Disruptive Technology: Economic Consequences of Artificial Intelligence and the Robotics Revolution

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We examine the possible economic impact of lost wages and tax revenues that artificial intelligence and machine learning could have in the U.S. within the next couple of decades. Using a probability-weighted methodology, provide decile-grouped estimates for the possible monetary implications of significant job losses due to this disruptive technological revolution. Furthermore, we examine the implied tax revenue losses associated with the displacement of the employees in these occupations. Our results suggest that within a few decades the economic impact may very well be in the hundreds of billions in lost wages and hundreds of millions in lost tax revenue.

INTRODUCTION

Artificial Intelligence and Machine Learning

Artificial Intelligence (AI) can be roughly defined as the study of computer systems performing tasks that would normally require human intelligence. A popular subfield of AI is Machine Learning (ML), which encompasses everything related to computer systems learning algorithms to perform a task by utilizing data. Traditionally, computers require that you "define a complete and correct algorithm for [a] task and then programme the algorithm into the computer" (Taiwo, 2010). With machine learning and other artificial intelligence systems, this is no longer the case. The most advanced computer systems are currently exposed to previously unthinkable amounts of data, and are rapidly learning how to rationalize the data by computing their own algorithms. In other words, ML can be thought of as computers learning how to perform tasks without being explicitly programmed. This is rapidly bringing forth a technological revolution, accomplishing feats that would not have been imaginable just a few years ago, and the implications are potentially staggering for economies across the globe.

Subfields of Machine Learning

Within the context of ML, there are numerous subfields, all of which in a myriad of approaches attempt to use algorithms to make sense of data. One of these subfields is known as Artificial Neural Network (ANN), because it attempts to simulate learning in the human brain. The concept of ANNs has been around since the 1950's; however, inadequate computer processing power, and lack of access to big (or deep) data slowed its advancement. That was until Google advanced the field of AI by creating a more efficient way to teach individual, layered computer systems and better replicate the human brain by forming connections between them. In simplified terms, each layer performs a specific task and then feeds the results into the next layer, which uses those results to perform its own unique task. As more layers are added, the computer system becomes capable of more complex tasks. In addition, by utilizing back propagation, these programs compare what their tasks (or predictions) were to what the actual outcomes were (or were supposed to be) and learn from their mistakes. They do this with processing speeds in the billions of calculations per second. In other terminology, the process of using pseudo-neural layers, each responsible for analyzing data and performing specific tasks, is known as Deep Learning (DL). DL machines are now capable of recognizing phonemes of speech and objects at an increasingly reliable rate.[1] The field of DL "has over the past few years given rise to a massive collection of ideas and techniques that were previously either unknown or known to be untenable" (Perez, 2016). In fact, DL has already led to advances in object recognition, natural language processing, toxicology and many other areas.[2]

There are many other subfields within the realm of Machine Learning, a couple of the most prominent being Machine Vision and Data Mining. Machine Vision allows for computer systems to not only record visual information, but process, analyze and measure that information for decision makers.[3] Such machines have the capability to measure and process images much more efficiently and correctly than their human counterparts. Additionally, Data Mining refers to the process of systems analyzing vast amounts of data to derive some previously unknown patterns or correlations – or "knowledge" from that data. Because computers are capable of analyzing information at an exponentially faster rate than humans, they are capable of seeing patterns that humans may not recognize. For example, Data Mining has amplified the capabilities in the field of computational statistics, wherein researchers use computers to enhance classic statistical methodology and are now performing previously unthinkable calculations, and graduates in these fields are in high demand in several sectors, from advertising to finance.

Other Artificial Intelligence Advances

Machine learning and its many subfields are not the only artificial intelligence systems advancing rapidly. In 2015, researchers at the Massachusetts Institute of Technology, New York University and the University of Toronto outlined advancements in a new method of artificial intelligence, known as Bayesian Program Learning (BPL). They programmed a system capable of recognizing people's handwriting after being exposed to only a handful of samples. BPL surpasses some of the limitations of machine learning, notably the ability to learn new concepts from just one or a few examples (Lake, Salakhutdinov, and Tenenbaum, 2015). The system has the capability to take a minimal amount of data or examples and formulate a rich response based solely on probability inference models. Furthermore, BPL has the capability to learn from its past mistakes when formulating its next probabilistic response. While a full discussion of the various fields of artificial intelligence is beyond the scope of this text, it is important to recognize that they have varying capabilities and are advancing rapidly.

