ABSTRACT

Occupational Gender Segregation and Underemployment Vulnerability during the Automation Economic Revolution

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Technology has reached a point where robotics and computerization can do many of the tasks that humans completed in the past. Occupations with the least amount of routine task are less vulnerable to being automated (Frey and Osborne 2017:2018). Automation resistant occupations require social intelligence, creative intelligence, and perception/manipulation; however, these qualities are often constructed to be innately gender specific, and gender constructs have segregated many occupations into female or male-dominated fields. This paper explores the effects of gender segregation on underemployment during the current stage of the fourth economic revolution. To do this, I compare 2017 to four panels through multivariate logistic regression to assess if the odds of underemployment for men and women have changed over time. I found that currently, there is no difference in underemployment for men and women at the gender occupational clustering rangers determined. However, individual level effects, particularly education, are increasing in importance.

Occupational Gender Segregation and Underemployment Vulnerability during the Automation Economic Revolution

by

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CHAPTER ONE

Introduction

Job loss due to automation is not just an irrational fear, as some suggest. Katz and Margo (2013) argue that technology is the “engine” of economic growth, and as such, automation of the labor force is inevitable. Researchers state that we are currently entering the fourth economic revolution, which is designated by the adoption of automation into the labor force, for example, robotics and artificial intelligence, rather than relying primarily on human capital to fulfill the role of the worker (Katz and Margo 2013; Schwab 2017; Ford 2015; Brynjolfsson and McAfee 2011:2012:2017; Frey and Osborne 2017:2018; Schwab 2017). Adoption of new technology will, in turn, determine which occupations remain available to human workers based on skillsets that technology cannot replicate (Katz and Margo 2013; Schwab 2017; Ford 2015; Brynjolfsson and McAfee 2011:2012: 2014:2017; Frey and Osborne 2017:2018).

The U.S. Bureau of Labor Statistics (2018) projects that the labor force will grow by .6 percent through 2026, and many economists assume that new technology will create industries as technology has in the past (Autor 2015; Arntz, Gregory, Zierahn 2016; Hemous and Olsen 2013; Ford 2015). Yet, other social scientists’ question these previously held notions of the possibilities of current technology creating work at an adequate rate to employ the displaced (Ford 2015; Katz and Margo 2013; Schwab 2017; McAfee and Brynjolfsson 2011:2012:2017; Greatz and Michaels 2015). Current of patterns of stagnant wages and declining labor participation as well as increased production, suggest that the economy may not need the same size labor force due to the rapid speed of technological development (Ford 2015; Katz and Margo 2013; Schwab 2017; McAfee and Brynjolfsson 2011:2012:2014:2017; Autor and Dorn 2013). In the current model of labor, production and services are rationalized in to simplified tasks (Ritzer 2011). This allows companies to maintain efficiency, the predictability of the products, as well as to control the production process (Ritzer 2011). It is this model, which incentivizes companies to minimize the components they have the least control over, namely human error (Weber 1930:2005; Ford 2015; Frey and Osborne 2017:2018;2018; McKinsey & Co Global Institute 2017; Ritzer 2011; Brussevich, Dabla-Norris, Kammunge, Karnane, Khalid and Kochhar 2018).

Formulating production into basic steps created an instruction manual for automated technologies to replicate the tasks as easily as humans (Ford 2015; Brynjolfsson and McAfee 2011:2012:2014:2017; Frey and Osborne 2017:2018). For example, in his book *McDonaldization*, Ritzer (2011) discusses the rationalization of tasks at length, documenting that the food industry, as well as many services that have implemented an assembly line model, in which one person completes one task in the manufacturing of a product. Ford (2015) contributes to Ritzer's analysis by demonstrating how contemporary industries have automated jobs that low and middle-tiered skilled labor had occupied in the past. For example, the modern farm is on an automated schedule crop rotation, watering, and harvesting, grocery store checkout lines are becoming self-checkout lines, and robotic implementation at various stages of fast food restaurants from meal preparation to customer service have become commonplace (Ritzer 2011; Ford 2015). As soon as the technology becomes available and affordable, companies adopt it to reduce the areas of weakness, to increase efficiency and remain competitive in the market. A recent example was Ford Car Manufacturing's decision to remain in the United States, instead of moving to Mexico, but installing robotics rather than hiring employees (Gilbert 2017).

While some researchers believe that total automation will occur for nearly half of occupations, rendering a large percentage of the work force in developed economies redundant, other researchers believe that a milder automation will take place, reducing tasks rather than whole occupations, thus eliminating fewer jobs (Frey and Osborne 2017:2018; Ford 2015; Brynjolfsson and McAfee 2011:2012:2017; McKinsey & Co Report 2017; Brussevich, Dabla-Norris, Kammunge, Karnane, Khalid and Kochhar 2018; Autor 2015; Arntz, Gregory, Zierahn 2016). The possibility of eliminating jobs has many researchers questioning whether men or women are more at risk (Morrison 2018). Research shows that women and men's employment is converging, slightly reducing male employment (Fukui, Nakamura, and Steinsson 2019). Some researchers found that men are more vulnerable to underemployment during economic shifts, as during previous recessions and deindustrialization (Nilsen 1984; Urquhart and Hewson 1983). Other studies found that women have more routinized tasks than men, and therefor may be more vulnerable to job-loss, and that a further hollowing out of middle-tier skilled labor, which women's employment makes up 37 percent (Tuzemen and Willis 2013; Morrison 2018; Young 2018). Middle skilled occupations have been targeted as occupations that help women leave poverty, but these occupations are disappearing (Black et al. 2017).

While social scientists agreed that routine tasks are vulnerable, they also argue that occupations which require social intelligence, creative intelligence, and perception/manipulation are less vulnerable to job loss (Frey and Osborne 2017:2018;

Brynjolfsson and McAfee 2011:2012:2017; Autor and Dorn 2013). Gender constructs are embedded in these skillsets, which have encouraged the gender segregation of occupations and may potentially affect underemployment vulnerability (Gupta, Turban, and Pareek 2013; Ingalhalikar et al. 2014; TEDx Talks Jacobson 2016; Proudfoot, Kay, and Koval 2015;England, Reid and Kilbourne 1996; Athanasopoulou, Moss-Cowan, Smets, and Morris 2018; Reskin and Bielby 2005; Proudfoot, Kay, and Koval 2015; Araujo, Arujo, Moreira, Herrman, and Andrade 2017).

In the following study, I analyze underemployment using the Labor Utilization Framework (LUF) by gender segregation, organized as female occupational clustering ranges, across the past forty years. My goal is to provide some insight into the effects of underemployment during this economic shift by examining the gendered disposition of occupations. Using data from the March releases of the Current Population Survey (ASEC) from 1979 to 2017, I examine underemployment by occupational gender clustering to compare women and men's reported odds of underemployment, as well as changes of underemployment reports over time. I also look at occupational changes and compare the clustering ranges I created to occupations automation vulnerability rates that Frey and Osborne found in their research (Frey and Osborne 2017:2018; Slack et al. 2018). First, the research will discuss how this economic revolution is different from the previous economic revolutions. The study will address the advancement of technology in various industries and discuss the history of women in the workplace. In the Methods and Data section, I will address my methods, my chosen dataset, and my analytical strategy. Finally, I will analyze the results and lastly discuss the conclusions and implications of the research.

CHAPTER TWO

Literature Review, Theory, and Hypotheses

Economic Revolutions: What is Different Now?

During the first Industrial Revolution, the introduction of machines (the steam engine and power loom) allowed for mass production for the first time. (Katz and Margo 2013; Schwab 2017). Although the implementation of the new technology deskilled medium-tier craft and trades people, it also provided a multitude of employment opportunities for low skilled persons and ushered women into a workforce (Pinchbeck 1977; Katz and Margo 2013; Schwab 2017). While machines had changed the capability for production, new rationalized models of work, namely the assembly line model, was developed to harness workers full output potential (Ritzer 2011; Katz and Margo 2013; Schwab 2017; McClure 2018). The assembly line production model quickly became the standard for production across industries, dividing labor into manageable roles for maximum efficiency (Ritzer 2011; Katz and Margo 2013; Schwab 2017; McClure 2018) (Taalbi 2017; Blanke 2016; Ristuccia and Solomou 2014).

In 1930, sociologist Maxwell Weber was studying modernity when he outlined in the Theory of Rationalization, which stated that motivations for modernization of economics and society were the increasing cultural value placed on calculability, procedure/organization, and reflexivity (Weber 1930:2005; Ritzer 2011 Appelrouth and Edles 2008:146-151: Gunderson 2016). Weber suggested that rationalization of processes was particularly compelling for society, and he worried that in society's haste to develop further, produce more, and remain efficient (Weber1939:2005:36; Giddens, Duneier, Appelbaum, Carr 2019:13-14; Ritzer 2011 Appelrouth and Edles 2008:146-151; Gunderson 2016). Eventually, society will become trapped in an iron cage (Weber1939:2005:36). The iron cage is the rational systems becoming irrational, or to put it another way, when the system fails but continues to function, dehumanizing individuals by means of only seeing humans as calculable data, which fits in the system of development and efficiency or not (Weber 1930:2005; Ritzer 2011:26-27; Appelrouth and Edles 2008:146-151; Gunderson 2016). Meanwhile contemporaries of Weber, economist John Keynes and mathematician Norbert Wiener became concerned about societies' inclination for rationalization of labor by introducing automated technologies into the workforce to maintain efficiency at the expense of the workers' livelihood (Weber 1930:2005; Ritzer 2011; Katz and Margo 2013; Ford 2015; Spencer 2017; McClure 2018; Brussevich et al. 2018; Correll, Kelly, O'Connor, Williams 2014).

The United States experienced the negative side of rationalization when technological replacement occurred during the early1980s' deindustrialization (Rowthorn and Ramaswamy 1997; Sablik 2013). During deindustrialization, companies outsourced work to developing countries and installed robotics, reducing the need for employees, to remain competitive in growing global markets (Katz and Margo 2013; Rowthorn and Ramaswamy 1997 Nilsen 1984; Urquhart and Hewson 1983; Sablik 2013). Deindustrialization left many factory workers unable to find manufacturing jobs, forcing displaced workers into other sectors of the market, such as the service sector which expanded through the early 2000's (Katz and Margo 2013; Rowthorn and Ramaswamy

1997; Nilsen 1984; Urquhart and Hewson 1983; Sablik 2013: Bureau of Labor Statistics 2014).

In 1981/82, Americans experienced a recession, however, unlike the previous recession, women's overall unemployment rate was lower than men's unemployment rate by almost two points (Urquhart and Hewson 1983; Auxier 2010; Sablik 2013; Bureau of Labor Statistics 2012; U.S. Bureau of Labor Statistics 2019). Researchers at the time theorized that women were less affected due to the types of work women which were predominantly in the, specifically because women were in health and service sector while employment in manufacturing was overwhelmingly male-dominated (Urquhart and Hewson 1983; Nilsen 1984; Ford 2015; Rowthorn and Ramaswamy 1997). Following the trend, in 1990/91 when the United States experienced another recession, which hollowed out middle-tier skilled jobs contributing to job polarization, women were less affected (Autor 2010; Autor and Dorn 2013; Canon and Marifian 2013; Frey and Osborne 2017:2018; Katz and Margo 2013; Fukiu, Nakmura and Steinsson 2019; Institute for Women's Policy Research 2019; Kutscher and Personick 1986). Although women largely occupy middle-tier jobs, economists from MIT found that women were again experiencing between .20 to .25 percent less unemployment compared to men (Autor 2010; Autor and Dorn 2013; Canon and Marifian 2013; Frey and Osborne 2017:2018; Katz and Margo 2013; Fukiu, Nakmura and Steinsson 2019; Institute for Women's Policy Research 2019; Cunningham 2018). When the economy finally recovered, the recovery was a jobless recovery, in which unemployment remained the same while the country experienced economic growth (The Economist 2010). During the 2002 recession after the dot com bubble popped, again women's unemployment rate increased to 5.2

percent while men's unemployment rate was at 5.5 percent (Bureau of Labor Statistics 2003)

More recently, during the Great Recession of 2008/9, the overall unemployment rate rose to 10.0 percent. Men's unemployment rate (11 percent), which was significantly higher than women's unemployment rate of 8.4 percent and some label the Great Recession the Mancession (U. S. Bureau of Labor Statistics 2012: Nasiripour 2010:2017). Again, researchers explained that women's employment loss was smaller because women concentrated in the types of industries less vulnerable to job loss (U.S. Bureau of Labor Statistics 2010; Wething 2014). In the past, the American economy tended to take 6 months to recover, but the Great Recession took 23 months (Canon and Marifian 2013; Frey and Osborne 2017:2018; Katz and Margo 2013). Economists found that one of the contributing factors to the slow recovery was the convergence of men and women in the labor force (Fukiu, Nakmura and Steinsson 2019; Autor 2010; Autor and Dorn 2013). Fukiu and colleagues (2019) found that males had experienced slight crowding out of employment by females, at a rate of 1 percent increase in female employment, there was .15% decrease in male employment, (Fukiu, Nakmura and Steinsson 2019). Technology was credited with contributing to the economic recovery after the Great Recession by increasing productivity and decreasing labor costs through the implementation of automation and expansion of technology market, but again there was low labor force participation and high production (Blinder and Zandi 2010; Dephillis 2018; Rosenberg 2018).

