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LOCAL LABOR MARKETS EXPOSURE TO ARTIFICIAL INTELLIGENCE

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by

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ABSTRACT

As more evidence builds that artificial intelligence (AI) is a new general-purpose technology driving a fourth industrial revolution, scholars have begun to consider its potential impact on labor markets. The current debate among researchers is centered on whether AI will ultimately produce net new job gains or losses and what type of workers will benefit or be displaced. While no consensus has developed yet within the literature on AI's predicted net employment impact, a majority of studies are forecasting that a skill-biased technological change will occur.

This exploratory study contributes to the current literature by operationalizing Webb's objective patent-based AI Exposure Index at a local labor market level. The study leveraged longitudinal data analysis to measure the effect of AI exposure on changes to employment at an occupational level from 2010-2019 in San Diego County, California. By applying this exploratory methodology, the study yielded several noteworthy findings. First, the analysis showed an overall positive association between employment totals and AI exposure across all levels of Webb's AI Exposure Index. Second, preliminary evidence of potential skill-bias change was noted with non-high-skill occupations exhibiting slower employment growth compared to high-skill occupations at similar levels of AI exposure. Lastly, specific occupational groups and occupations displayed potential early indications of employment loss attributable to AI exposure. For example, the occupation titled "Pickers and Packagers, Hand" within the material movers and transportation occupational group demonstrated both high levels of AI exposure and reductions in employment totals during the period analyzed. However, it is critical to emphasize that large standard errors limit the precision of model estimates.

This study has implications for local labor market leaders by providing insights into AI exposure and employment trends. This exploratory methodological approach has potential for application to other local labor markets and offers opportunities for further scholarly research. Finally, this study makes a novel contribution to the labor literature with its localized focus, objective methodology and preliminary occupational-level employment change findings.

DEDICATION

This dissertation is dedicated to the resilient citizens of my birthplace, Saginaw, Michigan, whose labor market endured significant challenges due to recent technological changes.

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ORDER OF PAGES

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION TO THE STUDY

In 2017, Oxford researchers Frey and Osborne published a study called *The future of employment: How susceptible are jobs to computerization?* which brought worldwide attention to artificial intelligence by grabbing headlines globally with its assertion that 47% of total U.S. employment is in the high-risk category for computer automation with the next two decades (Frey & Osborne, 2017). Follow-on global studies have predicted up to 800 million workers globally will be displaced by automation technologies primarily driven by artificial intelligence and robotics (Manyika et al., 2017). Consequently, researchers, the business world, and the media have begun to utilize labels like the *fourth industrial revolution* and the *age of artificial intelligence* to describe the significance of the artificial intelligence phenomenon. Lee describes the potential impact of this phenomenon by stating "Artificial intelligence will do the analytical thinking, while humans will wrap that analysis in warmth and compassion" (Lee, 2018, p. 37). This vision for the future has humans wondering whether artificial intelligence will create a utopia, mass societal upheaval, or some combination of both.

This study examines the artificial intelligence phenomenon by contributing to the emerging scholarly research focused on predicting the impacts of artificial intelligence on labor markets. To provide appropriate context, this initial section of the study details the evolution of artificial intelligence from concept to application, then discusses established theory related to technology and labor markets. Findings from related research focused specifically on artificial intelligence and labor markets are also briefly synthesized and knowledge gaps identified. Lastly, based on the existing knowledge gap, this study's purpose and research questions are described.

A Brief History of Artificial Intelligence

The renowned British scientist and World War II hero, Alan Turing, is often credited with initiating the age of artificial intelligence (AI) in 1950 when he stated in a paper "I propose to consider the question: Can machines think?" (Muggleton, 2014). Turing's paper also proposed the "Turing Test" which is an imitation game involving a machine and two humans. If a human is unable to distinguish between the machine and the other human during the game, then the machine is said to be intelligent. Building on Turing and subsequent research, Haenlein and Kaplan (2019) concisely defined AI as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation". From its inception as a research concept in the 1950s, there have been two generally accepted AI approaches: rules-based and neural networks. The rules-based approach, which often involves more human intervention and direction, is closely associated with machine learning and dominated the first five decades of AI research. Systems driven by rules-based AI are guided by *if X then Y* rules provided by humans through technological code. Consequently, the constraints of rules-based AI are similar to any other computer system: human expertise, time, and creativity. These human constraints inherently limited rules-based AI's adaptability leading to the slow progress of AI more broadly through the late 20th century.

In contrast to rules-based AI, the neural network approach has become the primary focus of AI research in the past two decades due to its high adaptability. Systems driven by neural networks are guided by human-built computing architecture which mimics the thought process of the human brain and is often called deep learning. Once the architecture is constructed, the system is no longer significantly constrained by humans but rather by data and processing power. The 21st-century computing boom driven primarily by high power semiconductors and cloud computing innovations was the main breakthrough that created a technological processing environment in which big data and neural network AI could thrive. Less constrained by humans, neural network AI has produced an explosion in practical applications leading to popular commercial products like Amazon's Alexa, Tesla's self-driving vehicles and Pandora's music recommender system. These applications are an indication that AI is now shifting broadly from its initial research-focused discovery phase to practical implementation. As Lee points out in his core work *AI Superpowers*, "Much of the difficult but abstract work of AI research has been done, and now it's time for entrepreneurs to roll up their sleeves and get down to the dirty work of turning algorithms into sustainable businesses" (Lee K.-F., 2018, p. 13).

The Rise of AI

Applying these technological advances, startups as well as established companies are disrupting entire industries. We have already seen significant AI investment and disruption within the automotive industry by emerging companies like Tesla, Nikola, and Neo among many others. The customer service industry is being revolutionized through AI-enabled customer bots developed by startups like Cedex Technologies and Botscrew. Established companies such as Apple, Google, and Amazon have focused on applying AI in the advertising and personal assistant space with Siri, Google Assistant, and Alexa. In 2018, Google famously demonstrated the latest version of its Google Assistant by allowing it to independently conduct a live phone call to schedule a hair appointment. Recent studies have also examined AI's current or potential impact on health care, food services, finance, and law (Hosny et al., 2018; Luo et al., 2018; Aini, 2020).

The geographic reach of AI is global with impacts estimated across all major economies including China, India, the United States, and the EU (Manyika et al., 2017). China has established itself as a primary global AI power by initiating governmentally supported programs to conduct AI research and rapidly operationalize its application (State Council, 2017). Within the last decade, China has closed the AI research gap substantially with Western nations. For example, Tsinghua University of China now has more total AI research citations than Stanford University (Lee K.-F. , 2018). Additionally, China's "big tech" companies such as Alibaba, Tencent, Baidu, and Huawei are rapidly building and launching their own AI applications. This strategic focus by China is expected to expedite the scale and scope of AI development further enhancing its global significance. From its slow start, AI is poised to leave its mark on history in the 21st century and beyond as a new general-purpose technology that scholars assert will drive the *Fourth Industrial Revolution* (Skilton & Hovsepian, 2017; Xu, David, & Kim, 2018; World Economic Forum, 2016; Zhou, Liu, & Zhou, 2015).

General Purpose Technologies and Technological Job Displacement

In order to assess the potential impact on labor markets of an AI-driven fourth industrial revolution, it is critical to understand the core employment aspects of the first three industrial revolutions. Technologies such as steam engines, electricity, internal combustion engines, and modern information technology systems are generally credited with driving the first three industrial revolutions. These technological innovations are commonly referred to as general-purpose technologies due to their technical dynamism, economic pervasiveness, and productivity gains produced (Bresnahan & Tratjenberg, 1992). General purpose technologies shifted global economies from agricultural to industrial and finally to digital. Additionally, these technologies significantly shifted employment by creating new occupations and industries as well as driving technological job displacement by making some jobs completely obsolete. Technological job displacement occurs when technological innovation replaces human labor in work tasks (Petropoulos, 2018). The steam engine, for example, led to the first era of industrialization where looms in large-scale production factories like textile mills replaced skilled manual laborers such as seamstresses and tailors. The internal combustion engine initiated mass production of machines replacing jobs like blacksmiths and buggy manufacturers. Information technologies (IT) then automated many aspects of mass production replacing manufacturing production workers with robots and software systems.

Technological Change Employment Theory

Prior to the emerging research on the impact of AI on employment, the most applicable scholarly work analyzing technology's impact on employment developed around the theory of technological change. The roots of the theory of technological change can be traced to economist John Maynard Keynes in the early twentieth century who first asserted that techno-scientific developments produced widespread improvements in standards of living (Mokyr et al., 2015). Numerous studies built upon Keynes' initial assertion by focusing on the association between the implementation of technology, often general-purpose technologies, and employment outcomes. Together, these studies can be categorized as technological change employment theory.

Scholarly debate within technological change employment theory has focused on two main themes: net employment impact and type of technological change. The general consensus of technological change employment theory asserts that when new technologies enter the labor market, they drive net employment growth over the long run (Aubert-Tarby et al., 2018; Mokyr et al., 2015). More simply, as the U.S. Bureau of Labor Statistics stated, "...technology ultimately creates more jobs than it destroys" (Mark, 1987). The theoretical foundation for this assertation is that technological change increases demand for goods and services through product innovation resulting in job opportunities faster than reducing demand for labor through process innovation which automates job tasks (Dachs, 2017; Vivarelli, 2014; Piva & Vivarelli, 2017). For example, during the IT revolution, it is estimated that computers enabled the creation of 15.8 million net new U.S. jobs since 1970, accounting for 10% of all employment (Manyika et al., 2017). Dach's study of EU-based firms during a similar period also demonstrated that, in terms of employment growth, innovating firms outperformed non-innovating firms (Dachs, 2017).

While the consensus within technological change employment theory asserts that technological change leads to overall employment growth, the impact on specific skills and jobs depends on whether the technical change is skill-replacing or skill-biased towards labor (Caselli, 1999; Acemoglu, 2002; Autor et al., 2003). Skill-replacing change is associated with technology that reduces the level of learning and skill required to conduct job tasks. Acemoglu points to the nineteenth-century technological shift to the factory system in Britain as a primary example of skill-replacing change (Acemoglu, 2002). Low-skill rural workers migrated to British cities and replaced skilled artisans by utilizing innovations in interchangeable parts and mass production. Consequently, this skill-replacing change increased lower-skill jobs while reducing specific higher-skill jobs directly impacted by the technical change.

Skill-bias change has the opposite impact of skill-replacing change. Skill-bias change increases the level of learning and skill required to conduct job tasks, thereby, reducing lower-skill jobs and increasing higher-skill jobs. Recent empirical studies have shown a shift to predominately skill-bias change towards the late twentieth century due primarily to a rapid increase in the global supply of highly educated skilled workers during the IT revolution (Dachs, 2017; Piva & Vivarelli, 2017; Acemoglu, 2002; Betts, 1997; Autor et al., 2003). A broad examination of Canada's industries between 1962 and 1986 also validated the skill-bias change during this period by showing a significant increase in demand for white-collar workers in relation to blue-collar workers (Betts, 1997). As Vivarelli (2014) states "...the evidence in favor of the skill-biased nature of new technologies is large, robust, and proven across different OECD countries, different economic sectors and different types of innovation”.

AI Employment Theory

Compared to technological change employment theory, artificial intelligence employment theory is still in its infancy with less than ten years of accumulated research to date. Additionally, the age of AI is evolving every day with new applications of AI-powered technologies emerging and subsequently shaping labor market dynamics in real-time. Consequently, no scholarly consensus has been established to date on either a generally accepted theoretical approach or the predicted employment impact of AI. The current debates among scholars examining the intersection of AI and employment focus on two main issues: first, whether AI will ultimately destroy more jobs than it creates and, secondly, what types of jobs will be most impacted by AI. Some scholars assert that AI’s impact on labor markets will closely resemble the predicted outcomes provided by technological change employment theory with overall net employment increasing and skill-bias change most likely occurring within labor markets (Manyika et al., 2017; World Economic Forum, 2016). Other researchers contend that AI will cause new and substantial risks to labor markets (Lee, 2018; Webb, 2019).

The vast majority of initial AI employment research has taken three main approaches, based on the study’s unit of analysis: task-based, occupation-based, and industry-based. Task-based AI employment research assesses the potential impact of AI on individual work tasks by cross-referencing known AI applications and detailed work task descriptions. Occupation-based research focuses on jobs as its unit of analysis and attempts to predict AI’s potential impact on national or global labor markets. The industry-based approach analyzes the potential disruption of entire business sectors by AI applications which correspondingly drive scaled technological displacement. A recent and compelling addition to the AI employment research landscape is Webb's (2019) study *The Impact of Artificial Intelligence on the Labor Market*. Webb's research focuses its analysis on actual patents that have been filed for AI technologies. By utilizing textual analysis, Webb associates the technological functionality found within the patent description with job tasks connected to specific occupations. Webb's objective-based analysis builds on the current task-level and occupation-level approaches to provide an AI exposure score index that can be applied to all U.S. occupations. As scores increase on Webb's index, exposure to AI technologies increases for occupations as well as predicted employment loss. This new objective methodology is significant because it leverages emerging AI applications found in patents to drive its predictive approach.

Problem Statement

With a consensus built around the global significance of the AI phenomenon, it is critical that scholars explore all aspects of its potential impact. While recent studies are reaching a critical mass of research focused on AI's potential influence on labor markets, two main knowledge gaps still persist in the literature. First, a common research approach within AI employment theory is to focus on the macro-level analysis of national, regional, industrial, or world labor markets. This macro-level tendency often creates a knowledge gap in the predicted net employment difference and type of technological change impact on local labor markets. This gap is significant because local labor markets often lack the diversification of national or global labor markets making them potentially more susceptible to the impacts of technological change. For example, while the IT industrial revolution created substantial net new job growth throughout the diverse U.S. labor market, local labor markets in the U.S. with high exposure to robots suffered negative labor demand shocks (Acemoglu & Restrepo, 2017). These negative labor demand shocks are associated with sudden and unexpected downward changes in demand for labor. Scholars have linked these negative labor demand shocks to higher unemployment, lower wages, and shifts to a lower-educated workforce within a labor market (Diamond, 2016; Notowidigdo, 2011). Consequently, these shocks can have serious impacts on local labor markets and the connected local workforce. Therefore, with AI predicted to continue playing a vital role in the evolution of labor markets, AI employment research should broaden its scope to address local labor market dynamics.

Second, because the AI phenomenon is so new and still evolving, studies rely heavily on the existing technological change employment theory or subjective-based methodologies like expert surveys and broad-based classifications to drive their predictive analysis. The dependence on technological change employment theory within studies generates reliability risk to their predictive models. Utilizing theory based on technologies from the past does not fully take into consideration how outcomes from AI might differ. These potential differences could then produce inconsistent findings within research models over time. Additionally, reliance on subjective-based methodologies increases the validity risk of these AI studies. As AI evolves and more is known about its impact, it is reasonable to assume expert opinions on AI will change as well. Consequently, research findings that depend on current expert opinions must be scrutinized. The tendency of AI researchers to apply subjective broad-based classifications to drive models also increases the potential for inaccurate findings. For example, several AI studies have grouped thousands of individual work tasks into general classifications (such as manual, cognitive, routine. and complex tasks) and then associated technological job displacement with a specific classification grouping. Going forward, to improve predictive accuracy, scholars should strive to build models that are more objective-based and avoid broad generalizations of work tasks or occupations.

Together these knowledge gaps create challenges for local labor market leaders and correspondingly local workforces. With limited valid and reliable models to predict the impact of AI on their labor markets, local leaders cannot conduct effective proactive workforce planning to prepare for possible labor demand shocks. Typical consequences of ineffective workforce planning include limited training programs in high-demand occupations and inadequate workforce transition resources. Without available training and resources, local workers have a higher likelihood of experiencing the negative impacts of technological job displacement through unemployment, wage stagnation, and fewer career opportunities. This vicious cycle can then lead to the decline of entire communities through the reduction of local revenue, public services, and human talent.

Purpose of the Study

To prevent this vicious cycle, local labor market leaders need access to locally focused, objective-based models that predict AI's specific impact on their local labor markets. This study seeks to fill this knowledge gap by employing an exploratory approach that operationalizes Webb's objective patent-based AI exposure index at a local labor market level. The purpose of this exploratory operationalization of Webb's instrument is to attempt to provide local labor market leaders with an objective-based model to assess their local labor market's exposure to current and future AI-driven technologies. The study utilizes San Diego County, California as the local labor market for analysis. The data foundation of the analysis of San Diego County is the Department of Labor's *Metropolitan and Nonmetropolitan Area Occupation Employment and Wage Estimates* which provides publicly available occupation-level local labor market data on an annual basis. By leveraging publicly available data, this study seeks to build a generalizable model that can be applied to any local labor market within the U.S. while providing local leaders with the necessary understanding of their labor market's exposure to AI. Ultimately, this model is intended to help prevent vicious cycles from occurring within local communities by equipping local leaders with a tool to provide the required knowledge to proactively plan for the age of AI.

Research Questions

This study's research questions focus on evaluating Webb's AI exposure index as a tool for local labor leaders by testing the predictive capability of the index when applied to the Bureau of Labor Statistics' (BLS) Metropolitan and Nonmetropolitan Area Occupation Employment and Wage Estimates for San Diego County. The first research question evaluates the net employment impact of AI at the occupational level: ***To what extent, if any, is there an association between changes in San Diego County employment at an occupational level from 2010-2019 and Webb's AI exposure index scores?*** Webb's research asserts that there will be a positive association between job losses and exposure score at an occupational level. The second research question evaluates the type of employment impact of AI at a skill designation level: ***To what extent, if any, is there an association between changes in San Diego County employment at an occupational skill designation level from 2010-2019 and Webb's AI Exposure Index scores?*** Webb predicts AI will drive skill-replacing change impacting higher skill occupations. As Webb's succinctly states, "AI is directed at high skill tasks" (Webb, 2019, p. 1). By evaluating these research questions, the predictive capability of Webb's AI exposure index can be assessed.

CHAPTER TWO

LITERATURE REVIEW

The literature review process began by identifying scholarly research focused on artificial intelligence and employment, eventually classified within the review as *artificial intelligence employment theory*. The global scope of the research examined was a critical component of the process because the global nature of the artificial intelligence phenomenon became apparent quickly during the initial review of the literature. Four main academic databases were utilized to conduct literature searches: EBSCOhost Academic Search Premier, ProQuest Dissertations & Theses Global, Journal of Artificial Intelligence Research (and other related journals), and Google Scholar. A standard search in Academic Search Premier for *artificial intelligence and employment* returned 225 peer-reviewed literature results. An initial review of the most relevant literature led to a secondary search for *fourth industrial revolution* due to its frequency of mention within works and its historical context. This led to an additional 49 pieces of literature to examine.

