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The Future of Work in Developing Economies: What can we learn from the South?

AUTHOR: EGAÑA, PABLO

School Of Business
Universidad Adolfo Ibáñez

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Pablo Egana del Sol
UAI Business School
Universidad Adolfo Ibanez
MIT Sloan School of Management

Abstract

In recent years, there has been an escalation of concern revolving around the effect that automation will have on the future of work. This anxiety has fueled the public and academic debate, fearing that soon this technology will displace jobs at a large scale. Numerous studies have begun to investigate automation's impact on labor markets, although all have focused on industrialized nations, which consist of more service and skilled occupations. Utilizing the World Bank's STEP Skills Measurement Program Database, we examine automation's effect on 10 developing countries throughout Latin America, Africa, and Asia. To address the heterogeneity of occupations across the country, we apply a task-based approach and re-calibrate the effect of automation on labor market while analyzing the task structure across countries. Modeling off previous studies, we created an expectation-maximization algorithm to predict the percentage of tasks that are likely to be automated. Jobs whose task automation output was 70% or higher were then considered to be highly automatable. Our results suggest that these developing countries have higher levels of predicted automation risk. Countries range in their level of highly automatable jobs from the lowest being Yunnan –a Chinese province— with 7.7% to the highest of Ghana with 42.4%. We find that occupations containing relatively more routine tasks are more likely to be automated, while workers with a higher level of education reduce their risks. This is the first paper to estimate automation risk rates for developing nations.

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Keywords: Automation, Developing economies, digitalization, technological change, labor demand.

Introduction

It seems that new automation is being announced every day, offering untold benefits through increased productivity and efficiency. With each advance, one or more tasks once completed by humans becomes redundant, and entire jobs become unnecessary (Winick, 2018). Advances in automation have not gone unnoticed: in 2013 two British economists, Frey and Osborne (2017), estimated an alarming 47% of US jobs were at a high risk of digitization.

Headlines rang: the end of work is nigh. Since then, the conversation has evolved, incorporating different perspectives on how technology will impact work and the automation estimations that result.

Studies estimating the impact of automation have predicted, on average, between 5-20% of jobs are at high risk of automation in the near future.[1] Regardless of the outcome effect, there is much homogeneity in the samples these studies investigate, with a majority focusing on industrialized nations, which consist of more service and skilled occupations.

Many camps have formed but two have really stood out: automation and augmentation. Led by the research conducted by Frey and Osborne, the former believes that technology will automate complete jobs. Envisioning a world where there are few jobs and the owners of capital reap all the rewards, they see technology as a threat to our current social contract. Directed by the research of Erik Brynjolfsson and Andrew McAfee the latter believes that computers and humans can grow together in order to create a growing, optimal economy. Believing that automation is still a tool for human workers, they see a future where humans work on the most enjoyable tasks, leaving the rest for computers.

Both of these factions believe that policy is necessary to prevent the ill effects created by automation, yet their approach to governmental intervention differs. Thus, recent research has begun to investigate the occupations that will be most likely to be automated and how they could be transitioned to better work. Most of these studies have focused on developed countries, those with higher levels of average education and infrastructure. While this data is useful in understanding how technology will alter the daily lives of many knowledge workers, it misses the preparation needed for the billions of physical laborers. Thus, we set out to investigate how technology is likely to impact those in developing nations.

Our path to developed nations

Since the results of the Frey and Osborne paper were published, fear around automation has spread, prompting several further studies to be conducted to refine and further estimate automation's potential impact. One of these was Arntz et al. (2017) who broke jobs into their component tasks to examine the potential of automation in OECD countries. Yielding a much lower average of 9% unemployment due to automation, these results called into question the previous estimate. Especially when evaluating these authors methodology, which used self-reported data of actual workers compared to Frey and Osborne's industry experts.

Similar to the evidence mentioned in the OECD countries, labor automation would impact both markets by driving down their labor demand. This would indirectly increase the unemployment rate and cause increased heterogeneous labor participation across occupations, skills, and tasks. In addition, calibrations of occupations conducted by these studies should not differ significantly from the OECD countries. The phenomenon of automation is global, and therefore the relevant automation potential of tasks is, in theory, the same regardless of geographic location.

