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ABSTRACT

Robots at Work: Automatable and Non Automatable Jobs*

This study builds on Autor and Dorn's (2013) classification of automatable work at the three-digit occupation code level to identify additional jobs that will be automatable in the next decade by drawing on patent data. Based on this new classification the study provides estimates of the share of jobs that we expect to be automatable in the EU and across 25 individual countries. The study highlights that aspects of 47% of jobs will be automatable over the next decade, with 35% of all jobs being fully automatable. It also provides some evidence that 'thinking' and 'people' skills will become increasingly important for the fourth industrial revolution. The study puts emphasis on the fact that these estimates are based on static models. Assuming that some of the rents from labor technology will filter back into the economy it is expected that other occupations will expand in number as people consume more goods and services.

JEL Classification: J23, J24, 020
Keywords: robots, labor markets, skills

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Introduction and Background:

Research on automation and the future of work has brought contributions that seek to determine the exact jobs that have been lost in the past, and also those that may be lost in the future. The critical component of this body of research is how 'automatable' work is defined. The seminal work in this regard is owed to Autor and Dorn (2013) and Autor et al. (2015) who define a job as automatable if it is high in routine task-intensity where routine task-intensity is measured by the level of routine, abstract and manual task content by occupation using the US *Dictionary of Occupation Titles*. Their work looks backwards and highlights clearly that the last three decades of automation have caused a hollowing out of jobs in the middle of the occupation distribution. To this end the types of occupations available to workers have become more polarized, with the majority of occupations falling into high and low skill categories, and mid skill jobs disappearing in large numbers. A second study by Frey and Osborne (2013) provides an alternative definition of automatable work based on ONET data on skills, knowledge and ability within three-digit occupation codes. Given this data, they develop an algorithm which estimates the probability of automation. The authors argue that their definition captures the jobs that will be automatable over the next decade. Based on their work they estimate that 47% of total US employment is at risk of computerization, with service jobs also being susceptible to automation (In the study computerization is defined as automation through computer-controlled equipment).

This study is complementary to these two studies. Specifically, its first contribution to the literature is to introduce a new classification of automatable work at the three-digit occupation code level based on patent data, rather than taking a task-based approach. By focusing on patent data it is argued that the strategy 'follows the money' and has a good chance of correctly identifying the jobs that will be automatable in the next decade if extensive patent activity in that area is recorded. Taking the jobs defined by Autor and Dorn (2013) and Autor et al. (2015) as automatable as accurate (given that it is backward looking and captures the jobs already automated well), the new classification involves studying the remaining occupations which they classify as non-automatable, with a view to re-classifying these jobs as automatable as appropriate. In essence, the Autor and Dorn (2013) and Autor et al. (2015) classifications are taken as adequately summarizing changes in jobs for the third industrial revolution, and this study amends this classification to account for new technologies coming on stream for the fourth industrial revolution. The estimates from this study should then be compared to Frey and Osborne (2013) who pursued a similar exercise.

The new classifications distinguish between two types of automatable jobs. First, there are jobs that are expected to be fully automatable within the next decade. A fully automatable job is a job where technology is at a stage of development whereby it is a viable substitute for a particular job (for example driverless car). The second type are jobs, which that are expected to be polarized automatable over the next decades. Polarized automatable jobs arise where patent technology has had some success, but it is envisaged that these developments will progress to a polarization, with human employees being needed where a personal interaction holds real value and robots being utilized where it does not. An example here is wait staff where the patents may have some success in replacing the service at budget or quirky establishments but are unlikely to displace waiters offering a fine dining experience.

The second contribution of this study is to provide estimates of the share of jobs that are expected to be automatable in the EU, and across 25 countries. This is achieved by matching the new classification of automatable work to the EU-LFS data from 2013-2016. The final contribution of this study is to provide some evidence that abstract thinking and people skills will become increasingly important for the fourth Industrial revolution. It is noted that the estimates that comprise the second and third contribution of this work have also subsequently been documented in two reports to the European Commission on the future of work where a working paper version of this chapter is referenced (see Lordan 2018b, and Lordan 2019).

The importance of understanding the type of work that will be automatable going forward is echoed in Lordan (2018a) and Lordan and Neumark (2018) who suggest that new jobs are now being automated, and highlight that there is already evidence of successful pilots of robots in industry whose purpose is to replace jobs traditionally held by low skilled individuals. Both of these studies also identify negative employment effects for the UK and US, respectively, caused by interactions between the minimum wage and automatable employment. Both pieces of research also rely on the definitions of automation laid out by Autor and Dorn (2013) and Autor et al. (2015) when drawing their conclusions, and emphasize larger effects for older low skilled workers.

Also related to this study are other studies that attempt to estimate the effects of automation on employment retrospectively. For example, Acemoglu and Restrepo (2018) investigate this phenomenon linking data on robot usage to local US labor market data. Overall, they find that an increase of one robot reduces the employment to population ratio by 0.18%-0.37% in the average commuting zone. Graetz and Michaels (2016) consider the effect of robot use (measured as actual robot use within countries by industry) on employment by skill for 17 countries from 1993-2007. They find no overall employment effects, however, they do identify a reduction in the low-skill shares of employment. Greenhalgh et al (2001) examine the relationship between technology and employment using UK company data from 1987-1994. In their work, technology is proxied by investments in research and development, intellectual property and trademarks at the firm-level. This work highlights overall positive effects of technology on employment, with particularly substantive increases in the technology sector. Finally, Piva and Vivarelli (2005) examine the effects of technology on employment, with a proxy that captures innovative investments in manufacturing firms in Italy for the period 1992-1997. The authors identify a small positive correlation between technology adoption and employment.

Overall, the literature received suggests that in the past technology has had little effect on employment overall but has had some negative impacts on individuals of low and medium skill. In contrast, the effects suggested by Frey and Osborne (2013) for the future are substantively larger and predict some erosion of jobs in the services industry. Overall, the shares of employment analysis in this study, based on the refined classification of automatable work, emphasizes that 47% of all current jobs are automatable over the next decade, with 35% of these jobs being fully automatable. This compares well to the estimates of 42% by Frey and Osborne (2013). It is noteworthy that the jobs that are safe from automation are those that involve abstract, strategic or creative thinking, and in particular jobs that involve this type of thinking alongside people interactions.