Ford (2015) states that there are several indicators that technological unemployment occurring currently. Two of these indicators are wage stagnation and increased production with decreased labor force participation. Wages have remained stagnate since 2001 (DeSilver 2018: Autor and Dorn 2013). Currently, workers have about as much purchasing power as they had in the 1970s ($4.03 an hour in 1973 had the same purchasing power as $23.68 an hour in 2018) which suggest that employers do not have an incentive to offer full-time employment (DeSilver 2018). The labor force participation rate fell and hit a low in September 2015 to 62.4 percent, and has been holding steady at around 63.1 percent even though productivity is on the rise (U.S. Bureau of Labor Statistics 2012: The Employment Situation Chart 2018; DeSilver 2018; U. S. Bureau of Labor Statistics 2012; Ford 2015). Researchers Graetz and Michaels (2015) found that although technology does increase production, there was also some indication of technology crowding low skilled workers. Examining economic history over the last forty years does present persuasive case that technology is not creating as many new jobs as it once had, by the occurrence of slow or jobless recoveries becoming more common since deindustrialization. However, women seem to have some resistance to job loss during these shifts, because of the types of jobs women have, which may also be mildly competing with men in the labor force.

Automation and the Future of Work

According to Moore's Law, computing power doubles every 18 to 24 months (Moore 1998:2019; McAfee and Brynjolfsson 2011:2012:2017; Ford 2015). The World Bank (2019) estimates that for every robot installed in manufacturing, six jobs are removed. For example, Foxconn Technology Group cut its work force from 1.3 million to 873,467 by installing manufacturing robotics (World Bank Report 2019). Work by Autor and Dorn (2013) found that many low-skilled employment and wages were declining.

The one exception to this was service occupations, which had an increase in hours and wages between 1998 and 2005 (Autor and Dorn 2013). Autor and Dorn theorize that while many low-skilled occupations are losing work and wages to computerization, lower skilled workers are moving into the middle-tier service sector because service jobs rely on creative and social intelligence as well as perception/manipulation (Autor and Dorn 2013; Frey and Osborne 2017:2018). They conclude that automation is not just a force for job loss among low skilled labor, but also wage polarization (the hollowing of middle income work) and "unbalanced technological progress" which refers to the increased use of inexpensive technology which replaces low and middle skilled workers (Autor and Dorn 2013).

In 2017, Frey and Osborne analyzed 702 occupational tasks to determine vulnerability though three criteria, perception and manipulation, creative intelligence, and social intelligence. They found that 47 percent of occupations are vulnerable to automation (Frey and Osborne 2017:2018). Since Frey and Osborne's (2017:2018) research on occupational vulnerability to automation, other researchers and interest groups have been replicating or reworking their study (World Bank 2019; McKinsey & Co 2017; McAfee and Brynjolfsson 2011:2012:2017; The Global Gender Gap Report 2018;2017; Arntz, Gregory, Zierahn 2016; Autor 2015; Brussevich et al. 2018).

One such study was conducted by the Organization for Economic and Co-operation and Development (OECD), which attempted to reproduce Frey and Osborne's report by analyzing individuals rather than occupations. The OECD's study applied the Program for International Assessment of Adult Competencies to analyze 21 OECD countries through a task-based approach to identify individuals' characteristic effects and job tasks (Arntz, Gregory, Zierahn 2016). They found that only 9 percent of occupations are vulnerable to automation (2016). The OECD stated that the total automation of the occupations would be difficult since occupations have varied tasks between organizations and incorporating new technology is difficult (Arntz, Gregory, Zierahn 2016). They argue that employees that lose tasks to preform for work will have other tasks to compensate, relaying on past conventions that new technology will provide more work opportunities (Arntz, Gregory, Zierahn 2016). However, other researchers and suggest that automation may be more disruptive to the labor force.

Autor (2015) attempted to reduce concerns regarding automation by referring to Polanyi's Paradox, which states that many occupational tasks require flexibility and commonsense. Thus, the understanding of these types of skills are tactile, and essentially are difficult to reproduce through programing. For example, if you use a search engine, you will generate search results that are commonly selected using the keywords you enter, but the search engine may not deliver the results the querier desires. Let us say an individual decides to search for "Walt Disney cryogenically frozen," but instead, the results are for Disney's animated movie *Frozen* (Dawson 2019). A human would know that they are not finding what they are looking for, but Autor (2015) assumed that emerging AI programs are unable to go beyond the programmer's skills or imagination. This lack of flexibility could prevent automation from competing with human labor. However, in 2016 a team at Google DeepMind developed an application called AlphaGo which was designed to determine subtle patterns on its own, which is the basic of learning (McAfee and Brynjolfsson 2017; DeepMind 2019). AlphaGo defeated a highranking human player four to one, essentially moving past the paradox (McAfee and Brynjolfsson 2017; DeepMind 2019).

In 2017, the McKinsey & Co Global Institute, a thinktank from the University of Pennsylvania, released a report concluding that automation has the potential of altering 60 percent of occupations in 46 countries (2017). In this study, the McKinsey & Co reported that 1/3 of occupations could be automated. The mid-range estimate of automation vulnerability globally is 15 percent, but the report states that automation vulnerability is greater in developed nations (McKinsey & Co Report 2017). The McKinsey & Co report (2017) also states that occupational growth will occur in medicine, education, and service sectors to expand opportunities to dislocated workers (2017).

The World Bank released the *2019 World Development Report*, which estimated that in 2019, 1.4 million new industrial robots would be installed, raising the total number of industrial robots to 2.6 million. Manufacturing is traditionally male-dominated, and currently, two thirds of manufacturing jobs are held by males (Laughlin and Christnacht 2017). A study conducted by Acemoglu and Restrepo (2017), found that one new robot per thousand workers reduced employment by 6.2 percent. Between 1993 to 2007, the effects on employment for men were 1.5-2 times greater than the effects for women (Acemoglu and Restrepo 2017). The World Bank believes that automation will change future employment opportunities because future occupations will require different skills. The skills that will be necessary for the future, according to the World Bank (2019), includes adaptability, technological savvy, creative intelligence, and social intelligence.

The reports suggest that the only way to ensure that automation will not be an issue in the future is to encourage education and training for future technological markets and developing skills in growth fields, like education and medicine. McAfee and Brynjolfsson (2011;2017a;2017b) agree that training and education will help the labor forces in the future. However, typically people learn a set of specific concrete skills to perform (McAfee and Brynjolfsson 2011:2012:2017; Goldin and Katz 2007; Acemoglu and Autor 2011). Skills for specific types of jobs are easily outdated when there are technological and economic changes, for example, manufacturing jobs (McAfee and Brynjolfsson 2011:2012:2017; Goldin and Katz 2007; Acemoglu and Autor 2011). Durable skills include interpersonal, creativity, and teamwork skills (McAfee and Brynjolfsson 2012:2017).

Similarly, Frey and Osborne (2017) also focused on durable skills, which they called perception and manipulation, creative intelligence, and social intelligence. These are skills that AI and automation have difficulty with, but at which humans excel (Frey and Osbourne 2017; Brussevich et al. 2018). Perception and manipulation tasks are identifying objects amongst a clutter of other objects (Frey and Osbourne 2017:2018). Children begin developing these skills as toddlers looking at, *I Spy* and *Where's Waldo*. Robots still have trouble handling irregular objects and recovery if they happen to make a mistake (Frey and Osbourne 2017:2018). Tasks that require these types of perception and manipulation will be less vulnerable to automation.

Creative intelligence is another skill that automation has not mastered yet and may never master (Frey and Osbourne 2017:2018). Creative intelligence involves developing “novel and valuable ideas” (Frey and Osbourne 2017:2018). Creative intelligence includes inventions but also art, comedy, science, and theories, formulating new ideas or taking ideas and combining them to move society forward, and although AI has been attempting to move into creativity, they have fallen short (Frey and Osbourne 2017:2018).

The social intelligence framework includes care, persuasion, and negotiation. Creators of robots and AI have indeed attempted to simulate human characteristics; these often are stunted by programing and what is called the uncanny valley (McAfee and Brynjolfsson 2017; Frey and Osbourne 2017:2018; Mathur and Reichling 2016). The uncanny valley is unease and even repulsion that humans get when interreacting with AI or robots that look or act human (Mathur and Reichling 2016). There is a sense of something missing, and often, people have negative rating when interacting with robots that look too human (Mathur and Reichling 2016). Humanoid and cartoonish robots are acceptable to humans (Mathur and Reichling 2016). AI also have difficulty recognizing human emotions and in experiments have failed to resemble human interaction (Frey and Osbourne 2017:2018; Mathur and Reichling 2016). The automation-resistant jobs are those that require these skills, which also require high levels of education and job experience and are associated with creativity and social intelligence. (McAfee and Brynjolfsson 2011:2012:2017; Frey and Osbourne 2017:2018). Women may be at an advantage for developing the criteria for automation resistant skillsets.

Female Clustered Occupations and Automation

Women's labor varies greatly between ethnicity, race, class, and historical periods (Renzetti and Curran 2003). During the 1970s, many more women entered the workforce in part because of the feminist movement (Renzettie and Curran 2003). Women's labor force participation rates jumped from 49.9 percent in 1969 to 61.7 percent in 1979 (Juhn and Potter 2006). Yet, the chronicle of women in the work force is fraught with stereotypes and sex segregation which has limited the occupational opportunities for women (Renzettie and Curran 2003; Ruble, Cohen and Ruble 1984; Stoper 1991; Gupta, Turban, Pareek 2013). Sex segregated jobs typically pay less (currently women are paid 82 percent of what male full-time salary workers are paid) and possess less prestige (Renzetti and Curran 2003; Bureau of Labor Statistics 2017; Reskin and Bielby 2005; Cohen and Hufman 2003; Stoper 1991; England, Reid, and Kilbourne 1996). Often employers that hire both male and female employees for the same occupation will have different tasks associated to the same occupational title (Renzettie and Curran 2003; Reskin and Bielby 2005; Falkenberg, Naswall, Lindfors and Sverke 2015; Ruble, Cohen and Ruble 1984; Bizopoulou 2017a: 2017b).

Reskin and Bielby (2005) explain that social differentiation, a process which emphasizes gender differences as important in society, legitimizing sex stratification in occupations (Ridgeway and Smith-Lovin 1999; Pearlman 2018). Sex differentiation and gender constructs influence which jobs are appropriate or suited for men and women to pursue and these constructs also influence employers gender preference for certain positions (Naffziger and Naffziger 1974; Reskin and Bielby 2005; Gupta, Turban and Pareek 2012; Pearlman 2018; Blackburn and Jarman 2006). The influence of gender segregation is seen in many occupations designated as pink-collar, or occupations that have an increase of female representation and low male representation (Ridgeway 2011). Common occupations that women are employed in are typically middle-tier skilled occupations, for example, in are sales workers, teachers, technicians, and healthcare workers. Conversely, men work primarily in manufacturing, material moving, mechanics, installation, and repair technology and science fields (Renzettie and Curran 2003; Reskin and Bielby 2005 McKinsey & Co 2017; The Global Gender Report 2018; Brussevich et al. 2018; Institute for Women's Policy Research 2019).[1]

However, Tuzemen and Willis (2013) found that in 1983, women made up 55 percent of middle-skilled labor while men were 62 percent of middle-tier skilled labor. In 2012, women's middles-skilled employment reduced to 37 percent, and high-skilled employment increased to 47%, and women in low-skilled labor increased slightly. Men also moved to low and high-skilled labor (Tuzemen and Willis 2013). In 1983, men were 62 percent of middle-skilled jobs and only 27 percent of high skilled employment and 11 percent of low-skilled employment (Tuzemen and Willis 2013). In 2012, men's employment in middle-skilled jobs fell to 57% and men's employment in high skills employment increased by 16 percent (Tuzemen and Willis 2013; Falkenberg, Naswall, Lindfors and Sverke 2015).

The report by Tuzemen and Willis (2013) was completed after the Great Recession, which considerably decreased employment for men and women. However, as shown earlier, recessions have not contributed to as much joblessness for women (8.4 percent) as it had for men (11 percent) (U.S. Bureau of Labor Statistics 2016:2019;). Currently, the Bureau of Labor Statistics reports that women's labor force participation

[1] Projective job growth will be in professional occupations, care providers, education, tech professional, and creative arts (The McKinsey & Co Report 2017; World Bank (2019); U.S. Bureau of Labor Statistics 2018). The bulk of that job growth will be in health care and education and decrease work opportunities in manufacturing, production, material moving, and mechanics (Frey and Osborne 2017; Ford 2015; McKinsey & Co 2017; World Bank Report 2019; Brussevich et. al 2018; The Global Gender Report 2018).

rate has declined and is holding steady at round 58.6 percent, however, the decline is parallel to the male labor force participation rate (U.S. Bureau of Labor Statistics 2017:2019; Black et al. 2017). In 2017, the unemployment rate for women was 4.3 percent, which was slightly lower than men's unemployment rate of 4.4 percent (U.S. Bureau of Labor Statistics 2018). Also, in 2017, women were 47.5 percent of employed persons ages 16 years, and older and men were 52.5 percent, a 5 percent difference. (U.S. Bureau of Labor Statistics 2018). Again, this shows that women are closing the employment gap, even if they are not closing the wage gap, and that women may even be at an advantage regarding underemployment and security by entering high skilled labor (Tuzemen and Willis 2013; Fukiu, Nakmura and Steinsson 2019).