However, a dearth of empirical evidence about the automation risk in developing economies was discovered. Therefore, by leveraging micro level data, we study the risk of automation on 11 developing economies[1]. This dataset offers detailed information about workers of developing nations including housing, family, and more importantly, occupation data. Respondents report the specific degree of multiple tasks that they complete while at work. Analyzing this data, we were able to determine estimations of the percentage of tasks within a job that are at risk for automation. Due to the detail of this data we were able to generate aggregates across multiple demographic and occupational dimensions.

Theoretical Background

Viewing Jobs as a collection of tasks and skills

To examine the likelihood that a job will be automated, it must be broken down into component parts. A commonly used approach is to view jobs as a collection of tasks which can be categorized according to Autor, Levy, and Murnane (2003) routine vs. non-routine and manual vs. cognitive matrix. These authors view tasks that can be broken down into easily repeatable parts as routine, they also view manual tasks as those requiring the use of physical labor compared to tasks which use mental labor termed cognitive.

Reviewing the US labor economy through the lens of this matrix Autor, Levy, and Murnane (2003) argues that US employment is moving towards nonroutine, highly cognitive, and emotion-intense interpersonal activity. Examples of these jobs include: elderly care, pre-school teaching, and management. By examining the shift in categories of tasks researchers are beginning to predict what the labor economy of the future will look like. Then when finite worker data is collected these broad theories can be applied to actual jobs. Arntz et al. (2016) were one of the first to apply this view of jobs to actual data. Their analysis of OECD data collected on individual employees yielded automation rates that were much lower than those previously predicted by Frey and Osborne (2018). For example, Frey and Osborne (2018) predicted that a retail salesperson faced a 92% of automation although Arntz et al. (2016) found that only 4% of these job holders perform their job without interacting with another human, a task which is unlikely to be automated soon.

Viewing jobs as collections of tasks also allow for a measurement of heterogeneity between jobs within an occupation category. Although office support workers encapsulate a holistic job, one that supports with office activities, the actual day-to-day activities of someone in this job can vary greatly. Breaking jobs into various tasks allows for the examination of differences among jobs creating degrees of automatability within occupations (Bessen, 2016).

Is this time different?

As more research is conducted into the effect that technology is having on the workforce, historical examples are used by both sides of the debate. Some view this wave of technology as nothing abnormal, instead just the regular cycle of technology displacement caused by

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[1] This data was collected by the World Bank in a program titled STEP.

innovation. While there may be pain felt by some as new technology enters the workforce, this can be viewed as a cost of the transition into a more efficient economy.

Following this line of thought, new technology will create more new jobs than it destroys old jobs. All one must do is look at a job posting site to see the number of jobs, with high salaries, which did not exist a decade ago. Acemoglu and Restrepo (2018) report that half of the employment growth between 1980 to 2010 was the introduction and expansion of new tasks and job titles. These authors argue that the future of work remains bright and those fearing the worst are just modern-day Luddites.

On the opposite side, there are many sounding the alarm that unless institutions prepare wide-spread unemployment will plague the future economy. A new artificial intelligence system begins to automate routine cognitive tasks and especially non-routine tasks, these individuals fear that there will be little work left for humans. Even if some tasks remain, it is unlikely that we will have a world of customer service agents and artists. These alarmists point to self-driving technology and cognitive systems such as IBM's Watson as examples of technology already spreading beyond what the majority expected was possible at the turn of the century.

What is apparent is through the task-based approach we can gauge the skill and expertise required to complete each task. Jobs which consist of mostly routine, manual work appear highly automatable. These jobs are typically low-skilled, requiring little education and experience. The same is true for jobs that primarily consist of routine cognitive tasks. Previous studies have found that those with a high level of routine tasks are the most likely to be automated (Autor and Dorn, 2013). Some examples of these tasks would be scanning the price of items at a grocery store counter or performing the same analysis repeatedly on similar sets of customer data. The more routine a task is, the more it can be broken down into component parts and programmed into software or robot. Thus, the more non-routine work becomes, the harder it is to operationalize and thus harder to automate. Yet these non-routine tasks require more knowledge and skills, requiring the worker to use judgment to decide on the appropriate action.