The findings in this study that 47% of jobs can be automated with technology becoming available shortly, with 35% of these being fully automatable may seem glib. However, these estimates are based on static models. Intuitively, if firms do automate it should stimulate growth, assuming that some of the rents from this new technology are recycled back into the economy, it is reasonable to expect other occupations will expand in number as people consume more goods and services. While it is hard to say what new occupations may come on stream, this work suggests that people and ‘thinking’ (the ability to problem solve, think strategically and navigate around problems) skills are the ones that will hold value for the fourth industrial revolution.

New Classification of Automatable Work:

To arrive at the new classification the definition of an occupation being automatable by Autor and Dorn (2013) is taken as given. That is, it is viewed that their definition describes well occupations that have been disappearing retrospectively. Specifically, they argue that jobs high in routine task-intensity are automatable given they are codifiable, with routine task-intensity in each three-digit occupation defined as:

$$RTI_k = \ln(T_k^R) - \ln(T_k^M) - \ln(T_k^A) \qquad (1)$$

where T_k^R, T_k^M, and T_k^A are the levels of routine, manual, and abstract task inputs for occupation k. These levels are defined using variables from versions of the *Dictionary of Occupation Titles*, where incumbent workers are asked to grade the level of their occupation with respect to particular attributes. Overall, equation (1) is increasing in the absolute and relative quantity of tasks that are routine (i.e. codifible) within any occupation. Given the values from equation 1, Autor and Dorn (2013) define the top tertile of three-digit occupation codes as automatable. These definitions are derived based on classifications put forward by Dorn (2009) which is a classification system that can be used to crosswalk US census codes across time. Overall there are 323 occupation codes, which implies that 201 codes are classified as non-automatable. This study relies on patent data to evaluate whether any one of these remaining 201 occupations are going to be automatable over the next decade. It is argued that a significant amount of promising research and development that is searching for a substitute for a particular job, defined as having filed a relevant patent, signals that this job is highly likely to be automatable. This work complements these classifications with information on whether a substitute for a specific three-digit occupation has been successfully piloted, and there are no major changes to the conclusions drawn in this work. To determine the level of patent activity Google Patents is drawn upon. Specifically, Google Patents covers over 87 million patent publications from the following patent offices: United

States, Europe, Japan, China, South Korea, WIPO, Russia, Germany, United Kingdom, Canada, France, Spain, Belgium, Denmark, Finland, Luxembourg and the Netherlands. Patents that are non-English have been translated by Google Patents and indexed. For the 201 three-digit occupations labelled as non-automatable according to Autor and Dorn (2013), (in summer 2017) Google Patents was searched to determine if a technology is actively being developed as a substitute for that occupation. a total of 216 3-digit occupations are revised. Specifically, the search is for variants of the occupation name, plus either the term 'robot', 'automation' or 'artificial intelligence'. For example, for registered nurses the search is for 'nurse' and 'robot' or 'automation' or 'artificial intelligence'. In this case there is one patent. For truck-driver the search is for 'truck' and 'driverless' or 'robot' or 'automation' or 'artificial intelligence'. In this case there are many patents. A record is kept of the top five. Finally, for waiter the search is for 'waiter' and 'robot' or 'automation' or 'artificial intelligence'. In this case five patents are found. The search is restricted to patents issued after 2002 given that older patents with an average duration of 15 years are likely to have expired or have already been implemented. Patents that have been abandoned, had expired or had been rejected are excluded. Results were grouped and sorted by relevance. Content was identified as relevant if it related directly to the automation of the respective job occupation searched for. Information on the relevant patents were documented in a separate document such that readers can replicate the search results. Information is recorded on up to five of the most informative patents.

Based on the the number of patents filed and the content of those patent descriptions it is possible to classify occupations as automatable, polarized automatable or non- automatable. Full details of how each occupation is classified is displayed in Table 1. Details of the top five associated patents can be provided by contacting the authors.

The overall aim is for the classifications of jobs outlined in Table 1 to capture well the jobs that will be automated within the next decade. To stress test the classification information is gathered on whether there have been successful pilots of a technology that substitutes for a worker, at a three-digit occupation level, or not. This was achieved by searching for a variant of the occupation name + 'robot' OR 'automation' OR 'artificial intelligence' in Google News. Google News is a computer-generated news site that aggregates headlines from news sources worldwide and groups similar stories together. How an article appears in a Google News search is determined by key word matching, alongside an automated evaluation of how popular a particular story is. In all cases, where it is determined that a viable patent exists, a link to the article is recorded which describes the trial of the new technology. Therefore, if a technology is classified as automatable or polarised automatable based on the Google patent review, but details of a successful pilot in the Google News review has not been found, they are classified as non-automatable in the second stress test definition. However, if a technology is classified as automatable or polarised automatable based on the Google patent review, and a successful pilot in our Google News review has been found, they are classified as automatable in the second definition. The correlation of these two measures is very high at 0.8526 and the conclusions of this work do not change substantively with this alternate definition.

Returning to Table 1, a few stylized facts are worth highlighting. First, jobs where interpersonal skills are required in order to gauge the specific tasks that are needed to be carried out are unlikely to be automated and are classified as non-automatable. These jobs involve interaction with people whether it be to provide strategic leadership (for example CEOs), provide care to patients or children (for example nurses and childcare workers) grooming customers (for example hairdressers), and fixing objects (for example a plumber or a mechanic). In all cases, engagement with people is required in unpredictable sequences, which are not easily replicated by machines and cannot be easily substituted by the customer themselves (i.e. a person cannot indicate on an app the haircut that they desire, and have a robot carry out the task of cutting the style). In all these examples people also care about who carries out the task because the quality of the work can be highly variable, and in many cases the interaction with the person gives utility in and of itself.