In 2017, 31 percent of women were employed in professional jobs compared to 20 percent of males (U.S. Bureau of Labor Statistics 2017). Of those professional occupations, 67 percent were within education and healthcare fields, and 10 percent were in computer and engineering fields (U.S. Bureau of Labor Statistics 2017). Nearly 20 percent of women worked in office and administration occupations compared to 5 percent of males, and roughly 18 percent of women were in management, business, and financial occupations compared to 16 percent of males (U.S. Bureau of Labor Statistics 2017).

Women are also attending college at a greater rate than men since 1996 (Bauman 2016). In 2015, 60 percent of women had at least some college compared to 58 percent of men and 33 percent of women had completed a bachelors degree, versus 32 percent of men (Ryan and Bauman 2016). In 2015, 3.1 million young people enrolled in college, 72 percent of women enrolled in college and 65.8 were male (U.S. Bureau of Labor Statistics 2017; National Center for Educational Statistics 2015). In 2013, women earned

51 percent of all doctoral degrees (Bernhagan and Gravett 2017; U.S. Bureau of Labor Statistics 2018).

Some researchers suggest that women are acquiring degrees as a form of "poverty insurance," in a time of increasing family instability (Bachmans, DiPrete and McDaniel 2008; Semuels 2017). In 2015, women received 87.75 percent of Family and Consumer Science degrees, 84.43 percent of Health and Family Services degrees, 58.96 percent of Biological and Biomedical Science degrees, 42.72 percent of Mathematics and Statistics degree, 38.48 percent of degrees in Physical Sciences and Science Technologies, and 18.03 percent of the degrees in Computer and Information Science degrees (National Center for Education Statistics 2015: Perry 2017).

Education and training, particularly in social intelligence and creativity and technology, will be necessary for long term job security in the fourth economic revolution. Women are developing these skills and are likely to enter work with interpersonal skills foci as well as creative intelligence fields, such as STEM occupations (McAfee and Brynjolfsson 2011:2012:2017; McKinsey & Co Report 2017; Frey and Osbourne 2017; Bernhagan and Gravett 2017; Baird 2012; National center for education Statistics 2015). In a study of male Labor Force Participation, Tuzemen (2018) found that the share of prime age men (ages 25 to 33), in the labor force decreased from 91.8 to 88.6 percent between 1996 to 2016. Nonparticipation rates were highest among men that had a high school degree only (14 percent) and men with some college or associates degree (11.1 percent). Tuzemen (2018) suggests that men not participating in the labor force have found other sources of income or have voluntarily not reentered because middle-tier skilled occupations are becoming more automated (Canon and Marifian 2013). Among women, labor force participation has decreased, but the dips in participation are highest among women with the with the lowest levels of education, while women with higher educations are entering the labor force (U.S. Bureau of Labor Statistics 2018).

In the IMF: *Gender, Technology and the Future of Work* report (Brussevich et al. 2018), researchers found that 10 percent of workers in 30 countries are at high risk of joblessness due to automation. Globally the report predicted that women are at a higher risk, 11 percent of working females versus 9 percent of working males (Brussevich et al. 2018). Particularly less educated and older female workers are at the highest risk, which also seems to be the case in the United States considering the Labor Force Participation dropout rates of women are generally less educated (Brusseviech et al. 2018; Black et al. 2017). The women with a high school diploma or less fell from a Labor Force Participation rate of 71 percent in 2000 to 62 percent in 2016 (Black et al. 2017). Women with only some college Labor Force Participation rate fell from 81 in 2000 percent to 76 percent in 2016 (Black et al. 2017). Yet, women with a college degree only fell two percent to 81 in 2016 (Black et al. 2017). Researchers' hypothesize that childcare responsibility and technological advances may have driven less educated women out of the work force (Black et al. 2017). Low skilled labor had to find other low skilled labor opportunities; many male and female workers transferred over to service occupations in female-dominated occupations (Rowthorn and Ramaswamy 1997). In 2014, the Pew Research Center found that 37.2 of discouraged workers cited other reasons, for being discouraged, including childcare and transportation issues which may affect women more due to constructs that women are primary childcare providers (DeSilver 2014)

Although women are advancing in many areas, men may benefit more from working in occupations with strong female representation. Dewan and Gebeloff (2018), reported that men were entering occupations typically held by women during the Great Recession. Research conducted by Cohen and Huffman (2003) found that, although female-dominated occupations inflict wage penalties for women, men do not seem as affected by these penalties. Often men are promoted more rapidly which is referred to as the glass escalator effect when the tokenism of men in female-dominated occupations benefit for structural advantages (Cohen and Huffman 2003; Wingfield 2009; Williams 1992). However, in 2018, Torre found that men that entered those fields, where leaving female-dominated positions because of low pay, low prestige, and stigma even though the jobs were secure, and she classified males entering and leaving female dominated occupations as *stop-gappers* (England 2010; Howe 2017; Sardi 2012; Young 2018). Stigmas such as being effeminate or being coded as potential 'sexual predators' or 'failures' were barriers to men in traditionally female occupations (Lupton 2006; Simpson 2005; Solberg and Laughlin 1995). Research showed that men are more likely to leave female-dominated employment regardless of the stability of full-time status (Torre 2018a:2018b).

Studies from multiple organizations, and researchers have stated that future occupations for humans will be contingent on soft-skills. There is growth health, personal care, education, and technology, but many jobs in health, personal care, and education are traditionally female-dominated (Global Institute 2017; Rocheleau 2017). If men do not take these jobs because of stigma, women will continue to fill them and other occupations. News reports reflect on women's ability in utilizing social intelligence when discussing women becoming CEO's, especially in times of economic troubles or business failures because women are perceived as more communal, considering the whole rather than only desiring personal gains (Athanasopoulouet al. 2018). Potentially women may also have an edge in the current economic revolution as they have in the past if social intelligence gender constructs remain the same and women begin to be recognized for their creative intelligence skills as they achieve further degree attainment and enter fields with low female representation.

Hypotheses

By examining the influence of gender occupational clustering on underemployment, we can determine if women and men are experiencing job insecurity within traditionally female occupations and more integrated occupations compared to male-dominated occupations. Weber's (1930) theory of rationalization states that society is becoming increasingly concerned with efficiency, and thus, tasks must continually be routinized and automated to maintain productivity (Ritzer 2011). Although some researchers have found that women are at greater risk for automation, the gender construction of occupations also suggests that automation resistant skills are already embedded in the occupations many women are in, and may decrease women's vulnerability to automation underemployment (Frey and Osborne 2017; Autor and Dorn 2013).

Women make-up 37 percent of middle-tier skills, which are occupations that are most vulnerable to automation (Tuzemen and Willis 2013; Canon and Marifina 2013; Brussevich et al. 2018: Autor and Dorn 2013). However, employment projections predict growth in several female-dominated occupations, and skills which Frey and Osborne

(2017) use to examine automations vulnerability (social intelligence, creative intelligence and perception, and manipulation) are skill sets that are often constructed as female attributes, in particular, social intelligence (Frey and Osborne 2017, Brynjolfsson and McAfee 2011:2012:2017.; Autor and Dorne 2013; Ridgeway 2011;U.S. Bureau of Labor Statistics 2017; England, Reid, and Kilbourne 1996). A study by Acemoglu and Restrepo (2018), found that women were less likely than men to be vulnerable to occupational automation. Men, by comparison, have historically had poorer outcomes regarding economic shifts and experienced higher job loss (Nilsen 1984; Tazeman and Willis 2013). Men also had less movement into more protected higher and low skilled occupations (Tazeman and Willis 2013). By comparing the results of this to Frey and Osbornes (2017) study on occupational automation vulnerability, we can assess if men or women in gender-clustered occupations are more vulnerable to underemployment. I chose to examine underemployment since society is in the early stages of the Fourth Economic Revolution and although other researchers have examined total unemployment due to automation seems less likely to occur and underemployment more likely to occur. Then the study will compare the findings to the automation vulnerability findings of Frey and Osborne (2017). I propose the following Hypotheses to guide my current study:

H1: There are gender differences in vulnerability to automation that men are at greatest risk for.

H2: These differences are not static over time.

CHAPTER THREE

Data and Methods

The study uses data from the Current Population Survey (CPS), which is sponsored by the U.S Census Bureau and Constructed by both the U.S. Census and U.S. Bureau of Labor Statistics (U.S. Census 2018). The CPS is the principal source for county level labor force statistics and is collected monthly through the implementation of supplemental surveys. For this study, I used the CPS supplemental survey the Annual Social and Economic Supplement (ASEC). The data is nationally representative and contains household and person level data. For this research, I pooled panel data from 1979-1980 (154,593-181,488 persons in sample), 1989-1990 (144,687-158,079 persons in sample), 1999-2000 (132,324-133,710 persons in data), 2009-2010 (207,921-209,802 persons in sample), and 2017 (185,914 persons in sample). The research focuses on persons of working age, between the ages of 18 and 64 years of age. The dataset was accessed through the Integrated Public Use Microdata Series (IPUMS USA 2018). IPUMS, based out of the University of Minnesota, synchronizes micro datasets, like the CPS, to increase user friendliness, rectifying coding schemes from decade to decade (IPUMS USA 2018). To this end, the variables, occupational crosswalks for occupations codes, and weights were provided by the IPUMS CPS data warehouse. Crosswalks between the CPS OCC Codes and the Standard Occupational Classification (SOC) system of coding was also provided IPUMS (IPUMS USA 2018).

Dependent Variable

The dependent variable used in this analysis is underemployment. Underemployment is a variable a composed of several categories: discouraged workers, unemployed workers, low-hour workers, low-income workers within the Labor Utilization Framework (LUF) (Clogg 1977; Clogg and Sullivan 1983; Sullivan 1978; Slack, Thiede, and Jensen 2018). In the LUF, the residual measure is adequate employment (Clogg 1977; Clogg and Sullivan 1983; Sullivan 1978). The measurement categories to define underemployment was developed by Clogg and Sullivan (Clogg 1977; Clogg and Sullivan 1983; Sullivan 1978; Slack et al. 2018), and specifically composed for the CPS. The definitions for the measurements to determine underemployment status used in the LUF as defined by Slack, Thiede, and Jensen (2018) continuing Clogg and Sullivan's work are:

Discouraged workers, persons who desire employment but are not employed and did not look for work in the last month due to discouragement, meaning they are not in the labor force currently (Slack, Thiede, and Jensen 2018). The variables used to construct this measure were

Unemployed workers, persons who are not employed but are looking for work are laid off but expecting to be called back to work.

Low-hour workers, involuntary part-time workers, because they are unable to find full-time work or are working slack jobs.

Low-income workers, full-time employees with earnings were less than 125 percent of the individual low-income level.

Each measure was constructed from multiple variables. The variables used to construct Discouragement are Adult Civilians (POPSTAT 1-Adult Civilian, 2- Armed Forces, 3-Child), Labor Force Status (LABFORCE 0-NIU 1-No, not in the labor force, 2-Yes, in the labor force), Weeks Looked for work last year, didn't work (NWLOOWK 00-Did not look for work/Wasn't on layoff, 01-52 weeks, 99-NIU), Usual hours worked per week last year (UHRSWORKLY 2 digit numeric value, 99-99 hours or more, 999-NIU), Reasons for working part-time last year (WHYPTLY 0-NIU, 1-Could not find full-time job, 2-wanted part-time, 3-slack work, 4-other), and Want a regular job now (WANTJOB 0-NIU, 1-No, 2-Yes, 3-Maybe, 4-Do not know, 9-unknown).

The variables used to construct the Unemployment measure are Adult Civilians (POPSTAT 1-Adult Civilian, 2- Armed Forces, 3-Child) and Employment Status (EMPSTAT 00-NIU, 01-Armed Forces, 10-At work, 12-Has job, not work in last week, 20-Unemployed, 21-Unemployed experience worker, 22-Umemployed new worker, 30-36-NILF for various reasons). The Low hours measurement was constructed using Adult Civilians (POPSTAT 1-Adult Civilian, 2- Armed Forces, 3-Child) and Full or part-time status (WKSTAT 10-Full-time schedules, 11-Full-time hours (35+), 12-Part-time for non-economic reasons, usually full-time, 13-Not at work, usually full-time, 14-Full-time hours usually part-time economic reasons, 15-Full-time hours, usually part-times for non-economic reasons, 20-Part-time for economic reasons, 21-Part-time for economic reasons, usually full-time, 22-Part-time hours, usually part-time for economic reasons, 40-Partime for non-economic reasons, usually part-time, 42-Not at work, usually part-time, 50-unemployed, seeking full-time work, 60-Unemployed, seeking part-time work, 99-NIU or NILF).

Lastly, the low-income workers measurement was constructed using the original PUMS poverty status (POVERTY 00-NIU, 10-Below Poverty, 20-Above Poverty, 21-100-124 percent of the low-income level, 22-125-149 percent of the low-income level, 22-125-149 percent of the low-income level, 23-150 percent and above the low-income level), Adult Civilians (POPSTAT 1-Adult Civilian, 2- Armed Forces, 3-Child) and Employment Status (EMPSTAT 00-NIU, 01-Armed Forces, 10-At work, 12-Has job, not worked in last week, 20-Unemployed, 21-Unemployed experience worker, 22-Unemployed new worker, 30-36-NILF for various reasons).

Once the operational states were constructed, the categories were recoded into a single dichotomous variable, Underemployment=1 (Underemployed) or 0 = adequately employed. Underemployed individuals will assist in an accurate assessment of underemployment status for females within a varying percentage of female clustering in occupations. The binary dependent variable allows me to conducted binary logistic regression models to test the probability that male and female clustered occupations at varying degrees of clustering have experienced underemployment.