Hypothesis 1: *The consistency of Routine and Non-Routine tasks will correlate with the estimated level of automation*

This discussion commonly reduces to two conflicting arguments. The first is that of the *productivity effect*. This posits that automation reduces the cost of producing certain tasks in the production function. This reduces the prices of outputs and thus increases real wages of workers, increasing the demand for other products and services in the economy (Autor, 2015). Looking through this lens would mean that as automation occurs, some tasks would be automated lessening the need for human input, but would be offset by increasing demand. Recent research also suggests as technology grows that this could lead to an intensive margin when automation builds upon each other to further exacerbate the productivity effect.

The second is the *displacement effect*, which occurs when an individual is completely overtaken by a machine. In this case, regardless of the productivity gains, capital would continue producing at any scale without increasing the need for human input. If both of these effects were to be present it would suggest that as automation increases, we would see human input continue to increase until it completely automates a position which would then cause the demand for labor to drop off entirely. Thus, Acemoglu and Restrepo (2018), highlighted the fact that we should focus on automation and technologies that are not sufficiently productive to produce large and substantial productivity effects (and thus generating general equilibrium effects that are likely beneficial for household via greater economic opportunities and lower prices) but are just productive enough to replace the labor.

Hypothesis 2: *Individuals who have higher levels of education and experience will be less likely to be automated than those who do not.*

With these two effects in mind, the employees who remain as automation increases should yield higher levels of non-routine work as they focus on more complex tasks (Bakhshi et al., 2017). An excellent example of this is that of bank ATMs. When these devices were originally being developed, many thoughts that it would be the end of the bank teller. Yet instead, these devices eliminated the routine tasks that were once completed by humans, allowing those human bank tellers to focus on more non-routine tasks. The result was more bank tellers who were receiving higher wages.

The literature is still inconclusive regarding whether this time is different. While there are many similarities to previous shifts in the labor market, this is the first time that routine cognitive task will also be impacted. For this reason, what is known is that change is occurring in the economy and more research must be done to prepare the labor force for the future to come.

How Developing Nations Differ

Prior research has primarily focused on developed economies which consist of higher percentages of service work (Winick, 2018). Yet, much less has been a study on the effect automation will have on developing nations. This is especially troublesome since countries with nascent economies are more likely to consist of routine skills (Aedo et al., 2013). It appears that only with economic growth do significant shifts in skill intensity of occupations begin to occur.

The other main reason for the large degrees of routine work is that many of the new work that has been generated in these countries occurred as developed countries outsourced jobs. To outsource a job, it must be operationalized enough that entire jobs are routine and de-skilled enough to transport to a new state. Therefore, these economies are potentially even more susceptible to automation, yet their economies are at higher risk for defaulting in cases of major economic setbacks.

As we have discussed, over the past decade's much work that consists of routine tasks have been outsourced to developing nations. Yet at the same time, the development of new technologies has also been eating away at these routine tasks. Starting in the mid-1900s into the turn of the century China was capturing much of this outsourced work, which combined with its dramatic increase in outsourcing lower-priced commodities led to its rapid growth bringing it to be the second largest economy in the world (Autor, Dorn, & Hanson, 2013).

As China's middle class begins to grow, they are beginning to outsource the more routine jobs, especially in the manufacturing setting.. Yet, while this phenomenon is occurring, it is not as large as the movement of work that China once received. Some speculate that this is due to automation capturing the work, resulting in restoring with fewer workers (International

Federation of Robotics, 2017). If this pans out, then this will drastically alter the cycle of development that has led to such rapid growth for countries like China.