Second, some client facing occupations are labelled as polarized automatable in Table 1. This arises because there is a lot of R&D into technology for jobs that historically require interpersonal interactions but there is a more predictable sequence of events. These jobs include waiting tables and bar tending. Here technology has had some success, with a few examples of successful substitution by robots. It is envisaged, however, that these developments will progress to a polarization, with, for example, human employees being kept in establishments where a personal interaction with a waiter or bar tender holds some value, and robots being utilized where it does not. A second type of polarization occurs for jobs that are comprised of reading large volumes of writing, and also involves interaction with people in an unpredictable sequence of events. An example here are lawyers where systems, such as for example Kira, can scan contracts and substitute for some of the work historically carried out by these professionals, giving them more time to interact with clients and engage in strategic thinking or decision making. In this case, all else equal (including quality and demand for these services) it is expected that there will be fewer lawyers in absolute number.

Third, there is considerable R&D in areas that customers may care less about whether the job is done by a robot or a human. These include delivery drivers and brick layers. So, the value to the customer of having a human carry out these roles is zero. In both of these areas there have been significant developments to the extent that a cull of jobs in the next decade is expected, assuming that legislation and infrastructure allow roll out of the new technologies.

Overall, Table 1 indicates that there are roughly three types of occupations with respect to automation potential. The first group are jobs where empathy and other non-cognitive skills are valued and a person cares about who carries out the work. Many of these occupations also leverage abstract, creative or strategic thinking. These occupations are unlikely to be automated in the next decade, and it is expected that they will increase in absolute number if the rents of technology are captured by society.

The second are occupations where in some cases a person may care who carries out the service, whereas in others they do not. Alternatively, they are occupations where some of the tasks that historically comprised them have been fully automated, leaving tasks that relate to abstract, strategic or creative thinking. Again, people and thinking skills will be of great value for the jobs that remain. It is envisaged that some of these jobs will be automated. However, at the same time they may be required in increased numbers if the rents from technology are shared within the economy and people demand more goods and services.

Third, are the jobs where there is no added value whether the work is carried out by a robot or a human. These are the jobs that will decline most sharply, with the main barrier to automation being laws and/or physical infrastructure. For example, in most countries driverless cars will need a legislation change, and a re-think of the infrastructure of cities.

Therefore, rather than sticking to the dichotomy of Autor and Dorn (2013) it is proposed that occupations have three distinct groupings. The first group are occupations where empathy and other soft skills are valued and a person cares about who carries out the work, and they often involve abstract/strategic/creative thinking. These occupations are classified as non-automatable. The second are occupations where in some cases a person may care who carries out the service, whereas in others they do not. These occupations are classified as polarized automatable. Third, are the jobs where there is no added value whether the work is carried out by a robot or a human. These are the jobs that are expected to decline the most sharply. Of course this decline also depends on other such as the costs of the technology as compared to the human labour, and also on preferences to substitute traditional labor with technology that can vary across countries (for example: self-checkout cashiers have been around for a while in the UK but are refused by customers in Germany as they prefer the human interaction.

Shares of Automatable Work:

In order to calculate the share of jobs that are at risk of being automated over the next decade the study utilizes the EU-LFS data from 2013-2016. These data are matched to the new classifications of automatable (fully automatable and polarized automatable combined), fully automatable and polarized automatable work based on cross walks from Lordan (2019). Shares of automatable employment are documented in Table 2, alongside the Autor and Dorn (2013) shares as a comparison.

From Table 2 it is noted that the new classifications suggest that a much larger share of jobs in the EU is at risk of being automated as compared to the Autor and Dorn (2013) classification (47% versus 27%). This compares well to the estimates of 42% by Frey and Osborne (2013). It is also noted that for every country the share of jobs that are fully automatable are significantly larger than the shares that are polarized automatable. In the EU these figures are 35% versus 12%. Finland is the country with the lowest share of jobs that are classified as automatable overall (approximately 21%), fully automatable (15%) and polarized automatable (6%). The Autor and Dorn (2013) shares of automatable employment stand at 11% for Finland. For the remaining Scandinavian countries (Norway, Sweden and Denmark), Table 2 suggests that about 37% of the jobs are automatable, similar to the shares for the Netherlands and Iceland. This is roughly 17% larger than the Autor and Dorn (2013) shares. In contrast, for Croatia, the Czech Republic, Italy and Latvia more than 50% of the jobs are automatable in the next decade, and the gap between these shares and Autor and Dorn (2013) is 20%+. Overall, Table 2 highlights that there is a lot of variation to automation across EU countries.

Methodology Main Analysis:

In is interesting to probe empirically the conclusions drawn from Table 1. That is, jobs that are high on people and abstract skills are less likely to be automated. To consider this the ONET database version 15 is retrieved with focus on the 79 items describing the work activities and context of a person's occupation. This study follows Lordan and Pischke (2016) and relies on exploratory factor analysis to reduce the dimensionality of these 79 variables and also retrieve a clear structure of three correlated latent factors which emerges in the first rotation. Consistent with Lordan and Pischke (2016) these latent factors can be labelled ‘people’ ‘brains’ and ‘brawn’. In essence:

1. ‘People’ is a proxy variable which distils the information from the domains in the ONET activities and skills data that relate to having interactions with people on a day to day basis.
2. ‘Brains’ is a proxy variable which distils the information from the domains in the ONET activities and skills data that relate to thinking that is strategic, creative or abstract.
3. ‘Brawn’ is a proxy variable which distils the information from the domains in the ONET activities and skills data that relate to interacting physically with objects, including making them on a daily basis.

By regressing the dummy indicator variable representing whether a job is automatable (combining fully automatable and polarized automatable- see column (1) in Table 2) on the ‘people’ ‘brains’ and ‘brawn’ proxy variables it is possible to directly assess how they relate .to the new classification of automatable work. Additionally, interactions between these three proxies and each other are included in the regression i.e people*brains, people*brawn and brains*brawn. This allows an empirical test of whether, for example, jobs that are high in *both* people and abstract content are more likely to be automated as compared to those that are high in people and brawn content. The regressions also control for country fixed effects and yearly fixed effects in our regression, and exclude jobs that were denoted by Autor and Dorn (2013) as automatable. These jobs are excluded given that the Autor and Dorn (2013) classifications are already task based (see equation 1), so finding a relationship would be mechanical. Essentially, the analysis is trying to relate the new occupations classified as automatable using the patent data in this work to the three proxies representing people, brains and brawn. This is represented by the difference between columns (4) and columns (1) in Table 2. The results from this analysis are documented in Table 3.

