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The impact of automation on employment and its social implications: evidence from Chile

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ABSTRACT
Building on the literature of labor implications from technological disruptions, this paper provides a comprehensive review of recent research carried out regarding the expected effects of automation on employment levels and performs diverse empirical approaches to estimate the effects for an emerging country. To illustrate the impact, the paper presents various empirical approaches to estimate jobs gains and losses using Chile as a case study. Results from the empirical estimates suggest that jobs lost to automation technology currently match the jobs being created, thereby resulting in a negligible overall impact on the labor force. However, the occupations being created require a higher number of highly educated workers. The findings, therefore, indicate potential social exclusion effects, as the most vulnerable groups facing a high risk of losing their jobs are low-skilled, low-income workers. To counteract these effects, active public policies need to be formulated and implemented in order to achieve the potential job gains while mitigating the potential negative effects on vulnerable and disadvantaged groups.

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1. Introduction

The purpose of this paper is to analyze the impact of the automation and digitization of production processes on the labor force and their social implications through the analysis of a case study of a developing economy. In particular, the objective is to quantify the effect on employment as a result of the introduction of digital technologies in production processes, analyzing whether automation results in a significant reduction of employment, or if on the contrary, new jobs induced by the digital revolution can counteract the losses. The study would be incomplete absent the additional analysis of worker skills and education: is the labor force disruption related to a mismatch between job skills supply and demand? The social implications are especially relevant, as new technologies may have very different impact on employment levels across different social groups and therefore require targeted policy interventions.

Several advanced economies have already launched strategies aimed to automate processes across their production chains in order to increase productivity levels and international competitiveness. That has been the case of Germany, France, United Kingdom, Italy, Korea, Japan, Australia, and Spain, among others. On the other hand, emerging countries currently lag in this process, although some nations, such as China and India, have also launched national programs. The focus of these

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programs is typically the manufacturing sector, although the impact on employment is expected to also affect the agricultural and service sectors.

Given the relevance of digitization and automation trends for the forthcoming decades, it is crucial to analyze the future of labor demand and the requirement for labor skills. If jobs are expected to be lost or restructured to meet the needs of the new economy, then public policies need to be formulated and implemented in order to maximize the expected benefits, as well as to mitigate negative consequences.

Our empirical analysis is focused on Chile, an emerging country which has achieved important economic progress over the past 30 years. Since the democratic opening of 1990, the country has followed a liberalization and competitiveness strategy, which in addition to a suitable institutional environment has contributed to a strong economic growth during that period, averaging annual GDP growth of 4.7%. Despite the recent political and social upheaval, it is undeniable that in the past decades the country has been able to improve considerably the living standards of the population. Moreover, the country currently holds a position of regional leader in terms of telecommunication development and digitization.[1]

Thus, the contribution of this paper is threefold. In the first place, we conduct a comprehensive research review of approaches estimating the impact of automation on the labor force. Secondly, by performing our empirical analysis through different methodologies applied to the same dataset, we are able to compare their results and to discuss their consistency. Finally, by conducting our empirical analysis for the case of Chile, we are concentrating our efforts in analyzing the effect of automation in an emerging economy, presumably more exposed to the employment risks, which, on the other hand, may provide evidence to anticipate the expected effects on the whole Latin American region.[2] Moreover, our analysis goes one step beyond the conventional literature, by assessing the social effects of automation, in terms of benefited and disadvantaged groups. This last point is crucial for the effective design of targeted policy interventions.

This paper is structured in five chapters: Chapter Two summarizes the state of research on the employment impact of automation, specifying the different approaches carried out by authors in the field. Chapter Three describes the theoretical framework and methodologies to be used in our analysis. Chapter Four provides the empirical results for the case of Chile; and finally, Chapter Five concludes with policy recommendations.

2. Research review

The first concerns on the impact of industrial revolutions on the labor force date back to the sixteenth century, as cited by Acemoglu and Robinson (2012)[3] and Eisenstein (1979).[4] Since the twentieth century, the economic literature has gradually incorporated the study of the impact of technological advances on employment (Keynes 1933; Nef 1957; Braverman 1974). However, it was not until the arrival of the digital revolution that this labor force impact has become a major concern for researchers and policymakers alike.