Shifting to a country such as India who at one point would have modeled their economic growth off China, they must determine an alternative growth route. Even as they capture some outsourced manufacturing routine jobs from China and other developed nations, it is not enough to rely on for substantial growth. As the technology becomes cheaper, some countries are choosing to re-shore the work that can be done with much fewer employees and more robots. This leaves India who has the second largest population, to question the best path to rapid growth.

Examining smaller countries with less skilled workers and less developed infrastructure, there will be even less work for them to capture as the cost of technology comes down. These countries must develop a new pathway to development to grow.

Hypothesis 3: *Due to the nature of jobs in developing nations, these countries will have higher levels of jobs with high levels of automatability compared to OECD member states.*

Methodology

For this paper, our primary source of data was the World Bank STEP dataset. This data set was collected over 4 years across 15 developing countries. The raw data is publicly available, and the authors had to harmonize the data set to streamline responses across countries. In total, we were able to use 11 countries data as the others were coded differently or did not ask all questions which were required for this analysis (same 11 which Di Carlo et al. (2016) was able to harmonize). Our total sample was 14763 respondents.

This data was unique in that individual workers gave a detailed view of the tasks that they complete at work. Along with this, a significant amount of demographic data was also captured giving a detailed view of the households in which these individuals live. Further differentiating this dataset, the individuals surveyed completed an in-depth reading literacy assessment including vocabulary, sentence processing, and passage comprehension.

The data consisted of individuals' responses to their tasks at work. This gave the authors an intricate look into the breakdowns of jobs and tasks that a worker completed. We were also able to capture the heterogeneity between jobs within an occupation, both within the countries and between countries. Responses were either binary (Ex. Do you drive a vehicle at work?) or ordinal (How often does the work have repetitive tasks?). We took out respondents who had most of their answers missing. For those employees who only had a few responses missing we used an expectation-maximization algorithm to estimate their responses.

Once the dataset was ready, the authors used the results from Frey and Osborne (2017) to ⊠train the expectation-maximization algorithm used to estimate the automation potentials. A mismatch in the coding of the data led the authors to use a crosswalk to match the OCC to ISCO-2 coding. Whenever there were multiple jobs, we created a weight, calculated as the inverse number of multiple matches.

This training data was determined at the occupation level, so we were able to regress it onto the tasks creating a likelihood that each task was to be automated. These values were then weighted by the product of the weight created by the STEP survey and our duplication weight.

The EM algorithm was then used to reweight the duplication weights to maximize the most likely automation variable. The outcome was an estimation of the percentage of tasks that were likely to be automated. Any jobs which had a result above 70% were considered highly automatable, the main unit of measurement for our analysis.

Equations

An expectation-maximization algorithm following Ibrahim (1990) was implemented to identify the percentage of task which are susceptible automatable. We begin by regressing the Frey and Osborne automobility onto N tasks of each duplicated job for every respondent.

$$y_{ij} = \sum_{n=1}^{N} \beta_n X_{in} + \epsilon_{ij}$$

y = F&O Automation
i = Participant
j = Duplicates
X = Tasks

Next, we recalculated the weights for each job duplication. This was calculated by taking the regression equations automation output and subtracting the training input (the Frey and Osborne (2013) outputs) then dividing it by the summation of all the duplicate automation value differences. The output was a new weight where $w_d < 1$.

$$w_d = \frac{\hat{y} - y_j}{\sum \hat{y} - y_j}$$

w = duplication weight
$\hat{y}$ = automation output
y = F&O automation
j = Duplicates

This entire process was repeated until the weights converged. Final automation probabilities were then created by using the multiplying the reweighted variables predicted automation output. This yielded the automation estimations at the individual job-level.

$$\text{AJ} = \sum_{n=1}^{N} w_j \hat{y}_j$$

AJ = final job-level automation percentage
w = duplication weight
$\hat{y}$ = automation output
j = Duplicates

Calculating the occupation-level results required one further step. Each job automation output was averaged using the weight provided by the data. This yielded one overall percentage of tasks likely to be automated per occupation.

$$\text{AO} = \frac{\sum_{n=1}^{N} STEPw_n \text{AJ}_n}{n}$$

AO = final occupation-level automation percentage
AJ = final job-level automation percentage
$STEPw$ = STEP weight
n = number of jobs in occupation

Results

Once the EM algorithm completed, we had our final predictions for every individual job. With this data, we were able to analyze trends among occupations and countries. We found the level of highly automatable jobs to range between 7.7% and 42.2%. Table 1 shows the level per country. We also calculated the average amount of tasks that are likely to be automated by country, shown in Table 1.

