



Microdata or Macrodata?

An Alternative Measure for the

Risk of Job Automation

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EXISTING ESTIMATIONS OF THE RISK OF THE JOB AUTOMATION DRAW ON MICRODATA TO ESTIMATE PROBABILITIES BASED ON A SUBJECTIVE SELECTION OF THE TASKS THAT ARE MOST LIKELY TO BE AUTOMATED. THIS ARTICLE ANALYSES THE DIFFERENT EXISTING METHODOLOGIES AND SUGGESTS A COMPLEMENTARY MEASURE: A COMPOUND INDEX THAT INCLUDES MACROECONOMIC SERIES IN THE CALCULATION AND ALLOWS PERMANENT MONITORING.

Throughout history, there has never been a shortage of apocalyptic predictions. From the prophecies of Nostradamus to the millennium bug, the end of the world has been forecast on countless occasions for very different reasons. And yet here we still are.¹

Current pronouncements hailing the end of work are causing panic just as the prophets of old once did. Looming on the horizon is an inescapable threat, one poised to send tremors through the history of humanity: tasks which workers currently earn a wage for performing will be automated using machines that are becoming increasingly efficient and will eventually be cheaper than humans.

Publications on this issue usually try to answer two questions: can a robot perform the work humans currently do? And what will happen if they can? There is no easy answer to either. The first question is hampered by fundamental methodological problems associated with the natural difficulty of making predictions using incomplete information. The second question entails certain aspects of complex socio-economic policy design, such as building new skills and capacities, the regulation of new labor markets, and income distribution mechanisms, among others.

This article focuses on a specific as-

pect of the first of these two problems: the need for better metrics that would allow us to carry out advance measurements and impact assessments or, as a second-best option, enable us to monitor trends on how technological change impacts our economies.

Technological unemployment is nothing new. In 1930, John Maynard Keynes wrote that “we are being afflicted with a new disease of which some readers may not yet have heard the name, but of which they will hear a great deal in the years to come—namely, technological unemployment.”

However, the current pace of innovation and the spread of technology to different aspects of economic life have totally changed the scale on which technological unemployment is unfolding. Brynjolfsson and McAfee (2014) call this new stage “the second machine age.” Schwab (2016) prefers a more historical frame of reference, using the term the “Fourth Industrial Revolution,” an idea started by Rifkin (1995). Government plans in different countries simply describe the phenomenon as Industry 4.0.² These terms all describe the same factors: the Internet of Things, smart cities, big data, driverless cars, artificial intelligence, 3D printing, blockchain, etc. New technologies have become part of the production structure,

creating new goods and services and new forms of production, but not necessarily new jobs.

According to the law of transformation, the accumulation of gradual, imperceptible quantitative change necessarily leads to vital qualitative leaps. One radical change that has affected the world of work is population growth. In 1800, there were 1 billion people in the world and it had taken 300 years for the 500 million people that existed in the 16th century to reach this point. In 1920, the global population stood at 2 billion—this time it had only taken 120 years for the population to double again. Today, it does so approximately every 40 years. There are currently around 6 billion people on Earth and this number is slated to increase to 9 billion by 2025. Can our economies generate proportionate numbers of jobs? What sort of jobs will be created and which professions will become obsolete? According to the World Bank (2016), recent decades have seen an increase in the share of occupations that are intensive in cognitive and socio-emotional skills (so-called soft skills), while occupations that are intensive in routine skills have decreased.³

Ever since Frey and Osborne (2013) estimated that 47% of jobs in the United States ran the risk of being automated in the following 20 years, a series of studies have proliferated which have attempted to estimate the number of jobs that could be lost, the most vulnerable sectors, the professions that are least likely to disappear, and so on.

Those who use Frey and Osborne’s methodology consider that the risk of automation for a given occupation can be transferred from one country to another. Thus, as Arntz, Gregory, and Zierahn (2016) state, the difference in potential job automation rates in dif-

ferent countries is exclusively due to differences in their employment structures. By way of example, if 100% of the jobs in a country were associated with the profession of librarian, which has a 99% risk of disappearing, the risk of job automation in that hypothetical country would be at least 99%. To put it simply, the relevant proportional adjustments are made to account for a different or more complex employment structure.

Using this methodology, Pajarinen and Rouvinen (2014) estimated the risk of job automation in Finland to be 35% while Brzeski and Burk (2015) put the rate at 59% in Germany, to name just a couple of examples. In Latin America, MECON (2016) estimated a risk of 62% for Argentina and Aboal and Zunino (2017) put Uruguay’s at 66%. In an extension of the aforementioned study by Frey and Osborne, the World Bank (2016) estimated the risk for other countries, such as China (77%) or Ecuador (68%), using the same methodology.