Research has been guided by a theoretical disaggregation of activities being conducted as part of any occupation. As pointed out by Autor, Levy, and Murnane (2003), jobs can be classified along two dimensions (routine-no routine and cognitive-non cognitive). Beyond the expected effect of routine non-cognitive jobs being replaced by technology, the authors stipulated that technological advances are potentially capable of automating some non-routine and cognitive tasks, such as document writing and vehicle driving. Among the several approaches that have been developed so far to quantitatively estimate the impact of automation on employment, we can highlight two specific tendencies: (1) assess the type of occupations and jobs likely to disappear as they are replaced by technology (labeled as occupational analysis), and (2) identify the tasks carried out within each occupation that will be automated (defined as task analysis).[5] This distinction is relevant, as most occupations include some potentially automatable tasks, but not all. Thus, some occupations with a significant portion of automatable tasks may disappear, while others may be significantly restructured as a result of the digital revolution.

Occupational analysis was launched by Frey and Osborne (2017), who attempted to quantify the occupations under risk of becoming automatable.[6] Their empirical analysis was carried out using the O*NET database from the United States Department of Labor, which provides a complete description of tasks, knowledge, training, skills, and education required for a list of occupations. By polling a group of experts regarding the subjective probability of automating a certain occupation, the authors considered that if the average probability value was over 0.70, then the occupation will be replaced by technology 'within the next one or two decades'. On this basis, they concluded that 47% of the US jobs are facing a high risk of becoming automatable within a period of twenty years. The occupations that were mostly at risk were found to be in the service sector, more specifically in office duties, as well as jobs demanding low educational levels. However, their study faced some limitations, such as ignoring factors such as the cost of capital-labor substitution and unemployment levels, as incorporated in the original framework developed by Autor, Levy, and Murnane (2003). This approach is also limited as the subjective probabilities assigned to each occupation may be biasing the analysis, for instance, by overestimating the real effect of technology (Autor 2015).

In recent years, other researchers followed the traditional occupational analysis to generate other estimates. That was the case of Pajarinen and Rouvinen (2014) who analyzed the labor market in Finland. For a total of 410 occupations considered, they concluded that 35.7% of workers faced high risk due to digitization. In turn, Deloitte (2015) applied a similar methodology to the United Kingdom economy, summarizing for that country a list of employments lost or gained by economic sector. Similarly, for Latin America, Micco and Soler (2018) applied the methodology of Frey and Osborne (2017) to estimate the percentage of occupations facing high risk due to automation, with percentages ranging from 62% (Dominican Republic) to 75% (El Salvador and Guatemala). In any case, according to Bosch, Pages, and Ripani (2018), those figures are possibly overestimating the negative impact of automation on jobs, because the cost of labor is notoriously lower in Latin America than in most advanced countries, making unclear the cost-effectiveness of replacing jobs with technology. This concern was reinforced by Katz (2018) who found the economic return to technological investment to be lower than current labor costs in countries such as Mexico. In addition, the annual report from the Broadband Regional Observatory from the UN Economic Commission for Latin America and the Caribbean (ECLAC 2017) applied Frey and Osborne (2017) probabilities to estimate the percentage of jobs at risk of becoming automatable for a sample of countries of Latin America, with percentages going from 56% for Chile to 68% for El Salvador. Also, Aboal and Zunino (2017) performed estimations for Argentina and Uruguay using data from household surveys, estimating the percentage of jobs under risk to be 64.1% and 66.4%, respectively.

Other studies criticized the methodology developed by Frey and Osborne (2017) and proposed alternative approaches. That is the case of an analysis performed by ITIF[7] in 2017 that assigned for 840 occupations from the United States *Bureau of Labor Statistics* a risk-score between 1 and 5 based on the education level, the training required, and the previous experience needed for those jobs. From this score, they were able to classify each occupation and estimate as a result that only 8% of jobs are facing high risk of automation, a much lower figure than that estimated by Frey and Osborne (2017).

In opposition to the previous theoretical framework, other authors have argued that automation affects tasks rather than occupations (Autor 2014, 2015), and as a result, if several jobs require tasks that are not automatable, then the number of jobs facing high risk should be considerably lower. In order to test this approach, Arntz, Gregory, and Zierahn (2016) used the database provided by the Program for the International Assessment of Adult Competencies (PIAAC), which includes micro-indicators such as skills, tasks, and training for each occupation. With such a dataset, they defined a probability of automation for each task carried out within the different occupations. If an occupation includes a large portion of automatable tasks, then it can be expected to be replaced by technology.

By establishing 70% of automatable tasks as a threshold to consider if a job was facing high risk, they concluded that in the US only 9% of jobs are under danger of being replaced. By expanding their analysis to other OECD countries, they concluded that occupations facing higher risks are those which require less education, and those carried out by low-income workers. This methodology has the advantage that allows for cross country heterogeneities, as occupations may differ in their required tasks from one country to another.