Robotics engineers are implementing the technological advances from these various fields of artificial intelligence into physical robotic devices, designed to perform specific tasks. For instance, consider that recent artificial intelligence advancements are already being utilized in areas such as mobile robotics, autonomous robotics, computer-aided design (CAD) systems, autonomous vehicle technology, and many others. Advanced robots, booted with the latest AI programs, are currently capable of performing at a level that is eerily similar to a science fiction film. Consider Amazon's Kiva robots that work alongside humans in large distribution centers. In July of 2014, Amazon began using Kiva robots in the U.S. Today there are over 15,000 of them spread across ten warehouses being used to carry and sort entire rows of items. Each Kiva robot is capable of performing a separate task, while navigating a large warehouse and communicating with one another, not impeding the work flow of Amazon's distribution process, but enhancing and making the distribution process more efficient. Currently one of the biggest hurdles to automating the e-commerce sector is developing robots capable of picking up objects, putting them into boxes and packaging them for shipping. Companies such as Kuka AG, Honeywell International Inc, JD, Hudson's BayCo and others are closing in on technology necessary automate the picking process, which has the potential to disrupt the distribution process of e-commerce.[4]

Corporations and Artificial Intelligence Advancements

Although exciting and extremely useful, artificial intelligence is still in its relatively early stages of development and implementation in the business sector. Other firms could – and most likely will at some point - create a robot better than Kiva at distributing goods, using a different AI methodology to expand the robot's capabilities beyond even picking up and packaging items for shipping. There is no consensus or standardization of design, because humanity has yet to discover the optimal AI system required for each task. Various current methodologies may need to be integrated before an optimal AI system exists for any given purpose. Technological advancements are occurring at such a rapid pace, that it is impossible to rationalize our possible capabilities over the next decade or so. Once we have developed a reasonable AI solution to specific problems, companies will undoubtedly begin to commercialize their technology.

When these technology companies begin to upscale the commercialization of their artificial intelligence systems, major shifts will occur in the United States' and other countries' workforce. Currently, most people have perceived automation as machines working on assembly lines, performing mundane, manual labor. Advances in artificial intelligence and robotics will – and already has – change(d) that perception, as jobs requiring mental skills will also be threatened by smart, deep-learning machines. The very notion of automation is changing. As technology progresses, more jobs are potentially at risk of being replaced by non-human capital. We may soon perceive automation as machines performing routine labor, regardless of it being a physical or mental task.[5]

Humanity is significantly advancing its capabilities in robotics and artificial intelligence, making it impossible to fully know our future capabilities even just a few years into the future. Moreover, there are many factors that drive companies to automate, making it difficult to quantify the extent that companies will automate their processes in the future. Nevertheless, it is evident that collectively, corporations are already taking steps to automate certain processes traditionally done by humans. AI systems are expanding their skillset to perform jobs that many believe only a human can handle. For example, in 2016 Anheuser-Busch InBev NV and Uber Technologies Inc. joined forces to make the first commercial delivery of Budweiser beer using a self-driving truck. While there was an actual truck driver in the backseat on standby in case something went wrong, the truck actually traversed the 120 miles and successfully made the delivery without the human needing to take over. Although this autonomous shipment of Budweiser is primarily a stunt in which to prove the technology can be implemented, it marks a technological milestone. Anheuser-Busch estimates that if it could implement autonomous trucks across its distribution channels, it would save $50 million annually.[6] Cost savings like this will drive more and more automation. Obviously, companies operating with fewer employees will reap the cost benefits: less wages, 401K and pension contributions, vacation time and healthcare costs. The possibilities of automating business processes appear endless. Currently an autonomous, electrically powered cargo ship named Yara Birkeland is under construction in Norway and is slated to hit the waters in 2018. Although leading the race, Yara Birkeland is not the only futuristic ship under construction; Rolls-Royce Holding PLC plans to launch its own robotic ship in 2020.[7] Although crewless ships are not expected to be governed until 2020, they have the potential to drastically lower transportation costs for a multitude of businesses.

Companies will be compelled to modernize and realize the increased efficiency that automation offers. Thus, AI systems have the potential to be a highly disruptive technology, impacting how companies operate in a wide array of sectors. From banks to law firms, companies are already initiating artificial intelligence projects, and collaborating towards making this automated robotics revolution a reality. For example, Toyota Motors plans to spend over $1 billion in its newly envisioned artificial intelligence research and development lab in Silicon Valley.[8] Additionally, Google, IBM, Intel and

Microsoft are all essentially creating different components to what could one day be a workable quantum computer.[9] This theoretical computer system would function differently by incorporating quasiparticles into computations; its capabilities would far surpass the limits of contemporary computers by pushing the very bounds of physics.