Far from being immune to criticism, these studies prompted a series of responses that fall into three groups. First, methodological criticism from those who, like Autor (2015), suggest that automation generally impacts specific tasks rather than entire occupations. In other words, a given occupation implies the execution of a diverse number of tasks. In the case of a retail salesperson, for example, these might range from modifying price tags to handling payment or attempting to persuade clients.⁴ This approach reduces the risk estimations calculated by Frey and Osborne (2013) and was adopted in Arntz et al. (2016) for OECD countries, who also observed that the same occupation entails different tasks when carried out in a different workplace.⁵

The second wave of criticism ze-

roed in on the fact that the authors of these studies took a static view rather than a dynamic one. New technologies will also give rise to cobotization (humans and robots working alongside one another in factories) and will come up against regulatory or institutional impediments to automating jobs (such as labor unions). New technologies also give rise to new occupations, as has been the case with data scientists or virtual reality architects. By calculating the risk of automation for a given job without taking into account the creation of new jobs (and the limits on the elimination of existing ones), it may be the case that the negative effect on employment is being blown out of all proportion.⁶ Along the same lines, Moretti (2012) argues that each technological job generates a multiplying effect of four new jobs, twice the rate as in traditional industry, due to higher salaries and the propensity of technology firms

to form clusters, a factor which is essential to the study of their dynamics in any prospective analysis.

The third source of criticism is historical. Gregory, Salomons, and Zierahn (2016) point out that rather than racing *against* the machines, work races alongside them, in that there is evidence of benefits associated with the increased demand and knowledge spillovers that new jobs generate. Mokyr (2017), meanwhile, observes that the past is a poor guide for predicting the future and that new technologies “will lead to continued improvement in economic welfare, even if these are not always measured in our National Income Accounts.” However, measuring this phenomenon precisely poses considerable difficulties. Not even a satellite account for innovation could fully describe probability-related phenomena such as exponential technologies before they are adopted into widespread use.⁷

TABLE 1:
METHODOLOGY AND RESULTS OF SELECTED STUDIES ON THE RISK OF JOB AUTOMATION

	FREY AND OSBORNE (2013)	OECD (2016 AND 2018)	WEF (2016)	WORLD BANK (2016)	MANYIKA ET AL. (2017)
METHODOLOGY	Occupation-oriented. O*NET database for the United States	Task-oriented. PIAAC database for OECD countries	Survey of companies from 15 countries in nine economic sectors	Extension of Frey and Osborne into other economies and adjusting for technology adoption lags	Disaggregation of 18 skills used in 2000 work activities in 800 occupations. Estimation of hours used in each activity
RESULTS	47% of jobs at risk of automation in the United States	9% risk of automation on average in 21 OECD countries	5.1 million jobs lost	66% of jobs in developing countries at risk of automation. This result is lower if it is adjusted for late adoption of technology	Less than 5% of occupations are fully automatable, but at least 30% of the activities that make up 60% of occupations are technically automatable

Source: Compiled by the author based on Manyika et al. (2017).

The so-called productivity paradox described by Roach (1987) shows that investment in innovation and information technology do not move the productivity needle. In other words, even when technology increases, productivity per worker remains the same. Roach's results are a snapshot from just before the internet became widespread, and thus reflect the outlook at the dawn of the IT revolution. Thirty years later, at the dawn of the age of automation, we may be about to witness the rise of a new paradox. This time the issue is undesirable effects not on productivity but on well-being. Automation may translate into lower quality of life for people, greater exclusion, and more unemployment. Why increase productivity if it brings about a more unequal society? How can we better distribute digital dividends to avoid the fragmentation of society in the future? Given this uncertain outlook, any public policy that puts forward alternative courses of action should include the best information available on the evolution of the automation process and the consequences it may have.

A METHODOLOGICAL FRUIT SALAD

The desire to measure a phenomenon as slippery as automation gave rise to a range of very diverse methodologies that brought equally diverse results. Frey and Osborne's (2013) pioneering study argues that there are three bottlenecks to automation, or tasks that cannot yet be automated: those requiring creative intelligence, social intelligence, and perception and manipulation. Frey and Osborne then disaggregate these into nine more specific tasks (such as negotiation, persuasion, originality, and so on) that are

used in 702 occupations included in the United States employment database (O*NET). The authors take a subset of 70 jobs and assign them a probability of 1 if they can be automated and 0 if they cannot. The decision in each case was based on consultation with a group of machine learning experts and was thus subjective and ad hoc. The final step in the process entailed generating an algorithm that would predict the automation potential of the 632 remaining occupations included in O*NET, based on the use of the nine task types that make up the bottlenecks.

World Bank (2016) stylizes Frey and Osborne's study to calculate automation risks in different countries depending on their employment structure. That is, the original figures are weighted by the share of different occupations in employment in each country. These results are referred to as being "unadjusted," and the study also includes a calculation that has been adjusted for differences in the rate of technology adoption in poor countries using the technology adoption lag in Comin and Mestieri Ferrer (2013).

The study by Arntz et al. (2016) draws on the database of the Programme for the International Assessment of Adult Competencies (PIAAC) for 21 OECD countries. What makes their analysis different is that it takes a task-based approach that further desegregates the skills used by Frey and Osborne, including microdata on each job relating to tasks such as teamwork or face-to-face interactions. Its results differ substantially from those reached using the earlier approach. While Frey and Osborne (2013) assign a probability of automation of 92% to a retail sales job, Arntz et al. (2016) assign one of just 4%. This difference is due not only to their approach but also to their data

source—the PIAAC database allows a much greater level of disaggregation than O*NET.