From Table 3, 42% of the variation in our automatable employment indicator is explained by the variables in the regression. Noteworthy is how substantive the coefficient is on the ‘brains’ factor, strongly implying that jobs which require thinking (abstract/strategic or creative) are those that are the safest in the 4th industrial revolution. In addition, the interaction between the ‘people’ and ‘brains’ factors is negative and significant. This highlights that jobs, which require thinking and social interactions are safer in the most recent wave of automation as compared to those that simply involve people interactions (as evidenced by the positive significant coefficient on the 'people' factor). This is more nuanced than the jobs conclusions that drawn from Table 1, but makes sense given the jobs that are classified as fully automatable, such as driver, also involve interaction with people. It is noted that the estimates in Table 3 imply that jobs that are high on 'Brawn' content are those that are most likely to be automated in the most recent wave of automation. These jobs include making objects and physically lifting items, for example, brick layer.

Summary:

The primary aim of this study is to improve the understanding of the scope for the future automation of work. The work builds directly on Autor and Dorn's (2013) classification of automatable work at the three-digit occupation code level by using patent data. By focusing on patent data, it is argued that the strategy 'follows the money' and can identify the jobs that will be automatable in the next decade. The new classification system introduced in this study distinguishes between three types of jobs: jobs that are fully automatable, jobs that are polarized automatable and jobs that are not expected to be automated. The second contribution of this study is to provide estimates of the share of jobs that are expected to be automatable in the EU and across 25 countries based on this new classification. Overall, it is highlighted that aspects of 47% of jobs are automatable over the next decade, with 35% of all jobs being fully automatable. This is relatively similar to the estimates of 42% by Frey and Osborne (2013). The final contribution of this study is to provide some evidence that 'thinking' and 'people' skills will become increasingly important for the fourth industrial revolution.

While the finding that aspects of 47% of jobs will be automatable in the near future, with 35% of these being fully automatable may seem gloomy, emphasis is put on the fact that these estimates are based on static models. It follows that if firms do automate, growth will be stimulated. Moreover, assuming that some of the rents from the technology adopted filter back into the economy (i.e. that they are not fully taken by large companies), it is expected that other occupations will expand in number as people consume more goods and services. It is very difficult to say what the new jobs will be. However, this study suggests that 'people' and 'thinking' skills will become more valuable in the fourth industrial revolution. The high value of people skills in terms of adult outcomes has become a topic of recent writings in economics (for example Heckman and Kautz (2014); Kautz et al., (2014) and Lordan and McGuire, 2019). The intuition that jobs that require high level thinking are safe from automation is also embedded directly in the definitions by Autor and Dorn (2013) and Autor et al. (2015) (see equation 1 which highlights that jobs are less likely to be classified as automatable if they are high in abstract tasks). Overall, this study concludes that people and thinking skills are worth emphasizing as necessary for individuals looking to job proof themselves for the advent of the fourth industrial revolution.

Cross Reference:

Innovation, technology adoption and employment: Findings from evidence synthesis Ugur, M.

Technology and employment: key stylized facts for the digital age. Pianta, M.

Innovation, employment and the business cycle. Dachs, B., Hud, M., Peters, B.

Robots, structural change and employment: future scenarios. Vermeulen, B., Pyka, A., Saviotti, P.

New technologies and the skill mismatch. Mavromaras, K.

References

Acemoglu, Daron, and Pascual Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review*, 108 (6): 1488-1542.

Autor, David, David Dorn, and Gordon Hanson. 2015. "Untangling Trade and Technology: Evidence from Local Labour Markets." *Economic Journal*, Vol. 125, No. 584, May, pp 621-46.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labour Market." *American Economic Review*, Vol. 103, No. 5, August, pp. 1553-97.

Dorn, David. 2009. "Essays on Inequality, Spatial Interaction, and the Demand for Skills." Dissertation University of St. Gallen no.3613, September.

Frey, C. and Osbourne, B. (2013). The future of employment: how susceptible are jobs to computerization? *Oxford Martin Programme on the Impacts of Future Technology.*

Graetz Georg and Michaels Guy (2018). Robots at Work. *The Review of Economics and Statistics.* 100:5, 753-768

Greenhalgh, C., M. Longland and D. Bosworth (2001). Technological Activity and Employment in a Panel of UK Firms. *Scottish Journal of Political Economy*, Vol. 48(3)

Heckman, J. J. and Kautz, T. (2014). Fostering and measuring skills: Interventions that improve character and cognition. In J. J. Heckman, J. E. Humphries, and T. Kautz (Eds.), The Myth of Achievement Tests: The GED and the Role of Character in American Life, pp. 341–430. Chicago, IL: University of Chicago Press.

Kautz, T. Heckman, J., Diris, R., et al. (2014), Fostering and Measuring Skill: Improving cognitive and non-cognitive skills to promote lifetime success, NBER Working Paper, 20749, Cambridge, NBER

Lordan, Grace (2018a). People Versus Machines in the UK:Minimum Wages and Labor Reallocation Towards Automatable Jobs. *Working Paper.*

Lordan, Grace. (2018b). Robots at Work: A Report on Automatable and Non-Automatable Employment Shares in Europe. *European Commission.*

Lordan, Grace and Mcguire, Alistair (2019). The Healthy Minds Program. Evaluating the impact on health and soft skills.

Lordan, Grace and Neumark, David (2018). People versus Machines: The impact of minimum wages in automatable jobs. *Labour Economics.* 52 (June), pp 40-53.

Lordan, Grace and Jorn-Steffen Pischke 2016. Does Rosie like riveting? Male and female occupational choices. *NBER working paper,* 22495. National Bureau of Economic Research, Cambridge, USA.

Piva, M., and Vivarelli, M. (2005). Innovation and employment: Evidence from Italian microdata. *Journal of Economics, 86*(1), 65-83.