Independent Variables

The primary independent variables used in the models were constructed to identify female-dominated occupations. Researchers' opinions vary as to the cutoff point for female-dominated (Pearlman 2018, Holder 2018, Bergmann 1971; Emerek, Figueiredo, Gonzalez, Gonas, Rubery 2003; Anker 1998; Duncan and Duncan .1955) The common definition of gender domination of occupations is 40 percent with an average mean of 27 to 58 percent (Anker 1998: 81). Some comparable worth measures use the 70 percent rule, which has a range of 30 to 70 percent (Anker 1998:81). Since I am comparing gender clustering, I constructed a four-part range to incorporate some of the recommendations and practices of previous researchers, and I used highly male-dominated occupations as my reference group.

For this study, the clustering measures are coded as Pink to indicate the focus on the percent of female clustering in occupations. Pink 0-29 percent, is the reference category since this range has the lowest percent of females (0-29 percent) of women working in these occupations. The next ranges are Pink 30-49 percent, Pink 50-74 percent Pink 75-100 percent. To construct these variables, I coded each occupation based on the percent of females versus males working in that occupation, instead of grouping occupations into industry categories. I did this to compare my occupational codes (SOC) to Frey and Osborne's (2017) occupational vulnerability to automation. Focusing on occupations prevented the analysis from overlooking the female-dominated occupations that may have fallen in male-dominated industries.

Often researchers use the Index of Dissimilarity (ID) to determine occupational segregation (Bergmann 1971; Emerek, Figueiredo, Gonzalez, Gonas, Rubery 2003; Anker 1998; Duncan and Duncan 1955). The ID divides the observed population for the expected population and then takes the absolute values of the difference and sums across occupations and divides by 2 (Rosburg 2010). The ID is measured on a 0 to 1 scale, 0 being integrated and 1 being segregated (Pearlman; 2001; Holder 2018; Bergmann 1971; Duncan and Duncan 1955). This scale was troublesome since I desired to measure under representation to over representation and not only gender-balanced occupations to female-dominated occupations. I would have to calculate an ID for male-dominated occupations to gender-balanced occupations. When I attempted the ID calculations, I found that the occupations identified as female-dominated and male-dominated were the occupations I had designated simply from looking at the percent of males and females occupying these occupations. Since the results are the same and women are nearly half of the labor force (Between 45-48 percent from 1979 to 2017), I decided to take the observed percent of males and female in the occupation.

For my second analysis, I conducted a multivariate regression in which I also incorporated several demographic controls variables including age, sex, race, marital status, number of children living in the household, and education. Age is measured as a continuous variable from 18 to 64, excluding persons within the age of retirement and education, is measured by degree attained (preschool-12 grade without a college degree to professional degree). Race (nonwhite= 1), sex (female = 1) and marital status (married =1) are as binary variables. The number of children residing with an individual (Nchild) are a continues variable from 0 to 9+ children.

Analytical Strategy

For this project, I employed binary and multivariate logistic regression to examine labor force utilization by gender occupational clustering across the pooled panel data; (1979-1980, 1989-1990, 1999-2000, 2009-2010, and 2017). This design enables me to compare men and women's reports of underemployment at each occupational clustering range, over time. Comparing panel data is critical for this research for three reasons. First, to see if there is a significant difference between men and women and their reported underemployment across the segregation ranges. Previous research suggests males benefit from tokenism in female-dominated occupation, including job security and promotions (Tazemen 2018; Tuzeman and Willis 2013). Yet repetitive jobs are at risk for automation and this has been seen in deindustrialization.

On the other hand, women are identified as a group that is at greater risk for automation. However, the researchers have targeted predominantly female-dominated occupations as growth sectors. Second, reports of increased underemployment may signal that there is automation-related occupational displacement and that one gender is being displaced more than another. Comparing the gender occupation cluster ranges to the growth sectors and Frey and Osborne's (2017) vulnerability scale may enhance the story as to why one gender is doing better than the other. Third, viewing the data across time helps me to distinguish whether the Fourth Economic Revolution is different from the previous economic changes like deindustrialization, development of the service economy, and the Great Recession. For example, a difference in underemployment may indicate that the current economic revolution is offering more or fewer opportunities for full-time employment that provides a healthy standard of living. Table one shows the descriptive statistics of the variables used in the models and Table 2 shows the descriptive statistics for each occupational measure in each panel.

Table 1

Descriptive Statistics for Variables Used in Binary Logistic Regression

Variables	N	Mean	Std Dev	Range
LUF	754,185	0.16	0.367	0.0-1.0
Sex	759,856	0.476	0.499	0.0-1.0
Age	759,856	38.373	12.463	18.0-64.0
Race	759,588	0.159	0.365	0.0-1.0
Marital Status	759,856	0.604	0.489	0.0-1.0
# of Children	759,856	1.001	1.218	0.0-1.0
Educational Attainment	759,856	2.292	1.203	1.0-5.0
Pink	700,312	2.35	1.18	0.0-4.0
*Pink 0-29%	237,686	33.94%		
*Pink 30-49%	156,721	22.38%		
*Pink 50-74%	130,832	18.68%		
*Pink 75-100%	175,073	25.00%		

Table 2

Descriptive Statistics Tabulation of Occupational Clustering by Gender

Variables	1979-1980		1989-1990		1999-2000		2009-2010		2017	
Sex	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Pink 0-29%	58,057 (88.5%)	7,543 (11.5%)	42,297 (88.62%)	5,432 (11.38%)	33,529 (87.89%)	4,620 (12.11%)	54,071 (87.63%)	7,636 (12.37%)	21,371 (87.23%)	3,130 (12.77%)
Pink 30-49%	14,827 (60.15%)	9,821 (39.85%)	21,174 (61.74%)	13,120 (38.26%)	22,146 (60.58%)	14,412 (39.42%)	25, 148 (60.4%)	16,497 (39.61%)	11,793 (60.24%)	7,783 (39.76%)
Pink 50-74%	7,693 (37.46%)	12,844 (62.54%)	9,910 (39.58%)	15,128 (60.42%)	7,326 (37.54%)	12,188 (62.46%)	16,337 (37.25%)	27,524 (62.75%)	8,060 (36.83%)	13,822 (63.17%)
Pink 75-100%	3,397 (8.85%)	34,968 (91.15%)	3,673 (10.04%)	32,914 (89,96%)	4,165 (12.38%)	29,473 (87.62%)	5,961 (12.27%)	42,631 (87.73%)	2,213 (12.37%)	15,678 (87.63%)
Total	83,974	65,176	77,054	66,594	67,166	60,693	101,517	94,288	43,437	40,413

N=700,312

CHAPTER FOUR

Results

In viewing the descriptive statistics in Table 2, the results show considerable stability in occupational segregation over time. The largest (but modest) category of movement is males into female-dominated occupations. There is a 3.52 percent growth of men working in occupations that employee 75 to 100 percent women between 1979/80 and 2017/18. The results are noteworthy since there is predicted growth in fields that are typically held by women within this cluster range, for example, primary education, nursing, and other medical technician occupations. Although researchers have addressed male stigma and resistance to working in pink collar jobs, there seems to be male movement into these areas of work. Likewise, there is a small movement of women in occupations that employ men more frequently. Women have seen 1.27 percent of the growth in occupations with 0-29 percent of female clustering. Many in the 0-29 cluster measure require physical labor, maintenances, and transportation, but they also include occupations in the sciences and other fields which women have had difficulty entering.

Table 3 presents the bivariate logistic regression results designed to assess the previously outlined hypotheses, first, there are gender differences in vulnerability to automation that men are at greatest risk for. Second, these differences are not static over time. The regressions were employed to estimate the reported odds of underemployment men and women over four decades. This research expects that gender will play a role in underemployment at each gender occupational clustering range.

Table 3 displays the results of empirical testing of both hypotheses for the dependent variable of underemployment, with gender occupational clustering ranges of men and women without controls. The table indicates that in 1979/80, men had statistically significant reductions in reported underemployment in occupations with gender occupation clustering with between 30-49 percent of women working in these occupations, compared to the low female occupational clustering reference group of 0-29 percent women. Between 1979 and 1980, men reported a 7.2 percent decrease in odds of underemployment in the 30-49 percent female occupational clustering group while they had a statistically significant increase in reported odds in the 50-74 percent clustering range and no significance difference in the 75-100 percent range. In 2017, men reported a decreased odds of 30.9 percent of underemployment in occupations with 30-49 percent of gender occupational clustering. Men who work in more gender integrated occupations, but still male-dominated (30-49 percent female) performed best in terms of avoiding underemployment over the last 4 decades. They had better experiences than men who were working in male-dominated occupations (0-29 percent). In contrast, women employed in these same occupations had weaker odds of avoiding underemployment across each decade. For example, in 2009/10, the odds that women avoided underemployment in the 30-49 percent female category are 4.8 times weaker than the odds a male avoided underemployment in this category.

Between 1979 and 2000, men report increased odds of underemployment in occupations that had gender occupational clustering (75-100 percent women). In 2009 and 2010 this trend seemingly broke with men reporting a decreased odds of underemployment in occupations with 75-100 percent women employed. This is an important result since other researchers and articles reported men going into female-dominated occupations (Pink collar jobs), during the Great Recession and it suggests that men moved into these more female-dominated positions because of job security when compared to male-dominated occupations (0-29 percent female clustering). In Table 3, we see how men moved in to more integrated occupations after deindustrialization and the Great Recession. In 2017, men had a 24.8 percent decreased odds of reporting being underemployed in occupations with 75-100 percent female dominate gender occupational clustering.

In Table 3, women's odds of reporting underemployment are not as one directional as males' odds of reporting underemployment are. In 1979 and 1980, women had 12.3 percent increased odds of reporting underemployment in occupations with gender occupational cluster clustering of 30-49 percent women. Women also had increased odds of 31.2 percent of reporting underemployment in occupations with 50-74 percent of female clustering in 1979 and 1980. In 2017 women had a 20.2 percent decreased odd of reporting underemployment in occupations with 30-49 percent female clustering, there was no significant difference for women in reporting underemployment in occupations with 50-74 percent clustering compared to occupations with 0-29 percent female cluttering. Women in occupations with clustering of 75-100 percent reported an 11.8 decrease in odds of underemployment in 2017, which is a 2.3 percent increase of reported odds from 1979 and 1980. These findings indicate that women are more at risk for underemployment in female-dominated positions in 2017 than in 1979/80 and may be an indication of automation affecting female-dominated occupations that are more routinized. The results could also indicate issues of gender disparity. For example, even in the same occupation men are generally given roles with more job security, such as supervisory positions or even a completely different set of tasks even though the men and women have the same title (Reskin and Bielby 2005; Falkenberg, Naswall, Lindfors and Sverke 2015 Bizopoulou 2017a:2017b).

Table 4 presents the results from the multivariate regression testing of both hypotheses. When the controls are added into the model, the effects of occupation on underemployment probabilities are inconsistent across time and gender. In Table 4, males in 2017 and have an 8.5 percent decreased odds of reporting underemployment for occupations with gender occupational clustering between 30-49 percent women. Males in occupations with female clustering at 30-49 percent have had decreased odds of underemployment for all four decades of the panels. In 1979 and 1980, there was an increase in odds of 16.4 percent of men reporting underemployment for occupations with 50-74 percent female clustering compared to occupations with 0-29 percent women of occupational gender clustering. Males reported an increase of underemployment in occupations with 75-100 percent female clustering from 1979 to the 1999-2000 panel.

However, in 2009/10, there was a 17 percent decrease in the reported odds of underemployment for males in occupations with 75-100 percent clustering. Again, 2009 at the height of the Great Recession, and there were accounts of more men going into traditionally female occupations, and it was the only instance of males reporting decreased unemployment in the 75-100 percent female occupational gender cluster range in the four decades examined. During the Great Recession, men reported a decrease in

Table 3

Bivariate Logistic Regression and Odds Ratios Predicting Underemployment

Variables	1979-1980		1989-1990		1999-2000		2009-2010		2017	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Constant	-1.9339***	-1.7624***	-1.7633***	-1.6847***	-1.8400***	-1.6489***	-1.3903***	-1.5123***	-1.8760***	-1.7184***
Pink 30-49%	-.0748*** (.928)	.1159* (1.123)	-.4243*** (.654)	-.2221*** (.801)	-.3746*** (.688)	-.2347*** (.791)	-.3927*** (.675)	-.0851* (.918)	-.3684*** (.692)	-.2740*** (.760)
Pink 50-74%	.1516*** (1.164)	.2713*** (1.312)	-.2819*** (.754)	-.1444* (.886)	-.3919*** (.676)	-.3079*** (.735)	-.3784*** (.685)	-.1469*** (.863)	-.2257*** (.812)	-.0743 (.928)
Pink 75-100%	.0774 (1.081)	-.0234 (.997)	.0480 (1.049)	-.0516 (.950)	.0166 (1.017)	-.1192* (.887)	-.1733*** (.841)	-.0636*** (.938)	-.2686*** (.723)	-.1946** (.823)