WEF (2016) is based on a survey of nine industrial sectors in 15 countries and includes 371 firms with a total 13 million employees. At the aggregate level, the analysis shows that new technologies will destroy 5.1 million net jobs.

Using a fairly similar method to Arntz et al. (2016), Manyika et al. (2017), in a study for the McKinsey Global Institute, focus on 18 human skills to estimate the automation potential of 2000 work activities from more than 800 occupations using data from the US Bureau of Labor Statistics. The study was carried out for 46 countries that accounted for 80% of the global workforce. The 18 skills they focus on fall into five categories: sensory perception, cognitive capabilities, natural language processing, social and emotional capabilities, and physical capabilities. An example of their analysis is shown in

The researchers then estimated the level of performance required for each skill used in each of the 2000 work activities on a scale of 1 to 4, where 1 is no performance (or no human skill required); 2 is below median human level; 3 is median human level; and 4 is a high human level of performance. This classification was based on the research group's subjective criteria (as Frey and Osborne's was). The final stage consisted of assigning a given number of hours worked to each activity in each occupation so as to include the risk of automation of the hours actually used for each activity in the probabilistic risk calculation.⁸ The result is that less than 5% of occupations are 100% automatable, but at least 30% of the activities that make up at least 60% of occupations have technical automation potential.⁹

The differences in these calcula-

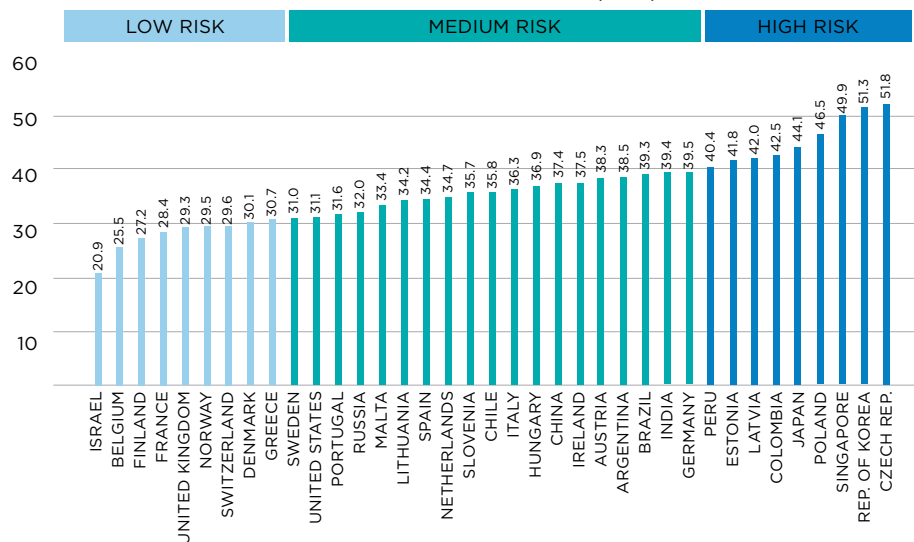
tions are noteworthy (see table 1). To cite just the best-known example, in the United States, Frey and Osborne (2013) and Frey et al. (2016) put the risk of automation at 47%, in contrast with the 10% found by Arntz et al. (2016) and the 14% by Nedelkoska and Quintini (2018), both of which were OECD studies. A simple correlation exercise between the different estimations actually yields negative results (a correlation of -0.35) between the values obtained by Manyika et al. (2017) and Arntz et al. (2016) for the 15 countries included in both samples.

These calculations also include two further problems. On the one hand, they do not allow for periodical comparisons except by recalculating the risk of automation for each activity depending on whatever (nonlinear) technological advances occur. On the other, all the estimations emphasize the impact of technologies on certain occupations/tasks/activities and leave out other relevant factors that form part of the risk of job automation from a broader perspective. These include the population's level of education and the economic structure of a country or its export basket, all of which are relevant when it comes to identifying potential risk factors.

A COMPOUND INDEX OF RISK OF AUTOMATION

There are other automation-related phenomena that are not taken into account in these early studies when they estimate the probability of a given task being computerized. For example, although automation is a risk for all types of tasks, routine tasks are easier to automate and are generally associated with lower levels of education.¹⁰ How does a population's education level af-

FIGURE 1
RISK OF AUTOMATION FOR 37 SELECTED COUNTRIES (IN %)

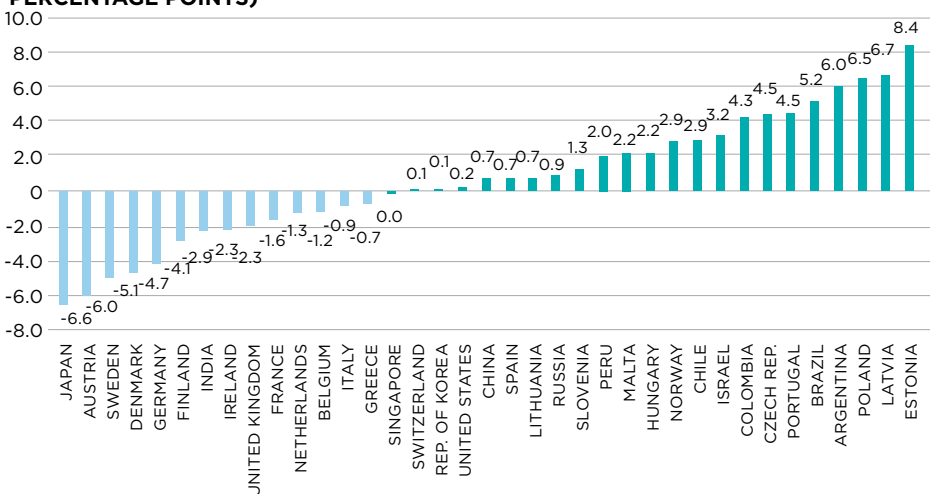


Source: Compiled by the author.