Guided by the focus of this study, three main research topics of the examined studies were excluded from this literature review. First, studies exploring artificial intelligence and ethics were excluded because this study does not inquire into the ethical issues of artificial intelligence. Second, research studies examining artificial intelligence's direct impact on labor wages (growth and/or suppression) were excluded because this study focuses on AI's net employment and skill outcomes. Lastly, governmental artificial intelligence policies and examinations of those policies were also deemed out of scope for this study. Additional separate searches were conducted to provide historical context and definitions of key terms as well as to explore technological change theory which became a foundational component of the literature upon initial examination of artificial intelligence employment research. Ultimately, this framework produced the 56 works of literature included in this review.

Utilizing this literature, key definitions, historical context, and established theory were provided in the background of the study section. Then, a process of discovery, synthesis, and analysis was conducted within AI employment research to categorize and assess the different scholarly approaches. A further detailed examination of Webb's study is also conducted to reinforce its novel approach and significance within the literature. Overall, this review seeks to present a concise and comprehensive overview of the current state of the emerging literature driving AI employment theory.

AI Employment Theory Research

With technological change employment theory established as the academic standard, scholarly research recently began to be published that examines AI's potential impact on employment. While some findings within this emerging literature aligned with the established consensus, other research findings appeared to challenge the status quo. This review synthesizes and categorizes AI employment research into three main approaches based on methodology: task-based, occupation-based, and industry-based. The review then examines the research findings associated with AI's net employment impact and type of technological change as well as scrutinizes each methodological approach.

Task-level research

Task-level research focuses its unit of analysis at the lowest level, job tasks. Frey and Osborne's (2017) study, *The future of employment: How susceptible are jobs to computerization?*, initiated and brought worldwide attention to the potential sweeping effects of AI on employment with its assertion that 47% of total U.S. employment is in the high-risk category for computer automation with the next two decades. This study applied a task-based model to 702 job occupations within the U.S. government's O'NET system. Frey and Osborne's task-based model mapped key indicators preventing what the authors term "computerization" or susceptibility to AI-driven technologies to job tasks found in the O'NET system. Lower levels of these indicators found within job tasks meant a higher risk for computerization. Utilizing this methodology, 47% of jobs were deemed high risk and 19% medium risk to computerization within the next two decades.

Frey and Osborne's (2017) findings focus primarily on the job displacement potential of AI driven technologies. Therefore, they do not attempt to directly predict the overall net employment impact of computerization. However, with 66% of total jobs assessed at high or medium risk of displacement, their analysis alludes to the correspondingly high levels of job creation that would need to occur to balance or exceed potential job destruction over the next two decades. While Frey and Osborne don't predict the overall net employment impact, their study does predict which types of jobs will be impacted. Unlike the IT revolution which increased low-skill service-oriented jobs, Frey and Osborne's analysis predicts these jobs will be at high risk for displacement in the near future. Other job categories deemed at risk include logistics, transportation, office support, and production occupations. In contrast, Frey and Osborne predict high-skill jobs, like science and engineering, are the least susceptible to computerization asserting a probable skill-bias change with AI-driven computerization.

Acemoglu & Restrepo (2018) built on Frey and Osborne's (2017) task-based approach by attempting to address the net employment effect of AI-driven automation. Their task-based framework accepts that job displacement will occur due to automation but also emphasizes the creation of new tasks which have the potential to balance the net employment impact. This assertion fills the central employment gap in Frey and Osborne's work. Additionally, Acemoglu and Restrepo challenge Frey and Osborne's skill-bias change assertion. Through a task-based model that examined both high and low-skill AI-driven automation, their findings conclude that AI will have a displacement effect on both high and low-skill jobs indicating the potential skill-replacing change of this new technology.

Duckworth, Graham & Osborne (2019) fill two additional gaps in the task-based approach in their study *Inferring Work Task Automatability from AI Expert Evidence*. First, by surveying over 150 AI academics on how automatable job tasks are today, their research methodology provides additional substantiation to the conceptual task-based frameworks of Frey and Osborne and Acemoglu and Restrepo. Second, by surveying academics across the world, their research includes broad non-western-based insights that support the generalizability of the findings. Regarding the potential net employment impact of AI, the study found that eight times as much work lies between "mostly" and "completely" automatable than between "mostly not" and "not at all" automatable. This finding indicates a significant probability that job displacement will outpace job growth. Their findings also show that higher income and educated workers are more likely to have less automatable jobs which forecasts a skill-bias technical change.

Nedelkoska & Quintini (2018) further enhanced the global scope of task-based AI employment predictions by applying Frey and Osborne's task-based methodology along with localized survey data to analyze the employment impact of AI-driven automation on 32 European-centric countries within the Organisation for Economic Co-operation and Development (OECD). Their study found that 14% of the jobs in OECD countries have more than a 70% probability of automation and another 32% have between 50-70% probability. Like

Frey and Osborne, Nedelkoska and Quintini avoid directly predicting the net employment impact of AI-driven automation, only mentioning the potential for job creation due to this technology. The research does, however, call out the skill-bias nature of AI in their findings noting that "... occupations with the highest estimated automatability typically only require basic to low level of education. At the other end of the spectrum, the least automatable occupations almost all require professional training and/or tertiary education" (Nedelkoska & Quintini, 2018, p. 8).

While a consensus within the task-based approach is still emerging, this methodology has dominated initial research efforts to date and early evidence is clearly challenging the general assertions of earlier research on the impact of technological change on employment. Currently, most of the task-based research is skeptical about overall employment growth due to AI and it is also unclear whether skill-bias or skill-replacing change will prevail. As task-based theory continues to develop, researchers should find additional data sources outside of the United States (U.S.) government's O'NET system to base their studies on. Continuing to build on studies focused on the O'NET system for task-level job details limits generalizability when applying findings outside of the U.S. Agrawal, Gans, and Goldfarb (2019) also challenged the reliability of analyzing AI-driven automation through the numerous job tasks listed in O'NET. Their study argues that only two tasks, prediction and decision, need to be analyzed to assess the potential risk of automation of a job. Corelli and Borland (2019) also challenged the "...replicability, internal consistency and subjectivity" of Frey and Osborne's methodology which is the foundation of most task-based research. They assert that jobs should be analyzed using the categories of routine/non-routine and cognitive/manual rather than O'NET task-level data.

Occupation-level research

Occupation-level research concentrates its study's unit of analysis on occupations that are comprised of multiple job tasks. In 2017, the business consulting firm McKinsey released their global employment assessment of AI-driven technologies in their report *Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation* (Manyika, et al., 2017). McKinsey employed a "micro-to-macro" methodology for this occupation-based analysis by applying economic labor theory in combination with interviews of global leaders which broadened the scope of the task-based approach making occupations rather than job tasks the main unit of analysis. The global scale of this study included 46 countries and 800 occupations. By 2030, McKinsey estimates 400 to 800 million workers globally will be displaced by automation technologies primarily driven by AI and robotics. This finding represents 15-30% of the total global workforce. Additionally, while few occupations were deemed fully automatable, 60% of all occupations were assessed to be at least 30% automatable. Based on their model, while 400 to 800 million workers will be displaced, future non-AI-impacted job growth in health care, energy and technology will create over 200 million global jobs. McKinsey also predicts, by 2030, another 8-9% of jobs will be "new occupations", resulting primarily from AI-driven automation, that does not currently exist.

While McKinsey's model suggests some periods of potentially high unemployment especially in advanced economies, McKinsey asserts that full employment will be reached by 2030 in spite of the technological displacement due to significant job creation driven by rising income levels, investments in infrastructure and sector growth in health care, energy, and technology. According to their findings, developing countries appear less susceptible to employment impacts of AI automation while advanced countries will require rapid reemployment of workers to reach full employment. McKinsey estimates up to 375 million workers will require job changes and the retraining of the workforce will be critical to reduce the risk of technological unemployment. From a skills perspective, McKinsey highlights that automation technologies will impact all skill levels of workers. However, their findings indicate primarily skill-bias change as the growing job categories in their model have higher educational requirements than the workers displaced by automation technologies. By 2030, their study predicts new job tasks will involve more application of expertise, stakeholder interaction, and people management with less involvement in data collection, data processing, and predictable physical activities. The advantage from a skills perspective appears to be higher-educated, traditionally high-skilled occupations.

Muro, Maxim & Whiton (2019) applied McKinsey's occupation-based methodology to a solely U.S. occupations data set to conduct a forward-looking analysis on U.S. occupations. Their findings assert that 25% of U.S. jobs will be highly exposed to AI-driven displacement and another 36% of jobs will experience medium exposure. The study predicts a *muted* impact on net employment due to job growth in new occupations driven by AI. The study also asserts that better-educated, higher-paid workers are half as likely (24% vs. 55%) to face exposure to AI job displacement. While this indicates skill-bias change, Muro, Maxim, and Whiton acknowledged this could shift as AI puts pressure on higher-wage, non-routine jobs in the future.

While its analysis expanded outside of just AI-driven technologies, the World Economic Forum's (WEF) *Future of Jobs* study also contributes to the occupation-based approach (World Economic Forum, 2016). By collecting employment survey data directly from global corporate leaders across 15 major developed and emerging economies and regional economic areas, the WEF produced potentially more generalizable findings on future employment impacts on job families (occupations). Among its findings, WEF asserts a net employment impact of 5.1 million jobs lost by 2020. Correspondingly, survey respondents identified AI as the second most important driver of job losses. The largest categories of AI job losses are predicted within the office administration, manufacturing, and construction job families. AI-driven job growth is predicted within the computer, mathematical, architecture, and engineering job families. Consequently, the study also indicates a skill-bias change favoring higher education level occupations.

A consensus is building with early research within the occupation-based theory that appears to indicate a skill-bias change will be occurring that favors high-skill workers. However, predictions on the net employment impact are currently mixed. The strength of the occupation-based approach is the broad scale and scope of studies which enhances their validity and potential generalizability. Global corporate leadership perspectives, macro-level economic growth projections, required workforce skill upgrades, labor market occupational mixes, and governmental transition support are all taken into consideration in the occupation-based research designs and methodologies. The significant differences in findings regarding net employment impact do call into question the overall reliability of this approach in measuring these outcomes. If future occupation-based studies continue to produce varied employment assertions, it could indicate that occupations are not an appropriate unit of analysis. Additionally, Susskind (2017) has challenged a core assumption of the occupation-based approach that new job tasks created by AI driven technologies will result in occupational job growth. Susskind's pessimistic view of the threat of automation argues that recent research has consistently underestimated the capabilities of machines. Therefore, Susskind predicts that machines will more broadly encroach on new job tasks in the future ultimately reducing potential job creation within occupations.

Hybrid approach: Webb's AI Exposure Index

Several recent studies have measured the unprecedented increase of AI patent filings in the U.S. and internationally (Abadi, H. H. N. & Pecht, M., 2020; World Intellectual Property Organization, 2019; Toole, A., et al., 2020). Recognizing key operational information contained within these patents, Webb built on aspects of both task and occupation-level research to construct a new objective method of assessing occupational-level job task exposure to AI. Webb's methodology leveraged the text within AI patents which describe the core functionality of these new technological applications. Through textual analysis of verb-noun combinations, Webb examined the overlap of tasks detailed within the patents to job tasks detailed for 964 occupations in the O'NET system. The frequency of verb-noun matches was then associated with an occupational exposure score based on a scaled index from 1 (lowest) to 100 (highest).

Webb validates the potential predictive capability of the study's AI Exposure Index by applying the same methodology to two other recent technologies, robots and software, and measuring their effects over a 30-year period from 1980-2010. The findings of this analysis associate higher exposure scores with actual reductions in employment levels in occupations exposed to these technologies. While this methodology doesn't directly address the overall net employment impact of technologies, it does enable researchers to focus measurement at an occupational level. Thus, the index can be applied to occupational data to conduct predictive analysis on labor markets. With regard to measuring the type of technological change, Webb's scaled index provides a direct exposure assessment of all examined occupations. The study's findings indicate a higher potential for skill-replacing change from AI. As Webb states "...I find that high-skill occupations are most exposed to AI, with exposure peaking at about the ninetieth percentile. While individuals with low levels of education are somewhat exposed to AI, it is those with college degrees, including master's degrees, who are most exposed" (Webb, 2020, pg. 4).

The measurement validity, occupational specificity, and task-level objective basis of Webb's AI Exposure Index provide an attractive foundation for further research to build on. While other AI employment theory studies leverage expert opinions, surveys, or broad task classifications, Webb's research is grounded in a transparent and replicable evidence-based methodology focused on known AI applications. A limitation of Webb's research, like other AI employment theory studies, is the sole reliance on the O'NET system for textual analysis of job tasks. This system is distinct to only U.S. occupations and therefore has somewhat limited generalizability globally. Additionally, while patent texts are trustworthy sources for functional descriptions of technology the actual application of the technology in real-world settings might expand or restrict the tasks it can execute. Consequently, the reliability limitations of patent texts as the single task-level source of measuring AI technologies capabilities must be acknowledged.

Industry-level research

Lee's (2018) work *AI Superpowers: China, Silicon Valley and the New World Order* is core to the debate within AI employment theory due to the unique AI expertise of the author and the significance of its findings. As a former published AI scholar that built AI research teams at Microsoft and Google before founding his own AI-focused venture capital firm in China, Lee's experience is novel and important in that he has expertise in the nuances of the productization of AI as well as China's potential role in the AI revolution (Lee K. F., 1988). Lee's methodology applies his experience and knowledge of existing research and approaches within both Silicon Valley and China to fill a practical gap in AI employment theory.

Rather than adopting a task or occupation-level perspective, Lee employs an industry-based approach to evaluating AI's impact on employment. His industry-based approach categorizes job displacement into two distinct categories, one-to-one replacements and ground-up disruptions. One-to-one replacements are similar to displacements described in Frey and Osborne and McKinsey's studies, essentially an AI-driven product or process replaces a job task, job, or occupation. In the U.S., Lee estimates 38% of job losses will be caused by one-to-one replacements. Ground-up disruptions, however, are the reimagining of entire industries utilizing AI. Lee asserts that the future capabilities of AI will drive such significant disruption within certain industries that their entire workforces from top to bottom will be substantially displaced. Lee predicts the grocery industry, for example, is highly susceptible to ground-up disruption as cashiers are replaced with computer vision, stockers are replaced with smart robots, and fewer store managers are required to lead the diminished workforce. Lee estimates an additional 10% job displacement due to ground-up industry disruption bringing his prediction to a total of 48% U.S. job loss due to AI-driven technologies within ten to twenty years. Lastly, while he does not provide a specific prediction, Lee argues that the rest of the world will exhibit potentially even higher rates of job displacement as AI technology will be largely controlled by Chinese and U.S. firms.

Lee concedes that entirely new occupations created by AI and governmental intervention will likely slow the rate of AI-driven job losses. Consequently, he asserts actual AI-induced net unemployment will be between 10-25% in the next ten to twenty years. Critical to Lee's assertion is that the 10-25% net unemployment could be persistent if not permanent and far worse outside of the "AI Elite", China, and the United States. His industry-based approach also challenges AI technologies as a skill-bias change. Lee's ground-up disruption dynamic produces a mixed bag of displacement winners and losers. Low-skill jobs requiring asocial, low dexterity, and structured environments are deemed high risk for displacement due to one-to-one replacement. However, traditionally high-skill industries such as finance, media, and healthcare are also identified as high risk for ground-up disruption. Lee's industry-based approach produces both skill-replacing and skill-bias outcomes that don't clearly benefit one specific skill level over another.

The strength of Lee's industry-based research is that it is heavily grounded in lived and directly observed experience rather than purely theoretical in nature. Lee has participated in the AI ecosystem at multiple levels, including as a scientist, entrepreneur, AI technology investor, and thought leader. This historical perspective and closeness to current AI developments provide significant credibility to his arguments. However, Lee's core concept of ground-up AI disruption must be able to stand up to scientific scrutiny to be considered a fully valid addition to AI employment theory. The ground-up disruption concept is clearly defined within his research so there is potential for follow-on studies building on this framework. To ultimately find an industry-based approach consensus, this approach must be scrutinized and empirically tested by the broader scientific community.

Summary

Compared to technological change employment theory, AI employment theory is still in its infancy with less than ten years of accumulated research to-date. Consequently, no scholarly consensus has been established on either a generally accepted theoretical approach or a projected employment impact and type of change. The different theoretical approaches within the literature produce diverse ranges of AI's employment impact from projections of 10-25% net unemployment to full employment. More consensus is beginning to develop regarding AI's impact on skills with the current majority of literature indicating a skill-bias change will occur that favors high-skill, higher-educated workers over low and middle-skill, less-educated workers. However, the minority skill-replacing change perspective from scholars such as Webb must still be considered due to the validity of their studies.

Holistically, AI employment theory literature has gaps in both methodology and application. Specifically, research design and methods rely heavily on subjective expert opinions or researcher assumptions based on established theory. Given the complexity and dynamic nature of AI, the reliability of these study's findings must be scrutinized over time. Additionally, the majority of these findings in each of the three approaches are applied at a macro-level such as global, regional or national labor markets. Consequently, the generalizability of the findings when applied at a reduced scale, local labor markets, is uncertain as local labor market often lack the occupational and industrial diversity of macro-level environments. Lastly, the majority of the studies do not publicly disclose the actual instruments utilized to develop the study's findings impeding both replicability of the methodologies and further research building on the studies.

CHAPTER THREE

METHODOLOGY

With the age of AI rapidly emerging, local labor market leaders are dependent on research to provide insights into the potential employment and skill level impact of this new technology. This section describes the data and methods utilized by this study to construct an exploratory model for local labor market leaders to assess their local labor market's exposure to AI-driven technologies. The area of analysis for this study is the San Diego County labor market which is comprised of more than 600 unique occupations. The period of analysis ranges from May 31, 2010, to May 31, 2019. This period of analysis was selected for two main reasons. First, consistent localized and occupational-level labor market data was unavailable from the Bureau of Labor Statistics (BLS) prior to 2010. Second, the Covid-19 pandemic began in February 2020 and led to drastic changes throughout global labor markets. As the BLS stated "The COVID-19 pandemic prompted an economic recession from February 2020 to April 2020, leading to substantial declines in output and employment. While the recession only lasted a few months, the pandemic persisted through 2021, continuing to disrupt economic activity, prevent or discourage individuals from re-entering the labor force, and impact other economic conditions that affect employment" (U.S. Bureau of Labor Statistics, 2022c, pg. 2). Consequently, labor market data from 2020 onward was excluded because it deviates significantly from the overall trend.