P-value *.05 **.001 ***.0001

Table 4

Multivariate Logistic Regression and Odds Ratios Predicting Underemployment

Variables	1979-1980		1989-1990		1999-2000		2009-2010		2017	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Constant	-.1831***	-.1633**	-.0150	.2745***	.3350***	.7714***	.6752***	.7683***	.12489***	.3299***
Pink 30-49%	-.0162*** (.928)	.1236** (1.132)	-.2105*** (.810)	-.1431*** (.867)	-.1342*** (.874)	-.1631* (.850)	-.2358*** (.790)	-.0704 (.932)	-.0891* (.915)	-.0666 (.936)
Pink 50-74%	.0528*** (1.164)	.1812*** (1.199)	-.1004** (.904)	-.0740 (.929)	-.0447 (.956)	-.1446** (.865)	-.1886*** (.828)	-.1293*** (.879)	-.0467 (.954)	-.00209 (.998)
Pink 75-100%	.0299*** (1.081)	-.0870** (.917)	.0436 (1.049)	-.0425 (.932)	.0601 (1.062)	-.1228* (.884)	-.1863*** (.830)	-.1375*** (.872)	-.0427 (.958)	-.00657 (936)
Age	-.231*** (.977)	-.0255*** (.975)	-.0234*** (.977)	-.0263*** (.974)	-.0225*** (.978)	-.0261*** (.974)	-.0161*** (.984)	-.0193*** (.981)	-.0202*** (.980)	-.0166*** (.984)
Race2	.5609*** (1.752)	.5355*** (1.708)	.4887*** (1.630)	.4346*** (1.544)	.3166*** (1.373)	.3502*** (1.419)	.3282*** (1.389)	.2738*** (1.315)	.3248*** (1.384)	.2628*** (1.301)
Marst2	-.8291*** (.436)	-.9466*** (.388)	-.7786*** (459)	-1.1414*** (319)	-.7511 (.472)	-1.3045*** (.271)	-.7555*** (.470)	-1.1281*** (.324)	-.6764*** (.508)	-1.3327*** (.264)
#Children	.2273*** (1.255)	.2629*** (1.301)	.2700*** (1.310)	.3176*** (1.374)	.32935*** (1.341)	.3780*** (1.459)	.1889*** (1.208)	.2761*** (1.318)	.2550*** (1.290)	.3490*** (1.418)
Educ	-.4557*** (.634)	-.3515*** (.704)	-.5097*** (601)	-.5268*** (.591)	-.6167*** (.540)	-.6025*** (.547)	-.5621*** (.570)	-.5350*** (.586)	-.5865*** (.556)	-.5326*** (.587)

P-value *.05 **.001 ***.0001

unemployment odds the 30-49 percent, 50-74 percent, and 75-100 percent range when compared to occupations with female clustering between 0-29 percent. In 2017, men reported an 8.5 percent decrease in underemployment for occupations with 30-49 percent clustering compared to the 0-29 percent female clustering range. However, there was no significant different between underemployment reporting at the 50-74 percent range and the 75-100 percent range of female occupational clustering.

In 2017, men reported a 2 percent decrease in odds for underemployment with every unit increase in age. Marital status also decreases males reported odds of underemployment by 49.2 percent in 2017, and education decreased men's reported odds of underemployment by 44.4 percent. However, the model also shows that non-white men have an increased odds of 38.4 percent of reporting underemployment in 2017. Although marital status decrease reports of underemployment, children increase the odds of males reporting underemployment by 29.0 percent.

In Table 4, I find that women have reported decreased odds of underemployment in 2017. However, the results are not significant indicating no difference of reported underemployment odds at those three clustering ranges when compared to the clustering range of 0-29 percent. The 79/80 decade panel shows that women reported an increased odds of being underemployed for the more integrated gender clustering ranges (30-49 and 50-74). Women working in female-dominated occupations during 1979/80 had an 8.3 percent decrease in reported underemployment compared to the occupational clustering range of 0-29 percent. In the 1999-2000 panel, the odds of women reporting underemployment decreased to roughly 13 percent at each level. Women also have lower odds of underemployment, and the odds remained low through the 2009-2010 panel.

In 2017, Women reported a 1.6 decreased odds in underemployment with every unit increase in age, when in 1979-1980, women reported a decreased odds of 2.5 underemployment. Being married also decreases women's reported odds of underemployment by 73.3 percent in 2017, which is more than in the previous decades. Education decreased females reported odds of underemployment by 41.3 percent, which is a significant improvement from the reported odds of 29.6 in the 1979-1980 panel. However, the effect on women is slightly smaller than for men. The model also shows that non-white women have a 30.1 increased odds of reporting underemployment in 2017. Again, while being married decreased reported odds of underemployment, children increase the odds of females reporting underemployment by 41.8 percent when compared to men.

When it comes to the difference in occupational clustering by gender, there were differences in underemployment reporting odds, but the differences seemed to have changed since the Great Recession, for the most part leveling out for men and women. During the Great Recession, men and women reported a decrease odds of underemployment by 17 percent for men with in clusters with 50 percent and greater women employed, and 12 percent for women with clustering of 50 percent and greater female occupational clustering. Seven years later and there is no difference for women at any level of clustering and their odds of underemployment and men's odds of underemployment in occupations with female clustering 50 percent and greater.

The reported odds of underemployment were greater for non-white respondents than white respondents. Although the figure has dropped from the reported increased odds of 70-75 percent in 1979-1980 to reported increased odds of 33-37 percent in 2017, it is still large. Underemployment entails the desire to work full-time, people who are laid off, and the working poor and having an increase in reported odds of underemployment touches on a history of racism, prejudices, and disadvantage that racial and ethnic groups have experienced in the workforce and other social structures. Further investigation must be made to see which aspects of underemployment are affecting non-white groups, and if the same factors effecting each gender are the same. Children is another issue that must be investigated. Women report 42 percent increased odds of underemployment over men who reported 30.2 percent increased odds of underemployment. These figures do suggest that childcare is potentially a contributing factor to underemployment and may be touching on the underlying issue of uneven domestic work distribution, the construct that childcare is a role for women more so than for men, and affordable childcare is a. problem.

The most important finding from these results is the effect of education on underemployment. Education has consistently reduced the reported odds of underemployment across the panels for both genders. Moreover, the benefit of education on reducing being underemployed has increased over time. In 2017, men had a decreased odds of 44 percent underemployment, and women had a decreased odds of 41 percent. However, the influence of education on employment security has increased more so for women than it has for men over time. Gender occupational inequality matters, but not as much as individual level effects, and more specifically education. The automation hypothesis put forth by researchers believes that higher education decreases the likelihood that employees will work jobs that rely on routine work and instead require more creative intelligence, social intelligence, and tactile manipulation. Education is more important than ever for decreasing underemployment.

During the Great Recession, many people lost their jobs and many occupations consolidated as the tasks were merged with other positions. The Great Recession forced many men to go into fields with increased gender diversity. It would seem that currently, there is no difference in underemployment for men and women. Also, more men seem to be moving into occupations that are traditionally held by women. I must reject the null of my first hypotheses, there is no difference in underemployment odds for men at the gender clustering ranges 50-74 percent and 75-100 percent female in 2017. There is also no difference in reported odds of underemployment for women at any range of gender clustering compared to 0-29 percent female gender occupational clustering. Labor force convergence maybe detected with these findings. I fail to reject my second hypotheses; the differences are not static over time.

Although my analysis was not statistically significant, this may be due to the occupational cluster ranges, including occupations that vary in predicted vulnerability to automaton. Figure 1, shows the major occupation sectors, including the first two digits of the SOC codes by occupational clustering. The figure also indicates which sectors are expected to grow based on the 2017 McKinsey Global Institute report, Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation and the Frey and Osborne's analysis on the probability of automation by occupation. The figure shows that with that between 50-100 percent of female clustering is within Healthcare Support and the Healthcare Practitioners and technical, a sector which is predicted to grow. The chart shows that 90 percent of the 50-100 female clustering range is also represented in in

Education, Training, and Library, which is another sector predicted to grow, except library sciences which predicted to experience stagnation and is vulnerable to automation.

Growth fields and low automation*, Non-Growth sectors and high automation**, Growth sectors and high automation***

Figure 1. Female Occupational Segregation by Employment Sector (SOC)

Other sectors that have high female employment are with in Legal and Office Administration, which are sectors with predicted stagnation and high probability of automation.

For sectors with the typically more male concentrated occupation, Installation, Maintenance and Repair, and Construction and Extraction, there is predicted growth and high probability of automation. There is expected growth and low probability of automation for architects and engineers. I could not find any predictions for Military specific occupation. The McKinsey report predicts stagnation for first responders, however, protective services occupations vary in the probability of automation. 60 percent Computer and Mathematics sector is male-dominated and will be experiencing growth except for mathematics jobs, which show a high probability of automation. This table shows that growth in one sector does not guarantee resistance to automation. The table implies that occupations requiring more education are less vulnerable to automation for both men and women.

CHAPTER FIVE

Discussion and Conclusion

While occupations provide an identity, a sense of purpose, and an avenue for social connection for many people, social inequity is also embedded at the occupational level. Women are paid less than men, incur more penalties such as disruptions in social security due to maternity leave, and generally, have fewer benefits then male workers (Cohen and Huffman 2003; Wingfield 2009 Williams 1992). Women also grapple with, glass ceilings, sexism, and bear the brunt of third shift domestic responsibilities (Scholarios and Taylor 2011; Pearlman 2018; England et al. 1996: Ridgeway 2011; Ridgeway and Smith-Lovin 1999). Although these issues must be corrected, women's increased degree attainment should decrease the risk of automation vulnerability in the future, considering that men's college degree attainment has been on the decline in the last few years and the development of low skills labor industries, which traditionally employ men, are not predicted to grow and have increased risk of being automated (Ryan and Bauman 2016; U.S. Bureau of Labor Statistics 2017; National Center for Educational Statistics 2015; Tuzemen 2018; Himes 2018; McKinsey Global Institute 2017;Frey and Osborne 2017a:2017b:2018).

Many researchers find that automation threatens to eliminate occupations and compete with employees. Currently, the United States is experiencing a decrease in labor force participation even though production is on the rise, an occurrence which is attributed to automation by some researches (Ford 2015; Frey and Osborne 2017a:2017b:2018; McAfee and Brynjolfsson 2011:2012:2017). Social scientists agree that the latest economic revolution will alter the demand for skill sets and the variety of occupational opportunities in the future (Frey and Osborne 2017:2018; McAfee and Brynjolfsson 2011:2012:2017. Autor and Dorn 2013). The Bureau of Labor Statistics reported that in 2017 the annual underemployment rate for two categories matching my underemployment definitions. The U-5 category (total unemployed, plus discouraged workers, plus all other marginally attached workers, as a percent of the civilian labor force plus all marginally attached workers), was 5.3 percent. The U-6 category (total unemployed, plus all marginally attached workers, plus total employed part-time for economic reasons, as a percent of the civilian labor force plus all marginally attached worker), was 8.3 percent. This means that in 2017 women and men at each of the gender clustering ranges I designated (except for the 30-49 percent range) were experiencing 5.3 to 8.5 percent underemployment.

Researchers have been assessing who is at greater risk of job-loss due to automation by examining the routinization of the occupations, and educational attainment, and gender of the workers. My analysis of occupational segregation and underemployment shows that while these factors are important, individual level attributes (education) is the strongest predictor of underemployment across time and occupational segregation measures. It also works statistically the same for men and women, despite other researchers finding that women are more vulnerable to underemployment (Glass Burning and Strada Institute 2018). However, women have made great strides in educational attainment and if these trends continue women may advance past men in the labor force as well as educational attainment.

In opposition to Hypothesis 1, the findings of this study do not support gender difference in vulnerability to automation that men are at greater risk for. There was no significant difference for women in 2017, at the three levels compared to the reference group of 0-20 percent. Women had a decrease in reported odds of underemployment for the 1999-2000 panel and through 2010. These findings support research conducted by Frey and Osbornes (2017), stating that gender is not a factor of automation risk. Men were less prone to underemployment compared to 0-29 percent of gender occupational clustering levels between 30-74 percent. In 2009 and 2010, men working within the 75-100 percent gender occupational clustering (the female-dominated grouping) had a decrease reported odds of underemployment. These results may suggest a convergence of men and women in the labor force as some researchers have suggested, or that automation is affecting men and women equally at the moment. The research also shows that during deindustrialization and the Great Recession, more men reported a decreased odds of underemployment in occupations with greater female representation and traditionally pink-collar occupations.

What is clear is that education is the most important factor in decreasing the reported odds of underemployment. The research supports that an increase in educational attainment reduces the odds of reporting underemployment, and previous researchers find that more education decreases the likelihood of being in an occupation that requires routinized tasks to be performed. Since industrialization, technology has grown in its capacity and human labor attempted to maintain a similar pace with technology, through our educational systems which evolved to meet the demand for the skillsets necessary to work in growing industries (Frey and Osborne 2017, Goldin and Katz 2007, Brynjolfsson and McAfee 2011:2012:2017; Ford 2015). However, there have been studies showing that demand for some skills is in decline and that higher skilled labor is displacing lower skilled labor in occupations that do not require advanced educations (Frey and Osborne 2017; Brynjolfsson and McAfee 2011:2012:2017; Glass Burning and Strada Institute 2018).

Yet, data presented here show that for the last forty years, the effects of education on decreasing underemployment is greater in 2017 than in previous years. This may suggest although education is very important in reducing an individual's odd of losing their job to automation, an individual must still choose an occupation that has qualities that cannot be automated. There are occupations that are over saturated with labor. The Glass Burning and Strada Institute find that 14 percent of all majors are underemployed after graduation and 29 percent will remain so for the next five years (i.e., the stereotypical English major working as a barista). Some researchers feel that the current educational system is antiquated, only able to teach skills for the current workforce, and not provide students with dynamic skills needed for the future. Brynjolfsson and McAfee (2017) have called for radical improvement in the structure of education, focusing on building general skills that develop social and creative intelligence, and perception/manipulation rather than teaching students a limited set of skills for a singular concentration. In a climate where many people feel that college is no longer worth the cost because of slow occupational gains, Brynjolfsson and McAfee's recommendations go against the talking points of making education more particle and encouraging trade schools rather than college degrees. If researchers are correct in their predictions of growth and potential for automations, trade-schools may not remedy underemployment.