fect the potential for jobs to be lost to new technologies? Another factor that is not contemplated in Frey and Os-

borne's (2013) calculation is also omitted is the current state of robotization within a given economy, as measured

FIGURE 2
VARIATION IN RISK OF AUTOMATION (DIFFERENCE BETWEEN 2017 AND 2014, IN PERCENTAGE POINTS)



Source: Compiled by the author.

by the number of robots that are already operational within it.

This missing yet relevant information has prompted me to seek an alternative measure for the risk of job automation. This article puts forward a compound index for automation potential which evidently intends to complement rather than replace the estimations analyzed above.

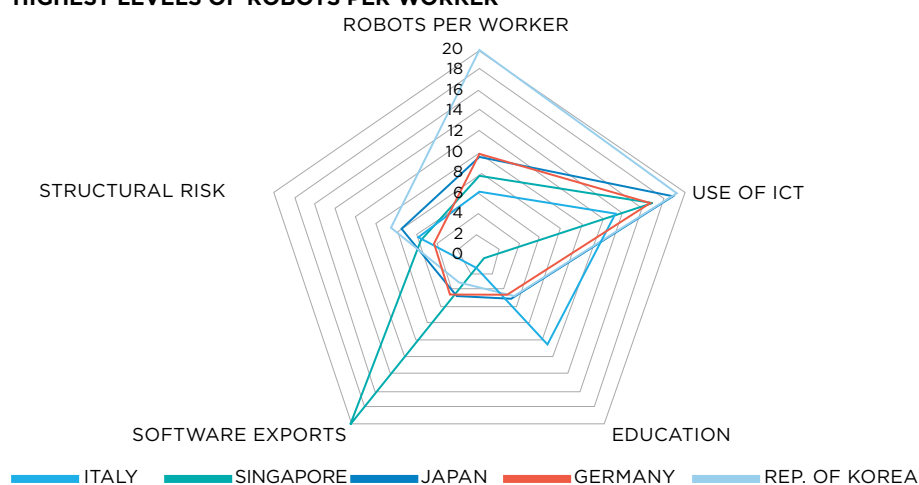
The diverse aspects of automation and the variety of data involved point to the potential usefulness of a compound index that would allow indicators to be aggregated, thus simplifying the analysis and providing economic policy makers with constructive input.

There are a series of well-documented advantages to aggregate indicators. As Jollands, Lermitt, and Patterson (2003) argue, "one way to assist policy makers is to develop aggregate indicators that summarize the information." Their study looks at a series of aggregate indices that brought solid results

in examinations of complex economic phenomena. These include the *Index of Sustainable Economic Welfare*, the *Human Development Index*, the *Unified Global Warming Index*, and many more. Jollands et al. (2003) claim that mathematical simplification is preferable to complexity in these cases and that these indicators are extremely helpful to policy makers because they allow a large amount of information to be summarized succinctly.

Among the potential weaknesses that they discuss, they warn that index aggregation always implies subjective choices and that important information may be lost in the aggregate. Echoing Meadows (1998), they warn: "If too many things are lumped together, their combined message may be indecipherable." The standard criticisms of compound indices run in two directions. First, the choice of the parameters to be aggregated always depends partly on the opinions of the experts

FIGURE 3
COMPONENTS OF RISK OF AUTOMATION FOR THE FIVE COUNTRIES WITH THE HIGHEST LEVELS OF ROBOTS PER WORKER



Source: Compiled by the author.

designing the index. Second, it is difficult for aggregate indices to “capture the interrelationships between individual variables.” As I observed above, even the most common measures of automation potential are not immune to accusations of subjectivism, while multicollinearity tests can be used to prevent the inclusion of variables that are highly correlated and thus can be thought of as substitutes for one another because they measure the same effect.

The appropriate approach to building compound indices must be based on a clear methodology. As Mazziotta and Pareto (2013) point out, “the heated debate within the scientific community, over the years, seems to converge towards the idea that there is not a composite index universally valid for all areas of application, and, therefore, its validity depends on the strategic objectives of the research.”

The OECD (2008) provides a com-

plete guide for building compound indices. The strengths of this type of indicator include the fact that it enables researchers to summarize a set of indices while preserving most variations from the initially released values. The guide thus warns that a prior standardization stage is necessary.