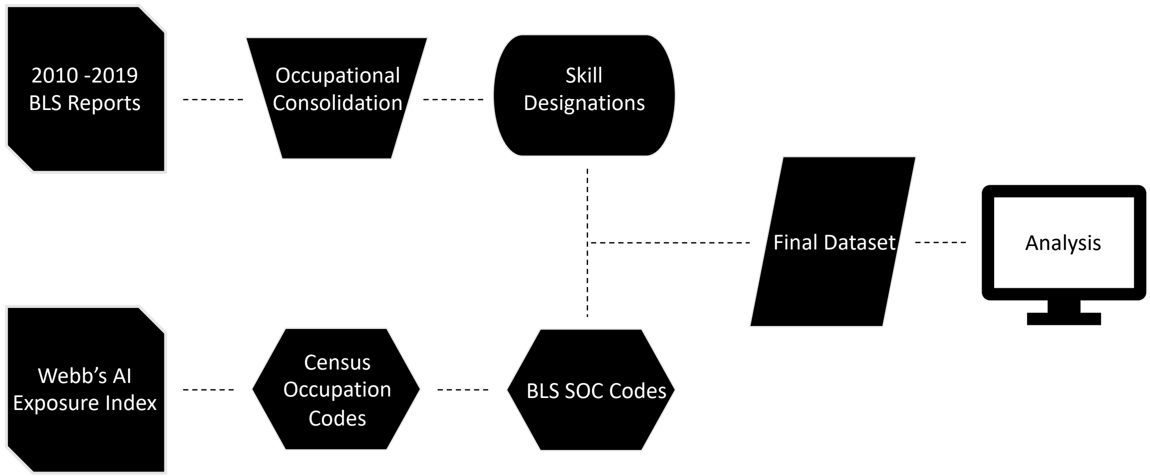
To assess San Diego County's potential susceptibility to known AI technologies, Webb's AI exposure index was applied to the San Diego County labor market by measuring changes in employment from 2010-2019 at an occupational level. Critical occupational level data including occupational codes and employment levels within San Diego County is measured annually through the BLS Metropolitan and Nonmetropolitan Area Occupation Employment and Wage

Estimates Report. To develop the final dataset for analysis, the BLS occupational data was associated to Webb's AI exposure index by leveraging a crosswalk utilizing Dorn's occupation system as well as census occupational codes. Lastly, occupations were further classified with skill designations utilizing workers' educational attainment levels in order to assess the potential skill-replacing or skill-bias employment changes.

A series of linear growth models were estimated to address the study's research questions. For research question #1, this study examines: To what extent, if any, is there an association between changes in San Diego County employment at an occupational level from 2010-2019 and Webb's AI Exposure Index scores? For research question #2, this study examines: To what extent, if any, is there an association between changes in San Diego County employment at an occupational skill designation level from 2010-2019 and Webb's AI Exposure Index scores? After detailed data cleaning procedures, the study's final dataset contains 352 occupations and 3,520 employment total observations over the period of analysis. The outcome variable is the occupational-level employment totals. Predictor variables for modeling include the years of analysis and categorized AI exposure index scores. The study also utilizes occupational-level skill designations and occupational groups as added interaction variables. Figure 1 provides an overview of this study's methodology.

Figure 1

Methodology Flow Chart



San Diego County Labor Market

According to the BLS, San Diego County is the 18th largest metropolitan labor market in the United States with total employment of 1,390,000 as of May 2021. The occupational breakdown of San Diego County's labor market is fairly representative of the broader U.S. national labor market with 16 of the 22 major occupational classifications employed within 1% of national employment averages. San Diego County's highest employed occupational classifications are office and administrative support, sales and food preparation and serving related occupations. It slightly exceeds national employment averages in management, architecture and engineer occupations as well as life, physical and social science occupations by between 1.0 - 1.3%. Production, office and administrative support, transportation and material moving occupations were recorded between 1.1-2.3% less than the national averages. Mean weekly wages within San Diego County in 2022 were measured at $1,484 which exceeds the national average of $1,374 (U.S. Bureau of Labor Statistics, 2022a). Unemployment in 2022 was also measured at 3.4% compared to the 3.8% national average. Overall, San Diego County has an occupationally diverse and balanced labor market with above average wages and employment levels. Table 1 displays San Diego County's labor market employment totals and percentages by occupational group and corresponding national employment percentages.

Table 1

San Diego County Occupational Group Breakdown (U.S. Bureau of Labor Statistics, 2022b)

OCC_CODE	OCCUPATION	SAN DIEGO - TOTAL EMPLOYMENT	PERCENTAGE OF SAN DIEGO EMPLOYMENT	PERCENTAGE OF NATIONAL EMPLOYMENT	DIFFERENCE
00-0000	All Occupations	1,390,410			
11-0000	Management Occupations	105,500	7.6%	6.3%	1.3%
13-0000	Business and Financial Operations Occupations	101,930	7.3%	6.4%	0.9%
15-0000	Computer and Mathematical Occupations	55,750	4.0%	3.3%	0.7%
17-0000	Architecture and Engineering Occupations	39,600	2.8%	1.7%	1.1%
19-0000	Life, Physical, and Social Science Occupations	25,900	1.9%	0.9%	1.0%
21-0000	Community and Social Service Occupations	24,110	1.7%	1.6%	0.1%
23-0000	Legal Occupations	12,290	0.9%	0.8%	0.0%
25-0000	Educational Instruction and Library Occupations	80,050	5.8%	5.8%	-0.1%
27-0000	Arts, Design, Entertainment, Sports, and Media Occupations	17,360	1.2%	1.3%	0.0%
29-0000	Healthcare Practitioners and Technical Occupations	78,970	5.7%	6.2%	-0.6%
31-0000	Healthcare Support Occupations	69,680	5.0%	4.7%	0.3%
33-0000	Protective Service Occupations	33,970	2.4%	2.4%	0.0%
35-0000	Food Preparation and Serving Related Occupations	118,300	8.5%	8.0%	0.6%
37-0000	Building and Grounds Cleaning and Maintenance Occupations	42,880	3.1%	2.9%	0.2%
39-0000	Personal Care and Service Occupations	29,600	2.1%	1.8%	0.3%
41-0000	Sales and Related Occupations	126,320	9.1%	9.4%	-0.3%
43-0000	Office and Administrative Support Occupations	162,010	11.7%	13.0%	-1.3%
45-0000	Farming, Fishing, and Forestry Occupations	3,040	0.2%	0.3%	-0.1%
47-0000	Construction and Extraction Occupations	61,890	4.5%	4.2%	0.3%
49-0000	Installation, Maintenance, and Repair Occupations	45,160	3.2%	4.0%	-0.7%
51-0000	Production Occupations	67,020	4.8%	6.0%	-1.1%
53-0000	Transportation and Material Moving Occupations	89,080	6.4%	9.0%	-2.6%

Primary Data Sources Overview

The first main dataset utilized to construct the proposed local labor market AI exposure model was the Metropolitan and Nonmetropolitan Area Occupation Employment and Wage Estimates Report. The BLS publishes the Metropolitan and Nonmetropolitan Area Occupation Employment and Wage Estimates Report annually based on employment and wage survey results from 131,000 U.S. businesses and governmental entities. In its most recent release covering June 2020 - May 2021, the report detailed employment and wage data for 682 occupations across 396 predefined local labor markets. Each occupation is also labeled with a six-digit code derived from the BLS' standard occupational classification (SOC) system. The first two SOC numbers correlate directly to broader “major” occupational group classifications while the last four SOC numbers provide unique occupation designations. For example, the occupation titled “Chief Executives” is labeled with the occupational code 11-1011 which represents it as part of the 11-0000 series of occupations associated with the master classification of “Management Occupations”. This occupational coding system helps facilitate multi-level analysis of the occupational data. This annual report is widely considered highly valid and reliable due to its large survey sample size and the historical accuracy of its findings. Therefore, it provides an outstanding foundation to analyze changes in occupational data over time.

The second primary dataset leveraged for this study is Webb’s AI Exposure Index. Webb’s instrument associates 341 occupations with corresponding AI exposure scores that range from the highest exposure score of 100 to the lowest score of 1 based on patent-level analysis (Appendix A). For example, the occupation title “Construction laborer” measured 48 on Webb’s index indicating moderate exposure to known AI technological applications. Some occupations that measured at the highest exposure score (100) include power plant operators, chemical engineers, and optometrists while funeral directors, food preparation workers, and animal caretakers were among the occupations with the lowest score (1) indicating very minimal susceptibility to known AI technologies. Webb utilizes a modified version of the census occupational coding system, “occ1990dd”, to associate his index scores to occupations. This “occ1990dd” coding was developed by Dorn (2009) to facilitate extended time period analysis of census occupational data.

Occupational Data Crosswalk Process

Occupations and, correspondingly, occupational coding systems change over time as new occupations emerge and non-active occupations diminish within labor markets. This perpetual change creates challenges for researchers seeking to accurately measure the effects of variables on employment over extended time periods. The bicentennial U.S. census was the first instrument utilized to collect consistent occupational-level data that could be aggregated for empirical studies. However, the census occupational coding system changed drastically from 1950-2000 as the number of census occupations ultimately increased from 287 to 543 (Meyer & Osbourne, 2005). In order to assist researchers, unified occupational classification systems were built, most recently by Dorn, using task-level analysis of occupations. Dorn's "occ1990dd" occupation system details 330 occupational classifications that unify the census occupational coding system from 1980 to 2000 with an additional crosswalk to 2010. Correspondingly, Webb associates his AI Exposure Index scores to occupations through Dorn's system.

In order to ultimately apply Webb's Index to the BLS Metropolitan and Nonmetropolitan Area Occupation Employment and Wage Estimates Report, multiple occupational system crosswalks were conducted from Dorn's system to the BLS' SOC system. First, Dorn's occupation system was matched to the census occupational system using the occ1990dd to 2010 census crosswalk (Autor, 2015). Then, the 2010 census occupational system coding was associated with the 2010 BLS SOC coding through the census' 2010 SOC crosswalk (U.S. Census Bureau, 2011). The 2010 BLS SOC coding provided the foundation for the BLS occupational data until 2018 when a major revision of BLS SOC codes required an additional crosswalk to match SOC codes covered in reporting since 2018 (U.S. Census Bureau, 2019). Ultimately, this crosswalk process matched a total of 482 SOC-coded occupations with associated AI Exposure Index scores.

BLS Occupational Data Consolidation

Before the study's model could be constructed based off the crosswalks, three data procedures were required to prepare the BLS occupational data from the BLS Metropolitan and Nonmetropolitan Area Occupation Employment and Wage Estimates Reports for analysis. The first procedure entailed the consolidation of BLS occupations from 2010-2019 into a uniform set of occupations that could be measured through the entire period of analysis. Similar to the census, the BLS combines, adds and removes occupations frequently from its SOC coding system. Consequently, a multi-year consolidation of BLS occupations from 2010-2019 was required in order to develop a uniform dataset to examine during this nine-year period. Starting with the 2010 BLS report, all reports were exported into excel and occupations were matched each year going forward, first by SOC code then by occupational title through a manual matching process. Unmatched occupations were removed from the dataset and not considered for analysis. Overall, a conservative approach was taken throughout this matching process and occupations without perfect code or job title matches were removed from the dataset.

Ultimately, 680 total reported occupations in 2010 were reduced to 492 through 2019. Then, a second data procedure was conducted to verify that all required employment data was recorded for the occupations. After this step, it was discovered that 118 occupations lacked the required employment data for at least one year. Consequently, these occupations were also removed from the dataset. Lastly, the remaining 374 occupations were matched to the crosswalked AI Exposure Index and 22 were removed due to no match being found. Ultimately, this occupational data consolidation procedure resulted in a final dataset 352 occupations that met all the criteria for examination (Appendix B). In total, 328 occupations were removed from the original 2010 BLS report (Appendix C). Table 2 displays the total occupations removed from the final dataset during each phase of the consolidation procedure.

Table 2

Occupations Removed by Data Consolidation & Cleaning Procedures

Data Source	No Occupational Match Found	No Occupational Data Recorded
2010-2019 BLS Reports	188	118
Webb's AI Exposure Index	22	

Occupational Skill Designations

With the skill-level impact of AI providing potential indications of its skill-replacing or skill-bias technological change, this study applies an occupational skill designation to all 352 occupations examined in the final dataset. For analysis purposes, the designation is binary with high skill distinguished from non-high skill occupations utilizing the average education level of the occupation's workers as the basis. The minimum education levels of workers for all examined occupations were obtained from the 2022 BLS Educational Attainment Report (U.S. Bureau of Labor Statistics, 2022d). A minimum of a bachelor's degree is commonly associated with high skill occupations which often require the execution of complex skills such as problem solving, analytical skills, human judgement or other cognitive soft skills (Holzer & Lerman, 2007; Acemoglu & Restrepo, 2018). Utilizing this BLS report, occupations with greater than 50% of their workforce attaining at least a bachelor's degree were designated as high skill occupations with all other occupations labelled non-high skill. This designation process produced 129 high skill and 223 non-high skill occupations.

Longitudinal Data Analysis - Linear Growth Curve Models

Singer and Willet (2003) identified three required features of any longitudinal study of change: multiple waves of data, a meaningful metric for time and an outcome that changes systematically. The study's final dataset which includes a consolidated list of 352 occupations with annual employment levels for each occupation from 2010-2019 as well as occupational-level AI exposure index scores and skill designations meets all of these requirements. Therefore, a growth modeling analysis approach was selected to model this longitudinal data to address the study's research questions (Bruin, 2006). More specifically, the study constructed multi-level linear growth curve models to assess the change in employment totals over time. Linear growth curve models are the appropriate analysis strategy for this longitudinal dataset because time can be included as a continuous variable predictor. The study's linear growth curve models are derived from the equation (1) below:

$$Y_{ij} = [g_{00} + g_{10} Year_{ij} + g_{01}\, AI\ Exposure_i + g_{11}\, (AI\ Exposure_i \times Year_{ij})] + [z_{0i} + z_{1i} Year_{ij} + e_{ij}] \quad (1)$$

Where:

Y_{ij} = *employment level for occupation i at year j*

g_{00} = *population average employment level in year 0 with AI Exposure 0*

g_{10} = *population average rate of employment level change over time*

g_{01} = *effect of AI Exposure$_i$ on the population average employment level in year 0*

g_{11} = *effect of AI Exposure$_i$ on the population average rate of employment level change over time*

$[z_{0i} + z_{1i} Year_{ij} + e_{ij}]$ = *difference between the observed and expected employment level for occupation i at year j*

To examine the first research question, the primary model's outcome variable is the occupational-level employment totals and the predictor variables are Year and the AI Exposure Index scores. For this analysis, the AI Exposure Index scores are clustered into four categories based on score quartiles with Category 1 containing the lowest level scores and Category 4 containing the highest. These categories help facilitate the measurement of the predicted net employment impact of AI at the occupational level. To examine the second research question, the secondary model adds a covariate for high-skill and non-high-skill designations as interaction variables. The designation segments facilitate the measurement of the predicted type of technological change occurring at the occupational level, skill-replacing or skill-bias. Table 3 outlines the core components of the primary and secondary linear growth curve models.

Table 3

Primary and Secondary Linear Growth Curve Models

Model	Research Question	Outcome Variable	Predictor	Predictor	Interaction	Why?
Primary	*To what extent, if any, is there an association between changes in San Diego County employment at an occupational level from 2010-2019 and Webb's AI Exposure Index scores?*	Employment totals from 2010-2019 at occupational level	Time	AI Exposure Index scores	N/A	Measure net employment impact of AI
Secondary	*To what extent, if any, is there an association between changes in San Diego County employment at an occupational skill designation level from 2010-2019 and Webb's AI Exposure Index scores?*	Employment totals from 2010-2019 at occupational level	Time	AI Exposure Index scores	Skill Designation	Measure type of tech change occurring (skill-replacing/skill-bias)

In accordance with the overall purpose of the study, additional models were also estimated at the occupational group level in order to enhance the practical applicability of the analysis for local labor market leaders. While San Diego County has a relatively balanced labor market, as detailed in Table 1, other local labor markets could be dominated by specific occupational groups. For example, the production occupational group would have higher employment totals in manufacturing focused labor markets. The office and administrative support occupational group would be over-represented in areas with the presence of large corporate headquarters. Therefore, it is critical for local labor leaders to understand whether Webb's AI exposure index has predictive capabilities when applied to these occupational groups. Consequently, each of the 352 occupations within the final dataset were assigned to one of the 22 BLS designated occupational groups that correspond to occupations conducting similar work tasks.

CHAPTER FOUR

FINDINGS

This section will report on the results of the study's quantitative analysis. All analysis within this section was conducted utilizing the Stata/BE version 17.0 statistical software. The section begins by providing descriptive statistics for all variables relevant for the primary and secondary linear growth curve models. Then, the results of the primary and secondary models are displayed utilizing both tables and figures to document and visualize the employment changes. A supplementary model focused on occupational groups follows the primary and secondary models in order to provide local labor market leaders with a deeper understanding of potential employment changes due to AI exposure when occupations are clustered. Finally, the supplementary model findings drove an exploratory model which explores Webb's AI exposure index's predictive capability on a single occupational group of interest. In the end, five separate linear growth curve models were estimated. The intent of this section and its analysis is to fully leverage the final dataset and selected methodology to address the study's purpose and research questions.

Descriptive Statistics

Before analyzing the model outputs, it is essential to describe the basic features of the key variables in the final dataset. The primary variables utilized for the growth curve models are: Total Employment and AI Exposure Index Score. These variables are further classified into AI Category's 1-4 as well as High-Skill and Non-High-Skill designations. Once again, the AI categories represent the quartiles of Webb's AI exposure index scores. The skill designations represent whether or not over 50% of the workforce within an occupation obtained at least a bachelor's degree. Table 4 displays the characteristics of these key variables.

Table 4

Descriptive Statistics of Key Variables

VARIABLES	N	mean	sd	min	max
Total Employment (All)	3,520	2,738	4,676	30	42,820
AI Category 1 Total Employment	830	3,833	6,705	30	42,820
AI Category 2 Total Employment	920	2,873	4,794	50	40,850
AI Categoiry 3 Total Employment	880	2,737	3,970	40	23,620
AI Category 4 Total Employment	890	1,578	1,667	40	8,590
High-Skill Total Employment	1,290	1,660	2,055	30	12,090
Non-High-Skill Total Employment	2,230	3,361	5,569	40	42,820
AI Exposure Index Score (All)	3,520	49.64	30.94	1	100
AI Category 1 Exposure Index Score	830	9.06	7.59	1	21
AI Category 2 Exposure Index Score	920	33.86	7.87	23	47
AI Category 3 Exposure Index Score	880	65.22	9.72	48	80
AI Category 4 Exposure Index Score	890	88.39	6.21	81	100
High-Skill AI Exposure Index Score	1,290	55.19	32.24	1	100
Non-High-Skill AI Exposure Index Score	2,230	46.43	29.69	1	100

The descriptive statistics show the longitudinal data analysis approach produces 3,520 observations within the dataset for the consolidated Total Employment and AI Exposure Index Score variables. This is the result of 352 occupations with 10 data points for each year from 2010-2019. It is important to note that the data points for the Total Employment variable are dynamic meaning that the employment levels can change each year during the period of analysis. However, the AI Exposure Index Score variable is static for each occupation throughout the period of analysis. The AI categories descriptive statistics show that the occupational-level observations are fairly balanced throughout the four categories with a range of 830-920. AI Category 2 which comprises occupations with AI exposure index scores between 23-47 has the largest number of observations ($N = 920$) and AI Category 1 with AI exposure index scores of 21 and below have the lowest number ($N = 830$). While the minimum levels for the Total Employment variable stay fairly consistent across categories, the maximum levels vary significantly from 8,590-40,850. The Non-High-Skill designation ($N = 2,230$) has significantly more observations than the High-Skill designation ($N = 1,290$). However, both designations contain occupations with a full range of AI exposure index scores ranging from 1-100. Non-High-Skill occupations (*Max = 42,820*) also contain occupations with higher employment levels than High-Skill (*Max = 12,090*). It is important to note that the mean AI exposure index score for High Skill occupations (*Mean = 55.19*) is closely comparable to Non-High Skill (*Mean = 46.43*) indicating relatively balanced AI exposure between High-Skill and Non-High-Skill occupations.