Country	Automation Risk	Highly Automatable
Armenia	49.6%	10.6%
Bolivia	57.3%	27.5%
China	56.5%	7.7%
Georgia	51.0%	12.5%
Ghana	64.0%	42.4%
Kenya	57.7%	22.5%
Lao PDR	66.0%	33.9%
Macedonia, FYR	52.4%	14.6%
Sri Lanka	62.8%	35.0%
Vietnam	58.2%	23.4%

Table 1: Breakdown of overall automation and highly automatable rates by all examined countries

To test the robustness of our results we compared them to various intuitive checks. Overall the more education that an individual receives, the less automatable the job. Professionals and managers, jobs which are high in knowledge work such as interpersonal communication and creativity were least likely to be automated, while elementary occupations, or those requiring the simplest of skills, were more likely. Finally, more experience required to complete a job also correlated with a decreased amount of automation percentage. Further diving into this we ran a regression with multiple variables and discovered that Education, Experience, and Age all explain a majority of the variance among these statistics (see table 2 for a breakdown). All these results suggest that our data follows a similar pattern as previous studies.

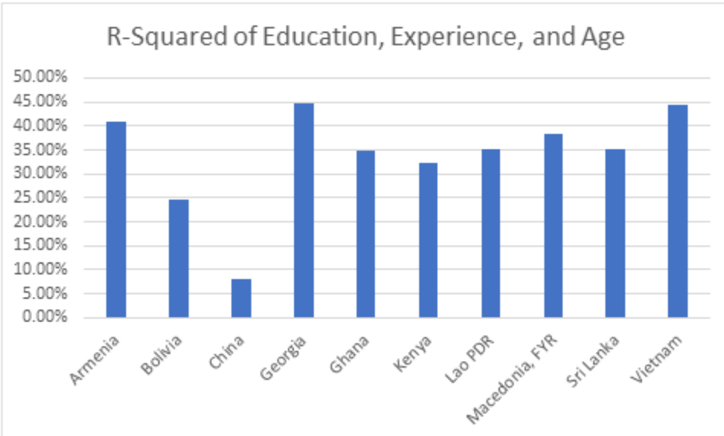

Figure 1: Total explained variance for Education, Experience, and Age

Due to the data being at the individual job level we were able to generate statistics for occupation categories at the aggregate and in between countries. Our research share similarities with other predictions suggesting jobs involving a lot of interpersonal and creative tasks are less likely to be automatable. Secondary Education Teachers were shown to have only 36.19% of their tasks to be automatable and Architects & Curators were estimated at 44.58%. A commonly discussed group, Heavy Truck, and Bus Drivers had a much higher automatable parts estimate of 63.28%. Lastly, the highest percentage was given to the group of Fishery and Aquaculture Laborer's who were estimated at 70.91%.

Further investigating heterogeneity between countries identifies some fascinating differences. For example, the occupation of Managing Directors and Chief Executives has a 25.47% difference in the percentage of automatable tasks. In the Yunnan province of China, those who hold these titles face a 43.48% percentage of tasks whereas those in Bolivia only face 27.67% of tasks. Yet then there are some occupations such as Food Processing and Related Trade Workers, which have less than a 15% difference between all countries. This suggests that the same career may have a different level of homogeneity in different countries and cultures.

Given the individualized data for each worker, tasks were analyzed to determine which contribute the most to automation. Although it varies by country, the more repetitive that an individual reported their job was, the higher their automation likelihood. Less creativity, autonomy, and mental effort in tasks also led to higher levels. Finally, more reading and writing resulted in less likelihood of automation, while more numerical work had no effect. This is fascinating as it points to the fact that humans can do some numerical tasks with proficiency where AI can handle others with much more precision.