In this case, I have opted for Min-Max normalization, which allows the results of different indicators to have an identical range [0, 1], which coincides with the scale that tends to be used for risk of automation, which has a range of [0, 100]. The normalization criterion is as follows:

$$(1) \quad I_{qc}^t = \frac{x_{qc}^t - \min_c(x_{qc}^{t0})}{\max_c(x_{qc}^{t0}) - \min_c(x_{qc}^{t0})}$$

where x_{qc}^t is the original value of an indicator and I_{qc}^t is its replacement value after the Min-Max normalization of each series. The different aggregate variables that will make up the compound index thus fulfill the criterion of

being scale-invariant, so a unit-based standardization can be carried out and the new values remain within the desired range.

Once the method of standardization has been selected, an aggregation methodology needs to be chosen. The OECD (2008) argues that “by far the most widespread linear aggregation is the summation of weighted and normalized individual indicators,” an equation given by:

$$(2) \quad C_c = \sum_{q=1}^Q w_q x_{qc}$$

where $\sum w_q = 1$, in other words w_q represents the weight of each variable in the indicator such that $0 \leq w_q \leq 1$ for each $q=1, \dots, Q$, and $c=1, \dots, M$. This article discusses a compound index in which all the components have the same weight, and leaves an analysis of the results so as to place more weight on some components than others for future studies to consider.¹¹

MICRODATA OR MACRODATA?

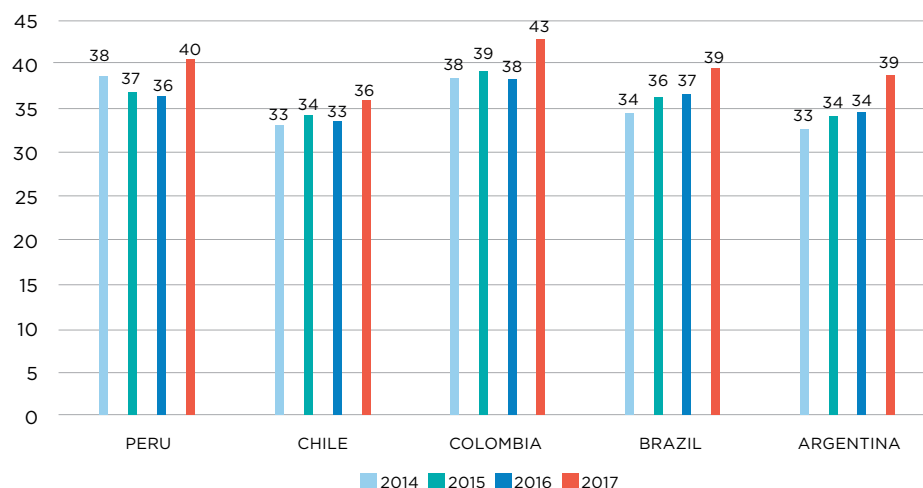
The index was built for a set of 37 countries (in North America, Latin America, Europe, and Asia) for a four-year period (2013–2016). The index frequency is annual, due to the types of data that technology- and innovation-related variables tend to include.

The variables chosen were connected to automation from a macroeconomic or sector-specific point of view. The aggregation of variables into a compound index thus generates a measure of comparison between the different countries.

Five components were selected to build the index, based on the usual criteria of credibility, coherence, relevance, accessibility, the research group’s experience, diversity of aspects observed, and so on.¹² The following variables were included:

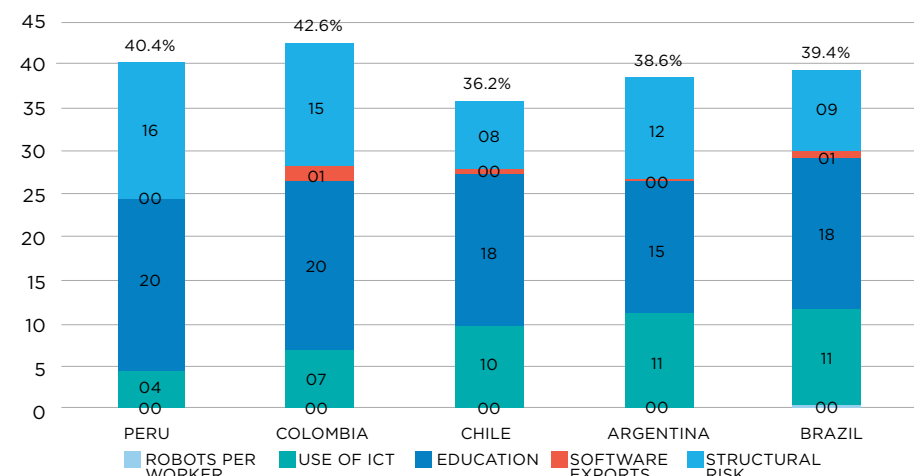
1. *Robot stock per worker*. This refers to each country’s stock of indus-

FIGURE 4 DYNAMICS OF THE RISK OF AUTOMATION, SELECTED COUNTRIES (%)



Source: Compiled by the author.

FIGURE 5 DECOMPOSITION OF RISK OF AUTOMATION FOR SELECTED COUNTRIES (%)



Source: Compiled by the author.

trial robots over time. The assumption is that increased robot density will have a positive effect on the risk of job automation. The sources for this indicator are publications from the International Federation of Robotics (IFR) and the World Bank.