Table 1: Occupations Classified by Autor and Dorn (2013) and Measure Proposed by this Work

Occupation	Autor and Dorn	Proposed Measure
Chief executives, public administrators, and legislators	Non-Automatable	Non- Automatable
Financial managers	Automatable	Automatable
Human resources and labour relations managers	Non-Automatable	Polarized Automatable
Managers and specialists in marketing, advert., PR	Non-Automatable	Polarized Automatable
Managers in education and related fields	Non-Automatable	Non- Automatable
Managers of medicine and health occupations	Non-Automatable	Non- Automatable
Managers of properties and real estate	Non-Automatable	Non- Automatable
Funeral directors	Automatable	Fully Automatable
Managers and administrators, n.e.c.	Non-Automatable	Non- Automatable
Accountants and auditors	Automatable	Fully Automatable
Insurance underwriters	Automatable	Fully Automatable
Other financial specialists	Automatable	Fully Automatable
Management analysts	Non-Automatable	Non- Automatable
Personnel, HR, training, and labour rel. specialists	Non-Automatable	Polarized Automatable
Purchasing agents and buyers of farm products	Automatable	Fully Automatable
Buyers, wholesale and retail trade	Non-Automatable	Non- Automatable
Purchasing managers, agents, and buyers, n.e.c.	Non-Automatable	Non- Automatable
Business and promotion agents	Non-Automatable	Non- Automatable
Construction inspectors	Non-Automatable	Non- Automatable
Inspectors and compliance officers, outside	Non-Automatable	Non- Automatable
Management support occupations	Non-Automatable	Polarized Automatable

Occupation	Autor and Dorn	Lordan and Josten
Architects	Automatable	Non- Automatable
Aerospace engineers	Non-Automatable	Non- Automatable
Metallurgical and materials engineers	Non-Automatable	Non- Automatable
Petroleum, mining, and geological engineers	Non-Automatable	Non- Automatable
Chemical engineers	Non-Automatable	Non- Automatable
Civil engineers	Non-Automatable	Non- Automatable
Electrical engineers	Non-Automatable	Non- Automatable
Industrial engineers	Non-Automatable	Non- Automatable
Mechanical engineers	Non-Automatable	Non- Automatable
Engineers and other professionals, n.e.c.	Non-Automatable	Non- Automatable
Computer systems analysts and computer scientists	Non-Automatable	Non- Automatable
Operations and systems researchers and analysts	Non-Automatable	Non- Automatable
Actuaries	Automatable	Fully Automatable
Mathematicians and statisticians	Non-Automatable	Non- Automatable
Physicists and astronomists	Non-Automatable	Non- Automatable
Chemists	Non-Automatable	Non- Automatable
Atmospheric and space scientists	Automatable	Non- Automatable
Geologists	Non-Automatable	Non- Automatable
Physical scientists, n.e.c.	Automatable	Fully Automatable
Agricultural and food scientists	Non-Automatable	Non- Automatable
Biological scientists	Non-Automatable	Non- Automatable
Foresters and conservation scientists	Non-Automatable	Non- Automatable

Occupation	Autor and Dorn	Lordan and Josten
Medical scientists	Non-Automatable	Non- Automatable
Physicians	Non-Automatable	Non- Automatable
Dentists	Non-Automatable	Non- Automatable
Veterinarians	Automatable	Non- Automatable
Optometrists	Automatable	Polarized Automatable
Podiatrists	Non-Automatable	Non- Automatable
Other health and therapy occupations	Non-Automatable	Non- Automatable
Registered nurses	Non-Automatable	Non- Automatable
Pharmacists	Automatable	Polarized Automatable
Dieticians and nutritionists	Automatable	Fully Automatable
Respiratory therapists	Non-Automatable	Non- Automatable
Occupational therapists	Non-Automatable	Non- Automatable
Physical therapists	Non-Automatable	Non- Automatable
Speech therapists	Non-Automatable	Polarized Automatable
Therapists, n.e.c.	Non-Automatable	Non- Automatable
Physicians' assistants	Non-Automatable	Polarized Automatable
Subject instructors, college	Non-Automatable	Non- Automatable
Kindergarten and earlier school teachers	Non-Automatable	Non- Automatable
Primary school teachers	Non-Automatable	Non- Automatable
Secondary school teachers	Non-Automatable	Non- Automatable
Special education teachers	Non-Automatable	Non- Automatable
Teachers, n.e.c.	Non-Automatable	Non- Automatable

Occupation	Autor and Dorn	Lordan and Josten
Vocational and educational counselors	Non-Automatable	Non- Automatable
Librarians	Non-Automatable	Polarized Automatable
Archivists and curators	Non-Automatable	Non- Automatable
Economists, market and survey researchers	Non-Automatable	Non- Automatable
Psychologists	Non-Automatable	Non- Automatable
Social scientists and sociologists, n.e.c.	Non-Automatable	Non- Automatable
Urban and regional planners	Automatable	Non- Automatable
Social workers	Non-Automatable	Non- Automatable
Clergy and religious workers	Non-Automatable	Non- Automatable
Welfare service workers	Non-Automatable	Non- Automatable
Lawyers and judges	Automatable	Polarized Automatable
Writers and authors	Automatable	Non- Automatable
Technical writers	Non-Automatable	Non- Automatable
Designers	Non-Automatable	Non- Automatable
Musicians and composers	Non-Automatable	Non- Automatable
Actors, directors, and producers	Non-Automatable	Non- Automatable
Painters, sculptors, craft-artists, and print-makers	Automatable	Fully Automatable
Photographers	Automatable	Fully Automatable
Dancers	Non-Automatable	Non- Automatable
Art/entertainment performers and related occs	Non-Automatable	Non- Automatable
Editors and reporters	Automatable	Non- Automatable
Announcers	Automatable	Non- Automatable