Researchers have been making countless breakthroughs in expanding the capabilities of technology as it relates to humans, creating a more effective human-computer interface. Recently Carnegie Mellon University's Robotics Institute taught a computer to understand the body language of multiple people in real time using a video.[10] Though the AI has yet to interact in the real world, it is able to distinguish hand poses. The hope is that computer systems will be able to interpret nonverbal communication between people, and interact when needed in social settings. Researchers at Bielefeld University created a multi-fingered robotic hand capable of learning how to interact with objects by exploring its surrounding on its own.[11] The hand is strong enough to easily crush an apple, but gentle enough to move a banana; its sensors enable it to push a button and distinguish objects based on shape, color and texture. Human-computer interface breakthroughs will indubitably make their way into the business world, facilitating AI integration into the workforce and expediting the automation of certain tasks. Quantum computing, robotic interfaces and machine learning are just a few of many areas of artificial intelligence which are receiving funding and investment from corporations around the globe. As these projects come to fruition, more and more companies around the world will adopt these technological creations. Thus, inherently, more and more jobs will become susceptible to automation as these robotic technologies improve.

PREVIOUS LITERATURE

The topic of jobs being lost to automation and new technologies is not a new one. Perhaps, the most notable event of humans being displaced in the workforce was the Industrial Revolution, which began in Great Britain in the 1700's. Economists believe there have actually been three Industrial Revolutions. Dhaka (2016) states in an article on Industrial Revolution, "Three prior industrial revolutions were based on steam/water/mechanical production in the first from the 1780s; electricity and mass production from the 1870s in the second; and electronics/information technological (IT) production from the 1970s in the third." Many economists believe that the fourth Industrial Revolution is beginning now with jobs being lost to computers and robotics.

Since the Industrial Revolution, companies have been implementing and continuously creating machines to complete jobs. With automation being more efficient and cost effective, companies are able to make products faster, offer more and better services, complete tasks faster, etc. Today, companies continue make advancements by implementing new technologies, while the technology itself is continuing to advance. These technological advances are beneficial to the economy; however, there are side effects. Economists believe that the result of advancing in Artificial Intelligence(AI) and Machine Learning (ML) will lead to many unemployed workers. Studies, discussed below, exemplify the effects of automation, AI, ML, and other technological advancements on current occupations.

Autor et al. (2003) argues that computer capital substitutes for workers performing routine cognitive and manual tasks and complements workers in performing nonroutine and communication tasks. Using task input data for 1960 to 1998, they show that as the price of information and communication technology (ICT) capital decreases, the need for workers performing routine tasks decreases. Additionally, computer capital serves to complement nonroutine workers that have varying capabilities. The authors also assert that the increased demand for workers performing nonroutine work has driven the demand for college educated workers. This is because they have a comparative advantage in performing flexible work over non-college graduates.

Michaels et al. (2014) tested the hypothesis of Autor et al. (2003) wherein labor markets have become polarized due in part to (ICT) complimenting analytical, nonroutine tasks performed by highly educated workers, and substituting routine tasks normally performed by on middle educated workers. The authors create industry-level skill share equations, grouping workers into three education classes—low, middle and high—and relating them to both ICT and R&D investments in 11 OECD countries over a 25-year span. The results support the polarization hypothesis of Autor et al. (2003), as industries that grew ICT the fastest experienced the greatest increase in demand for highly educated workers and the biggest drop in demand for middle educated workers. The results show minimal effect on lower education employees. Surprisingly, industries upgraded their workers skillset in a similar manner for all countries in the study. The authors model also predicts that ICT and R&D accounts for roughly a quarter of the growth in the college wage share of the economy.

Adermon and Gustavsson (2015) examined jobs data in Sweden from 1975-2005 for evidence of job polarization as a result of task based technological change (TBTC) i.e. growth of nonroutine jobs and decline of routine jobs. The results do not support TBTC causing polarization during the 1970s or 1980s; however, stronger evidence exists to supports this in the 1990s and 2000s but the results are inconclusive. The authors do note that they found growth of nonroutine jobs and a decline of routine jobs that support TBTC, but the results for wage differentials paint a different picture. Changes in between occupation wage differentials do not support TBTC, whereas changes in within occupation wage differentials do support it. Using a regression analysis, the authors found that 44 percent of job polarization between 1990 and 2005 can be explained by the differences in routine versus nonroutine tasks.

Goos et al. (2014) separate the total change in employment share by occupations into within-industry and between-industry components for 16 Western European countries from 1993 to 2010. The authors model shows that both higher and lower skill based occupations saw increases in their total employment share of the economy, whereas middle skilled occupations saw a decrease in all of the countries studied. They also note that both the within-industry and between-industry components of job polarization are economically important. Additionally, the model shows that skill-biased technological change (SBTC) does a better job of explaining job polarization than offshoring.