2. *Use of ICTs.* This is an indicator that captures the intensity and use of ICTs. It assumes that greater use of ICTs has a positive effect on the risk of job automation via greater availability of digital automation technology. The source for this indicator is the International Telecommunication Union (ITU).

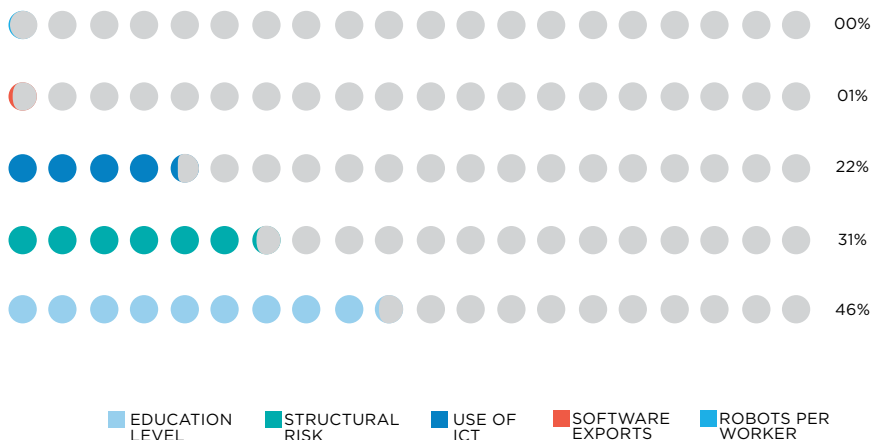
3. *Education level.* This is an aggregate of variables that include, for example, numbers of science and technology graduates, numbers of students enrolled in higher education programs, numbers of researchers, and education expenditure per country. The source for this indicator is the education section of the Global Innovation Index and the assumption is that the higher the edu-

cation level, the lower the risk of job automation.¹³

4. *Share of software exports.* This indicator is the share of software exports in each country's total exports, as captured by codes 8523 and 8524 of the Harmonized System (HS). It is assumed that the export baskets of countries whose economies are totally automated will contain high levels of software content.

5. *Structural risk.* This is the weight of employment in sectors that are more susceptible to being automated (where there are more robots per worker). These include agriculture, manufacturing, commerce and transportation, and the hospitality industry, in relation to total employment. These sectors are indicated to be the ones with the greatest risk of automation (Manyika et al., 2017).¹⁴ The greater the weight of the sectors with automation potential, the greater the risk of automation across the economy.

FIGURE 6
DECOMPOSITION OF RISK OF AUTOMATION FOR LATIN AMERICAN COUNTRIES (% OF TOTAL)



Source: Compiled by the author.

Following a correlation analysis to discard any possible multicollinearity, these five components were weighted identically when the index was calculated so as not to bias the final results toward any of the areas covered. It would be perfectly feasible to change the weighting to place more importance on the present (robot stock) than the future (education) or vice versa. It is important to note that the result will not reflect the absolute risk of job automation but rather the relative risk, given that by normalizing the index components using a range of [0, 100], what is being examined in each case is the relative difference between the countries in question.

RESULTS

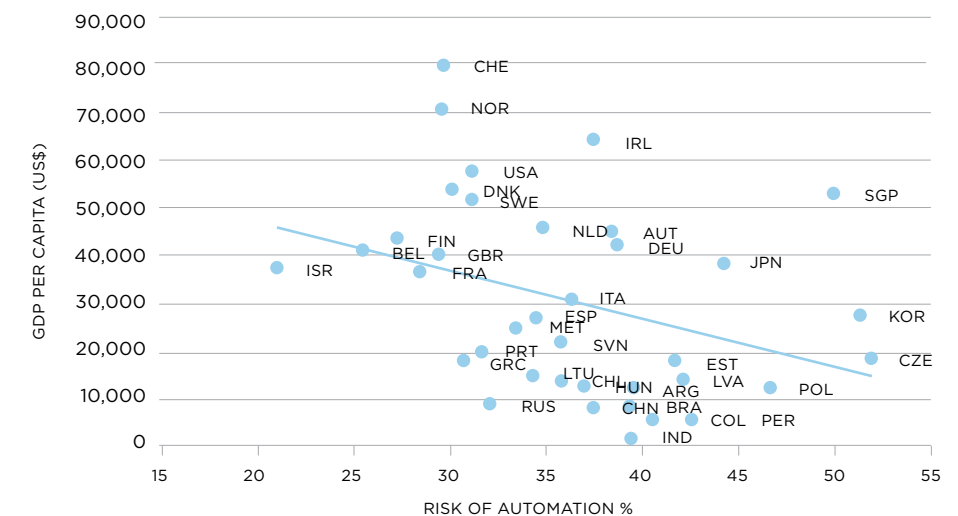
Figure 2 shows the results for the 37 countries included in the compound index for risk of automation. At one ex-

treme lies Israel, with the lowest risk (20.9%), which is particularly due to its high levels of education and low structural risk. At the other extreme is the Czech Republic, with the greatest risk (51.9%), which is due to high levels of digitization, high software exports, and high levels of robot usage in the production process. The classification of countries into low-, medium-, and high-risk groups was purely subjective (as tends to be the case): here, 31% was the cut-off line between low and medium risk, and 40% was the threshold for high risk, such that there are nine countries at each end of the spectrum and 19 in the central stretch of the curve.