To determine the effect of routine and non-routine tasks, two approaches were taken. First, the coefficients were analyzed for all the countries. Second, all tasks which were deemed to be non-routine were bundled together and principal component analysis (PCA) was conducted. The first three components of this analysis were regressed onto the automation percentages and while it was not present in all countries, most suggested that the higher non-routine task PCA variable was, the lower the automation probability.

When regressing the routine task PCA onto the automation outcomes, it suggests that increasing repetitive tasks yields a slightly decreased automation likelihood although when breaking down to the country level it appears that some experience a slight increase while others a slight decrease. Combining these two indices variables suggests that there is evidence to accept hypothesis 1, yet it is not a large and direct effect.

Moving onto the second hypothesis, non-routine tasks require more knowledge as there is not a set operation to complete them, thus they generally require more education and/or experience. To determine if this held true with this analysis, automation outputs were compared against the experience and education that the jobholders had acquired. From an initial overview of the average automation by these variables, our hypothesis seemed to be correct. Furthermore, two regressions were conducted, and both yielded high effects (education = -4.9% and experience = -4.6%) although neither was statistically significant. Lastly, a complete breakdown of average automation variables per breakdown of education and experience was conducted. Representing the highest level of both variables was an individual with a Ph.D. and over 10 years of experience who has an average of 33.3% and the lowest an individual with early childhood education and no experience has an average of 66.6%.

Education Level	Automation Estimation
Early Childhood	0.65
Primary	0.63
Secondary	0.58
Vocational	0.51
Bachelors	0.47
Masters	0.45
PhD	0.43

TABLE 2: Average Automation outputs by education and years of experience

Experience Level	Automation Estimation
None	0.63
Less than 1 year	0.58
1-2 years	0.52
3-5 years	0.48
More than 10 years	0.46
6-10 years	0.46

TABLE 3: Average Automation outputs by education and years of experience

Experience Level	Automation Estimation
15-19	0.62
20-29	0.56
30-39	0.56
40-49	0.57
50-59	0.56

60-69	0.56

TABLE 4: Average Automation outputs by age range

When comparing education to the predicted automation outputs there was a significant correlation. Education variables were listed differently in the surveys given to each represented country, therefore they were recorded using the ISCO education codes. Early childhood education was the lowest level of education used (excluding no education). Comparing this to those who have pursued higher education a stark difference can be witnessed with bachelors, masters, and PhDs averaging at 33.45%. This offers evidence that Hypothesis 3 can be accepted as more education lowered the percentage of tasks that are likely to face automation. The full breakdown can be seen in Table X. All of these results suggest we can accept Hypothesis 2.

Finally, when comparing the final results between our analysis of developing countries compared to the OECD's similar analysis of developed countries, a few fascinating insights were uncovered. In the OECD study, the authors reviewed 21 developed nations. In these countries, the share of people at high risk, the main variable of measurement for this study ranged from 6% to 12% with a median of 9%, where our results ranged from 8% to 42% with a median of 23%. Although, when reviewing overall percentages of automation their results ranged from 35% to 44% with a median of 38% where our results ranged from 50% to 66% with a median of 58%. Hypothesis 3 can, therefore, be accepted as the developing nations automation results are significantly higher than those discovered by the OECD.

	High Risk		Overall Automation	
	Range	Medium	Range	Medium
OECD	6%-12%	9%	35%-44%	38%
Developing Country	8%-42%	23%	50%-66%	58%

TABLE 5: Comparison of this study's automation predictions for developing countries compared to those made by the OECD.

Discussion

This article is the first to look at automation impact on developing nations. Using STEP data collected by the World Bank we estimated the percentage of tasks that were likely to be automated. We used a task-based approach that looked at the specific tasks of each job as reported by the worker. Setting a threshold of 70% or higher of tasks which are highly automatable, we identified which countries face a significant amount of job loss by automation. Through this, we found among all 11 countries that automation will have a significant impact, with some impacted even more.