The model also shows that non-white men have an increased odd of 38.4 percent of reporting underemployment in 2017. The model also shows that non-white females have a 30.1 increased odds of reporting underemployment in 2017. All though this is an improvement from 1979/80, it is still low and is mostly likely related to disparities in K-12 preparedness, low college graduations rates and employment discrimination (Nichols and Schak 2018; Shierholz 2013). Deindustrialization, which severely affected people of color and the current automation revolution may reduce occupations in Food Preparation, Production, Sales, Administration, Transportation, Management and Farming which employs many middle and low skills workers African Americans historically have worked in (Wilson 1996). Racial and economic segregation inhibit social mobility through the acquisition of desired skillsets through college attainment (Wilson 1996). There should be future research on racial division of labor and automation.

This work is a snapshot of gender segregation and underemployment, and there are a few limitations. First, grouping occupations by gender clustering without including education to determine occupational groupings prevents me from analyzing higher skilled occupations from lower skilled occupations in each gender cluster range. This means that I am not able to establish how men and women in high skilled occupations compared to men and women in low skilled occupations. I am also not able to discern how men in high skilled occupations compared to women in high-skilled occupations. The picture presented in this paper may be too vague due to the interactions of high and low skilled occupations muting the reported odds of underemployment. Looking at the skill level and gender clustering may change the results for men and women should be investigated in the future. Finally, the research presented does not account for regional variances, which may have unique economies that differ from the nation.

Despite the limitations, the research is supported by theoretical arguments that gender segregation may influence vulnerability for underemployment and that the automation of tasks and occupations may be contributing to underemployment. Through the decade panels, we see that men moving into more integrated occupations experienced a decrease in reported odds of underemployment. Women also had decreasing odds of underemployment in occupations that had been integrated or female-dominated. Seven years after the recession, men and women have no difference in odds of reporting underemployment at any gender integration cluster, except for men at the 30-49 percent female occupational clustering range. When occupation growth and automation are compared, many male-dominated occupations are expected to growth. However, these positions have a higher probability of automation compared to occupations that women work in. We are only in the beginning stages of this current economic revolution and it will take time to truly know how it will affect the labor force.

APPENDIX

Table A.1

Gender Occupational Clustering 2017

Title and Soc	0-29% Female Frequency	30-49% Female Frequency	50-74% Female Frequency	75-100% Female Frequency	Automation Vulnerability Probability by Frey and Osborne
29-1181 (Audiologists)	0	0	0	6	0.0033
29-1122 (Occupational Therapists)	0	0	0	71	0.0035
29-1031 (Dieticians and Nutritionists)†	0	0	0	69	0.0039
29-1127 (Speech Language Pathologists)	0	0	0	89	0.0064
29-1111 (Registered Nurses)†	0	0	0	1873	0.009
29-2061 (Licensed Practical and Licensed Vocational Nurses)†	0	0	0	362	0.058
29-1126 (Respiratory Therapists)	0	0	0	56	0.066
39-9011 (Childcare Workers)†	0	0	0	732	0.084
41-3041 (Travel Agents)	0	0	0	30	0.099
39-5012 (Hairdressers, Hairstylists, and Cosmetologists)†	0	0	0	431	0.11
19-4021 (Biological Technicians)	0	0	0	15	0.3
29-1124 (Radiation Therapists)	0	0	0	8	0.34
43-3041 (Gaming Cage Workers)	0	0	0	14	0.39
45-2041 (Graders and Sorters, Agricultural Products)	0	0	0	82	0.41

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
43-4031 (Court, Municipal, and License Clerks)	0	0	0	62	0.46
31-9091 (Dental Assistants)†	0	0	0	170	0.51
31-9011 (Massage Therapists)	0	0	0	90	0.54
25-9041 (Teacher Assistants)†	0	0	0	609	0.56
25-4021 (Librarians)	0	0	0	89	0.65
29-2021 (Dental Hygienists)†	0	0	0	93	0.68
37-2012 (Maids and Housekeeping Cleaners)	0	0	0	924	0.69
29-2081 (Opticians, Dispensing)	0	0	0	26	0.71
51-9192 (Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders)	0	0	0	2	0.81
43-9022 (Word Processors and Typists)†	0	0	0	50	0.81
51-6050 (Tailors, Dressmakers, and Sewers)†	0	0	0	44	0.84
35-3041 (Food Servers, Nonrestaurant)	0	0	0	103	0.86
29-2071 (Medical Records and Health Information Technicians)†	0	0	0	102	0.91
43-4131 (Loan Interviewers and Clerks)	0	0	0	78	0.92

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
29-2050 (Health Diagnosing and Treating Practitioner Support Technicians)	0	0	0	352	0.92
43-4111 (Interviewers, Except Eligibility and Loan)	0	0	0	95	0.94
23-2011 (Paralegals and Legal Assistants)	0	0	0	236	0.94
43-4121 (Library Assistants, Clerical)†	0	0	0	44	0.95
43-2011 (Switchboard Operators, Including Answering Service)	0	0	0	9	0.96
43-3021 (Billing and Posting Clerks)†	0	0	0	247	0.96
43-4171 (Receptionists and Information Clerks)†	0	0	0	712	0.96
43-9061 (Office Clerks, General)†	0	0	0	716	0.96
43-3051 (Payroll and Timekeeping Clerks)†	0	0	0	66	0.97
43-4071 (File Clerks)	0	0	0	94	0.97
35-9031 (Waiters and Waitresses)	0	0	0	138	0.97
43-9041 (Insurance Claims and Policy Processing Clerks)	0	0	0	145	0.98
43-3071 (Bank Tellers)†	0	0	0	172	0.98
43-3031 (Bookkeeping, Accounting, and Auditing Clerks)†	0	0	0	581	0.98
25-4031 (Library Technicians)	0	0	0	17	0.99
43-4141 (New Account Clerks)	0	0	0	24	0.99

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
41-9041 (Telemarketers)	0	0	0	40	0.99
13-2053 (Insurance Underwriters)	0	0	0	44	0.99
43-9021 (Data Entry Keyers)†	0	0	0	143	0.99
29-11XX (Clinical Nurse Specialist)†	0	0		1996	.0028-.35*
21-1020 (Social Workers)	0	0	0	661	.0031-.25*
29-1129 (Therapists, nec)	0	0	0	98	.0035*
25-2010 (Preschool and Kindergarten Teachers)†	0	0	0	453	.0042-.15*
25-2050 (Special Education Teachers)	0	0	0	239	.0077-.016*
39-5090 (Personal Appearance Workers, nec)	0	0	0	188	.01-.29*
31-2010 (Occupational Therapy Assistants and Aides)	0	0	0	17	.018-.28*
23-201X (Legal Support Workers, nec)	0	0	0	94	.06-.98*
43-4199 (Information and Record Clerks, All Other)	0	0	0	57	.16-96*
31-909X (Medical Assistants and Other Healthcare Support Occupations, nec)†	0	0	0	543	.27-.78*
31-1010 (Nursing, Psychiatric, and Home Health Aides)†	0	0	0	1135	.28-47*
41-9010 (Models, Demonstrators, and Product Promoters)†	0	0	0	30	.51*

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
39-9021 (Personal Care Aides)	0	0	0	871	.74*
43-6010 (Secretaries and Administrative Assistants)†	0	0	0	1450	.81-.96*
25-2020 (Elementary and Middle School Teachers)†	0	0	0	1900	0.0044-.26*
19-2021 (Atmospheric and Space Scientists)	0	0	2	0	0.67
29-1125 (Podiatrists)	0	0	3	0	0.0028
11-3121 (Human Resources Managers)	0	0	236	0	0.0055
11-9151 (Social and Community Service Managers)	0	0	254	0	0.0067
11-9111 (Medical and Health Services Managers)	0	0	356	0	0.0073
29-1051 (Pharmacists)	0	0	175	0	0.012
43-1011 (First-Line Supervisors of Office and Administrative Support Workers)	0	0	735	0	0.014
19-1020 (Biological Scientists)	0	0	64	0	0.015
29-1199 (Health Diagnosing and Treating Practitioners, nec)	0	0	23	0	0.02
29-1123 (Physical Therapists)	0	0	161	0	0.021
21-2021 (Directors, Religious Activities and Education)	0	0	41	0	0.025
11-3061 (Purchasing Managers)	0	0	100	0	0.03
15-2031 (Operations Research Analysts)	0	0	94	0	0.035
27-3043 (Writers and Authors)	0	0	108	0	0.038

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
29-1131 (Veterinarians)	0	0	39	0	0.038
39-9041 (Residential Advisors)	0	0	26	0	0.064
11-3031 (Financial Managers)	0	0	671	0	0.069
39-1021 (First-Line Supervisors of Personal Service Workers)	0	0	109	0	0.076
11-9051 (Food Service Managers)	0	0	756	0	0.08
13-1041 (Compliance Officers, Except Agriculture)	0	0	173	0	0.08
39-2011 (Animal Trainers)	0	0	24	0	0.1
19-3051 (Urman and reginal Planners)	0	0	26	0	0.13
29-1071 (Physician Assistants)	0	0	53	0	0.14
13-2061 (Financial Examiners)	0	0	9	0	0.17
27-3031 (Public Relations Specialists)	0	0	74	0	0.18
15-2011 (Actuaries)	0	0	9	0	0.21
13-1022 (Wholesale and Retail Buyers, Except Farm Products)	0	0	129	0	0.29
53-2031 (Flight Attendants and Transportation Workers and Attendants)†	0	0	65	0	0.35
51-9051 (Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders)	0	0	7	0	0.37
53-7064 (Packers and Packagers, Hand)†	0	0	325	0	0.38
33-9091 (Crossing Guards)	0	0	28	0	0.49

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
41-3011 (Advertising Sales Agents)	0	0	127	0	0.54
43-4051 (Customer Service Representatives)	0	0	1275	0	0.55
43-4181 (Reservation and Transportation Ticket Agents and Travel Clerks)	0	0	83	0	0.61
51-3093 (Food Cooking Machine Operators and Tenders)	0	0	7	0	0.61
35-1012 (First-Line Supervisors of Food Preparation and Serving Workers)	0	0	331	0	0.63
53-7041 (Conveyor operators and tenders, and hoist and winch operators)	0	0	10	0	0.65
43-4061 (Eligibility Interviewers, Government Programs)	0	0	44	0	0.7
51-3092 (Food Batchmakers)	0	0	51	0	0.7
51-6011 (Laundry and Dry-Cleaning Workers)	0	0	110	0	0.71
35-3011 (Bartenders)	0	0	224	0	0.77
43-9011 (Computer Operators)	0	0	33	0	0.78
51-6021 (Pressers, Textile, Garment, and Related Materials)	0	0	21	0	0.81
39-2021 (Nonfarm Animal Caretakers)	0	0	116	0	0.82
43-9081 (Proofreaders and Copy Markers)†	0	0	3	0	0.84
35-2021 (Food Preparation Workers)	0	0	552	0	0.87

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
43-5061 (Production, Planning, and Expediting Clerks)	0	0	119	0	0.88
27-3042 (Technical Writers)	0	0	38	0	0.89
51-3011 (Bakers)	0	0	139	0	0.89
51-6031 (Sewing Machine Operators)	0	0	131	0	0.89
43-4161 (Human Resources Assistants, Except Payroll and Timekeeping)	0	0	34	0	0.9
35-3021 (Combined Food Preparation and Serving Workers, Including Fast Food)	0	0	186	0	0.92
41-2031 (Retail Salespersons)	0	0	1700	0	0.92
41-3021 (Insurance Sales Agents)	0	0	321	0	0.92
43-9071 (Office Machine Operators, Except Computer)	0	0	22	0	0.92
13-2081 (Tax Examiners and Collectors, and Revenue Agents)	0	0	41	0	0.93
53-7063 (Machine Feeders and Offbearers)	0	0	18	0	0.93
13-2011 (Accountants and Auditors)	0	0	914	0	0.94
35-3031 (Waiters and Waitresses)†	0	0	1130	0	0.94
41-9091 (Door-to-Door Sales Workers, News and Street Vendors, and Related Workers)	0	0	74	0	0.94
43-4081 (Hotel, Motel, and Resort Desk Clerks)	0	0	79	0	0.94

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
43-3011 (Bill and Account Collectors)	0	0	64	0	0.95
43-5051 (Postal Service Clerks)	0	0	65	0	0.95
43-5111 (Weighers, Measurers, Checkers, and Samplers, Recordkeeping)	0	0	31	0	0.95
51-6062 (Textile bleaching and dyeing, and cutting machine setters, operators, and tenders)	0	0	3	0	0.95
51-9191 (Adhesive Bonding Machine Operators and Tenders)	0	0	3	0	0.95
35-3022 (Counter Attendant, Cafeteria, Food Concession, and Coffee Shop)†	0	0	105	0	0.96
39-3031 (Ushers, Lobby Attendants, and Ticket Takers)	0	0	25	0	0.96
51-6064 (Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders)	0	0	5	0	0.96
43-2021 (Telephone Operators)†	0	0	17	0	0.97
43-4041 (Credit Authorizers, Checkers, and Clerks)	0	0	24	0	0.97
43-3061 (Procurement Clerks)	0	0	10	0	0.98
43-4151 (Correspondent clerks and order clerks)	0	0	79	0	0.98
51-9111 (Packaging and Filling Machine Operators and Tenders)	0	0	194	0	0.98