There is a correlation of 0.57 between these results and those obtained by Manyika et al. (2017) and one of 0.44 with the adjusted version in World Bank (2016).

One of the advantages of this approach is that it allows dynamic observations to be made based on annual

FIGURE 7
RISK OF AUTOMATION AND GDP PER CAPITA, SELECTED COUNTRIES



Source: Compiled by the author.

updates of the index components. The percentage difference gained or lost in the last four years are shown in figure 3. Japan, Austria, and Sweden are the countries that have managed to reduce their comparative risk of automation the most, largely by diversifying their productive structure into sectors that are less vulnerable to automation. At the other extreme, Estonia, Latvia, and Poland were the countries that moved up the index most, generally due to a relative decline in the quality of education.

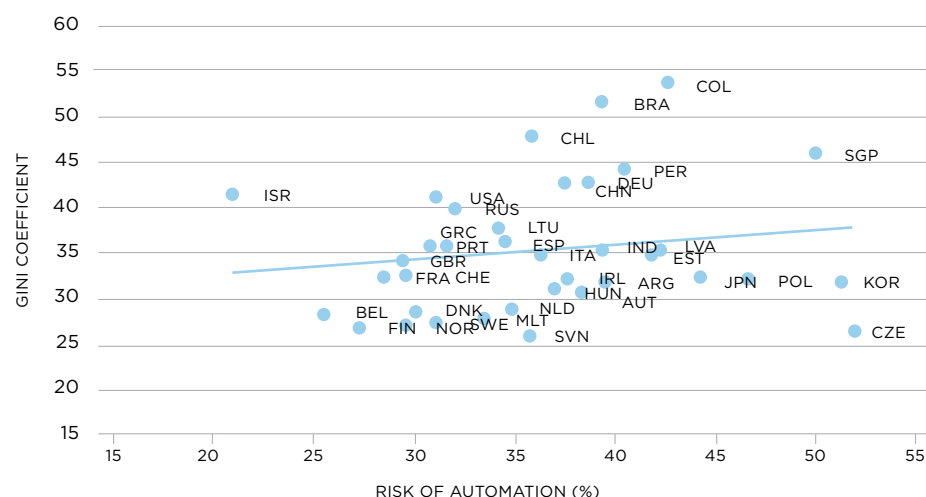
The methodology also allows us to observe the particular composition of risk for each of the countries included. For example, if we look at the five countries with the highest robot stocks per worker, all except Singapore have similar indicator structures, including low levels of structural risk, high levels of education (except Italy), and widespread use of ICTs (figure 4).

As I mentioned above, one of the

criticisms leveled at the most widely publicized studies on the risk of automation is that their methodologies prevent the use of prevent dynamic analyses that allow short-term changes in trends to be monitored. The compound index for risk of automation resolves this problem by analyzing the different time series that make it up. With regard to the Latin American countries included in the sample, over the last four years, it can be seen that the risk of automation has increased in Argentina, Brazil, Colombia, and Peru (figure 5).¹⁵

The decomposition of the risk of automation for Latin American countries shows the most critical factor to be education—the region’s levels are relatively low in comparison with the rest of the countries in the sample, and this factor explains 45.8% of total risk. The next-most-significant factor is structural risk, which accounts for 30.6% of the total risk of automation, on average (figures 6 and 7).

FIGURE 8
RISK OF AUTOMATION AND INEQUALITY, SELECTED COUNTRIES



Source: Compiled by the author.

The relationship of the compound index can also be compared with traditional economic variables. The following section contains three examples of this: the relationship with GDP per capita, income inequality, and the unemployment rate.¹⁶ First, the compound index shows a negative correlation with GDP per capita of 0.35. Although this information does not constitute an analysis of causality, the empirical evidence shows that employment in countries with higher GDP per capita is at less risk of automation (these also tend to be the countries with the highest education levels; see figure 8).

Furthermore, there is a positive (albeit weak) correlation with the Gini coefficient, one of 0.16. In other words, the countries with the highest Gini coefficients (the greatest inequality) are also those where risk of job automation is greatest (figure 9).