Autor (2015) states that automation may soon prevent the economy from creating enough new jobs to replace the ones lost. He asserts that historically, new industries would hire more people than industries going out of businesses would displace. But as technology progresses, there are fewer new industries that require unskilled routine labor. While acknowledging that historically technological change increased employment, he asserts this does not necessarily have to be the case. The author lists three factors that may cause increased automation to result in decreased employment. Firstly, workers who provide tasks that complement automation should see their value rise, while workers who provide tasks that substitute automation will not be so lucky. Secondly, he believes that the elasticity of the labor supply may hold back wage gains. Meaning that an increase in the overall supply of workers may "temper any wage gains that would emanate from complementarities between automation and human labor" (Autor, 2015). And lastly, the gains from automation can either dampen or amplify the amount of household income spent on a particular product. The author uses the historical agricultural and healthcare industry to illustrate, both industries underwent technological changes, yet we spend less on food and more on healthcare today. Another key point is that "rapid automation may create distributional challenges that invite a broad policy response" (Autor, 2015). Additionally, he states that workers will likely need time to get the degrees necessary for the highly skilled workforce. Autor also believes that job polarization is unlikely to continue forever and that if automation makes human labor superfluous, our new economic problem may be of distribution rather than scarcity.

Marcolin et al. (2016) used data on 28 OECD countries from 2000 to 2011 to analyze how global value chains, workforce skills, information communication technologies (ICT), innovation and industry structure explain employment levels of routine and nonroutine occupations. This study incorporates different data than prior research, as it describes polarization in terms of routine intensity index (RII) rather than skill intensity of occupations. The RII is calculated for each country, occupation and sector, then grouped into four quartiles: nonroutine (NR), low routine-intensive (LR), medium routine-intensive (MR) and high routine-intensive (HR) occupations. The results show that ICT intensity has a positive correlation with employment in all quartiles except the (HR) occupations. Still, technological innovation correlates positively with employment for all intensity levels. Interestingly the U.S. was found to have a general decline in routine employment as a percentage of total employment and European countries display more routine intensity in the manufacturing sector. The results also lend support to the notion that the relationship between routine occupations and the ability to offshore is weak.

Since AI and ML are relatively new topics, articles have just started to appear, speculating on which specific jobs may be impacted or replaced by robots or automation in the future. One article, by futurist Thomas Frey (2014), provides a list of 101 jobs that could be lost by 2030. Frey provided a "cause of destruction" for each of the jobs. For example, the driverless Budweiser truck example mentioned earlier, represents a technological innovation that could eventually replace jobs in transportation such as taxi drivers, truck drivers, bus drivers, and other jobs related to transportation. Other publications are starting to appear that address the elimination of occupations wherein AI and related technologies represent a threat to traditional human capital. For example, Comen and Stebbins (2016) discuss 18 jobs being replaced by robots. They discuss the projected loss of jobs, causes of the job losses, and the median wage for each job possibly lost. Elkins (2015) lists 20 jobs that are most likely being taken over by robots and the associated probability of being replaced from a well-known NPR paper. On the other hand, Manyika, Chui, and Miremadi (2016) discuss jobs that are least likely to be lost to robots. They note that jobs such as managers, teachers, and dental hygienists have the least probability of being replaced by a robot. Thus, there are many occupations which are not currently in danger of AI-related replacement.

However, many occupations that would seem unlikely to be threatened by these new technologies are in fact, beginning to replace the traditional human input. In the Financial Services Worldwide journal (2017), there was a section on 'Chatbots and Artificial Intelligence: Market Assessment, Application Analysis, and Forecasts 2017 – 2022.' Chatbots are advancing customer relationship, as they are automating communications between businesses and customers. The article states, "Existing User Interfaces (UI) do not scale very well. Chatbots represent a way for brands, businesses and publishers to interact with users without requiring them to download an app, become familiar with a new UI, or configure and update regularly". The interface between humans and computers is evolving to more conversational interfaces. Therefore, the analysis of the Chatbots market concludes that by 2021, approximately $262.7B of wages will be lost due to lost jobs, as Chatbots will contribute 40% of the market for customer relationships (2017).