Figure 2

Histogram of Total Employment 2010-2019

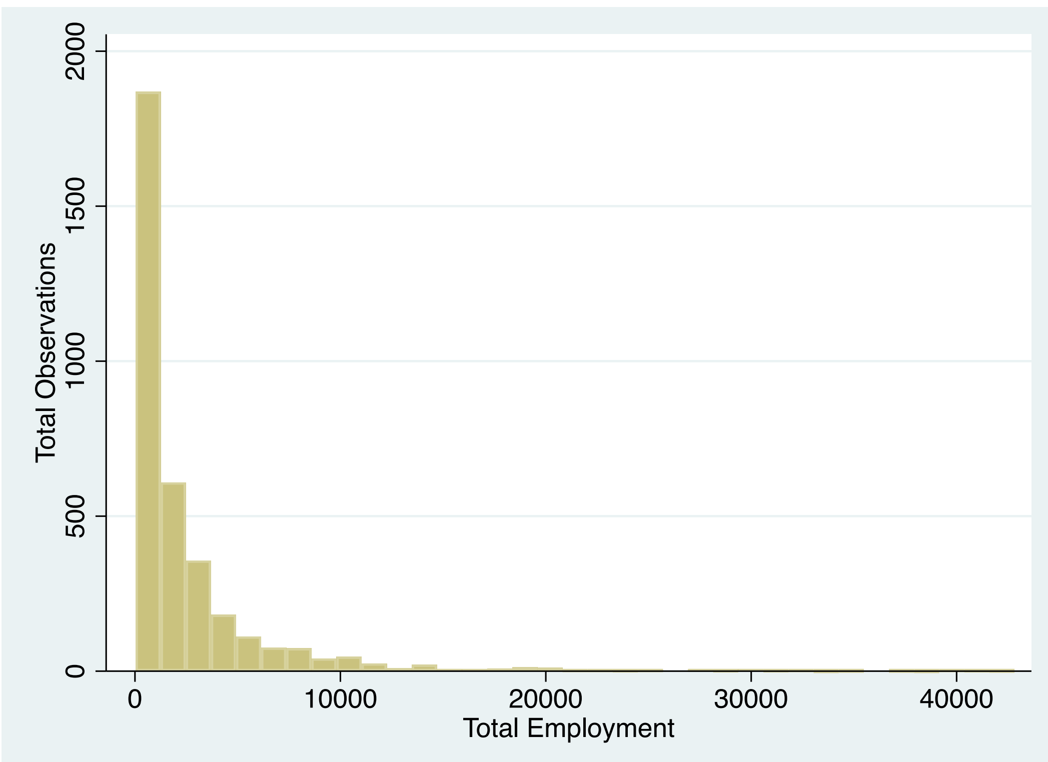


Figure 2 shows the distribution of the consolidated Total Employment variable representing all 3,520 observations from 2010-2019. The histogram has a heavy right skewed distribution with limited outliers above 15,000. The distribution is unique in that the majority of the observations have employment totals within the first bin of the histogram. This corresponds to the median (*Median = 1,110*) for the consolidated Employment Total variable in Table 4.

Figure 3

Histogram of AI Exposure Index Score

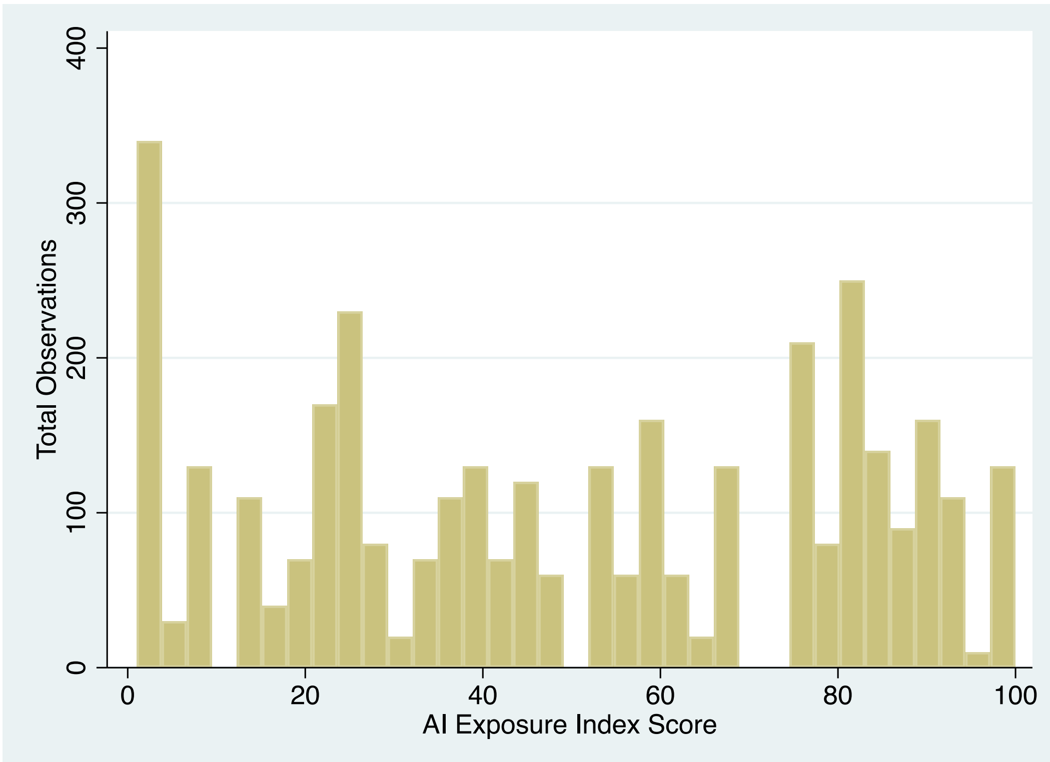


Figure 3 shows that the consolidated AI Exposure Index Score variable has a unimodal distribution with the highest peak at the beginning of the range and lesser peaks between scores of 20-40 and 80-100. The distribution is fairly balanced with no apparent outliers.

Primary Model

A linear growth curve model was constructed with the outcome variable of Total Employment from 2010-2019 for each occupation and the predictor variables of Year and AI Exposure Index Score. For analysis, AI Exposure Index Score was segmented into four exposure level categories as previously noted. Table 5 displays the primary growth curve model output.

Table 5

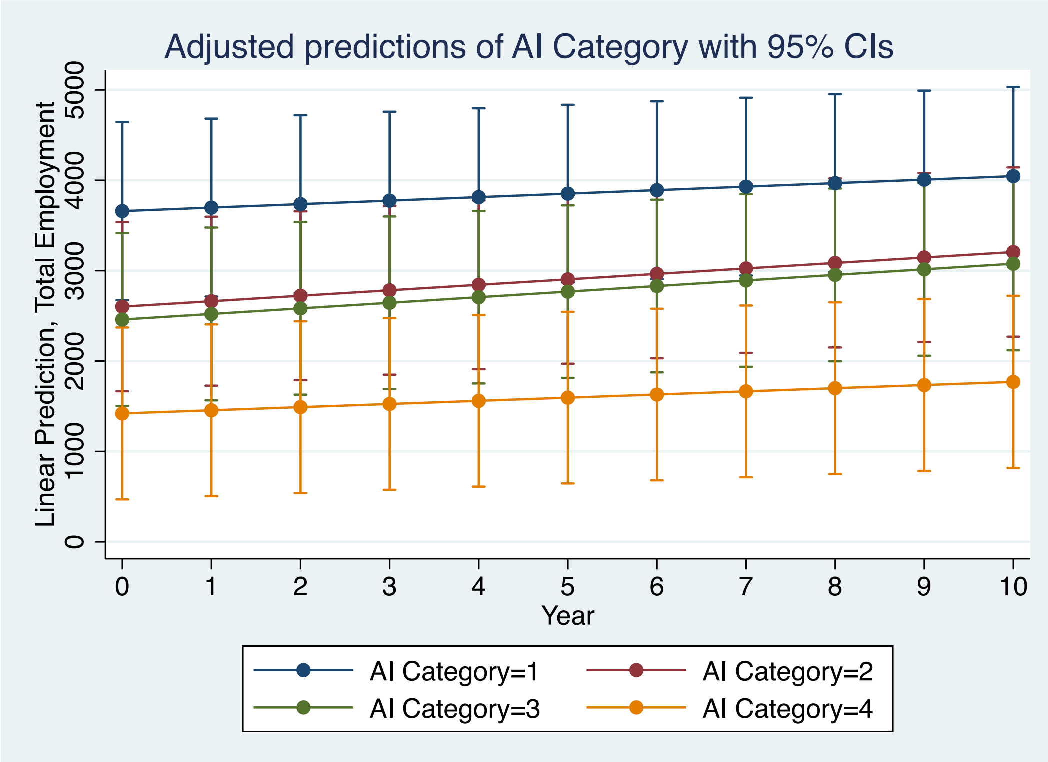
Primary Growth Curve Model Output

VARIABLES	Total Employment
AI Category 2	-1057
	(693.1)
	-2,416 - 301.2
AI Category 3	-1,199
	(700.6)
	-2,573 - 173.6
AI Category 4	-2,239***
	(698.6)
	-3,608 - -869.4
Year	38.67***
	(7.37)
	24.23 - 53.12
AI Category 1:Year	0
	(0)
	0 - 0
AI Category 2:Year	21.76**
	(10.16)
	1.837 - 41.68
AI Category 3:Year	23.04**
	(10.27)
	2.909 - 43.18
AI Category 4:Year	-3.773
	(10.24)
	-23.85 - 16.31
Constant	3,659***
	(502.6)
	2,674 - 4,644
Observations	3520
Number of groups	352
Prob > chi2	0.0000
*** p<0.01, ** p<0.05	

Figure 4 displays the primary model predicted growth curves with 95% confidence intervals from 2010-2019.

Figure 4

Primary Model Predicted Growth Curves 2010-2019



The primary model contains 3,520 observations across 352 occupations. The model output shows the model is statistically significant ($p < .00$). However, the significance of intercept and slope coefficients vary across the model's output. Statistical significance ($p < .05$) was found in five coefficients with three coefficients not meeting this threshold. AI Category 1 was the only category that had significance in both its intercept and slope coefficients. AI Category 4 is the only category with a slope coefficient that did not meet statistical significance. The highest significant slope coefficient s AI Category 3 (23.04) and all other significant slope coefficients demonstrated positive measurements indicating increasing levels of employment over the period of analysis. Correspondingly, the highest significant intercept coefficient is AI Category 1 (3,659) with AI Category 4 (-2,239) representing the lowest significant intercept output. The confidence intervals of the model's growth curves are broad and overlap consistently across the period of analysis (Figure 5).

Secondary Models

Two linear growth curve models were constructed by segmenting the dataset in the primary model by occupational-level high-skill and non-high-skill designations. Table 6 shows the model outputs for both high-skill and non-high-skill occupations for the period of analysis.

Table 6

Secondary Growth Curve Models Outputs

VARIABLES	High-Skill Total Employment	Non-High-Skill Total Employment
AI Category 2	1,141**	-2,248**
	(560.6)	(964)
	42.72 - 2,240	-4,138 - -358.7
AI Category 3	1,116**	-2,155**
	(494)	(1041)
	148.2 - 2,085	-4,195 - -115.3
AI Category 4	784.6	-3,717***
	(479.3)	(1070)
	-154.7 - 1,724	-5,814 - -1,620
Year	5.017	54.90***
	(9.138)	(10.15)
	-12.89 - 22.93	35.00 - 74.80
AI Category 1:Year	0	0
	0	0
	0 - 0	0 - 0
AI Category 2:Year	42.05***	9.73
	(13.64)	(13.62)
	15.32 - 68.78	-16.97 - 36.43
AI Category 3:Year	60.02***	4.405
	(12.02)	(14.71)
	36.47 - 83.58	-24.42 - 33.23
AI Category 4:Year	46.99***	-35.99**
	(11.66)	(15.12)
	24.14 - 69.84	-65.62 - -6.353
Constant	681.8	5,095***
	(375.6)	(718.5)
	-54.45 - 1,418	3,686 - 6,503
Observations	1290	2230
Number of groups	129	223
Prob > chi2	0.0000	0.0000
*** p<0.01, ** p<0.05		

Figure 5 displays the secondary model predicted growth curves for high-skill occupations with 95% confidence intervals from 2010-2019.

Figure 5

Secondary Model Predicted Growth Curves For High-Skill Occupations 2010-2019

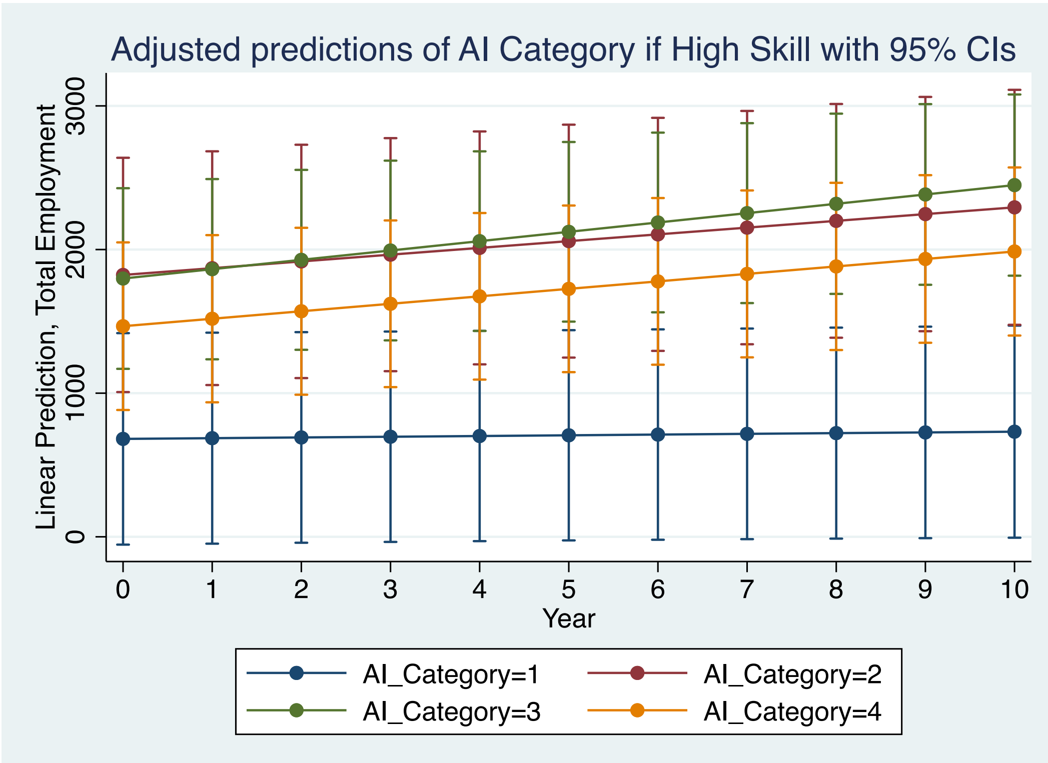
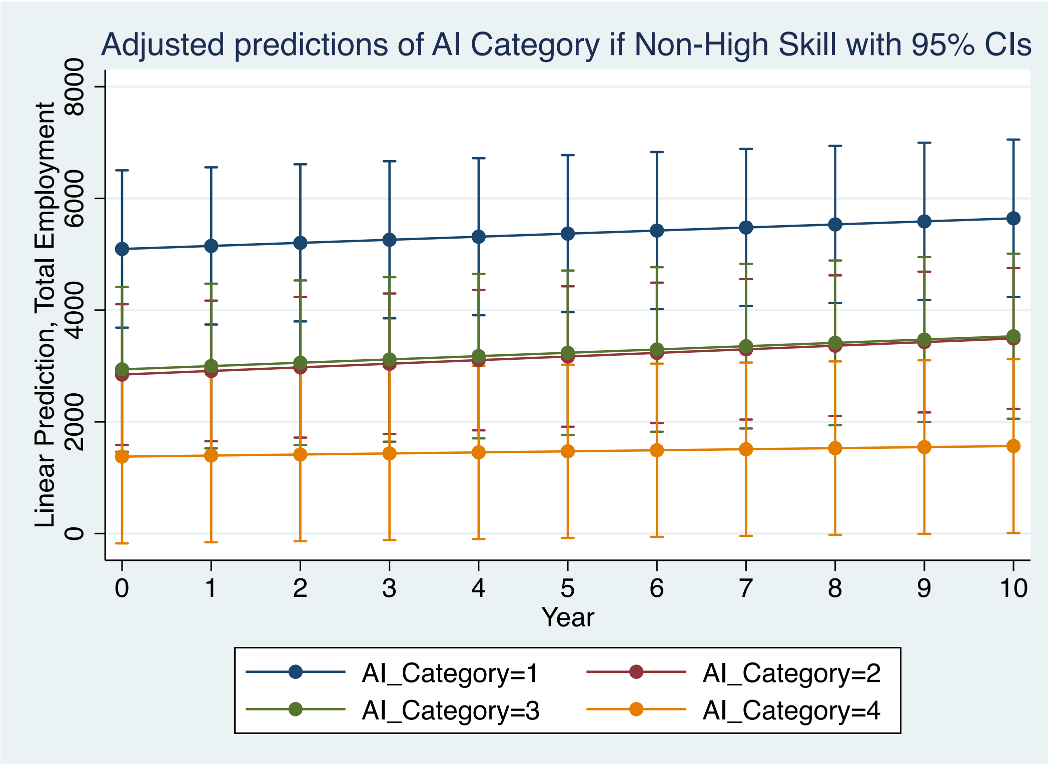


Figure 6 displays the secondary model predicted growth curves for non-high-skill occupations with 95% confidence intervals from 2010-2019.