Meanwhile, the correlation of risk of automation with unemployment is,

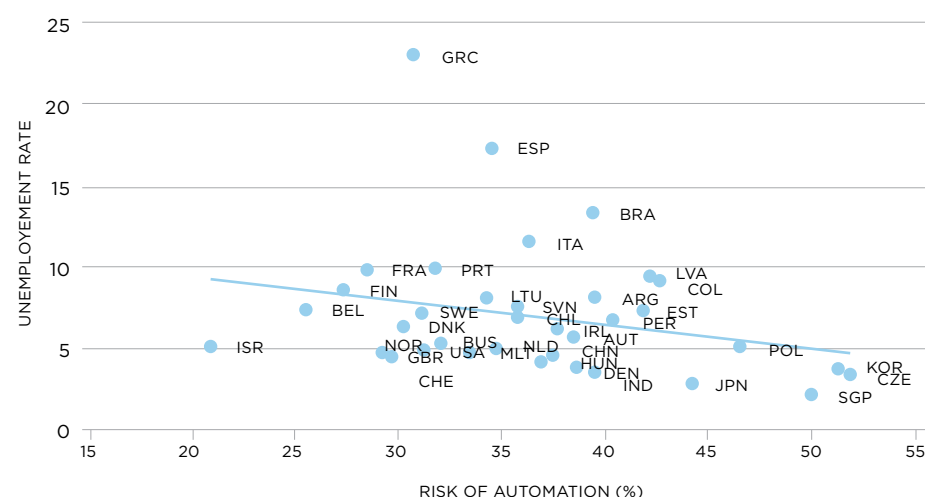
contrary to what one might expect, negative, with a value of 0.24. In other words, the countries at greatest risk of automation, often due to their high current concentrations of robots per worker, also have low unemployment rates, as is the case in Germany, Singapore, or South Korea, to name just a few examples.

This may be because the productivity increases that are generated by digitization or the automation of production counterbalance loss of employment, as some of the literature predicts.¹⁷

HARMONIZED METRICS

We need more and better measures to monitor the risk of job automation. The variety of results and methodologies that have been used up to now confirm the potential usefulness of harmonized metrics that would allow different countries and different situations

FIGURE 9
RISK OF AUTOMATION AND UNEMPLOYMENT, SELECTED COUNTRIES



Source: Compiled by the author.

to be compared and monitored over time so as to achieve a reasonable consensus around results.

This article sketches out a possible alternative: a compound index based on other robust indicators. This could also include other components that have not been taken into account in this study, such as data from the private sector on the evolution of employment demand. This is a complementary measure that does not intend to replace microdata-based studies.

The potential advantages of this compound index include its simplicity, the possibility of disaggregating results into the different relevant aspects of automation, and the fact that the calculation can be updated periodically as fresh data is released for the indicator components (this could be done on a yearly basis if annual series are used, as is the case in this article).

The results confirm the need for the Latin American countries included in

this sample to diversify their exports into sectors that are less at risk of automation, as one third of the potential risk in these countries is currently explained by their productive structures, in which high-risk sectors abound. Alternative sectors these countries could explore include the cultural industries, the orange economy, and knowledge-based services, where the risk of automation remains low.

The reverse empirical correlation found between GDP per capita and risk of automation is a call for developing countries to redouble their efforts to mitigate the negative consequences of the current incorporation of technology into their production processes, as they will be affected more by this factor than developed countries will. Likewise, the negative correlation with unemployment rates raises questions, at the very least, around the bleaker predictions that have been made regarding automation. ✓

NOTES

¹The author wishes to thank Luca Sartorio and Bianca Pacini for their assistance in organizing the databases to create this index.

²Germany, Spain, the United Kingdom, Japan, Canada, and many other countries have launched official strategies for incorporating new technologies into industrial production.

³MECON (2016) also highlights this point.

⁴Frank Levy of MIT was far harsher in his methodological criticism when he argued that Frey and Osborne's article "is a set of guesses with lots of padding to increase the appearance of scientific precision. The authors' understanding of computer technology appears to be average for economists (poor for computer scientists)." See <http://curriculumredesign.org/wp-content/uploads/Comments-on-Oxford-and-Martin-Study.pdf>

⁵Indeed, the skills required by a dressmaker in a Western country would be different to those needed in an Asian country, where more traditional or, in some cases, more sophisticated clothing is the norm.

⁶WEF (2016) attempts to correct this defect by calculating the number of jobs created and lost due to

new technologies.

⁷Coremberg and Nofal (2017) look at the need to measure intangible processes. Mokyr (2017) adds that the problem it is complicated by the fact that "the nature of work and the meaning of a job may well change radically as work becomes less and less confined in time and space".

⁸AlphaBeta (2017) contains a similar calculation for Australia.

⁹Manyika et al. (2017) calculate that the adoption of technologies such as personal computers or cell phones took between 5 and 16 years depending on the region.

¹⁰This claim does not intend to ignore the existence of a vast literature describing polarization and the hollowing out effect, whereby medium-skilled jobs give way to low- or high-skilled jobs (McIntosh, 2013). The situation is similar for white-collar workers who perform skilled jobs that nonetheless run the risk of being automated (accountants, librarians, travel agents, etc.).

¹¹An approach based on principal components analysis (PCA) would achieve this. For more, see Jollands et al. (2003).

¹²A complete list of these criteria can be found in

OECD (2008, 49).

¹³This assumption is corroborated in the study by Aboal and Zunino (2017), who observed that risk of automation decreases as education level increases.

¹⁴Sectors where the risk of automation is low or medium were left out of the calculation. This is the case for construction, financial intermediation, real estate, public administration, and education, among others.

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¹⁵The compound index for 2017 was based on data from the 2016 time series; the 2016 index was based on data from 2015; and so on.

¹⁶The data source used for all three of these factors—GDP per capita, the Gini coefficient, and the unemployment rate—is the latest information available on each country from the World Bank.

¹⁷This is true of Moretti (2012) and Gregory et al. (2016), among others.

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