Shambler (2017) predicts that many jobs in a variety of industries will be automated by robots in the next five to ten years. He states, "A report by Citibank in partnership with the University of Oxford predicted that 47 percent of US jobs are at risk of automation, 35 percent in the UK, and in China, it's a whopping 77 percent." Along with the most known automations in legal and accounting fields, Shambler provides examples of automation in insurance, banking, construction, retail, farming, transportation, manufacturing, and even Hollywood. For example, in the finance sector, Shambler states, "In fact, financial analyst jobs could be one of the worst hit in the automation revolution - an estimated 30 percent of banking sector jobs will be lost to AI over the next five to ten years."

Even executive leadership in Washington is taking notice. Alex Knapp (2016) disseminates a report from the White House concerning jobs being lost due to these AI technologies. Knapp, using data from the Bureau of Labor Statistics, asserts that a staggering 83% of jobs with a median hourly range below $20 will be automated. Additionally, Knapp provides evidence that roughly 44% of jobs that require less than a high school education will be automated, and 19% of jobs that require a high school degree education will be automated. He does note that new jobs will be created with AI, in that "programmers and developers are needed to make AI a reality". This gives rise to the ever-growing discussion and debate regarding income inequality in the U.S.

With respect to this notion of income inequality, Arthur MacEwan (2016) explores the impact of artificial intelligence in business industries within the context of underemployment. He states, "Even though artificial intelligence won't generate massive unemployment, it may reinforce, and perhaps increase, economic inequality." The main topic of the article is the notion that artificial intelligence in business will lower the wages of the workers that lost their jobs due to automation advances. Furthermore, Bessen (2015) discusses the relationship between technology and occupation as it relates to computers and job losses or wage inequality. He purports that as technology expands, an expansion of the workforce and difference in pay will result. He states, "While automation does not appear to have a major effect on overall employment, automation is associated with substantial job losses for some groups of occupations and job gains for other occupations. In particular, low-wage occupations tend to lose jobs while high-wage occupations gain." Bessen concludes that, "Computers automating tasks doesn't imply that occupations that use computers will necessarily suffer job losses. In fact, computer-using occupations have had greater job growth to date. Instead, it is the occupations that use few computers that appear to suffer computer-related job losses."

The U.S. manufacturing industry has lost 7 million jobs since peak employment in 1979. Politicians and main-stream media have focused on jobs being outsourced, shipped to overseas manufacturers that have lower wages. This certainly has been an issue for this industry over the last several years. However, Paul Wiseman (2016) of the Associated Press provides compelling evidence that robots, not trade, are the reason for factory job losses. However, he notes a study by the Ball State University Center for Business and Economic Research, and this research shows that, 'trade accounted for just 13 percent of America's lost factory jobs. The vast majority of the lost jobs — 88 percent — were taken by robots and other homegrown factors that reduce factories' need for human labor.'

The contribution of this study is to attempt to quantify the potential downside economic consequences associated with this technological disruption. We examine the number of workers that could potentially be replaced, the salaries and wages that would be eliminated and finally how that may affect federal tax revenues in the U.S. over the coming decades.

DATA

Frey and Osborne (2013) from the University of Oxford assessed the susceptibility of computerization on the future U.S. labor market. Taking 702 occupations and applying a Gaussian process classifier, Frey and Osborne computed the probabilities that these jobs would be impacted by the commercialization of artificial intelligence advances. They refer to occupations with probabilities of 30% or less as low risk, probabilities of 31%-69% as average risk, and probabilities of 70% or higher as high risk. They conclude that 47 percent of total U.S. employment is at high risk of automation, meaning that people in these "associated occupations are potentially automatable over some unspecified number of years, perhaps a decade or two." Because the focus of this study is on the potential economic impact of automation, we chose 80% of the selected jobs identified by Frey and Osborne as having a high risk of automation, and the remaining 20% as average risk. Thus, a total of fifty jobs and their probabilities were selected from the Oxford study for our analysis. See Appendix 1 for a list of the jobs included in this study.

We then obtained data on the number of people employed and the median salary percentile within each occupation. This information was obtained online from the U.S. Bureau of Labor and Statistics and the Office of Occupational Statistics and Employment Projections, respectively. Specifically, the median pay for 2015, and the number of workers in 2014 was used in compiling the data. This was the most recent data for each job category selected at the time of this writing. In addition, we utilized a nested-algorithm to determine the marginal effective tax rates associated with differing levels of income. These rates were obtained from the U.S. Tax Center. Appendix 2 illustrates how these rates are determined.

METHODOLOGY AND RESULTS

The results of our analysis are presented in Table 1. We created deciles to show the different possible impact scenarios, from 10% to 100% of the probability-weighted median-employment salaries and total employees in the 50 different job categories. Our calculations were very straightforward and simple. For example, the numbers shown for the 50% decile were calculated as follows:

$$\sum_{i=1}^{t}(.5)(P\text{i x }N\text{i x }S\text{i}) \tag{1}$$

where, P_i represents the probability given in the Frey, et. al. study, N_i represents the number of employees in the ith to the tth occupations (i = 1 – 50) and S_i represents the median wage for the relevant occupation.