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
13-2082 (Tax Preparers)	0	0	72	0	0.99
43-5011 (Cargo and Freight Agents)	0	0	11	0	0.99
51-9151 (Photographic Process Workers and Processing Machine Operators)	0	0	14	0	0.99
21-1010 (Counselors)	0	0	459	0	.0035-.033*
29-2090 (Health Technologists and Technicians, nec)	0	0	84	0	.0039*
25-90XX (Education, Training, and Library Workers, nec)	0	0	98	0	.0042.-99*
19-3030 (Psychologists)	0	0	87	0	.0043-.12*
19-10XX (Medical Scientists, and Life Scientists, All Other)	0	0	88	0	.0045*
51-6099 (Textile, Apparel, and Furnishings workers, nec)	0	0	22	0	.0049-.99*
27-1020 (Designers)	0	0	474	0	.0055-037*
25-4010 (Archivists, Curators, and Museum Technicians)	0	0	25	0	.0068-.74*
25-2030 (Secondary School Teachers)	0	0	592	0	.0088*
13-11XX (Other Business Operations and Management Specialists)	0	0	491	0	.014-.64*
27-1010 (Artists and Related Workers)	0	0	111	0	.042*
39-7010 (Tour and Travel Guides)	0	0	25	0	.057*
27-3090 (Media and Communication Workers, nec)	0	0	59	0	.082-.11*

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
39-9099 (Personal Care and Service Workers, All Other)	0	0	95	0	.085*
39-9030 (Recreation and Fitness Workers)	0	0	213	0	.085-0.72*
27-2030 (Dancers and Choreographers)	0	0	3	0	.13*
29-2030 (Diagnostic Related Technologists and Technicians)	0	0	180	0	.13-.23*
43-9XXX (Office and administrative support workers, nec)†	0	0	304	0	.16-.99*
25-3000 (Other Teachers and Instructors)	0	0	513	0	.19*
21-109X (Community and Social Service Specialists, nec)†	0	0	40	0	.25*
39-1010 (First-Line Supervisors of Gaming Workers)	0	0	104	0	.28*
39-3010 (Gaming Services Workers)	0	0	47	0	.28*
43-5030 (Dispatchers)	0	0	155	0	.49-.96*
13-1070 (Human Resources, Training, and Labor Relations Specialists)	0	0	483	0	.61*
31-2020 (Physical Therapist Assistants and Aides)	0	0	46	0	.61*
43-2099 (Communications Equipment Operators, All Other)	0	0	8	0	.86-.96*
51-9080 (Medical, Dental, and Ophthalmic Laboratory Technicians)	0	0	37	0	.89-.97*
43-3099 (Financial Clerks, nec)	0	0	45	0	.95-.98*

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
29-2010 (Clinical Laboratory Technologists and Technicians)	0	0	204	0	.9*
41-2010 (Cashiers)†	0	0	1763	0	.97*
41-9020 (Real Estate Brokers and Sales Agents)	0	0	448	0	.97*
13-1030 (Claims Adjusters, Appraisers, Examiners, and Investigators)	0	0	166	0	.98*
13-2070 (Credit Counselors and Loan Officers)	0	0	196	0	.98*
11-9030(Education Administrators)	0	0	497	0	0.0046 -.015*
21-2099 (Religious Workers, nec)	0	0	40	0	
51-3091 (Food and Tobacco roastinf, baking, drying, machine operators and tendors)	0	5	0	0	0.91
29-2041 (Emergency Medical Technicians and Paramedics)	0	132	0	0	0.0042
13-1081 (Logisticians)	0	54	0	0	0.012
29-1060 (Physicians and Surgeons)	0	518	0	0	0.014
11-1011 (Chief executives and legislators/public administration)	0	817	0	0	0.015
11-9121 (Natural Science Managers)	0	9	0	0	0.018
17-2131 (Materials Engineers)	0	16	0	0	0.021
29-1020 (Dentists)	0	82	0	0	0.027
15-1141 (Database Administrators)	0	41	0	0	0.03

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
25-1000 (Postsecondary Teachers)	0	780	0	0	0.032
23-1011 (Lawyers, and judges, magistrates, and other judicial workers)	0	622	0	0	0.035
29-9000 (Healthcare Practitioners and Technical Occupations, nec)	0	77	0	0	0.049
19-3041 (Sociologists)	0	18	0	0	0.059
35-1011 (Chefs and Cooks)	0	1593	0	0	0.1
35-9011 (Food preparation and serving related workers, nec)	0	173	0	0	0.1
13-1111 (Management Analysts)	0	492	0	0	0.13
29-1041 (Optometrists)	0	32	0	0	0.14
11-1021 (General and Operations Managers)	0	569	0	0	0.16
33-9011 (Animal Control)	0	9	0	0	0.21
13-2051 (Financial Analysts)	0	147	0	0	0.23
13-1011 (Agents and Business Managers of Artists, Performers, and Athletes)	0	20	0	0	0.24
41-2021 (Counter and Rental Clerks)†	0	59	0	0	0.28
41-1011 (First-Line Supervisors of Sales Workers)	0	2466	0	0	0.28
33-9021 (Private Detectives and Investigators)	0	47	0	0	0.31
27-2011 (Actors, Producers, and Directors)	0	92	0	0	0.37

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
19-3011 (Economists and market researchers)	0	38	0	0	0.43
19-2099 (Physical Scientists, nec)	0	161	0	0	0.43
13-2052 (Personal Financial Advisors)	0	254	0	0	0.58
51-2020 (Electrical, Electronics, and Electromechanical Assemblers)	0	73	0	0	0.64
53-30XX (Bus and Ambulance Drivers and Attendants)	0	255	0	0	0.66
43-5053 (Postal Service Mail Sorters, Processors, and Processing Machine Operators)	0	29	0	0	0.68
43-5052 (Postal Service Mail Carriers)	0	172	0	0	0.68
51-6063 (Textile Knitting and Weaving Machine Setters, Operators, and Tenders)	0	10	0	0	0.73
11-3011 (Administrative Services Managers)	0	84	0	0	0.73
13-1023 (Purchasing Agents, Except Wholesale, Retail, and Farm Products)	0	151	0	0	0.77
43-5071 (Shipping, Receiving, and Traffic Clerks)	0	312	0	0	0.79
11-9141 (Property, Real Estate, and Community Association Managers)	0	366	0	0	0.81
13-2021 (Appraisers and Assessors of Real Estate)	0	44	0	0	0.9

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
51-3099 (Food Processing, nec)	0	86	0	0	0.91
37-1011 (First-Line Supervisors of Housekeeping and Janitorial Workers)	0	189	0	0	0.91
13-2031 (Budget Analysts)	0	40	0	0	0.94
37-201X (Janitors and Building Cleaners)	0	1326	0	0	0.94
51-9198 (Helpers--Production Workers)	0	32	0	0	0.95
51-7042 (Woodworking Machine Setters, Operators, and Tenders, Except Sawing)	0	10	0	0	0.97
19-4011 (Agricultural and Food Science Technicians)	0	26	0	0	0.97
41-3031 (Securities, Commodities, and Financial Services Sales Agents)	0	121	0	0	0.97
13-2041 (Credit Analysts)	0	19	0	0	0.98
51-9071 (Jewelers and Precious Stone and Metal Workers)	0	32	0	0	0.98
51-9061 (Inspectors, Testers, Sorters, Samplers, and Weighers)	0	428	0	0	0.98
43-5081 (Stock Clerks and Order Fillers)	0	834	0	0	0.98
17-1010 (Architects, except Navel)	0	146	0	0	-
19-409X (Life, Physical, and Social Science Technicians, nec)	0	83	0	0	..0095-.77*

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
11-916X (Managers, nec (including Postmasters Emergency management directors))	0	2364	0	0	.003*
19-1030 (Conservation Scientists and Foresters)	0	20	0	0	.0081-.016*
27-2020 (Athletes, Coaches, Umpires, and Related Workers)	0	148	0	0	.013-.28*
27-2040 (Musicians, Singers, and Related Workers)	0	86	0	0	.015-.074*
41-3099 (Sales Representatives, Services, All Other)	0	235	0	0	.016-.92*
19-1010 (Agricultural and Food Scientists)	0	16	0	0	.021-.077*
19-2030 (Chemists and Materials Scientists)	0	49	0	0	.021-.1*
27-3020 (Editors, News Analysts, Reporters, and Correspondents)	0	156	0	0	.069-.11*
29-1011 (Chiropractors)	0	22	0	0	.1-.33*
53-2020 (Air Traffic Controllers and Airfield Operations Specialists)	0	11	0	0	.13-.71*
39-6010 (Baggage Porters, Bellhops, and Concierges)	0	43	0	0	.21-.83*
33-909X (Law enforcement workers, nec)	0	80	0	0	.21-.95*
41-4010 (Sales Representatives, Wholesale and Manufacturing)	0	627	0	0	.25-.85*

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
27-2099 (Entertainers and Performers, Sports and Related Workers, All Other)	0	22	0	0	.28-.98*
39-40XX (Funeral Service Workers and Embalmers)	0	22	0	0	.37-.59*
51-2090 (Assemblers and Fabricators, nec)	0	566	0	0	.93-.99*
39-3090 (Entertainment Attendants and Related Workers, nec.43-.72*)	0	107	0	0	.43-.96*
15-2090 (Mathematical science occupations, nec)	0	58	0	0	.99*
11-20XX (Managers in Marketing, Advertising, and Public Relations)	0	623	0	0	0.039*
41-9099 (Sales and Related Workers, All Other)	0	130	0	0	0.94*
51-2011 (Aircraft structure, surface, rigging, and systems assemblers)	2	0	0	0	0.79
49-1011 (First-Line Supervisors of Mechanics, Installers, and Repairers)	118	0	0	0	0.003
33-1021 (First-Line Supervisors of Fire Fighting and Prevention Workers)	26	0	0	0	0.0036
41-9031 (Sales Engineers)	14	0	0	0	0.0041
33-1012 (First-Line Supervisors of Police and Detectives)	61	0	0	0	0.0044
21-2011 (Clergy)	193	0	0	0	0.0081

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
17-2121 (Marine Engineers and Naval Architects)	7	0	0	0	0.01
17-2141 (Mechanical Engineers)	152	0	0	0	0.011
17-2199 (Engineers, all other)	292	0	0	0	0.014
17-2041 (Chemical Engineers)	45	0	0	0	0.017
51-1011 (First-Line Supervisors of Production and Operating Workers)	415	0	0	0	0.016
17-2011 (Aerospace Engineers)	68	0	0	0	0.017
11-9041 (Architectural and Engineering Managers)	76	0	0	0	0.017
17-2081 (Environmental Engineers)	23	0	0	0	0.018
17-2051 (Civil Engineers)	233	0	0	0	0.019
33-1011 (First-Line Supervisors of Correctional Officers)	32	0	0	0	0.025
15-1142 (Network and Computer Systems Administrators)	113	0	0	0	0.03
11-3051 (Industrial production managers)	134	0	0	0	0.03
11-3021 (Computer and information systems manager)	326	0	0	0	0.037
11-9013 (Floral designers)	533	0	0	0	0.047
11-9021 (Constructions Managers)	37	0	0	0	0.071
11-9021 (Construction Managers)	1899	0	0	0	0.074
11-9071 (Gaming Managers)	16	0	0	0	0.091

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
49-9051 (Electrical Power-Line Installers and Repairers)	80	0	0	0	0.097
47-2111 (Electricians)	497	0	0	0	0.15
33-2011 (Firefighters)	155	0	0	0	0.17
47-1011 (First-Line Supervisors of Construction Trades and Extraction Workers)	406	0	0	0	0.17
17-2061 (Computer Hardware Engineers)	44	0	0	0	0.22
33-3021 (Police Officers and Detectives)	434	0	0	0	0.34
53-706X (Cleaners of Vehicles and Equipment)	199	0	0	0	0.37
47-4021 (Elevator Installers and Repairers)	20	0	0	0	0.39
51-6093 (Upholsterers)	23	0	0	0	0.39
51-2041 (Structural Metal Fabricators and Fitters)	20	0	0	0	0.41
47-5031 (Explosives Workers, Ordnance Handling Experts, and Blasters)	6	0	0	0	0.48
15-1131 (Computer Programmers)	234	0	0	0	0.48
49-9052 (Telecommunications Line Installers and Repairers)	107	0	0	0	0.49
47-4041 (Hazardous Materials Removal Workers)	22	0	0	0	0.53
49-3022 (Automotive Glass Installers and Repairers)	15	0	0	0	0.55

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
19-4031 (Chemical Technicians)	35	0	0	0	0.57
13-1051 (Cost Estimators)	66	0	0	0	0.57
37-1012 (First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers)	136	0	0	0	0.57
49-9044 (Millwrights)	17	0	0	0	0.59
11-3071 (Transportation, storage, and distribution managers)	165	0	0	0	0.59
49-3023 (Automotive Service Technicians and Mechanics)	513	0	0	0	0.59
49-2096 (Electronic Equipment Installers and Repairers, Motor Vehicles)	7	0	0	0	0.61
51-8031 (Water Wastewater Treatment Plant and System Operators)	55	0	0	0	0.61
47-4011 (Construction and Building Inspectors)	40	0	0	0	0.63
49-9071 (Maintenance and Repair Workers, General)	330	0	0	0	0.64
49-2097 (Electronic Home Entertainment Equipment Installers and Repairers)	36	0	0	0	0.65
51-4041 (Machinists)	178	0	0	0	0.65
49-9021 (Heating, Air Conditioning, and Refrigeration Mechanics and Installers)	225	0	0	0	0.65
15-1150 (Computer Support Specialists)	270	0	0	0	0.65