Occupation	**Autor and Dorn**	**Lordan and Josten**
Athletes, sports instructors, and officials	Non-Automatable	Polarized Automatable
Clinical laboratory technologies and technicians	Non-Automatable	Fully Automatable
Dental hygienists	Automatable	Fully Automatable
Health record technologists and technicians	Automatable	Fully Automatable
Radiologic technologists and technicians	Non-Automatable	Fully Automatable
Licensed practical nurses	Non-Automatable	Non- Automatable
Health technologists and technicians, n.e.c.	Non-Automatable	Polarized Automatable
Engineering technicians	Non-Automatable	Non- Automatable
Drafters	Automatable	Fully Automatable
Surveryors, cartographers, mapping scientists/techs	Non-Automatable	Polarized Automatable
Biological technicians	Non-Automatable	Polarized Automatable
Chemical technicians	Non-Automatable	Polarized Automatable
Other science technicians	Non-Automatable	Polarized Automatable
Airplane pilots and navigators	Non-Automatable	Polarized Automatable
Air traffic controllers	Automatable	Fully Automatable
Broadcast equipment operators	Non-Automatable	Polarized Automatable
Computer software developers	Non-Automatable	Non- Automatable
Programmers of numerically controlled machine tools	Non-Automatable	Non- Automatable
Legal assistants and paralegals	Automatable	Fully Automatable
Technicians, n.e.c.	Non-Automatable	Polarized Automatable
Sales supervisors and proprietors	Non-Automatable	Non- Automatable
Insurance sales occupations	Automatable	Fully Automatable

Occupation	Autor and Dorn	Lordan and Josten
Real estate sales occupations	Automatable	Fully Automatable
Financial service sales occupations	Automatable	Fully Automatable
Advertising and related sales jobs	Automatable	Fully Automatable
Sales engineers	Non-Automatable	Non- Automatable
Salespersons, n.e.c.	Non-Automatable	Non- Automatable
Retail salespersons and sales clerks	Non-Automatable	Non- Automatable
Cashiers	Automatable	Fully Automatable
Door-to-door sales, street sales, and news vendors	Non-Automatable	Non- Automatable
Sales demonstrators, promoters, and models	Non-Automatable	Polarized Automatable
Office supervisors	Automatable	Fully Automatable
Computer and peripheral equipment operators	Non-Automatable	Non- Automatable
Secretaries and stenographers	Automatable	Fully Automatable
Typists	Automatable	Fully Automatable
Interviewers, enumerators, and surveyors	Automatable	Non- Automatable
Hotel clerks	Automatable	Fully Automatable
Transportation ticket and reservation agents	Automatable	Fully Automatable
Receptionists and other information clerks	Automatable	Fully Automatable
Correspondence and order clerks	Automatable	Fully Automatable
Human resources clerks, excl payroll and timekeeping	Automatable	Fully Automatable
Library assistants	Non-Automatable	Polarized Automatable
File clerks	Automatable	Fully Automatable
Records clerks	Automatable	Fully Automatable

Occupation	Autor and Dorn	Lordan and Josten
Bookkeepers and accounting and auditing clerks	Automatable	Fully Automatable
Payroll and timekeeping clerks	Automatable	Fully Automatable
Billing clerks and related financial records processing	Automatable	Fully Automatable
Mail and paper handlers	Automatable	Fully Automatable
Office machine operators, n.e.c.	Automatable	Fully Automatable
Telephone operators	Automatable	Fully Automatable
Other telecom operators	Automatable	Fully Automatable
Postal clerks, exluding mail carriers	Automatable	Fully Automatable
Mail carriers for postal service	Non-Automatable	Fully Automatable
Mail clerks, outside of post office	Automatable	Fully Automatable
Messengers	Automatable	Fully Automatable
Dispatchers	Automatable	Fully Automatable
Shipping and receiving clerks	Automatable	Fully Automatable
Stock and inventory clerks	Automatable	Fully Automatable
Meter readers	Automatable	Fully Automatable
Weighers, measurers, and checkers	Automatable	Fully Automatable
Material recording, sched., prod., plan., expediting cl.	Automatable	Fully Automatable
Insurance adjusters, examiners, and investigators	Automatable	Fully Automatable
Customer service reps, invest., adjusters, excl. insur.	Automatable	Fully Automatable
Eligibility clerks for government prog., social welfare	Automatable	Fully Automatable
Bill and account collectors	Automatable	Fully Automatable
General office clerks	Automatable	Fully Automatable

Occupation	Autor and Dorn	Lordan and Josten
Bank tellers	Automatable	Fully Automatable
Proofreaders	Automatable	Fully Automatable
Data entry keyers	Automatable	Fully Automatable
Statistical clerks	Automatable	Fully Automatable
Teacher's aides	Non-Automatable	Polarized Automatable
Administrative support jobs, n.e.c.	Automatable	Fully Automatable
Housekeepers, maids, butlers, and cleaners	Non-Automatable	Polarized Automatable
Laundry and dry cleaning workers	Automatable	Fully Automatable
Supervisors of guards	Non-Automatable	Non- Automatable
Fire fighting, fire prevention, and fire inspection occs	Non-Automatable	Polarized Automatable
Police and detectives, public service	Non-Automatable	Non- Automatable
Sheriffs, bailiffs, correctional institution officers	Non-Automatable	Non- Automatable
Crossing guards	Non-Automatable	Non- Automatable
Guards and police, except public service	Automatable	Fully Automatable
Protective service, n.e.c.	Non-Automatable	Polarized Automatable
Supervisors of food preparation and service	Non-Automatable	Non- Automatable
Bartenders	Automatable	Polarized Automatable
Waiters and waitresses	Non-Automatable	Polarized Automatable
Cooks	Automatable	Fully Automatable
Food preparation workers	Non-Automatable	Polarized Automatable
Miscellanious food preparation and service workers	Non-Automatable	Polarized Automatable
Dental Assistants	Automatable	Fully Automatable

Occupation	Autor and Dorn	Lordan and Josten
Health and nursing aides	Non-Automatable	Non- Automatable
Supervisors of cleaning and building service	Non-Automatable	Non- Automatable
Superv. of landscaping, lawn service, groundskeeping	Non-Automatable	Polarized Automatable
Gardeners and groundskeepers	Non-Automatable	Polarized Automatable
Janitors	Non-Automatable	Polarized Automatable
Pest control occupations	Non-Automatable	Fully Automatable
Barbers	Automatable	Non- Automatable
Hairdressers and cosmetologists	Automatable	Non- Automatable
Recreation facility attendants	Non-Automatable	Polarized Automatable
Guides	Non-Automatable	Polarized Automatable
Ushers	Non-Automatable	Polarized Automatable
Baggage porters, bellhops and concierges	Non-Automatable	Polarized Automatable
Recreation and fitness workers	Non-Automatable	Polarized Automatable
Motion picture projectionists	Automatable	Fully Automatable
Child care workers	Non-Automatable	Non- Automatable
Personal service occupations, n.e.c	Non-Automatable	Polarized Automatable
Supervisors of personal service jobs, n.e.c	Non-Automatable	Polarized Automatable
Public transportation attendants and inspectors	Non-Automatable	Polarized Automatable
Animal caretakers, except farm	Non-Automatable	Non- Automatable
Farmers (owners and tenants)	*Automatable*	Fully Automatable
Farm managers	*Automatable*	Fully Automatable
Farm workers, incl. nursery farming	*Automatable*	Fully Automatable