TABLE 1
DOLLAR LOSSES BY PERCENTILES

US Total Percentiles	$ Impact (Lost by Workers)	Workers Displaced	% of Workforce	$ Lost as % of 2016 GDP
10%	$68,393,573,506	2,544,365	2%	0.37%
20%	$136,787,147,012	5,088,730	4%	0.74%
30%	$205,180,720,517	7,633,095	6%	1.11%
40%	$273,574,294,023	10,177,460	8%	1.47%
50%	$341,967,867,529	12,721,826	10%	1.84%
60%	$410,361,441,035	15,266,191	12%	2.21%
70%	$478,755,014,541	17,810,556	14%	2.58%
80%	$547,148,588,047	20,354,921	16%	2.58%
90%	$615,542,161,552	22,899,286	18%	2.95%
100%	$683,935,735,058	25,443,651	20%	3.68%

Table 2 displays the associated tax implications associated with the numbers shown in Table 1. Again, the tax dollars represent the effective marginal tax rates associated with the median salaries for the 50 occupations in our study. The tax rates were calculated by dividing the average federal taxes paid (using a nested algorithm for marginal rates) divided by the median salary for each quintile. Tax and workforce data were gathered from the Bureau of Labor Statistics (as of 01/2017).

TABLE 2
TAX REVENUES LOST BY PERCENTILES

Percentiles	Tax Loss	Tax Loss as % of 2016 Tax Rev
10%	$10,074,930,054	0.29%
20%	$20,149,860,109	0.58%
30%	$30,224,790,163	0.86%
40%	$40,299,720,217	1.15%
50%	$50,374,650,271	1.44%
60%	$60,449,580,326	1.73%
70%	$70,524,510,380	2.01%
80%	$80,599,440,434	2.30%
90%	$90,674,370,488	2.59%
100%	$100,749,300,543	2.88%

CONCLUSION

We have provided evidence from a number of different published sources which strongly suggest what is being termed a *technological revolution* – an economically disruptive event that has already impacted the way business is being conducted around the world. We have witnessed what automation has done to the workforce in areas like manufacturing. What is more remarkable is that while automation will continue to displace traditional human capital for the repetitive, more routine tasks required of many jobs, the technology is now encroaching on people with more sophisticated skill sets. From financial and accounting analysts, to those who practice law or even medicine may find technological competition in the relatively near future. While these technological advances will certainly bring forth new occupational opportunities, workers in the future will need different skill sets, and this transition may take time.

We are the first to provide different probability-weighted scenarios (by decile groupings) which quantify the magnitude the disruption these emerging technologies pose to the U.S. economy. Our results indicate that hundreds of billions of dollars of salaries and wages could very well disappear over the next decade or so. We also provide the federal tax revenues that could be lost as a result. These could be in the hundreds of millions of dollars.

IMPLICATIONS OF OUR FINDINGS

One implication is that we may have to adjust our welfare system in the event that AI advances do cause mass unemployment. Although the initial idea is older than our country itself, universal basic income has recently gained new proponents as it is seen as a way to combat the negative consequences of a disruptive robotics revolution.[12] Universal Basic Income (UBI) is essentially guaranteed cash payments sent by the government to citizens, with no strings attached. The money provided by a UBI program is solely meant to provide citizens with their basic needs. Such an idea is seen by many as a more efficient welfare method than our current system. Nevertheless, we lack sufficient data to determine if UBI will be able to provide relief in the event that artificial intelligence causes mass unemployment. Studies are currently being conducted in Finland, Holland, Ontario, the Dutch city of Utrecht and New Zealand are also exploring their own versions of UBI (Trilling, 2017). Perhaps when enough data is gathered, the impact of UBI can be explored in conjunction with the consequences of the commercialization of AI systems.