In turn, a study developed by the McKinsey Global Institute (2017a) analyzed each occupation in terms of their required activities (a functional equivalent to task) for a sample of six countries (Mexico, United States, Japan, India, Germany, China). By assigning a score reflecting the probability of automation of each activity, they developed a matrix structured around occupations and tasks and the assigned automation probability. They found that 62% of the occupations presented at least 30% of automatable tasks, while only 5% of occupations included 100% of automatable tasks. Moreover, this study provided an important contribution as they differentiated the impact of automation as driven from three factors: technological progress, capital-labor substitution, and innovation diffusion. They concluded that, in the aggregate, 26% of occupations presented 70% or more of its activities potentially automatable. While Mexico was the only Latin American country assessed in their sample, the authors also extrapolated estimates for Argentina, Brazil, Colombia, and Perú.

PwC (2018) analyzed a sample of 27 OECD countries plus Singapore and Russia, following the task approach developed by Arntz, Gregory, and Zierahn (2016). In the same vein as Santos, Monroy, and Moreno (2015) and McKinsey (2017a), they did not consider an immediate impact, relying instead in a process of three technological waves. By using the PIAAC database, but refining the algorithm used by Arntz, Gregory, and Zierahn (2016), they concluded that the percentage of occupations at risk of automation is positively related to the size of the manufacturing sector. Moreover, the risk of automation was substantially lower in those sectors employing high-educated workers. For Chile, they estimated that over the three technological waves (by mid-2030s), the jobs under risk were 27% of current total jobs.

In a similar fashion, Nedeloska and Quintini (2018) carried out a task-analysis following the framework proposed by Arntz, Gregory, and Zierahn (2016), although they used benchmark data from Canada rather than that of the United States since they considered it to be more reliable. The analysis was carried out by applying a logit regression to determine automation probabilities for 70 occupations. These coefficients were applied to other countries to obtain the predicted values. They added analyses on the threshold required to consider an occupation to be automatable, considering not only the 70% threshold suggested by Arntz, Gregory, and Zierahn (2016), but also a 50% in order to contrast results. For Chile, their results indicated that approximately 22% of jobs were under risk (for the 70% threshold) with an additional 31% under risk if the threshold is lowered to 50%.

Complementing the work on job elimination, another line of research has focused on job creation resulting from the digital revolution. As stated by Aghion and Howitt (1994), technological progress triggers a capitalization effect which can counteract, at least partially, some of the job losses due to automation. As the adoption of new technologies increases, there is a positive economic effect whereby the returns to capital increase, contributing in turn to reduce unemployment. Beyond capitalization, there are other potential drivers of job creation. Automation may promote a restructuring of the tasks carried out within occupations. According to Spitz-Omer (2016), Autor and Dorn (2013) and Acemoglu and Restrepo (2015), workers may redefine their tasks, shifting them to those expected to be more complementary with technology. According to this view, jobs may be redefined rather than eliminated. In this context, improving skills and training is key to avoid job losses.

In a different perspective, as technological adoption raises the competitiveness of firms, economic activity is expected to increase, which will in turn demand more workforce. Similarly, cost reductions induced by technology adoption may contribute to reduce prices, which should increase sales, and consequently, the demand for workers (Goos, Manning, and Salomons 2014; Graetz and Michaels 2015; Gregory, Salomons, and Zierahn 2015). Productivity increases due to new technological developments may also raise wages, therefore inducing increases in consumption levels. This effect was tested by Wolter et al. (2015) and by McKinsey (2017b), both relying on input-output matrices.

In addition, a portion of the jobs lost could be compensated by employment growth in the ICT sector, particularly those required to develop technologies as technology demand increases (Crandall, Lehr, and Litan 2007; Atkinson, Castro, and Ezell 2009; Katz et al. 2010; Katz 2012; Wolter et al. 2015).

The overall impact of automation on employment levels, after the positive and negative effects are considered is inconclusive, with research results pointing in alternative directions. For a worldwide sample, both Gartner (2017) and McKinsey (2017b) found an overall positive net effect in terms of job creation. This positive result was also verified by Rüßmann et al. (2015) in the case of Germany. In contrast, some studies indicate job losses as larger than those gained: WEF (2016) in a sample of 15 countries, Forrester (2017) in the United States economy, and Wolter et al. (2015) in the manufacturer and agricultural sectors in Germany.

Based on the findings of previous studies, we can now formulate the questions to be tackled in the case of Chile. Is Chile presenting a higher percent of jobs at risk than advanced economies? Is the percentage of jobs facing high risk of elimination in Chile higher or equal than those being created? In addition, we will test the impact on workforce educational categories, expecting low educated social groups to be facing larger risks. We will try to determine if other disadvantaged groups, such as low-income segments, native populations and foreign workers are more exposed to these risks. Finally, we will also test if there are differences of potential employment impact by gender.