Occupation	**Autor and Dorn**	**Lordan and Josten**
Graders and sorters of agricultural products	*Automatable*	Fully Automatable
Inspectors of agricultural products	*Automatable*	Fully Automatable
Timber, logging, and forestry workers	*Automatable*	Fully Automatable
Fishers, marine life cultivators, hunters, and kindred	*Automatable*	Fully Automatable
Supervisors of mechanics and repairers	Non-Automatable	Non- Automatable
Automobile mechanics and repairers	Non-Automatable	Non- Automatable
Bus, truck, and stationary engine mechanics	Non-Automatable	Non- Automatable
Aircraft mechanics	Non-Automatable	Non- Automatable
Small engine repairers	Non-Automatable	Non- Automatable
Auto body repairers	Automatable	Fully Automatable
Heavy equipement and farm equipment mechanics	Non-Automatable	Non- Automatable
Industrial machinery repairers	Non-Automatable	Non- Automatable
Machinery maintenance occupations	Automatable	Fully Automatable
Repairers of industrial electrical equipment	Automatable	Fully Automatable
Repairers of data processing equipment	Automatable	Fully Automatable
Repairers of household appliances and power tools	Non-Automatable	Non- Automatable
Telecom and line installers and repairers	Non-Automatable	Non- Automatable
Repairers of electrical equipment, n.e.c.	Non-Automatable	Non- Automatable
Heating, air conditioning, and refrigeration mechanics	Non-Automatable	Non- Automatable
Precision makers, repairers, and smiths	Automatable	Fully Automatable
Locksmiths and safe repairers	Non-Automatable	Polarized Automatable
Repairers of mechanical controls and valves	Non-Automatable	Non- Automatable

Occupation	Autor and Dorn	Lordan and Josten
Elevator installers and repairers	Non-Automatable	Non- Automatable
Millwrights	Non-Automatable	Non- Automatable
Mechanics and repairers, n.e.c.	Non-Automatable	Non- Automatable
Supervisors of construction work	Non-Automatable	Non- Automatable
Masons, tilers, and carpet installers	Non-Automatable	Polarized Automatable
Carpenters	Non-Automatable	Non- Automatable
Drywall installers	Non-Automatable	Non- Automatable
Electricians	Non-Automatable	Non- Automatable
Electric power installers and repairers	Non-Automatable	Non- Automatable
Painters, construction and maintenance	Non-Automatable	Polarized Automatable
Paperhangers	Non-Automatable	Polarized Automatable
Plasterers	Non-Automatable	Polarized Automatable
Plumbers, pipe fitters, and steamfitters	Non-Automatable	Non- Automatable
Concrete and cement workers	Non-Automatable	Polarized Automatable
Glaziers	Non-Automatable	Non- Automatable
Insulation workers	Non-Automatable	Non- Automatable
Paving, surfacing, and tamping equipment operators	Non-Automatable	Non- Automatable
Roofers and slaters	Non-Automatable	Non- Automatable
Structural metal workers	Non-Automatable	Non- Automatable
Drillers of earth	Non-Automatable	Fully Automatable
Misc. construction and related occupations	Non-Automatable	Polarized Automatable
Drillers of oil wells	Non-Automatable	Fully Automatable

Occupation	Autor and Dorn	Lordan and Josten
Explosives workers	Non-Automatable	Polarized Automatable
Miners	Non-Automatable	Polarized Automatable
Other mining occupations	Non-Automatable	Polarized Automatable
Production supervisors or foremen	Non-Automatable	Polarized Automatable
Tool and die makers and die setters	Automatable	Fully Automatable
Machinists	Automatable	Fully Automatable
Boilermakers	Automatable	Fully Automatable
Precision grinders and fitters	Automatable	Fully Automatable
Patternmakers and model makers	Automatable	Fully Automatable
Engravers	Automatable	Fully Automatable
Other metal and plastic workers	Non-Automatable	Polarized Automatable
Cabinetmakers and bench carpeters	Non-Automatable	Non- Automatable
Furniture/wood finishers, other prec. wood workers	Automatable	Fully Automatable
Dressmakers, seamstresses, and tailors	Non-Automatable	Polarized Automatable
Upholsterers	Automatable	Fully Automatable
Shoemakers, other prec. apparel and fabric workers	Non-Automatable	Fully Automatable
Hand molders and shapers, except jewelers	Automatable	Fully Automatable
Optical goods workers	Automatable	Fully Automatable
Dental laboratory and medical applicance technicians	Non-Automatable	Polarized Automatable
Bookbinders	Non-Automatable	Fully Automatable
Other precision and craft workers	Automatable	Fully Automatable
Butchers and meat cutters	Automatable	Fully Automatable