Figure 6

Secondary Model Predicted Growth Curves For Non-High-Skill Occupations 2010-2019



Both secondary linear growth curve models were significant (*p* < *.00*). The high-skill and non-high-skill models analyzed 1,290 and 2,230 observations respectively. For the high-skill model, five coefficients demonstrated statistical significance with AI Category 1 the only slope coefficient not meeting the significance threshold, and the AI Category 1 and AI Category 4 intercept coefficients also not meeting the threshold. AI Category 2 (1,141) had the highest significant intercept and AI Category 3 (60.02) recorded the highest significant slope value. Once again, all significant slope coefficients had positive values indicating predicted employment growth over the period of analysis for high-skill occupations in AI Categories 2-4. For the non-high-skill model, six coefficients were significant including all the intercept values while the AI Category 2 and AI Category 3 slope coefficients lacked significance. AI Category 1 had the highest significant intercept coefficient (5,095) and slope coefficient (54.90). Correspondingly, AI Category 4 represented the lowest significant intercept (-3,717) and slope coefficient (-35.99) values. While both slope coefficients indicate employment growth during the period of analysis, the higher exposed non-high-skill occupations in AI Category 4 showed lower growth rates than the least exposed non-high-skill occupations in AI Category 1. Similar to the primary model, the secondary models' predicted growth curve confidence intervals are broad and overlap consistently throughout the period of analysis for both high-skill and non-high-skill occupations (Figure 5; Figure 6).

Supplemental Model: Highest AI Exposure Occupations by Occupational Group

The purpose of this study is to understand the potential impact of AI at a local labor market level, San Diego County. In order to measure the potential impact of AI on San Diego County more broadly, an additional linear growth curve model was constructed leveraging the SOC system occupational groups instead of individual occupations. Total Employment remained the outcome variable for this analysis and the model examined only the occupational groups with occupations associated with AI Category 4, the highest quartile AI exposure index scores. Once again, the period of analysis remained from 2010-2019. Table 7 shows the occupational group model outputs.

Table 7

Occupational Groups Growth Curve Model Outputs

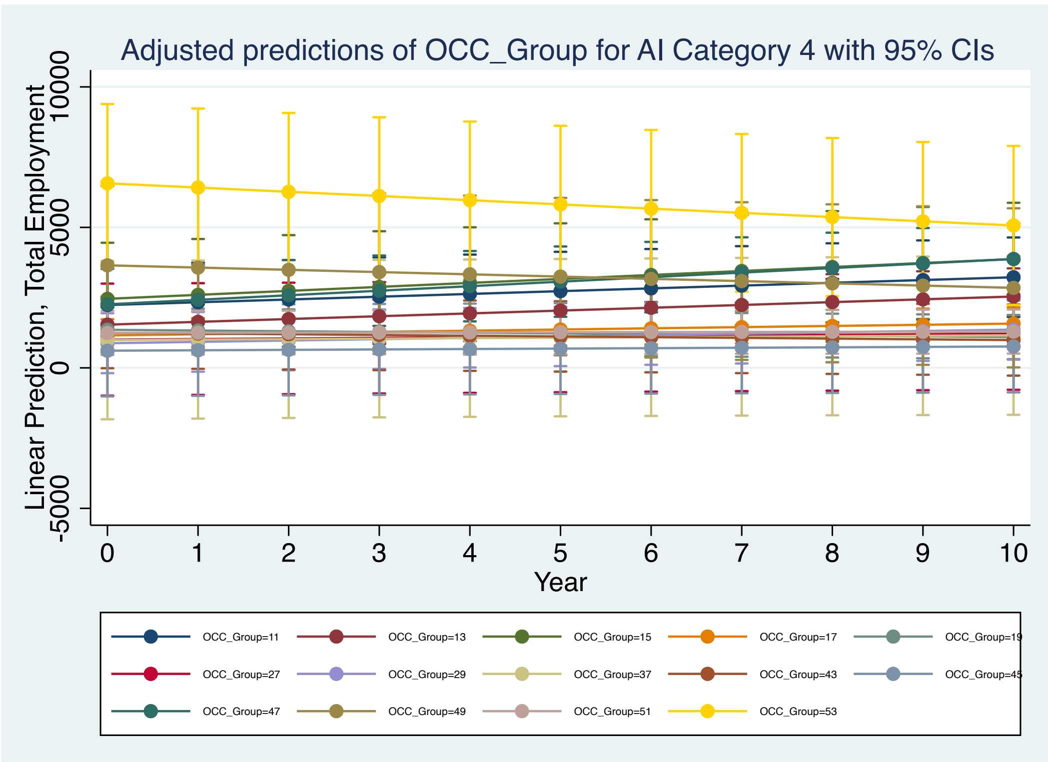
VARIABLES	Total Employment AI Category 4
Occupation Group 13	-698.4
	(881.2)
	-2,426 - 1,029
Occupation Group 15	220.7
	(1246)
	-2,222 - 2,663
Occupation Group 17	-1081
	(777.2)
	-2,605 - 441.9
Occupation Group 19	-880.9
	(822.8)
	-2,494 - 731.8
Occupation Group 27	-1232
	(1246)
	-3,675 - 1,210
Occupation Group 29	-1359
	(902)
	-3,127 - 408.8
Occupation Group 37	-1247
	(1609)
	-4,401 - 1,906
Occupation Group 43	-987.7
	(965.3)
	-2,880 - 904.3
Occupation Group 45	-1625
	(1099)
	-3,779 - 529.4
Occupation Group 47	24.18
	(965.3)
	-1,868 - 1,916
Occupation Group 49	1414
	(1609)
	-1,740 - 4,567
Occupation Group 51	-990.2
	(822.8)
	-2,603 - 622.4
Occupation Group 53	4,331***
	(1609)
	1,178 - 7,484
Year	98.85***
	-19.74
	60.16 - 137.5
Occupation Group 11:Year	0
	(0)
	0 - 0
Occupation Group 13:Year	1.318
	(24.18)
	-46.07 - 48.71
Occupation Group 15:Year	42.73
	(34.19)
	-24.29 - 109.7
Occupation Group 17:Year	-56.75***
	(21.32)
	-98.54 - -14.96
Occupation Group 19:Year	-124.8***
	(22.58)
	-169.0 - -80.53
Occupation Group 27:Year	-77.18**
	(34.19)
	-144.2 - -10.16
Occupation Group 29:Year	-50.44**
	(24.75)
	-98.94 - -1.938
Occupation Group 37:Year	-81.94
	(44.14)
	-168.5 - 4.579
Occupation Group 43:Year	-124.7***
	(26.49)
	-176.7 - -72.83
Occupation Group 45:Year	-83.90***
	(30.16)
	-143.0 - -24.80
Occupation Group 47:Year	62.72**
	(26.49)
	10.80 - 114.6
Occupation Group 49:Year	-179.0***
	(44.14)
	-265.5 - -92.51
Occupation Group 51:Year	-94.17***
	(22.58)
	-138.4 - -49.93
Occupation Group 53:Year	-248.9***
	(44.14)
	-335.4 - -162.4
Constant	2,236***
	(719.5)
	826.0 - 3,646
Observations	890
Number of groups	89
Prob > chi2	0.0000

*** p<0.01, ** p<0.05

Figure 7 displays the occupational groups model predicted growth curves for AI Category 4 occupations from 2010-2019.

Figure 7

Occupational Groups Model Predicted Growth Curves For AI Category 4 Occupations 2010-2019



From the twenty-two total occupational groups, fourteen groups had occupations in AI Category 4 and therefore were included in this analysis. Holistically, the model analyzed 890 observations representing roughly 25% of the study's total observations, and was significant ($p < .00$). While only two intercept coefficients were significant, eleven slope coefficients met the significance threshold. Occupational Group 53 (Transportation and Material Moving Occupations) and Occupational Group 11 (Farming, Fishing and Forestry Occupations) represented the highest (4,331) and lowest (2,236) intercept coefficient values respectively. With regard to slope coefficients, Occupational Group 11 (Management Occupations) had the highest

(98.85) significant value and Occupational Group 53 measured the lowest (-248.9) significant value. The output for Occupational Group 53 demonstrates a predicted overall decrease in employment during the period of analysis for AI Category 4 occupations within the group. Similar to the primary and secondary models, the occupational groups model has predicted growth curve confidence intervals that overlap consistently. Additionally, it is critical to note that the confidence intervals for some occupational groups range below zero total employment which would not be a valid employment measurement.

Exploratory Model: Transportation and Material Moving Occupational Group (Occupational Group 53)

Based on the supplemental analysis model, an exploratory linear growth curve model was constructed for Occupational Group 53 due to its substantial negative slope coefficient (-248.9) indicating potential predicted job loss for these occupations within AI Category 4. This exploratory model expanded the supplementary model by including all occupations within Occupational Group 53 in each AI category for analysis. The purpose of the model is to further understand the potential net employment impact of AI on all transportation and material moving occupations in San Diego County. Total Employment continued to be the outcome variable with Year and the categorized AI Exposure Index Score utilized as the predictors. Table 8 shows the model outputs for the transportation and material moving occupational group.

Table 8

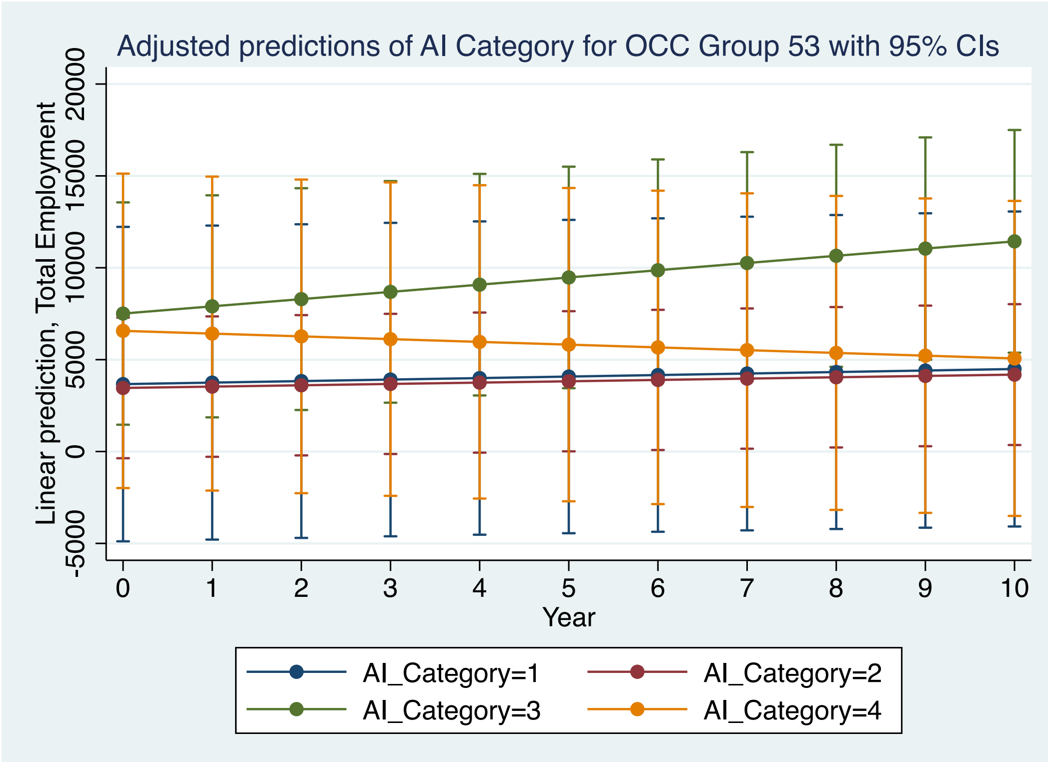
Occupational Group 53 Exploratory Growth Curve Model Outputs

VARIABLES	Trans. & Material Moving Occupations Total Employment
AI Category 2	-208.1
	(4782)
	-9,580 - 9,164
AI Category 3	3840
	(5346)
	-6,639 - 14,319
AI Category 4	2898
	(6173)
	-9,201 - 14,998
Year	82.24
	(81.86)
	-78.19 - 242.7
AI Category 1:Year	0
	(0)
	0 - 0
AI Category 2:Year	-9.673
	(89.67)
	-185.4 - 166.1
AI Category 3:Year	310.7***
	(100.3)
	114.2 - 507.2
AI Category 4:Year	-232.3**
	(115.8)
	-459.2 - -5.414
Constant	3669
	(4365)
	-4,887 - 12,225
Observations	90
Number of groups	9
Prob > chi2	0.0000
*** p<0.01, ** p<0.05	

Figure 8 displays the Occupational Group 53 exploratory model predicted growth curves from 2010-2019.

Figure 8

Occupational Group 53 Model Predicted Growth Curves 2010-2019



This model analyzed 90 observations for the 9 occupations comprising Occupational Group 53, representing roughly 3% of total occupations. Overall, the model was significant (*p* < *.00*). However, only two coefficients were measured as significant, the slope coefficients for AI Category 3 (310.7) and AI Category 4 (-232.3). Building on the supplementary analysis, the significant slope coefficients not only reinforce the potential predicted employment loss in AI Category 4 occupations within this group during the period of analysis but also show predicted employment growth outside of AI Category 4. Consequently, it is less likely that AI exposure is associated with consistent employment loss throughout all 9 occupations within Occupational Group 53. The confidence intervals of the exploratory model show the most extreme overlap in comparison to the previous models which is driven by the consistently high standard error levels found in the model output (Figure 8).

In summary, five total linear growth curve models were constructed and executed for the primary, secondary, supplementary and exploratory areas of analysis. All models were found to be statistically significant but coefficient significance varied extensively between the models with the primary and secondary models containing the highest proportion of significant coefficients. A commonality among all the models was substantial standard errors across the model coefficients which was visually apparent in the predicted linear growth curves confidence intervals. Overall, the models provide a broad perspective on the final dataset by analyzing all occupations, a majority of occupational groups and finally a deeper dive into a single occupational group.

CHAPTER FIVE

DISCUSSION OF FINDINGS AND CONCLUSIONS

This final section will focus on connecting the study's purpose, research questions and exploratory methodology to the findings of the longitudinal data analysis as well as fitting those findings within the established AI employment literature. The section will begin with the interpretation of the results of the primary and secondary models in relation to the study's research questions. Additional interpretation will also be conducted to associate the study's findings with the relevant literature. Then, the supplementary and exploratory models will be interpreted to further support the overall purpose of the study and its implications for San Diego County's local labor market leaders. This section will then summarize the limitations of the study and all procedures utilized to mitigate the limitations. Lastly, this section will discuss recommendations for future research.

Research Question #1: To what extent, if any, is there an association between changes in San Diego County employment at an occupational level from 2010-2019 and Webb's AI Exposure Index scores?

The primary model produced an overall positive net employment impact throughout the AI Categories with significance during the period of analysis. As AI exposure levels grew, predicted employment levels also grew as indicated by the most exposed occupations, AI Category 3, recording the highest significant slope coefficient (23.04). Consequently, it can be asserted from the primary model output that Webb's AI exposure index is currently positively associated with predicted employment growth. It is crucial to also note the high standard errors of the model coefficients which produced wide and overlapping confidence intervals for the employment growth curves (Figure 4). For example, the slope coefficients for AI Category 2

(21.76) and AI Category 3 (23.04) are relatively similar and both have wide confidence intervals, AI Category 2 (1.837 - 41.68) and AI Category 3 (2.909 - 43.18), due to high standard errors. With such a large range of potential outputs, future measurements utilizing the primary model could produce varied or opposing findings. Consequently, the study's level of conviction in the model's findings for this period of analysis is relatively low.

The primary model's finding of a positive net employment impact during the period of analysis aligns with the established technological change employment theory as well as several studies within AI employment theory. Specifically, the finding directionally aligns with McKinsey's (2018) prediction that positive net employment impact could occur by 2030 from AI and similar automation technologies. Nedelkoska & Quintini (2018) and Muro, Maxim & Whiton (2019) also assert the potential for AI to be a job creator instead of job destroyer. However, this finding currently conflicts with Webb's prediction that there will be a positive association between the AI exposure index scores and employment loss. It is critical to note that Webb based his prediction on a thirty-year period of analysis which is significantly longer than the scope of this study. Given the current differences in the periods of analysis between the studies and the elevated standard errors within the primary model, it is precipitous to make any definitive assertion against Webb's prediction at this time.

Research Question #2: To what extent, if any, is there an association between changes in San Diego County employment at an occupational skill designation level from 2010-2019 and Webb's AI Exposure Index scores?

This study's second research question explores the potential type of technological change that is occurring in San Diego County due to AI. Both secondary models utilize the interaction variable Skill Designation to segment the data into 129 high-skill occupations and 223 non-high-skill occupations. For high-skill occupations, an examination of the secondary model output and growth curves provides early indications of potential skill-bias change occurring with high-skill occupations in each AI category demonstrating predicted employment growth and the most exposed occupations in AI Category 3 and AI Category 4 recording the strongest positive slope coefficients at significant levels. Consequently, it can be asserted that AI exposure is currently positively associated with high-skill employment. In contrast, the non-high-skill occupations' model output shows a large negative difference at a significant level between the most exposed occupations, AI Category 4, and the least exposed occupations, AI Category 1. While AI Category 4's growth curve is still minimally positive, this finding could be a potential early indication that AI exposure is negatively associated with employment growth for non-high-skill occupations.

Overall, the findings in the secondary models provide initial support for a skill-bias technological change occurring within San Diego County due to AI. Although the critical coefficients for this assessment were statistically significant, it is vital to consider the standard errors throughout the models when assessing the findings. As the growth curves (Figure 5; Figure 6) show, there is substantial overlap within the confidence intervals among most of the AI categories. For the high-skill model, AI Category 2 and AI Category 4 have similar slope coefficients, 42.05 and 46.99 respectively, with fairly similar confidence intervals, AI Category 2 (15.32 - 68.78) and AI Category 4 (24.14 - 69.84), A shift to the upper bound of the interval for AI Category 2 and lower bound of the interval for AI Category 4 would reduce the evidence for a potential skill-bias change occurring due to AI. Therefore, the possibility exists that the models' assertations could change due to movements within the confidence intervals.

Both secondary models' support for a potential skill-bias change aligns with a limited consensus that is building in AI employment theory as well as recent studies within technological change employment theory that focus on the third industrial revolution. Specifically, the finding aligns with AI employment task-based literature such as Frey and Osborne (2017), Duckworth, Graham & Osborne (2019), and Nedelkoska & Quintini (2018). However, the skill-bias support challenges Webb's assertion that AI will negatively impact predominately high-skill occupations indicating potential skill-replacing change. Once again, it is critical to call out the differences in the periods of analysis between this study and Webb's research when comparing the findings to Webb's predictions. However, this study did examine actual occupational-level employment data in relation to Webb's index which strengthens the validity of its findings.

Purpose of the Study: This exploratory study sought to build a generalizable model that could be applied to any local labor market within the U.S. while providing local leaders with the necessary understanding of their labor market's exposure to AI.

In regard to the purpose of the study, the supplemental and exploratory models' findings will be analyzed to examine the potential impact of AI more fully on the study's local labor market. Then, the generalizability of the study's models and findings will be assessed holistically based on commonly accepted criteria. The study showed indications of positive net employment impacts and skill-bias changes associated with AI in San Diego County during the period of analysis. The supplementary model provided a more detailed examination of employment impact through clustering by segmenting the occupations into occupational groups. Occupations with the highest AI exposure, AI Category 4, were then selected for employment level analysis. The model output produced ten positive growth curves implying potential job growth and four negative growth curves implying potential job loss.