Hypothesis 1 predicted that the task consists of a job will correlate with the automation estimate. Previous research suggested that more non-routine tasks would correlate with a decrease in the number of tasks likely to be automated while routine tasks would increase automation. Overall this mostly panned out to be supported by the results. Four variables were identified as non-routine tasks prior to any analysis. When these were then combined with the output from the EM equation, all four correlated with decreased automation likelihood.

Alternatively, repetitive tasks were the only to be identified as to routine. When comparing this to the automation scores, no significant patterns were observed but this could have been due to a variety of factors but most likely because it was not suitable as a proxy for routine tasks.

Hypothesis 2 examined the roles that education and experience play in the likelihood of automation. The authors, guided by previous research, suggested that as one gains more education and experience, they would progress into jobs that consisted of more non-routine tasks. As was suggested in hypothesis 1 this would then lead to lower automation levels. Overall hypothesis 2 was supported as those with increased experience and education levels had higher levels of non-routine tasks and thus lower automation.

Lastly, hypothesis 3 was significantly supported. Using the main variable from the OECD study, highly automatable jobs (those consisting of >70% automatable tasks), the two studies' mediums differ by 14%. Furthermore, the upper bound of the developing countries trumps that of the OECD countries by 30% suggesting the potential impact of automation to be significantly higher in the worst-off developing country compared its OECD counterpart. When looking at the overall percentage of automatable tasks the developing countries range is absolutely greater than the OECD range, suggesting the potential impact on all developing countries is much more. Although further research will have to be conducted to diagnose this difference, it surely alludes to the need to continue investing automation's impact on developing economies.

Within all these results, Yunnan (Chinese Province) and Ghana stood out as outliers. Yuanna had a significantly low percentage of automation at 7.7%. On the other side, Ghana had a high percentage of automatable jobs at 42.4%. At first look, these numbers can appear as errors caused by the data, which is possible. Yet, with further analysis, these numbers may represent the realities for these countries, especially when factoring in the heterogeneity between tasks composition of similar coding jobs.

Comparing to Other Automation Studies

Comparing to the article we designed our methodology from, Arntz et al. (2017) that was conducted on OECD countries yielded somewhat similar results. With the 21 countries they reviewed, the share of people at high risk, the main variable of measurement for this study, ranged from 6% to 12% with a median of 9% and our results ranged from 5% to 22.5% with a median of 6%. Although, when reviewing overall percentages of automation their results ranged from 35% to 44% with a median of 38% where our results ranged from 46% to 59% with a median of 56%. This suggests provides evidence towards hypothesis 5 that these countries are more susceptible to automation as a whole. Although, it is not as likely that this will be shown through widespread employment reduction but instead a significant shift in what tasks are performed by workers.

Compared to another recent study conducted by McKinsey (2017), our results yielded surprising some complementary predictions and others that deviated. Not taking (or at least not fully reporting) a similar task-based approach there is no specific threshold defined when an employee is considered at high risk for automation based on the percentage of tasks of there which will be automated. Overall their analysis suggests that the percentage of workers in the countries analyzed ranged from 5% to 26%. Their analysis overlaps with some of the countries studied in this article. The McKinsey article suggested that Kenya will have5% of current work activities displaced by automation by 2030, where our research suggested 23% of Kenyan workers are at high risk for automation. These are starkly different results, although they do not reflect the exact same variables.

Regardless of these minor differences to these two articles, this study follows along with the trend of disproving the predictions yielded by Frey and Osborne (2017). As previously described, their study used an occupation-based approach that did not factor in heterogeneity between jobs, nor did it factor in actual employee reported data. Results from their analysis suggested that 47% of American jobs were at risk for automation, a higher figure than any of the countries analyzed in the two previous studies and this one. Thus, this article provides further evidence for using a task-based approach when estimating automation likelihood for occupations.