Another possible implication is that future generations will need to adjust their skills to meet the demands of a changing labor force. Computer courses may need to become compulsory for students young and old so that future employees are capable of working alongside robots. The education system will be forced to place greater emphasis on courses in computer science, coding and encrypting, engineering, and many other technology-related areas. No longer should technology concepts be "lumped together" into a basic computer course, required to be taken for a short period of time. New areas of teaching will have to be explored if technology fundamentally changes the labor force. There is even growing interest for courses that solely teach data mining, a skill that allows one to better utilize the technology around us and is in high demand.[14]

LIMITATIONS OF STUDY

While this study indicates that there is a significant portion of U.S. taxable revenue and jobs at risk of disappearing due to the upcoming robotics revolution, it fails to include any potential jobs created by the new technologies. At this stage, it is impossible to verify the types of jobs that AI will create in the future, let alone quantify them. Nevertheless, it is possible to see that collectively corporations from all over the globe are taking AI advances seriously. Moreover, it is not just technology companies that are seeking automation advances. For example, Yum! Brands partnered with Baidu to open the world's first restaurant with robots capable of taking customer orders in Shanghai, China.[16]Their collaborative innovation does not end there, as KFC and Baidu plan to open a different AI-concept restaurant. Using Baidu's advanced facial recognition technologies, the new restaurant is designed to use characteristics such as customer age, gender, mood and order history to suggest menu items.[15] Admittedly, jobs will be created by the new technologies but the focus of this study is on the downside risk. With such a wide array of companies interested in hiring cheaper, robotic labor, it seems unlikely at this point that more jobs will be created than displaced over the next decade or two. This is because it will take time for new positions to be created, and for the workforce to adjust and learn the skills to work alongside advanced technologies.

Another limitation is that it is difficult to pinpoint when these technologies will become commercialized and enter the market in mass. Inevitably, mass commercialization is dependent on technological advances. In many cases the implementation of such disruptive technology may also be limited by regulatory approval. For example, the implementation of self-driving vehicles will likely face stiff resistance from politicians in various states. Regardless, politics will eventually play a part in the implementation of such technologies, especially if robots become mainstreamed as ‘job-killers.’ Additionally, we do not account for the possibility of wage growth or stagnation affecting the favorability trade-off between human and computerized labor. Still, artificial intelligence systems do not require healthcare or 401K contributions, making it appear highly unlikely that human labor will be more cost effective than computerized labor in the future.

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Appendix 1: Jobs and Their Descriptions Included in this Study

(1) Taxi Cab Driver/Chauffer- Drive people to and from places that they need to go, such as to the airport or place of work. They must memorize streets and know quick routes through cities.
(2) Bus Drivers –Workers transport people from various places, may also collect fares. Data refers to transit and intercity bus drivers; includes charters and private buses, but excludes school bus drivers.
(3) Accountants and Auditors- Prepare and examine financial documents to ensure accuracy. Their work helps companies efficiently manage liabilities and meet regulatory requirements.
(4) Credit Analysts- Analyze personal or company data to determine the relative safety of extending credit to the individual. They prepare detailed credit reports so that lenders can properly make decisions.
(5) Telemarketer- Call and solicit individuals to order a particular good, service or make a donation.
(6) Cashiers- Process customer payments of goods and services across all parts of the economy.
(7) Retail Sales Person- This category includes workers selling retail merchandise such as clothes, furniture or cars, as well as replacement car parts and equipment. Regardless, a retail sales associate helps customers find products and processes payments to close the sale.
(8) (Garbage) Refuse and Recyclable Material Collectors- Workers physically dump trash or recyclables from containers into trucks. Some may also drive the trucks.
(9) Parking Lot Attendant- Park vehicles, give out parking garage tickets, and possibly collect fees.
(10) Driver/ Sales Worker- Workers either sell or deliver goods on an established route. This category includes truck deliveries to and from businesses and even newspaper delivery services. Workers may also help stock items, take orders or collect payment upon delivery. Category excludes workers that deliver take-out food items.
(11) Insurance Sales Agents- Workers contact potential customers, explain various insurance policies, and help people find the plan that is right for them.
(12) Bakers- Bakers prepare baked goods such as bread, cookies and pastries by using various cooking methods.
(13) Butchers and Meat Cutters- Workers cut and package meat for resale.
(14) Manicurists and Pedicurists- Workers clean and beautify customer's feet and hands.
(15) Tellers- Workers are responsible for processing routing bank transactions such as deposits, withdrawals, cashing checks and loan payments.
(16) Legal Secretary- Workers provide secretarial service while utilizing legal terminology, prepare legal documents such as summonses, complaints, motions, and subpoenas, and may also assist in research.
(17) Postal Service Mail Carriers- Workers either sort or deliver mail. May make deliveries by car or on foot.
(18) Postal Service Clerks- Workers provide numerous services at the post office such as selling postage, envelopes and money orders. Workers also examine and sort mail.
(19) Paralegals/ Legal Assistants- Support lawyers by organizing and maintaining files, conducting research and drafting legal documents.
(20) Restaurant Cooks- Prepare various meals at restaurants, may also order supplies or create dishes and price items.
(21) Waiters and Waitresses- Workers take customer orders for food and beverages in restaurants.
(22) Cooks, Institution and Cafeteria- Workers prepare large amounts of food for institutions such as schools, hospitals and cafeterias.
(23) Construction and building inspectors- Workers ensure that constructed buildings meet all requirements such as national and local building codes and ordinances, contract specifications and zoning regulations.