The four negative slope coefficients were all statistically significant and associated with Occupational Group 19 (Life, Physical and Social Science Occupations), Occupational Group 43 (Office and Administrative Support Occupations), Occupational Group 49 (Installation, Maintenance and Repair Occupations) and Occupational Group 53 (Transportation and Material Moving Occupations). Based on the BLS labor market breakdown (Table 1), the percentage of San Diego County's employment for these occupational groups is 1.9%, 11.7%, 3.2%, and 6.4% respectively. Consequently, a potential negative association between AI exposure and employment totals was identified within occupational groups that make up 23.2% of San Diego County's total employment. It is critical to emphasize that this supplementary model only analyzed the highest exposed occupations in AI Category 4. Therefore, a broader analysis of the model's findings should be conducted across diverse exposure levels to assess the applicability of the finding more thoroughly across all occupations within the four occupational groups identified.

To provide a foundation for this broader analysis, a deeper dive into this finding was conducted in the exploratory model which selected the occupational group with the highest negative growth curve, Occupational Group 53, for further examination. Instead of only analyzing AI Category 4 occupations, occupations at all exposure levels within this group were included in this model in order to assess the relationship more comprehensively between Webb's AI exposure index and employment changes at a group level. The inclusion of all occupations produced a model with a significant positive growth curve, AI Category 3, indicating predicted employment growth. This finding suggests that employment loss could be potentially isolated to only the most exposed occupations in AI Category 4 within this occupational group. This assertion was further reinforced by the significant negative growth curve of AI Category 4 within the model. It is important to note that AI Category 4 only contained one occupation though, occupational code 53-7064 titled “Pickers and Packagers, Hand”. This non-high-skill occupation recorded an AI exposure index score of 92 and experience an actual decrease of 2,030 in total employment from 7,230 in 2010 to 5,200 in 2019. It is critical to note however that the exploratory model demonstrated elevated standard errors throughout the model’s output and only reached statistical significance for 2 of 8 coefficients.

There are a few key takeaways for San Diego County’s labor market leaders based on the findings from this study’s primary, secondary, supplementary, and exploratory models. First, with regard to the overall net employment impact of AI, this study suggests that leaders should focus on monitoring employment levels rather than taking any specific actions at this time. It appears too early to identify a specific direction for potential broad-based reskilling or labor market shifts. It is recommended to consistently review the annual BLS employment reports from 2022 onward to reassess the study’s positive net employment impact finding. Second, the study’s finding associating AI with skill-bias technology change can be utilized by San Diego’s labor market leaders to reinforce the importance of upskilling programs for non-high-skill workers. The goal of these upskilling programs should be to transition workers in the potentially threatened non-high-skill occupations to higher-skilled occupations less associated with potential job loss. Lastly, this study identifies four occupational groups and one specific occupation in the San Diego County labor market which have early indications of potential job loss due to AI. Leaders can leverage this finding to possibly begin planning for labor shifts out of these occupational groups into growing occupational groups in the near term. The “Pickers and Packagers, Hand” occupation specifically could be a starting point for leaders to initiate reskilling or preferably upskilling programs for the thousands of San Diego County workers in that occupation.

An additional purpose of this exploratory study was to assess whether the models' findings could be generalizable to other local labor markets. To examine generalizability, it is critical to assess both the study's methodology and findings. From a methodology perspective, the study's final dataset contained 352 occupations, 52% of all San Diego County occupations, with more than one occupation in all 22 major occupational groups. Consequently, the final dataset is assumed to be a valid representation of the San Diego County labor market. Due to the uniformity of the BLS employment classifications and data, the study's final dataset also represents a reliable foundation for analysis across different local labor markets. Additionally, Webb's AI Exposure Index and the BLS-based occupational skill designations will not change across different local labor markets. Therefore, the study's methodology is reasonably generalizable.

However, the findings from the study's models must be scrutinized heavily in regard to precision. While all models within the study were found to be statistically significant the significance of the intercept and slope coefficients varied dramatically both within and across models. Numerous coefficients throughout the study did not reach the significance threshold which reduces the validity of the findings. The standard errors for the coefficients were also consistently elevated throughout the model outputs. The visualizations of the confidence intervals of the growth curves clearly illustrate the impact of the elevated standard errors with a large overlap in the outcome variable curves. This overlap substantially lowers the overall validity and reliability of the study's findings which correspondingly reduces its precision. Overall, the study's methodology could be reasonably generalized across local labor markets but its findings have low precision at this time due to inconsistent significance and consistently elevated standard errors within the models.

Limitations

This study seeks to provide local labor market leaders with an objective-based model to assess their local labor market's exposure to current and future AI-driven technologies. Consequently, it is critical to note the limitations of this exploratory study's design and methodology for their situational awareness. The study's most significant limitation is the increasingly dynamic and evolving nature of AI. As a still emerging technology, AI cannot be regarded as a constant yet and it is still uncertain where and how its applications will impact the future of work. Therefore, Webb's AI Exposure Index's relevance must be consistently scrutinized based on its patent-level foundation. Undoubtedly, substantial new AI patents have been filed since Webb's research was first published in 2019. It is reasonable to contend that these new patent filings would change Webb's AI Exposure Index scoring and therefore augment the final dataset of this study impacting the validity of the study's findings. Due to this limitation, it is important for local labor market leaders to utilize this study's findings as one of several inputs to understand AI's potential impact rather than an absolute solution. Through triangulation with other research literature and current news, leaders can build the necessary context required to adequately plan for the age of AI.

This exploratory study's findings face another limitation in terms of validity due to its heavy reliance on Webb's AI exposure index. The study employs longitudinal analysis techniques which apply the static AI exposure index scores to nine years of employment data at an occupational level. While Webb's index is based on longitudinal analysis, the index itself is not longitudinal in nature. However, the occupational employment totals from 2010-2019 represent a valid longitudinal dataset. To enhance the precision of the AI exposure index, it would have been preferable to have annual scoring for each occupation throughout the period of analysis rather than a single point-in-time index score in 2019. Additionally, Webb's index is the sole AI exposure measurement instrument utilized in the study's analysis. This is a limitation to the reliability of the study's findings because Webb just recently published this index (2019) and it has not undergone extensive scholarly peer review. Optimally, multiple AI exposure indexes that mapped back to the occupations in the final dataset would have been included within the study's design. Consequently, the accuracy of the study's findings and their generalizability need to be carefully considered. Although Webb's AI exposure index has its limitations, other instruments were considered during the study's design and it was deemed the most suitable mechanism for analyzing the final dataset and addressing the research questions of the study.

The robustness of this exploratory study must also be acknowledged as a limitation due to the condensed time span of the period of analysis, 2010-2019. The limited consistency of BLS reporting imposed a data constraint that resulted in only nine years of BLS employment data in the final dataset. While nine years may provide some insights, it is a relatively short period of analysis to comprehensively analyze the impact of a technology on labor markets. In comparison, Webb employed a thirty-year period of analysis to validate his AI exposure methodology. Given the study's truncated analysis period and the recency of AI applications in the labor market, it is unlikely to identify significant impacts of AI at this time. However, to address this limitation, the study exclusively utilized publicly available data for the analysis. This approach allows for simpler replication facilitating future research that includes a more extensive range of employment data, thereby enhancing the robustness of the findings.

Lastly, it is important to note the complexity and data bias involved in the construction of the final dataset utilized for analysis. First, the multiple crosswalks executed to apply Webb's AI Exposure Index to the BLS employment data necessitated reliance on multiple researcher and organizational methodologies. The manual nature of the crosswalks also increased the potential for human error during documentation. Second, the consolidation process of the BLS occupations was also conducted manually and required consistent human judgment. While the process produced a final dataset of 352 occupations to examine, it is critical to note that 328 occupations were excluded from analysis because either their occupational code could not be matched or aspects of their data were not recorded between 2010-2019. Therefore, there are replicability and completeness limitations within the final dataset. To address these limitations, this study makes every effort to document for the reader not only the data being used for testing but also the data that was excluded from examination.

Implications For Future Research

While this study has limitations, a core benefit of its exploratory approach is that it expands the knowledge base of this topic and opens up new directions for research. Specifically, the study developed a new methodology and produced several initial findings that can be foundational to future research efforts. Additional research can be instrumental in improving the validity of the methodology and findings as well as assessing the robustness of the overall study. Building on this study as a foundation, scholars can continue to provide local labor market leaders with critical new insights to properly prepare for the coming age of AI.

In terms of methodological considerations, future research should aim to expand the period of analysis and incorporate additional relevant instruments to enhance the study's validity. As the labor market gradually normalizes following the Covid-19 pandemic, a more consistent and reliable dataset from the BLS will become available which offers valuable data to include in future analysis. Furthermore, with the increasing availability and adoption of AI applications impacting the workforce, it is crucial to incorporate these developments into future studies. By combining larger employment datasets with broader AI adoption, the likelihood of identifying meaningful trends is heightened which should enable researchers to obtain more precise measurements from the study's models. To further strengthen the study's methodological approach, it is recommended to also incorporate additional empirically driven instruments that measure the impact of AI on employment. While Webb's patent-based index serves as one approach to quantify AI's impact at the occupational level, recent research from institutions like the Massachusetts Institute of Technology (MIT) offers alternative methodologies (Acemoglu, D.; Autor, D.; Hazell, J.; Restrepo, P., 2022). Integrating these evolving alternative approaches with Webb's AI Exposure Index has the potential to significantly enhance the overall robustness of the study's methodology.

Given the limited amount of existing research on AI employment theory focused on local labor markets, direct comparisons to this study's findings are currently limited. Therefore, future research should aim to expand upon these findings to conduct a more comprehensive assessment of their validity. By applying the methodology used in this study to other local labor markets, a broader range of empirical evidence can be accumulated to assess AI's net employment impact, type of technological change, and most affected occupations. It is important to diversify the research across various regions in the United States to identify potential regional trends that may be occurring. Additionally, localized international studies could provide valuable insights into the global impact of AI. Alternatively, the study's findings also offer opportunities for a deeper analysis of the labor market in San Diego County. In the supplementary model, negative growth curves were observed for four occupational groups with high AI exposure but this study only analyzed one of those groups (Occupational Group 53) in its exploratory model. Analyzing the other three occupational groups would provide additional insights into potential occupations that exhibit indications of job loss. By either expanding the scope of local labor markets studied or conducting more in-depth analyses of San Diego County, the study's findings can be further validated and more valuable empirical knowledge can be provided to local labor market leaders.

The current data bias within this study could also be reduced during future research in order to potentially enhance the methodology's generalizability and the models' precision. During the data cleaning and consolidation process, 328 occupations were removed from the final dataset. Future studies could develop a more scientifically rigorous method to add or remove occupations. A benefit of longitudinal data analysis is that not all observations of an outcome variable need to be recorded to conduct linear growth curve analysis. Consequently, less occupations with incomplete employment totals could be removed increasing the total number of occupations in the final dataset for analysis. The inclusion of these occupations can assist in testing the validity of the methodology and findings of this study.

Conclusion

This exploratory study addresses the research questions and fills a crucial knowledge gap in AI employment theory by introducing a novel methodology for evaluating AI exposure at the local labor market level. Applying this new methodology to the San Diego County labor market from 2010-2019 yielded several noteworthy findings. First, the primary model demonstrated an overall positive association between employment changes and AI exposure throughout multiple levels of Webb's AI exposure index. Second, the secondary models provided preliminary evidence of potential skill-biased changes with non-high-skill occupations exhibiting slower employment growth compared to high-skill occupations at similar levels of Webb’s AI exposure index. Lastly, the supplementary and exploratory models identified specific occupational groups and occupations that displayed potential early indications of employment loss attributable to AI exposure. While these findings are novel at the local labor market level, it is important to emphasize that the lack of consistency in significance and the presence of high standard errors in the model coefficients hinder precision and impede generalizability beyond San Diego County at this point in time. However, the new methodology holds high potential for application to other local labor markets which offers opportunities for further research and analysis.

Circling back to the fundamental purpose of this study, its methodology and findings provide local labor market leaders with valuable models and sets of insights to begin preparing for the age of AI. Based on this study’s findings, there still appears to be time for leaders to monitor and assess AI’s impact in order to properly build programs to address any upcoming labor demand shocks. By utilizing publicly available data, the replicability of the study was greatly enhanced which offers leaders the opportunity to continue to add annual employment totals to the models. By broadening the period of analysis, future models can test the reliability and validity of the study’s findings while increasing its overall robustness. Consequently, local labor market leaders are highly encouraged to continue to build on this study to assess their local labor market’s exposure to AI going forward.

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APPENDIX A

Webb's AI Exposure Index

occ1990dd Code	Occupation Title (occ1990dd)	Exposure Index Score
28	Purchasing agents and buyers of farm products	100
35	Construction inspectors	100
45	Metallurgical and materials engineers	100
48	Chemical engineers	100
58	Marine engineers and naval architects	100
69	Physicists and astronomists	100
74	Atmospheric and space scientists	100
87	Optometrists	100
203	Clinical laboratory technologies and technicians	100
359	Dispatchers	100
455	Pest control occupations	100
494	Supervisors, forestry and logging workers	100
543	Elevator installers and repairers	100
694	Water and sewage treatment plant operators	100
695	Power plant operators	100
739	Knitters, loopers, and toppers textile operatives	100
824	Locomotive operators: engineers and firemen	100
736	Typesetters and compositors	99
743	Textile cutting and dyeing machine operators	98
799	Production checkers, graders, and sorters in manufacturing	98
628	Production supervisors or foremen	96
229	Computer programmers	94
385	Data entry keyers	94
473	Farmers, ranchers, and other agricultural managers	94
503	Supervisors of mechanics and repairers	94
66	Actuaries	93

83	Medical scientists	93
99	Occupational therapists	93
103	Physical therapists	93
384	Proofreaders	93
479	Farm workers, incl. nursery farming, and marine life cultivation workers	93
489	Inspectors of agricultural products	93
733	Misc. woodworking machine operators	93
764	Washing, cleaning, and pickling machine operators	93
834	Miscellanious transportation occupations	93
848	Hoist and winch operators	93
356	Mail clerks, outside of post office	92
699	Other plant and system operators	92
713	Forge and hammer operators	92
738	Winding and twisting textile and apparel operatives	92
813	Parking lot attendants	92
888	Packers and packagers by hand	92
75	Geologists	91
214	Engineering and science technicians	91
644	Precision grinders and fitters	91
709	Grinding, abrading, buffing, and polishing workers	91
729	Nail, tacking, shaping and joining mach ops (wood)	91
828	Ship and boat captains and operators	91
59	Engineers and other professionals, n.e.c.	90
637	Machinists	90
68	Mathematicians and statisticians	89
76	Physical scientists, n.e.c.	89
616	Miners	89
734	Bookbinders and printing machine operators, n.e.c.	89
774	Photographic process machine operators	89
849	Crane and tower operators	89

254	Real estate sales occupations	88
43	Architects	87
55	Electrical engineers	87
166	Economists, market and survey researchers	87
169	Social scientists and sociologists, n.e.c.	87
347	Office machine operators, n.e.c.	87
558	Supervisors of construction work	87
29	Buyers, wholesale and retail trade	85
47	Petroleum, mining, and geological engineers	85
53	Civil engineers	85
73	Chemists	85
86	Veterinarians	85
167	Psychologists	85
233	Programmers of numerically controlled machine tools	85
567	Carpenters	85
589	Glaziers	85
707	Rollers, roll hands, and finishers of metal	85
15	Managers of medicine and health occupations	84
24	Insurance underwriters	84
56	Industrial engineers	84
173	Urban and regional planners	84
218	Surveryors, cartographers, mapping scientists/techs	84
223	Biological technicians	84
523	Repairers of industrial electrical equipment	84
723	Metal platers	84
749	Miscellanious textile machine operators	84
753	Cementing and gluing machne operators	84
64	Computer systems analysts and computer scientists	83
65	Operations and systems researchers and analysts	83
844	Operating engineers of construction equipment	83

853	Excavating and loading machine operators	83
13	Managers in marketing, advert., PR	82
78	Biological scientists	82
228	Broadcast equipment operators	82
235	Technicians, n.e.c.	82
488	Graders and sorters of agricultural products	82
598	Drillers of earth	82
25	Other financial specialists	81
217	Drafters	81
594	Paving, surfacing, and tamping equipment operators	81
647	647=Jewelers and precious stone and metal workers	81
668	Upholsterers	81
678	Dental laboratory and medical applicance technicians	81
26	Management analysts	80
33	Purchasing agents and buyers, n.e.c.	80
44	Aerospace engineers	80
184	Technical writers	80
189	Photographers	80
226	Airplane pilots and navigators	80
706	Punching and stamping press operatives	80
757	Separating, filtering, and clarifying machine operators	80
178	Lawyers and judges	79
95	Registered nurses	78
79	Foresters and conservation scientists	77
185	Designers	77
364	Shipping and receiving clerks	77
418	Police and detectives, public service	77
765	Paper folding machine operators	77
204	Dental hygienists	76
426	Guards and police, except public service	76

448	Supervisors of cleaning and building service	76
467	Motion picture projectionists	76
519	Machinery maintenance occupations	76
688	Batch food makers	76
789	Painting and decoration occupations	76
8	Human resources and labor relations managers	75
57	Mechanical engineers	75
645	Patternmakers and model makers, metal and plastic	75
684	Miscellaneous precision workers, n.e.c.	75
696	Plant and system operators, stationary engineers	75
708	Drilling and boring machine operators	75
22	Managers and administrators, n.e.c.	68
308	Computer and peripheral equipment operators	68
7	Financial managers	67
386	Statistical clerks	67
525	Repairers of data processing equipment	67
526	Repairers of household appliances and power tools	67
825	Railroad brake, coupler, and switch operators	67
518	Industrial machinery repairers	66
255	Financial service sales occupations	64
779	Machine operators, n.e.c.	64
856	Industrial truck and tractor operators	64
14	Managers in education and related fields	63
175	Religious workers, n.e.c.	63
368	Weighers, measurers, and checkers	63
408	Laundry and dry cleaning workers	63
243	Sales supervisors and proprietors	61
174	Social workers	60
516	Heavy equipement and farm equipment mechanics	60
575	Electricians	60

98	Respiratory therapists	59
104	Speech therapists	59
319	Receptionists and other information clerks	59
507	Bus, truck, and stationary engine mechanics	59
755	Extruding and forming machine operators	59
859	Misc. material moving equipment operators	59
206	Radiologic technologists and technicians	58
413	Supervisors, firefighting and fire prevention occupations	58
417	Fire inspection, fire fighting, and fire prevention occupations	58
527	Telecom and line installers and repairers	58
549	Mechanics and repairers, n.e.c.	57
599	Misc. construction and related occupations	57
653	Sheet metal workers	57
666	Tailors, dressmakers, and sewers	57
159	Teachers, n.e.c.	55
496	Timber, logging, and forestry workers	55
785	Assemblers of electrical equipment	55
37	Management support occupations	54
85	Dentists	54
97	Dieticians and nutritionists	54
105	Therapists, n.e.c.	54
158	Special education teachers	54
509	Small engine repairers	54
579	Painters, construction and maintenance	54
595	Roofers	54
617	Other mining occupations	54
766	Furnance, kiln, and oven operators, apart from food	54
77	Agricultural and food scientists	53
84	Physicians	53
375	Insurance adjusters, examiners, and investigators	53