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
43-9111 (Statistical Assistants)†	8	0	0	0	0.66
37-2021 (Pest Control Workers)	51	0	0	0	0.66
51-9196 (Paper Goods Machine Setters, Operators, and Tenders)	14	0	0	0	0.67
47-2011 (Boilermakers)	11	0	0	0	0.68
49-2091 (Avionics technicians)	3	0	0	0	0.7
49-3011 (Aircraft Mechanics and Service Technicians)	84	0	0	0	0.71
49-9031 (Home Appliance Repairers)	23	0	0	0	0.72
47-2031 (Carpenters)	749	0	0	0	0.72
47-2121 (Glaziers)	27	0	0	0	0.73
49-3031 (Bus and Truck Mechanics and Diesel Engine Specialists)	208	0	0	0	0.73
49-2011 (Computer, Automated Teller, and Office Machine Repairers)	105	0	0	0	0.74
49-2092 (Electric Motor, Power Tool, and Related Repairers)	18	0	0	0	0.76
49-9094 (Locksmiths and Safe Repairers)	14	0	0	0	0.77
35-9021 (Dishwashers)	173	0	0	0	0.77
49-9098 (Helpers--Installation, Maintenance, and Repair Workers)	11	0	0	0	0.79
39-5011 (Barbers)	62	0	0	0	0.8
51-2031 (Engine and Other Machine Assemblers)	6	0	0	0	0.82

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
49-2098 (Security and Fire Alarm Systems Installers)	36	0	0	0	0.82
47-2211 (Sheet Metal Workers, metal-working)	77	0	0	0	0.82
47-2071 (Paving, Surfacing, and Tamping Equipment Operators)	8	0	0	0	0.83
51-4023 (Rolling Machine Setters, Operators, and Tenders, metal and Plastic)	8	0	0	0	0.83
53-5011 (Sailors and marine oilers, and ship engineers)	17	0	0	0	0.83
45-3011 (Fishing and hunting workers)	29	0	0	0	0.83
53-4031 (Railroad Conductors and Yardmasters)	36	0	0	0	0.83
47-2221 (Structural Iron and Steel Workers)	37	0	0	0	0.83
53-6031 (Automotive and Watercraft Service Attendants)	47	0	0	0	0.83
53-6021 (Parking Lot Attendants)	43	0	0	0	0.87
47-2161 (Plasterers and Stucco Masons)	19	0	0	0	0.84
51-4111 (Tool and Die Makers)	27	0	0	0	0.84
47-5021 (Earth Drillers, Except Oil and Gas)	12	0	0	0	0.85
43-5041 (Meter Readers, Utilities)	16	0	0	0	0.85
45-2090 (Agricultural workers, nec)	519	0	0	0	0.87

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
51-4034 (Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic)	6	0	0	0	0.84
53-7062 (Laborers and Freight, Stock, and Material Movers, Hand)	1092	0	0	0	0.85
49-9043 (Maintenance Workers, Machinery)	13	0	0	0	0.86
51-7041 (Sawing Machine Setters, Operators, and Tenders, Wood)	19	0	0	0	0.86
13-1021 (Buyers and Purchasing Agents, Farm Products)	10	0	0	0	0.87
51-7021 (Furniture Finishers)	11	0	0	0	0.87
45-4011 (Forest and Conservation Workers)	22	0	0	0	0.87
47-4051 (Highway Maintenance Workers)	71	0	0	0	0.87
51-4194 (Tool grinders, filers, and sharpeners)	3	0	0	0	0.88
47-2061 (Construction Laborers)	866	0	0	0	0.88
47-4061 (Rail-Track Laying and Maintenance Equipment Operators)	7	0	0	0	0.89
49-9096 (Riggers)	12	0	0	0	0.89
51-8021 (Stationary Engineers and Boiler Operators)	39	0	0	0	0.89
53-3041 (Taxi Drivers and Chauffeurs)	282	0	0	0	0.89
47-2171 (Reinforcing Iron and Rebar Workers)	7	0	0	0	0.9

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
53-6051 (Transportation Inspectors)	16	0	0	0	0.9
51-9195 (Molders, Shapers, and Casters, Except Metal and Plastic)	23	0	0	0	0.9
53-7021 (Crane and Tower Operators)	27	0	0	0	0.9
47-2181 (Roofers)	161	0	0	0	0.9
19-4041 (Geological and Petroleum Technicians, and Nuclear Technicians)	7	0	0	0	0.91
49-3021 (Automotive Body and Related Repairers)	81	0	0	0	0.91
51-4193 (Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic)	10	0	0	0	0.92
47-4031 (Fence Erectors)	21	0	0	0	0.92
51-7011 (Cabinetmakers and Bench Carpenters)	39	0	0	0	0.92
51-9041 (Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders)	12	0	0	0	0.93
53-7081 (Refuse and Recyclable Material Collectors)	57	0	0	0	0.93
53-7051 (Industrial Truck and Tractor Operators)	329	0	0	0	0.93
51-9197 (Tire Builders)	5	0	0	0	0.94

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
45-2011 (Agricultural Inspectors)	15	0	0	0	0.94
43-9051 (Mail Clerks and Mail Machine Operators, Except Postal Service)	37	0	0	0	0.94
43-5021 (Couriers and Messengers)	103	0	0	0	0.94
51-4033 (Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic)	21	0	0	0	0.95
47-2073 (Construction equipment operators except paving, surfacing, and tamping equipment operators)	251	0	0	0	0.95
17-3031 (Surveying and Mapping Technicians)	45	0	0	0	0.96
51-5111 (Prepress Technicians and Workers)	12	0	0	0	0.97
43-4011 (Brokerage Clerks)	3	0	0	0	0.98
51-9194 (Etchers, Engravers, and Lithographers)	6	0	0	0	0.98
41-2022 (Parts Salespersons)	59	0	0	0	0.98
17-21XX (Petroleum, mining and geological engineers, including mining safety engineers)	31	0	0	0	.01-.16*
19-2010 (Astronomers and Physicists)	7	0	0	0	.041-.1*

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
19-2040 (Environmental Scientists and Geoscientists)	54	0	0	0	.014-63*
17-2070 (Electrical and Electronics Engineers)	163	0	0	0	.025-.1*
17-2110 (Industrial Engineers, including Health and Safety)	82	0	0	0	.028-.029*
53-1000 (Supervisors of Transportation and Material Moving Workers)	110	0	0	0	.029-.42*
17-3020 (Engineering Technicians, Except Drafters)	221	0	0	0	.03-.84*
15-113X (Software Developers, Applications and Systems Software)	791	0	0	0	.042-.48
27-3010 (Announcers)	27	0	0	0	.1-.72*
27-4010 (Broadcast and Sound Engineering Technicians and Radio Operators, and media and communication equip)	55	0	0	0	.13-.98*
53-2010 (Aircraft Pilots and Flight Engineers)	74	0	0	0	.18-.55*
49-909X (Other Installation, Maintenance, and Repair Workers Including Wind Turbine Service Technicians, and "Commercial Divers, and Signal and Track Switch Repairers")	116	0	0	0	.18-.96*

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
53-5020 (Ship and Boat Captains and Operators)	22	0	0	0	.27-.62*
49-9060 (Precision Instrument and Equipment Repairers)	22	0	0	0	.27-.99*
27-4030 (Television, Video, and Motion Picture Camera Operators and Editors)	37	0	0	0	.31-.60*
47-2150 (Pipelayers, Plumbers, Pipefitters, and Steamfitters)	327	0	0	0	.35-.63*
33-3010 (Sheriffs, Bailiffs, Correctional Officers, and Jailers)	221	0	0	0	.36-.6*
51-4010 (Computer Control Programmers and Operators)	39	0	0	0	.36-86*
49-2020 (Radio and Telecommunications Equipment Installers and Repairers)	63	0	0	0	.36-93*
47-50XX (Extraction workers, nec)	58	0	0	0	.37-.96*
53-7199 (Material moving workers, nec)	31	0	0	0	.37-72*
17-1020 (Surveyors, Cartographers, and Photogrammetrists)	30	0	0	0	.38-.88*
49-209X (Electrical and electronics repairers, transportation equipment, and industrial and utility)	12	0	0	0	.38-71*
49-3040 (Heavy Vehicle and Mobile Equipment Service Technicians and Mechanics)	129	0	0	0	.4-.88*
33-2020 (Fire Inspectors)	12	0	0	0	.48*

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
17-3010 (Drafters)	70	0	0	0	.52-.81*
51-604X (Shoes and Leather workers machine operators and tenders)	3	0	0	0	.52-97*
47-5010 (Derrick, rotary drill, and service unit operators, and roustabouts, oil, gas, and mining)	22	0	0	0	.53-.93*
47-5040 (Mining Machine Operators)	53	0	0	0	.54-.59*
45-1010 (First-Line Supervisors of Farming, Fishing, and Forestry Workers)	37	0	0	0	.57*
47-3010 (Helpers, Construction Trades)	41	0	0	0	.57-.94*
49-904X (Industrial and Refractory Machinery Mechanics)	241	0	0	0	.59-.86*
49-3090 (Vehicle and Mobile Equipment Mechanics, Installers, and Repairers, nec)	58	0	0	0	.59-94*
51-3020 (Butchers and Other Meat, Poultry, and Fish Processing Workers)	189	0	0	0	.61-.94*
47-2080 (Drywall Installers, Ceiling Tile Installers, and Tapers)	106	0	0	0	.62-.79*
51-4120 (Welding, Soldering, and Brazing Workers)	362	0	0	0	.62-.94*
49-9010 (Control and Valve Installers and Repairers)	13	0	0	0	.63-.91*
47-2130 (Insulation Workers)	37	0	0	0	.64-.83*

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
51-8010 (Power Plant Operators, Distributors, and Dispatchers)	28	0	0	0	.64-.95*
51-9030 (Cutting Workers)	38	0	0	0	.64-86*
51-9199 (Other production workers including semiconductor processors and cooling and freezing equipment operators)	536	0	0	0	.66-98*
51-4070 (Molders and Molding Machine Setters, Operators, and Tenders, Metal and Plastic)	25	0	0	0	.67-.95*
51-9120 (Painting Workers and Dyers)	72	0	0	0	.69-.92*
53-3099 (Motor Vehicle Operators, All Other)	19	0	0	0	.69-.98*
53-3030 (Driver/Sales Workers and Truck Drivers)	1139	0	0	0	.69-.98*
47-2040 (Carpet, Floor, and Tile Installers and Finishers)	87	0	0	0	.75-.87*
47-214X (Painters, Construction and Maintenance)	347	0	0	0	.75-.87*
53-60XX (Transportation workers, nec)	22	0	0	0	.75-97*
51-9010 (Chemical Processing Machine Setters, Operators, and Tenders)	34	0	0	0	.76-.88*
45-4020 (Logging Workers)	46	0	0	0	.76-.97*

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
37-3010 (Grounds Maintenance Workers)	583	0	0	0	.77-.97*
51-8090 (Plant and System Operators, nec)	32	0	0	0	.78-.86*
51-4030 (Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic)	41	0	0	0	.78-.98*
47-2020 (Brickmasons, Blockmasons, and Stonemasons)	106	0	0	0	.82-.89*
47-4090 (Construction workers, nec)	25	0	0	0	.83*
53-40XX (Subway, Streetcar, and other Rail Transportation Workers)	4	0	0	0	.83-.96*
51-9020 (Crushing, Grinding, Polishing, Mixing, and Blending Workers)	56	0	0	0	.83-.97*
51-5010 (Bookbinders, Printing Machine Operators, and Job Printers)	106	0	0	0	.83-.97*
53-7070 (Pumping Station Operators)	17	0	0	0	.84-.91*
51-4199 (Metal workers and plastic workers, nec)	240	0	0	0	.84-.92*
33-9030 (Security Guards and Gaming Surveillance Officers)	467	0	0	0	.84-.95*
51-4050 (Metal Furnace Operators, Tenders, Pourers, and Casters)	13	0	0	0	.87-.88*

(Continued)

Title and Soc	0-29% Female	30-49% Female	50-74% Female	75-100% Female	Automation Vulnerability Probability by Frey and Osborne
53-7030 (Dredge, Excavating, and Loading Machine Operators)	20	0	0	0	.92-.94*
33-1099 (Supervisors, Protective Service Workers, All Other)	49	0	0	0	0.0036-024*
49-3050 (Small Engine Mechanics)	24	0	0	0	0.66-.93*
40-9095 (Manufactured Building and Mobile Home Installers)	5	0	0	0	NA
51-7099 (Woodworkers including model makers and patternmakers, nec)	18	0	0	0	NA
55-9830 (Military, Rank Not Specified)	20	0	0	0	NA
Total	24501	19576	21882	19881	

* Approximation of probability estimates based on occupational categories that fall within the first 3 digits of the Standard Occupational Classification coding schema. occupations that also share the first three digits may require similar types of task and skills, so are used as a proxy for the specified occupations.

†Occupations that had high female clustering (75-100%) during 1979/80.

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