(24) Carpenters- Workers build and repair structures and building frameworks made of wood and other materials. They also may construct specific items such as kitchen cabinets, siding and drywall work.
(25) Brick masons and Block masons- Workers use concrete and other natural and manmade stones to construct walls and other structures.
(26) Highway Maintenance Workers- Workers maintain highways and other roads in counties across the country. Specifically, they repair old pavement, guard rails, highway markers and other signs. They may also mow or plow snow along specific roads.
(27) Roofers- Workers repair and install roofs of buildings using a variety of materials.
(28) Tax Preparer- Workers prepare tax returns for small businesses and individuals.
(29) Loan Officer- Workers evaluate and makes decisions on loan applications for businesses and individuals.
(30) Budget Analyst- Workers prepare budget reports and monitor institutional spending in order to assist organizations with their finances.
(31) Maids and Housekeeping Cleaners- Workers maintain the cleanliness of a household or establishment, such as a hotel, hospital or resort. Tasks may include vacuuming, changing sheets and towels, and many other things.
(32) Janitors and Custodians- Workers act as building cleaners and ensure everything is in good, working condition.
(33) Umpires and Referees- Workers preside over competitive games and ensure fair play. They act as the deciding authority for penalties in athletics.
(34) Technical Writers- Workers prepare instructions manuals, how-to guides, journal articles and other documents that help communicate technical information.
(35) Cartographers and Photogrammetrists- workers collect and interpret geographic information as well as create and update maps for a variety of purposes.
(36) Electrical and Electronics Drafters- Workers prepare inputs used in the manufacture, installation and repair of electrical equipment. Specifically, they may prepare wiring diagrams, circuit boards assembly diagrams or simple illustrate information with drawings.
(37) Packaging and Filling Machine Operators and Tenders- Workers operate machines used to prepare industrial or consumer products for shipping or storage. This category includes cannery workers that pack food products into cans.
(38) Grinding and Polishing Workers Hand- This category includes chippers, buffers and finishers. Workers grind, sand or polish of wide array of objects made of wood, stone, plastic, clay or glass.
(39) Electrical and Electronic Equipment Assemblers- Assemble or repair electronic equipment, such as computers, batteries, and test equipment systems.
(40) Milling and Planing Machine Setters Operators and Tenders- Workers operate machines that mill, plane, shape, or profile metal and plastic pieces.
(41) Jewelers and Precious Stone and Metal Workers- Workers design, manufacture and sell jewelry. They may also adjust, repair or appraise jewelry.
(42) Cabinetmakers and Bench Carpenters- Workers cut, shape and assemble wooden items, and may use power saws and other woodworking tools.
(43) Rolling Machine Setters Operators and Tenders Metal and Plastic- Workers set up, operate or tend machines that roll steel or plastic to make adjustments to the material.
(44) Machinists- Workers set up and operate an array of computer or mechanically controlled machine tools to make precision metal parts and tools.
(45) Meat Packers- Workers routinely slaughter, cut and prepare meat for packaging or reselling.
(46) Structural Metal Fabricators and Fitters- Workers fabricate and fit parts of structural metal products. Included in this category are shipfitters.
(47) Market Research Analysts- Workers study market conditions to help companies better understand the demographics interested in a particular product, and the price they are willing to pay for it.

(48) Medical Secretaries- Workers act as secretaries but utilize knowledge in medical terminology, and hospital and laboratory procedures. Regular duties may include scheduling appointments, billing patients or compiling medical reports and information.
(49) Librarians- Workers help people find information and books as well as conduct research.
(50) Tour Guides and Escorts- Workers escort people on tours and other sightseeing activities.

Appendix 2: Computing the Marginal Federal Tax Rate using a Nested-If-Loop for Marginal Tax Effects

Tax Range	Maximum Value	Tax Rate	Included Tax	Notes
0 to 9,225	$9,225.00	10%		
9,226 to 37,450	$37,450.00	15%	$922.50	922.50 plus 15% of the amount over 9,225
37,451 to 90,750	$90,750.00	25%	$5,156.25	5,156.25 plus 25% of the amount over 37,450
90,751 to 189,300	$189,300.00	28%	$18,481.25	18,481.25 plus 28% of the amount over 90,750