614	Drillers of oil wells	53
875	Garbage and recyclable material collectors	53
188	Painters, sculptors, craft-artists, and print-makers	52
199	Athletes, sports instructors, and officials	52
451	Gardeners and groundskeepers	52
634	Tool and die makers and die setters	52
769	Slicing and cutting machine operators	52
889	Laborers, freight, stock, and material handlers, n.e.c.	49
23	Accountants and auditors	48
869	Construction laborers	48
258	Sales engineers	47
719	Molders and casting machine operators	47
744	Textile sewing machine operators	47
318	Transportation ticket and reservation agents	46
427	Protective service, n.e.c.	46
535	Precision instrument and equipment repairers	46
539	Repairers of mechanical controls and valves	46
809	Taxi drivers and chauffeurs	46
505	Automobile mechanics and repairers	45
803	Supervisors of motor vehicle transportation	45
808	Bus drivers	45
27	Personnel, HR, training, and labor rel. specialists	44
155	Kindergarten and earlier school teachers	44
577	Electric power installers and repairers	44
593	Insulation workers	44
157	Secondary school teachers	43
187	Actors, directors, and producers	43
585	Plumbers, pipe fitters, and steamfitters	43
727	Sawing machine operators and sawyers	43
36	Inspectors and compliance officers, outside	42

208	Health technologists and technicians, n.e.c.	42
376	Customer service reps, invest., adjusters, excl. insur.	42
156	Primary school teachers	40
163	Vocational and educational counselors	40
459	Recreation facility attendants	40
508	Aircraft mechanics	40
276	Cashiers	38
348	Telephone operators	35
450	Superv. of landscaping, lawn service, groundskeeping	35
533	Repairers of electrical equipment, n.e.c.	35
563	Masons, tilers, and carpet installers	35
573	Drywall installers	35
724	Heat treating equipment operators	35
804	Driver/sales workers and truck Drivers	35
865	Helpers, constructions	35
18	Managers of properties and real estate	34
205	Health record technologists and technicians	34
544	Millwrights	34
597	Structural metal workers	34
649	Engravers	34
677	Optical goods workers	34
703	Lathe and turning machine operatives	34
823	Railroad conductors and yardmasters	34
878	Machine feeders and offbearers	34
253	Insurance sales occupations	33
686	Butchers and meat cutters	33
756	Mixing and blending machine operators	33
453	Janitors	31
783	Welders, solderers, and metal cutters	30
227	Air traffic controllers	29

303	Office supervisors	29
414	Supervisors, police and detectives	29
4	Chief executives, public administrators, and legislators	28
34	Business and promotion agents	28
89	Other health and therapy occupations	28
165	Archivists and curators	28
186	Musicians and composers	28
344	Billing clerks and related financial records processing	28
423	Sheriffs, bailiffs, correctional institution officers	28
458	Hairdressers and cosmetologists	28
498	Fishing and hunting workers	28
88	Podiatrists	26
164	Librarians	26
433	Supervisors of food preparation and service	26
447	Health and nursing aides	26
583	Paperhangers	26
658	Furniture and wood finishers	26
754	Packers, fillers, and wrappers	26
234	Legal assistants and paralegals	25
468	Childcareworkers	25
675	Hand molders, shapers, and casters, except jewelers	25
885	Garage and service station related occupations	25
106	Physicians' assistants	24
336	Records clerks	24
383	Bank tellers	24
534	Heating, air conditioning, and refrigeration mechanics	24
873	Production helpers	24
9	Purchasing Managers	23
183	Writersandauthors	23
197	Specialists in marketing, advert., PR	23

207	Licensed practical nurses	23
224	Chemical technicians	23
373	Material recording, sched., prod., plan., expediting cl.	23
584	Plasterers	23
615	Explosives workers	23
177	Welfare service workers	21
328	Human resources clerks, excl payroll and timekeeping	21
377	Eligibility clerks for government prog., social welfare	21
389	Administrative support jobs, n.e.c.	21
436	Cooks	21
462	Ushers	21
470	Supervisors of personal service jobs, n.e.c	21
514	Auto body repairers	21
643	Boilermakers	21
747	Clothing pressing machine operators	21
829	Sailors and deckhands, ship/marine engineers	21
269	Parts salesperson	20
461	Guides	20
588	Concrete and cement workers	20
657	Cabinetmakers and bench carpeters	20
887	Vehicle washers and equipment cleaners	20
274	Sales occupations and sales representatives	18
365	Stock and inventory clerks	18
96	Pharmacists	17
256	Advertising and related sales jobs	16
379	General office clerks	16
425	Crossing guards	16
193	Dancers	14
195	Editors and reporters	14
316	Interviewers, enumerators, and surveyors	14

337	Bookkeepers and accounting and auditing clerks	14
445	Dental Assistants	14
464	Baggage porters, bellhops and concierges	14
466	Recreation and fitness workers	14
687	Bakers	14
814	Motor transportation occupations, n.e.c.	14
866	Helpers, surveyors	14
277	Door-to-door sales, street sales, and news vendors	13
357	Messengers	13
469	Personal service occupations, n.e.c	13
669	Shoe and leather workers and repairers	13
198	Announcers	9
313	Secretaries and administrative assistants	9
315	Typists	9
329	Libraryassistants	9
366	Meter readers	9
378	Bill and account collectors	9
763	Food roasting and baking machine operators	9
387	Teacher's aides	7
435	Waiters and waitresses	7
444	Miscellanious food preparation and service workers	7
471	Public transportation attendants	7
536	Locksmiths and safe repairers	7
335	File clerks	6
434	Bartenders	6
405	Housekeepers, maids, butlers, and cleaners	5
270	Sales workers	3
354	Postal clerks, exluding mail carriers	3
176	Clergy	2
275	Sales counter clerks	2

283	Sales demonstrators, promoters, and models	2
317	Hotel clerks	2
326	Correspondence and order clerks	2
338	Payroll and timekeeping clerks	2
457	Barbers	2
745	Shoemaking machine operators	2
19	Funeral directors	1
154	Subject instructors, college	1
194	Art/entertainment performers and related occs	1
355	Mail carriers for postal service	1
439	Food preparation workers	1
472	Animal caretakers, except farm	1
285	Auctioneers and sales support occupations, n.e.c.	1
349	Other telecom operators	1
415	Supervisors of guards	1

APPENDIX B

Final Dataset Occupation List

OCC CODE	OCC TITLE
11-1021	General and Operations Managers
11-1031	Legislators
11-2011	Advertising and Promotions Managers
11-2021	Marketing Managers
11-2022	Sales Managers
11-3021	Computer and Information Systems Managers
11-3031	Financial Managers
11-3051	Industrial Production Managers
11-3061	Purchasing Managers
11-3071	Transportation, Storage, and Distribution Managers
11-3111	Compensation and Benefits Managers
11-3121	Human Resources Managers
11-3131	Training and Development Managers
11-9021	Construction Managers
11-9031	Education Administrators, Preschool and Childcare Center/Program
11-9032	Education Administrators, Elementary and Secondary School
11-9041	Architectural and Engineering Managers
11-9051	Food Service Managers
11-9071	Gaming Managers
11-9111	Medical and Health Services Managers
11-9121	Natural Sciences Managers
11-9141	Property, Real Estate, and Community Association Managers
13-1031	Claims Adjusters, Examiners, and Investigators
13-1041	Compliance Officers

13-1051	Cost Estimators
13-1081	Logisticians
13-1111	Management Analysts
13-1121	Meeting, Convention, and Event Planners
13-1141	Compensation, Benefits, and Job Analysis Specialists
13-1151	Training and Development Specialists
13-1161	Market Research Analysts and Marketing Specialists
13-2011	Accountants and Auditors
13-2021	Appraisers and Assessors of Real Estate
13-2031	Budget Analysts
13-2041	Credit Analysts
13-2052	Personal Financial Advisors
13-2053	Insurance Underwriters
13-2061	Financial Examiners
13-2072	Loan Officers
15-1121	Computer Systems Analysts
15-2031	Operations Research Analysts
17-1011	Architects, Except Landscape and Naval
17-1021	Cartographers and Photogrammetrists
17-1022	Surveyors
17-2011	Aerospace Engineers
17-2031	Biomedical Engineers
17-2041	Chemical Engineers
17-2051	Civil Engineers
17-2061	Computer Hardware Engineers
17-2071	Electrical Engineers
17-2072	Electronics Engineers, Except Computer

17-2081	Environmental Engineers
17-2111	Health and Safety Engineers, Except Mining Safety Engineers and Inspectors
17-2112	Industrial Engineers
17-2131	Materials Engineers
17-2141	Mechanical Engineers
17-2199	Engineers, All Other
17-3011	Architectural and Civil Drafters
17-3012	Electrical and Electronics Drafters
17-3013	Mechanical Drafters
17-3019	Drafters, All Other
17-3022	Civil Engineering Technicians
17-3023	Electrical and Electronics Engineering Technicians
17-3025	Environmental Engineering Technicians
17-3026	Industrial Engineering Technicians
17-3027	Mechanical Engineering Technicians
17-3031	Surveying and Mapping Technicians
19-1021	Biochemists and Biophysicists
19-1029	Biological Scientists, All Other
19-1042	Medical Scientists, Except Epidemiologists
19-2012	Physicists
19-2031	Chemists
19-2032	Materials Scientists
19-2041	Environmental Scientists and Specialists, Including Health
19-2042	Geoscientists, Except Hydrologists and Geographers
19-2099	Physical Scientists, All Other
19-3051	Urban and Regional Planners
19-3099	Social Scientists and Related Workers, All Other

19-4021	Biological Technicians
19-4031	Chemical Technicians
19-4099	Life, Physical, and Social Science Technicians, All Other
21-1012	Educational, Guidance, School, and Vocational Counselors
21-1013	Marriage and Family Therapists
21-1015	Rehabilitation Counselors
21-1021	Child, Family, and School Social Workers
21-1022	Healthcare Social Workers
21-1093	Social and Human Service Assistants
21-2011	Clergy
21-2021	Directors, Religious Activities and Education
23-1011	Lawyers
23-2011	Paralegals and Legal Assistants
23-2099	Legal Support Workers, All Other
25-1011	Business Teachers, Postsecondary
25-1021	Computer Science Teachers, Postsecondary
25-1022	Mathematical Science Teachers, Postsecondary
25-1032	Engineering Teachers, Postsecondary
25-1042	Biological Science Teachers, Postsecondary
25-1052	Chemistry Teachers, Postsecondary
25-1054	Physics Teachers, Postsecondary
25-1061	Anthropology and Archeology Teachers, Postsecondary
25-1062	Area, Ethnic, and Cultural Studies Teachers, Postsecondary
25-1063	Economics Teachers, Postsecondary
25-1065	Political Science Teachers, Postsecondary
25-1066	Psychology Teachers, Postsecondary
25-1067	Sociology Teachers, Postsecondary

25-1112	Law Teachers, Postsecondary
25-1121	Art, Drama, and Music Teachers, Postsecondary
25-1122	Communications Teachers, Postsecondary
25-1123	English Language and Literature Teachers, Postsecondary
25-1125	History Teachers, Postsecondary
25-1194	Vocational Education Teachers, Postsecondary
25-2011	Preschool Teachers, Except Special Education
25-2012	Kindergarten Teachers, Except Special Education
25-2021	Elementary School Teachers, Except Special Education
25-2022	Middle School Teachers, Except Special and Career/Technical Education
25-2031	Secondary School Teachers, Except Special and Career/Technical Education
25-3021	Self-Enrichment Education Teachers
25-4012	Curators
25-4021	Librarians
25-4031	Library Technicians
25-9099	Education, Training, and Library Workers, All Other
27-1011	Art Directors
27-1021	Commercial and Industrial Designers
27-1022	Fashion Designers
27-1023	Floral Designers
27-1024	Graphic Designers
27-1025	Interior Designers
27-1026	Merchandise Displayers and Window Trimmers
27-1027	Set and Exhibit Designers
27-2012	Producers and Directors
27-2022	Coaches and Scouts
27-2041	Music Directors and Composers

27-3031	Public Relations Specialists
27-3041	Editors
27-3042	Technical Writers
27-3043	Writers and Authors
27-3099	Media and Communication Workers, All Other
27-4012	Broadcast Technicians
27-4021	Photographers
29-1021	Dentists, General
29-1031	Dietitians and Nutritionists
29-1041	Optometrists
29-1051	Pharmacists
29-1071	Physician Assistants
29-1122	Occupational Therapists
29-1123	Physical Therapists
29-1124	Radiation Therapists
29-1125	Recreational Therapists
29-1126	Respiratory Therapists
29-1127	Speech-Language Pathologists
29-1131	Veterinarians
29-2021	Dental Hygienists
29-2031	Cardiovascular Technologists and Technicians
29-2032	Diagnostic Medical Sonographers
29-2033	Nuclear Medicine Technologists
29-2051	Dietetic Technicians
29-2052	Pharmacy Technicians
29-2055	Surgical Technologists
29-2061	Licensed Practical and Licensed Vocational Nurses

29-2081	Opticians, Dispensing
31-2011	Occupational Therapy Assistants
31-2021	Physical Therapist Assistants
31-2022	Physical Therapist Aides
31-9011	Massage Therapists
31-9091	Dental Assistants
31-9092	Medical Assistants
31-9094	Medical Transcriptionists
31-9095	Pharmacy Aides
31-9096	Veterinary Assistants and Laboratory Animal Caretakers
33-1021	First-Line Supervisors of Fire Fighting and Prevention Workers
33-9031	Gaming Surveillance Officers and Gaming Investigators
33-9032	Security Guards
33-9091	Crossing Guards
33-9092	Lifeguards, Ski Patrol, and Other Recreational Protective Service Workers
35-1012	First-Line Supervisors of Food Preparation and Serving Workers
35-2011	Cooks, Fast Food
35-2012	Cooks, Institution and Cafeteria
35-2014	Cooks, Restaurant
35-2015	Cooks, Short Order
35-2021	Food Preparation Workers
35-3011	Bartenders
35-3031	Waiters and Waitresses
35-3041	Food Servers, Nonrestaurant
35-9011	Dining Room and Cafeteria Attendants and Bartender Helpers
35-9021	Dishwashers
35-9031	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop

37-1011	First-Line Supervisors of Housekeeping and Janitorial Workers
37-1012	First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners
37-2012	Maids and Housekeeping Cleaners
37-2021	Pest Control Workers
37-3011	Landscaping and Groundskeeping Workers
39-2021	Nonfarm Animal Caretakers
39-3011	Gaming Dealers
39-3031	Ushers, Lobby Attendants, and Ticket Takers
39-3091	Amusement and Recreation Attendants
39-3092	Costume Attendants
39-3093	Locker Room, Coatroom, and Dressing Room Attendants
39-5012	Hairdressers, Hairstylists, and Cosmetologists
39-5092	Manicurists and Pedicurists
39-5094	Skincare Specialists
39-6011	Baggage Porters and Bellhops
39-6012	Concierges
39-9011	Childcare Workers
39-9031	Fitness Trainers and Aerobics Instructors
39-9032	Recreation Workers
39-9041	Residential Advisors
41-1011	First-Line Supervisors of Retail Sales Workers
41-1012	First-Line Supervisors of Non-Retail Sales Workers
41-2011	Cashiers
41-2012	Gaming Change Persons and Booth Cashiers
41-2021	Counter and Rental Clerks
41-2022	Parts Salespersons

41-2031	Retail Salespersons
41-3011	Advertising Sales Agents
41-3021	Insurance Sales Agents
41-3031	Securities, Commodities, and Financial Services Sales Agents
41-3041	Travel Agents
41-4011	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products
41-9011	Demonstrators and Product Promoters
41-9031	Sales Engineers
41-9041	Telemarketers
43-1011	First-Line Supervisors of Office and Administrative Support Workers
43-3011	Bill and Account Collectors
43-3021	Billing and Posting Clerks
43-3031	Bookkeeping, Accounting, and Auditing Clerks
43-3041	Gaming Cage Workers
43-3051	Payroll and Timekeeping Clerks
43-3061	Procurement Clerks
43-3071	Tellers
43-4011	Brokerage Clerks
43-4031	Court, Municipal, and License Clerks
43-4041	Credit Authorizers, Checkers, and Clerks
43-4051	Customer Service Representatives
43-4071	File Clerks
43-4081	Hotel, Motel, and Resort Desk Clerks
43-4111	Interviewers, Except Eligibility and Loan
43-4121	Library Assistants, Clerical
43-4131	Loan Interviewers and Clerks

43-4151	Order Clerks
43-4161	Human Resources Assistants, Except Payroll and Timekeeping
43-4171	Receptionists and Information Clerks
43-4181	Reservation and Transportation Ticket Agents and Travel Clerks
43-4199	Information and Record Clerks, All Other
43-5011	Cargo and Freight Agents
43-5021	Couriers and Messengers
43-5031	Police, Fire, and Ambulance Dispatchers
43-5032	Dispatchers, Except Police, Fire, and Ambulance
43-5051	Postal Service Clerks
43-5052	Postal Service Mail Carriers
43-5053	Postal Service Mail Sorters, Processors, and Processing Machine Operators
43-5061	Production, Planning, and Expediting Clerks
43-5071	Shipping, Receiving, and Traffic Clerks
43-5111	Weighers, Measurers, Checkers, and Samplers, Recordkeeping
43-6011	Executive Secretaries and Executive Administrative Assistants
43-6012	Legal Secretaries
43-6013	Medical Secretaries
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive
43-9021	Data Entry Keyers
43-9022	Word Processors and Typists
43-9041	Insurance Claims and Policy Processing Clerks
43-9051	Mail Clerks and Mail Machine Operators, Except Postal Service
43-9061	Office Clerks, General
43-9071	Office Machine Operators, Except Computer
45-1011	First-Line Supervisors of Farming, Fishing, and Forestry Workers
45-2011	Agricultural Inspectors

45-2092	Farmworkers and Laborers, Crop, Nursery, and Greenhouse
45-2093	Farmworkers, Farm, Ranch, and Aquacultural Animals
47-1011	First-Line Supervisors of Construction Trades and Extraction Workers
47-2021	Brickmasons and Blockmasons
47-2031	Carpenters
47-2041	Carpet Installers
47-2051	Cement Masons and Concrete Finishers
47-2061	Construction Laborers
47-2071	Paving, Surfacing, and Tamping Equipment Operators
47-2073	Operating Engineers and Other Construction Equipment Operators
47-2081	Drywall and Ceiling Tile Installers
47-2082	Tapers
47-2111	Electricians
47-2141	Painters, Construction and Maintenance
47-2152	Plumbers, Pipefitters, and Steamfitters
47-2161	Plasterers and Stucco Masons
47-2181	Roofers
47-2211	Sheet Metal Workers
47-2221	Structural Iron and Steel Workers
47-4011	Construction and Building Inspectors
49-1011	First-Line Supervisors of Mechanics, Installers, and Repairers
49-2011	Computer, Automated Teller, and Office Machine Repairers
49-2022	Telecommunications Equipment Installers and Repairers, Except Line Installers
49-2091	Avionics Technicians
49-2094	Electrical and Electronics Repairers, Commercial and Industrial Equipment
49-2098	Security and Fire Alarm Systems Installers
49-3011	Aircraft Mechanics and Service Technicians