Conclusion

This study set out to identify the automation likelihood of occupations in developing nations. Data collected on 10 developing nations were broken down into over 14,000 independent jobs and a percentage of tasks that are automatable were calculated. Leveraging each of these outputs, a final number was calculated for each nation along with each occupation. These results suggest that developing nations are much more susceptible to automation than OECD countries.

Limitations

Training Data. Although the pure results of the Frey and Osborne (2017) study have not been replicated, the work that they did, and their results are useful for creating a new system to analyze jobs. For this reason, the authors trained the EM model using their results. This data was the first to attach automation estimations to occupations and has been used in other studies (Artnz et al., 2017). Although, many critiques question its validity due to the methodology used. Instead of breaking down jobs into tasks, the authors of this study took an occupation approach and had experts rate the automation likelihood of various attributes. Likely inflating the estimations, this method has lost favor in value of a task or skill-based approach such as the one used in this study. Although the algorithm we chose was intended to de-bias these initial results, it could have still resulted in overestimating the automation likelihood of various occupations.

Mismatch of job codes. Another area of concern is the matching of Frey and Osborne outputs and the STEP data. This required the use of a crosswalk that compared SOC (US O*NET Codes) and ISCO (World Standard) coding. The authors used the official crosswalk created by the O*NET, although this still yielded an imperfect match and, in some cases, multiple jobs on the SOC side had to be merged to create one value for an ISCO job. Ideally, this captured the degree of different jobs which is created between ISCO and SOC coding, but the authors were not able to ensure that every match was perfect.

Bad Sampling, no accounting for jobs. STEP data was collected on a sample of households located in each of the developing nations. Since this was the only data used in the analysis, it held as an assumption that the sample chosen by the World Bank was representative of the labor economy in each nation. With this assumption, the authors were able to use the estimation of automation for each occupation to compute national likelihoods of automation. In the case that these samples were not representative, then it would yield incorrect national estimations. For example, if doctors are rated at 10% automation likelihood and 25% of the Armenian sample were doctors this would create a lower country automation likelihood number as it overrepresents the number of doctors in the country.

(Lacking Data) Outside of the data that was used, there were multiple data points which we would have preferred to include in our model to further estimate the probability of automation. Firstly, our model did not account for any individual economic characteristics of the countries. Kenya was rated as having the highest amount of jobs at high risk for automation, although it is also a country with limited infrastructure and expendable capital. Some jobs which would quickly be automated in many other countries may not in Kenya as labor can be pushed to a price lower than the amount of capital required to develop robots to do it instead. As more research is conducted to gauge how open countries are to automation's spread, the variable must be included in future models.

Further Research

Studying the potential impact of automation on developing nations yielded some fascinating new insights while further suggesting the task-based model of predicting automation is valid. At the same time, it resulted in many new areas of the question as if the results of this study are correct, developing nations are at significant risk. To further dive into these results the authors suggest that there are multiple areas in which this research can continue.

First, regardless of the automation potential of a country, it is not of a concern if automation is never adopted. A study conducted to understand the current efforts of companies headquartered in these developing nations to automate the workforce. Governments of these countries must also be interviewed and analyzed to determine if automation is an issue of concern for them and if so are there any projects underway to ameliorate this concern.

Even if companies in these developing nations decide that they would like to pursue automation, it is bottlenecked by the infrastructure of each respective country. A common issue of concern for any company attempting to outsource to an underdeveloped country, lack of roads, electricity, or other modern utilities can stall any automation development. Studies must both be conducted to understand the role that a countries infrastructure plays in the growth of automation and to also determine if this relationship holds true in developing nations.

Diving further into each of these developing economies, another extension to this study would be to chart out the changes to a subset of jobs. Starting with when these jobs were created, either from a local organization or due to outsourcing done by a company located in a developed nation, and following through present day, charting out task changes would provide evidence of any impacts due to automation.

The final category of additional research which is recommended by the results of this study and by the many others completed in recent years is the need to understand paths from currently highly automatable jobs to those which are much less likely to be automated. This research must be conducted to assist with the transitioning economies of all nations but especially those of developing nations which are likely to get hit hardest.

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