Occupation	Autor and Dorn	Lordan and Josten
Bakers	Automatable	Fully Automatable
Batch food makers	Automatable	Fully Automatable
Water and sewage treatment plant operators	Non-Automatable	Polarized Automatable
Power plant operators	Non-Automatable	Fully Automatable
Plant and system operators, stationary engineers	Non-Automatable	Polarized Automatable
Other plant and system operators	Non-Automatable	Polarized Automatable
Lathe, milling, and turning machine operatives	Automatable	Fully Automatable
Punching and stamping press operatives	Non-Automatable	Fully Automatable
Rollers, roll hands, and finishers of metal	Non-Automatable	Non- Automatable
Drilling and boring machine operators	Automatable	Fully Automatable
Grinding, abrading, buffing, and polishing workers	Automatable	Fully Automatable
Forge and hammer operators	Non-Automatable	Polarized Automatable
Molders and casting machine operators	Automatable	Fully Automatable
Metal platers	Automatable	Fully Automatable
Heat treating equipment operators	Non-Automatable	Polarized Automatable
Sawing machine operators and sawyers	Non-Automatable	Fully Automatable
Nail, tacking, shaping and joining mach ops (wood)	Automatable	Fully Automatable
Other woodworking machine operators	Automatable	Fully Automatable
Printing machine operators, n.e.c.	Automatable	Fully Automatable
Typesetters and compositors	Automatable	Fully Automatable
Winding and twisting textile and apparel operatives	Automatable	Fully Automatable
Knitters, loopers, and toppers textile operatives	Automatable	Fully Automatable

Occupation	Autor and Dorn	Lordan and Josten
Textile cutting and dyeing machine operators	Automatable	Fully Automatable
Textile sewing machine operators	Non-Automatable	Fully Automatable
Shoemaking machine operators	Non-Automatable	Fully Automatable
Clothing pressing machine operators	Non-Automatable	Polarized Automatable
Miscellanious textile machine operators	Automatable	Fully Automatable
Cementing and gluing machine operators	Automatable	Fully Automatable
Packers, fillers, and wrappers	Non-Automatable	Fully Automatable
Extruding and forming machine operators	Automatable	Fully Automatable
Mixing and blending machine operators	Automatable	Fully Automatable
Separating, filtering, and clarifying machine operators	Non-Automatable	Non- Automatable
Food roasting and baking machine operators	Automatable	Fully Automatable
Washing, cleaning, and pickling machine operators	Automatable	Fully Automatable
Paper folding machine operators	Automatable	Fully Automatable
Furnance, kiln, and oven operators, apart from food	Non-Automatable	Polarized Automatable
Slicing, cutting, crushing and grinding machine	Automatable	Fully Automatable
Photographic process workers	Automatable	Automatable
Machine operators, n.e.c.	Non-Automatable	Polarized Automatable
Welders, solderers, and metal cutters	Non-Automatable	Polarized Automatable
Assemblers of electrical equipment	Automatable	Fully Automatable
Painting and decoration occupations	Non-Automatable	Polarized Automatable
Production checkers, graders, and sorters in manufacturing	Automatable	Fully Automatable
Supervisors of motor vehicle transportation	Non-Automatable	Non- Automatable

Occupation	**Autor and Dorn**	**Lordan and Josten**
Truck, delivery, and tractor drivers	Non-Automatable	Fully Automatable
Bus drivers	Non-Automatable	Fully Automatable
Taxi cab drivers and chauffeurs	Non-Automatable	Fully Automatable
Parking lot attendants	Non-Automatable	Polarized Automatable
Railroad conductors and yardmasters	Non-Automatable	Non- Automatable
Locomotive operators: engineers and firemen	Non-Automatable	Polarized Automatable
Railroad brake, coupler, and switch operators	Non-Automatable	Polarized Automatable
Ship crews and marine engineers	Non-Automatable	Non- Automatable
Miscellanious transportation occupations	Non-Automatable	Polarized Automatable
Operating engineers of construction equipment	Non-Automatable	Non- Automatable
Crane, derrick, winch, hoist, longshore operators	Non-Automatable	Non- Automatable
Excavating and loading machine operators	Non-Automatable	Polarized Automatable
Stevedores and misc. material moving occupations	Non-Automatable	Polarized Automatable
Helpers, constructions	Non-Automatable	Polarized Automatable
Helpers, surveyors	Non-Automatable	Polarized Automatable
Construction laborers	Non-Automatable	Fully Automatable
Production helpers	Automatable	Fully Automatable
Garbage and recyclable material collectors	Non-Automatable	Fully Automatable
Machine feeders and offbearers	Non-Automatable	Polarized Automatable
Garage and service station related occupations	Automatable	Fully Automatable
Vehicle washers and equipment cleaners	Automatable	Fully Automatable
Packers and packagers by hand	Automatable	Fully Automatable

Occupation	Autor and Dorn	Lordan and Josten
Laborers, freight, stock, and material handlers, n.e.c.	Non-Automatable	Polarized Automatable

Table 2: Shares of Automatable Employment

	(1) Automatable	(2) Fully Automatable	(3) Polarized Automatable	(4) Autor and Dorn (2013)
E.U.	0.474	0.352	0.123	0.268
Austria	0.516	0.379	0.137	0.312
Belgium	0.443	0.306	0.137	0.248
Croatia	0.565	0.470	0.095	0.280
Cyprus	0.512	0.357	0.155	0.282
Czech Republic	0.516	0.379	0.138	0.313
Denmark	0.370	0.252	0.118	0.205
Estonia	0.458	0.345	0.113	0.248
Finland	0.207	0.148	0.059	0.112
France	0.478	0.311	0.168	0.239
Germany	0.474	0.359	0.115	0.301
Greece	0.574	0.484	0.089	0.285
Hungary	0.544	0.414	0.130	0.282
Iceland	0.374	0.271	0.103	0.228
Ireland	0.481	0.381	0.100	0.282
Italy	0.508	0.134	0.374	0.302
Latvia	0.525	0.398	0.127	0.281
Lithuania	0.527	0.411	0.116	0.267
Luxembourg	0.442	0.339	0.103	0.286
Netherlands	0.374	0.276	0.098	0.227
Norway	0.363	0.224	0.119	0.192
Portugal	0.485	0.363	0.122	0.283
Spain	0.474	0.474	0.131	0.252
Sweden	0.378	0.271	0.107	0.217
Slovakia	0.513	0.382	0.131	0.296
UK	0.405	0.303	0.101	0.249

Table 3: ‘People’ “Brains’ and ‘Brawn’ Estimates

Variable	Marginal Effect
People	0.009
	(0.000)
Brains	-0.070
	(0.000)
Brawn	0.032
	(0.000)
People * Brains	-0.002
	(0.000)
People* Brawn	0.003
	(0.000)
Brains* Brawn	0.000
	(0.000)
N	2,698,151
R squared	42%