49-3021	Automotive Body and Related Repairers
49-3023	Automotive Service Technicians and Mechanics
49-3031	Bus and Truck Mechanics and Diesel Engine Specialists
49-3042	Mobile Heavy Equipment Mechanics, Except Engines
49-3093	Tire Repairers and Changers
49-9012	Control and Valve Installers and Repairers, Except Mechanical Door
49-9021	Heating, Air Conditioning, and Refrigeration Mechanics and Installers
49-9031	Home Appliance Repairers
49-9041	Industrial Machinery Mechanics
49-9043	Maintenance Workers, Machinery
49-9051	Electrical Power-Line Installers and Repairers
49-9052	Telecommunications Line Installers and Repairers
49-9062	Medical Equipment Repairers
49-9071	Maintenance and Repair Workers, General
49-9096	Riggers
49-9098	Helpers--Installation, Maintenance, and Repair Workers
51-1011	First-Line Supervisors of Production and Operating Workers
51-3011	Bakers
51-3021	Butchers and Meat Cutters
51-3092	Food Batchmakers
51-4031	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic
51-4033	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51-4034	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51-4041	Machinists
51-4072	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic
51-4111	Tool and Die Makers

51-4121	Welders, Cutters, Solderers, and Brazers
51-4191	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic
51-5111	Prepress Technicians and Workers
51-5112	Printing Press Operators
51-5113	Print Binding and Finishing Workers
51-6011	Laundry and Dry-Cleaning Workers
51-6021	Pressers, Textile, Garment, and Related Materials
51-6031	Sewing Machine Operators
51-6093	Upholsterers
51-7011	Cabinetmakers and Bench Carpenters
51-7042	Woodworking Machine Setters, Operators, and Tenders, Except Sawing
51-8021	Stationary Engineers and Boiler Operators
51-8031	Water and Wastewater Treatment Plant and System Operators
51-9012	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders
51-9023	Mixing and Blending Machine Setters, Operators, and Tenders
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers
51-9081	Dental Laboratory Technicians
51-9111	Packaging and Filling Machine Operators and Tenders
51-9123	Painting, Coating, and Decorating Workers
51-9151	Photographic Process Workers and Processing Machine Operators
51-9192	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders
51-9195	Molders, Shapers, and Casters, Except Metal and Plastic
51-9198	Helpers--Production Workers
53-3031	Driver/Sales Workers
53-3032	Heavy and Tractor-Trailer Truck Drivers
53-3033	Light Truck or Delivery Services Drivers
53-6031	Automotive and Watercraft Service Attendants

53-7051	Industrial Truck and Tractor Operators
53-7061	Cleaners of Vehicles and Equipment
53-7062	Laborers and Freight, Stock, and Material Movers, Hand
53-7064	Packers and Packagers, Hand
53-7081	Refuse and Recyclable Material Collectors

APPENDIX C

2010 BLS Report Occupations Removed from Final Dataset

OCC_CODE	OCC_TITLE
00-0000	All Occupations
11-0000	Management Occupations
11-1011	Chief Executives
11-2031	Public Relations and Fundraising Managers
11-3011	Administrative Services Managers
11-9033	Education Administrators, Postsecondary
11-9039	Education Administrators, All Other
11-9081	Lodging Managers
11-9131	Postmasters and Mail Superintendents
11-9151	Social and Community Service Managers
11-9161	Emergency Management Directors
11-9199	Managers, All Other
13-0000	Business and Financial Operations Occupations
13-1011	Agents and Business Managers of Artists, Performers, and Athletes
13-1021	Buyers and Purchasing Agents, Farm Products
13-1022	Wholesale and Retail Buyers, Except Farm Products
13-1023	Purchasing Agents, Except Wholesale, Retail, and Farm Products
13-1032	Insurance Appraisers, Auto Damage
13-1078	Human Resources, Training, and Labor Relations Specialists, All Other*
13-1199	Business Operations Specialists, All Other*
13-2051	Financial Analysts
13-2071	Credit Counselors
13-2082	Tax Preparers
13-2099	Financial Specialists, All Other
15-0000	Computer and Mathematical Occupations
15-1111	Computer and Information Research Scientists
15-1131	Computer Programmers
15-1132	Software Developers, Applications
15-1133	Software Developers, Systems Software
15-1141	Database Administrators
15-1142	Network and Computer Systems Administrators*
15-1150	Computer Support Specialists
15-1179	Information Security Analysts, Web Developers, and Computer Network Architects
15-1799	Computer Occupations, All Other*

15-2011	Actuaries
15-2021	Mathematicians
15-2041	Statisticians
15-2099	Mathematical Science Occupations, All Other
17-0000	Architecture and Engineering Occupations
17-1012	Landscape Architects
17-2121	Marine Engineers and Naval Architects
17-2161	Nuclear Engineers
17-3021	Aerospace Engineering and Operations Technicians
17-3024	Electro-Mechanical Technicians
17-3029	Engineering Technicians, Except Drafters, All Other
19-0000	Life, Physical, and Social Science Occupations
19-1012	Food Scientists and Technologists
19-1013	Soil and Plant Scientists
19-1022	Microbiologists
19-1023	Zoologists and Wildlife Biologists
19-1031	Conservation Scientists
19-1099	Life Scientists, All Other
19-2021	Atmospheric and Space Scientists
19-2043	Hydrologists
19-3011	Economists
19-3022	Survey Researchers
19-3031	Clinical, Counseling, and School Psychologists
19-3039	Psychologists, All Other
19-3091	Anthropologists and Archeologists
19-3093	Historians
19-4011	Agricultural and Food Science Technicians
19-4061	Social Science Research Assistants
19-4091	Environmental Science and Protection Technicians, Including Health
19-4092	Forensic Science Technicians
19-4093	Forest and Conservation Technicians
21-0000	Community and Social Service Occupations
21-1011	Substance Abuse and Behavioral Disorder Counselors
21-1014	Mental Health Counselors
21-1019	Counselors, All Other
21-1023	Mental Health and Substance Abuse Social Workers
21-1029	Social Workers, All Other
21-1091	Health Educators
21-1798	Community and Social Service Specialists, All Other*

21-2099	Religious Workers, All Other
23-0000	Legal Occupations
23-1012	Judicial Law Clerks
23-1022	Arbitrators, Mediators, and Conciliators
23-2093	Title Examiners, Abstractors, and Searchers
25-0000	Education, Training, and Library Occupations
25-1031	Architecture Teachers, Postsecondary
25-1051	Atmospheric, Earth, Marine, and Space Sciences Teachers, Postsecondary
25-1053	Environmental Science Teachers, Postsecondary
25-1069	Social Sciences Teachers, Postsecondary, All Other
25-1071	Health Specialties Teachers, Postsecondary
25-1072	Nursing Instructors and Teachers, Postsecondary
25-1081	Education Teachers, Postsecondary
25-1082	Library Science Teachers, Postsecondary
25-1111	Criminal Justice and Law Enforcement Teachers, Postsecondary
25-1124	Foreign Language and Literature Teachers, Postsecondary
25-1126	Philosophy and Religion Teachers, Postsecondary
25-1191	Graduate Teaching Assistants
25-1199	Postsecondary Teachers, All Other
25-2032	Career/Technical Education Teachers, Secondary School
25-2041	Special Education Teachers, Preschool, Kindergarten, and Elementary School*
25-2053	Special Education Teachers, Middle School
25-2054	Special Education Teachers, Secondary School
25-3011	Adult Basic and Secondary Education and Literacy Teachers and Instructors
25-3999	Teachers and Instructors, All Other*
25-4013	Museum Technicians and Conservators
25-9011	Audio-Visual and Multimedia Collections Specialists
25-9031	Instructional Coordinators
25-9041	Teacher Assistants
27-0000	Arts, Design, Entertainment, Sports, and Media Occupations
27-1012	Craft Artists
27-1014	Multimedia Artists and Animators
27-1029	Designers, All Other
27-2011	Actors
27-2023	Umpires, Referees, and Other Sports Officials
27-2032	Choreographers
27-2042	Musicians and Singers
27-2099	Entertainers and Performers, Sports and Related Workers, All Other
27-3011	Radio and Television Announcers

27-3012	Public Address System and Other Announcers
27-3021	Broadcast News Analysts
27-3022	Reporters and Correspondents
27-3091	Interpreters and Translators
27-4011	Audio and Video Equipment Technicians
27-4014	Sound Engineering Technicians
27-4031	Camera Operators, Television, Video, and Motion Picture
27-4032	Film and Video Editors
27-4099	Media and Communication Equipment Workers, All Other
29-0000	Healthcare Practitioners and Technical Occupations
29-1011	Chiropractors
29-1023	Orthodontists
29-1029	Dentists, All Other Specialists
29-1061	Anesthesiologists
29-1062	Family and General Practitioners
29-1063	Internists, General
29-1064	Obstetricians and Gynecologists
29-1065	Pediatricians, General
29-1066	Psychiatrists
29-1067	Surgeons
29-1069	Physicians and Surgeons, All Other
29-1081	Podiatrists
29-1111	Registered Nurses*
29-1128	Therapists, All Other*
29-1181	Audiologists
29-1199	Health Diagnosing and Treating Practitioners, All Other
29-2011	Medical and Clinical Laboratory Technologists
29-2012	Medical and Clinical Laboratory Technicians
29-2037	Radiologic Technologists and Technicians*
29-2041	Emergency Medical Technicians and Paramedics
29-2053	Psychiatric Technicians
29-2054	Respiratory Therapy Technicians
29-2056	Veterinary Technologists and Technicians
29-2071	Medical Records and Health Information Technicians
29-2799	Health Technologists and Technicians, All Other*
29-9011	Occupational Health and Safety Specialists
29-9012	Occupational Health and Safety Technicians
29-9091	Athletic Trainers
29-9799	Healthcare Practitioners and Technical Workers, All Other*

31-0000	Healthcare Support Occupations
31-1011	Home Health Aides
31-1012	Nursing Aides, Orderlies, and Attendants*
31-1013	Psychiatric Aides
31-9093	Medical Equipment Preparers
31-9799	Healthcare Support Workers, All Other*
33-0000	Protective Service Occupations
33-1012	First-Line Supervisors of Police and Detectives
33-1099	First-Line Supervisors of Protective Service Workers, All Other
33-2011	Firefighters
33-2021	Fire Inspectors and Investigators
33-3041	Parking Enforcement Workers
33-3051	Police and Sheriff's Patrol Officers
33-9011	Animal Control Workers
33-9021	Private Detectives and Investigators
33-9093	Transportation Security Screeners* (federal only)
33-9099	Protective Service Workers, All Other *
35-0000	Food Preparation and Serving Related Occupations
35-1011	Chefs and Head Cooks
35-2019	Cooks, All Other
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food
35-3022	Counter Attendants, Cafeteria, Food Concession, and Coffee Shop
35-9099	Food Preparation and Serving Related Workers, All Other
37-0000	Building and Grounds Cleaning and Maintenance Occupations
37-3012	Pesticide Handlers, Sprayers, and Applicators, Vegetation
37-3013	Tree Trimmers and Pruners
37-3019	Grounds Maintenance Workers, All Other
39-0000	Personal Care and Service Occupations
39-1011	Gaming Supervisors
39-1012	Slot Supervisors
39-1021	First-Line Supervisors of Personal Service Workers
39-2011	Animal Trainers
39-3012	Gaming and Sports Book Writers and Runners
39-3019	Gaming Service Workers, All Other
39-3021	Motion Picture Projectionists
39-3099	Entertainment Attendants and Related Workers, All Other
39-4021	Funeral Attendants
39-4831	Funeral Service Managers, Directors, Morticians, and Undertakers
39-5093	Shampooers

39-7011	Tour Guides and Escorts
39-9021	Personal Care Aides
39-9099	Personal Care and Service Workers, All Other
41-0000	Sales and Related Occupations
41-3099	Sales Representatives, Services, All Other
41-9021	Real Estate Brokers
41-9022	Real Estate Sales Agents
41-9091	Door-to-Door Sales Workers, News and Street Vendors, and Related Workers
41-9799	Sales and Related Workers, All Other*
43-0000	Office and Administrative Support Occupations
43-2011	Switchboard Operators, Including Answering Service
43-4021	Correspondence Clerks
43-4141	New Accounts Clerks
43-5041	Meter Readers, Utilities
43-5081	Stock Clerks and Order Fillers
43-9011	Computer Operators
43-9031	Desktop Publishers
43-9081	Proofreaders and Copy Markers
43-9111	Statistical Assistants
43-9799	Office and Administrative Support Workers, All Other*
45-0000	Farming, Fishing, and Forestry Occupations
45-2041	Graders and Sorters, Agricultural Products
45-4011	Forest and Conservation Workers
47-0000	Construction and Extraction Occupations
47-2011	Boilermakers
47-2022	Stonemasons
47-2042	Floor Layers, Except Carpet, Wood, and Hard Tiles
47-2043	Floor Sanders and Finishers
47-2044	Tile and Marble Setters
47-2053	Terrazzo Workers and Finishers
47-2121	Glaziers
47-2131	Insulation Workers, Floor, Ceiling, and Wall
47-2151	Pipelayers
47-2171	Reinforcing Iron and Rebar Workers
47-3011	Helpers--Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters
47-3012	Helpers--Carpenters
47-3013	Helpers--Electricians
47-3014	Helpers--Painters, Paperhangers, Plasterers, and Stucco Masons

47-3015	Helpers--Pipelayers, Plumbers, Pipefitters, and Steamfitters
47-3016	Helpers--Roofers
47-3019	Helpers, Construction Trades, All Other
47-4041	Hazardous Materials Removal Workers
47-4051	Highway Maintenance Workers
47-4071	Septic Tank Servicers and Sewer Pipe Cleaners
47-4799	Construction and Related Workers, All Other*
47-5081	Helpers--Extraction Workers
49-0000	Installation, Maintenance, and Repair Occupations
49-2092	Electric Motor, Power Tool, and Related Repairers
49-2093	Electrical and Electronics Installers and Repairers, Transportation Equipment
49-2095	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay
49-2096	Electronic Equipment Installers and Repairers, Motor Vehicles
49-2097	Electronic Home Entertainment Equipment Installers and Repairers
49-3041	Farm Equipment Mechanics and Service Technicians
49-3051	Motorboat Mechanics and Service Technicians
49-3052	Motorcycle Mechanics
49-3053	Outdoor Power Equipment and Other Small Engine Mechanics
49-3091	Bicycle Repairers
49-3092	Recreational Vehicle Service Technicians
49-9011	Mechanical Door Repairers
49-9044	Millwrights
49-9069	Precision Instrument and Equipment Repairers, All Other
49-9091	Coin, Vending, and Amusement Machine Servicers and Repairers
49-9092	Commercial Divers
49-9094	Locksmiths and Safe Repairers
49-9799	Installation, Maintenance, and Repair Workers, All Other*
51-0000	Production Occupations
51-2021	Coil Winders, Tapers, and Finishers
51-2022	Electrical and Electronic Equipment Assemblers
51-2023	Electromechanical Equipment Assemblers
51-2031	Engine and Other Machine Assemblers
51-2041	Structural Metal Fabricators and Fitters
51-2091	Fiberglass Laminators and Fabricators
51-2092	Team Assemblers
51-2099	Assemblers and Fabricators, All Other
51-3022	Meat, Poultry, and Fish Cutters and Trimmers
51-3093	Food Cooking Machine Operators and Tenders
51-4011	Computer-Controlled Machine Tool Operators, Metal and Plastic

51-4012	Computer Numerically Controlled Machine Tool Programmers, Metal and Plastic
51-4021	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic
51-4022	Forging Machine Setters, Operators, and Tenders, Metal and Plastic
51-4023	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic
51-4032	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51-4035	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic
51-4061	Model Makers, Metal and Plastic
51-4081	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic
51-4122	Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders
51-4192	Layout Workers, Metal and Plastic
51-4193	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic
51-4194	Tool Grinders, Filers, and Sharpeners
51-4199	Metal Workers and Plastic Workers, All Other
51-6041	Shoe and Leather Workers and Repairers
51-6051	Sewers, Hand
51-6052	Tailors, Dressmakers, and Custom Sewers
51-6062	Textile Cutting Machine Setters, Operators, and Tenders
51-6063	Textile Knitting and Weaving Machine Setters, Operators, and Tenders
51-6092	Fabric and Apparel Patternmakers
51-7021	Furniture Finishers
51-7041	Sawing Machine Setters, Operators, and Tenders, Wood
51-7099	Woodworkers, All Other
51-8012	Power Distributors and Dispatchers
51-8013	Power Plant Operators
51-8091	Chemical Plant and System Operators
51-8099	Plant and System Operators, All Other
51-9011	Chemical Equipment Operators and Tenders
51-9021	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders
51-9022	Grinding and Polishing Workers, Hand
51-9031	Cutters and Trimmers, Hand
51-9032	Cutting and Slicing Machine Setters, Operators, and Tenders
51-9041	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders
51-9083	Ophthalmic Laboratory Technicians
51-9121	Coating, Painting, and Spraying Machine Setters, Operators, and Tenders
51-9122	Painters, Transportation Equipment

51-9141	Semiconductor Processors
51-9194	Etchers and Engravers
51-9196	Paper Goods Machine Setters, Operators, and Tenders
51-9399	Production Workers, All Other*
53-0000	Transportation and Material Moving Occupations
53-1011	Aircraft Cargo Handling Supervisors
53-1021	First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand
53-1031	First-Line Supervisors of Transportation and Material-Moving Machine and Vehicle Operators
53-2012	Commercial Pilots
53-2022	Airfield Operations Specialists
53-3011	Ambulance Drivers and Attendants, Except Emergency Medical Technicians
53-3021	Bus Drivers, Transit and Intercity
53-3022	Bus Drivers, School or Special Client
53-3041	Taxi Drivers and Chauffeurs
53-3099	Motor Vehicle Operators, All Other
53-5011	Sailors and Marine Oilers
53-5021	Captains, Mates, and Pilots of Water Vessels
53-5031	Ship Engineers
53-6021	Parking Lot Attendants
53-6051	Transportation Inspectors
53-6061	Transportation Attendants, Except Flight Attendants
53-6099	Transportation Workers, All Other
53-7011	Conveyor Operators and Tenders
53-7021	Crane and Tower Operators
53-7063	Machine Feeders and Offbearers
53-7199	Material Moving Workers, All Other