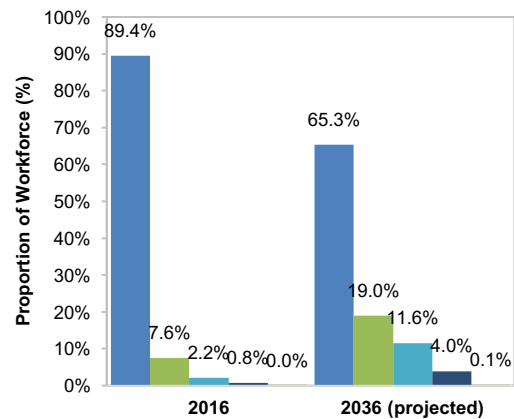
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Arts, Entertainment, and Recreation



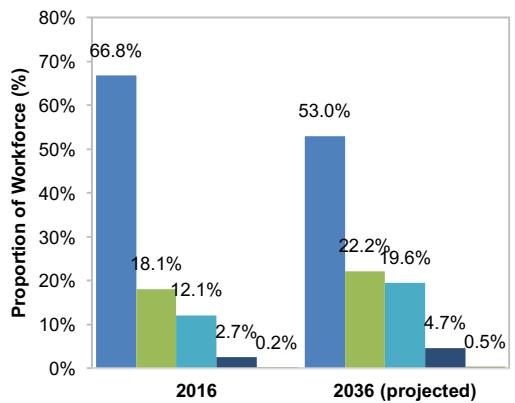
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Accommodation and Food Services



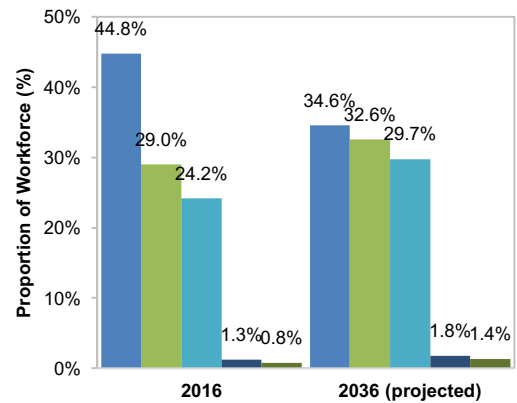
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Other Services



■ Stratum I ■ Stratum II ■ Stratum III ■ Stratum IV ■ Stratum V

Federal, State, and Local Government



■ Stratum I ■ Stratum II ■ Stratum III ■ Stratum IV ■ Stratum V