3. Methodology for the empirical analysis

In light of the research literature, the theoretical framework to be taken as a reference for the empirical analysis will consist of two of the existing approaches estimating job losses and three alternative procedures for measuring job creation.

3.1. Occupational analysis

In the case of job losses, we will apply the methodology of Frey and Osborne (2017) to Chile. As explained in Chapter 2, this approach consists in identifying those occupations which are based on repetitive and routine tasks, considered to be under risk of being replaced by robotics platforms and algorithms. The probability of replacement of an occupation is based on whether the technology can compensate the social intelligence, creativity, perception and manipulation performed by a human. To assign a probability, Frey and Osborne relied on the O*NET database from the United States, which provides a description of the tasks, capabilities, skills and education needed for each of the 903 occupations. After grouping those occupations in 702 (for consistency with the employment statistics from the *Bureau of Labor Statistics*), the authors assigned a subjective automation probability to each occupation depending on the characteristics required and on the variety of tasks involved. They followed the Delphi methodology, by which, a binary probability is assigned to 70 occupations by a group of researchers of the Oxford University (1 if can be automatized, 0 in the other case).[8] These subjective values were then expanded to the remaining 632 occupations, through an algorithm that computes the automation probability based on seven descriptive components in each occupation of the original dataset.

To apply this methodology to the Chilean case, we rely on the CASEN[9] surveys from 2013 to 2017 performed by the Ministry of Social Development. The survey is carried out every two years and contains information of more than 200,000 individuals considered to be representative of the whole Chilean population. Unemployed individuals, as well as those linked to military activities, are excluded from the sample.

Before applying Frey and Osborne (2017) probabilities to our dataset, it was first necessary to convert their estimates from the *Standard Occupation Classification* (SOC) used in the study to the *International Standard Classification of Occupations* version 88 (ISCO-88),[10] as this is the taxonomy considered by the CASEN database.[11] The probability indicator was computed following a weighted average by the expansion factor of the probabilities of each occupation in the survey, following this formula:

$$\text{Automatization Probability} = \frac{\sum_{1}^{n} \text{Registration Probability}_i * \text{Expansion Factor}_i}{\text{Total occupied workforce}}$$

The analysis was carried out for 2013, 2015, and 2017 editions of the survey.

3.2. Task analysis

In an alternative approach, we conducted a task analysis, relying on the PIAAC survey carried out in Chile in 2015, containing 5212 observations. Each observation includes answers to 100 questions, grouped across three components: (1) Direct evaluation (literacy, lecture, problem resolution); (2) Use of skills (use of cognitive skills, personal and social interaction, physical aptitudes, learning capabilities); and (3) Baseline questionnaire (demographic characteristics, education and training, social and linguistic origin, employment and income, use of ICTs). More detail on the main components of the questionnaire is provided in Appendix (Table A1).

The task analysis was performed following the methodology conducted by Nedeloska and Quintini (2018), which is similar to Arntz, Gregory, and Zierahn (2016). As mentioned in the research literature review, by using the answers reported by Canadian workers for each of the 10 questions (details in Appendix-Table A2), Nedeloska and Quintini (2018) performed a logistic regression, which predicts automation probabilities as a result of the required use of skills:

$$\begin{aligned} \text{Individual value} = {} & 0.363 + 0.105*\text{dexterity} + 0.057*\text{simple problems} - 0.069 \\ & *\text{complex problems} - 0.069*\text{teaching} - 0.199*\text{advise} - 0.308 \\ & *\text{plan others} + 0.214*\text{communication} + 0.046*\text{negotiate} - 0.235 \\ & *\text{influence} + 0.160*\text{sell} \end{aligned}$$

Were *dexterity* refers to physical aptitudes, *simple problems* and *complex problems* refer respectively to the resolution of technical problems exhibiting a difficulty level, *teaching* refers to employee training, *plan others* refer to planning, *influence* refers to influence on coworkers, while *advise*, *negotiate*, *communication* and *sale* refer to activities related to those concepts. All the coefficients from the logistic regression reported above where found by the authors to be statistically significant.

We proceeded to use those parameters to estimate automation probabilities for the case of Chile.[12] Given the nature of logistical regressions, individual probabilities were computed as follows:

$$\text{Probability} = \frac{\exp^{(\text{Individual value})}}{1 + \exp^{(\text{Individual value})}}$$

3.3. Job-creation analysis

Finally, to estimate the jobs created as a result of automation, we implemented three different approaches. First, we analyzed the evolution of the Chilean workforce from 2013 to 2017 according to the CASEN dataset, which includes information on employment levels on those economic sectors which are prone to increase employment due to technology adoption, according to the WEF (2016). We estimated the evolution of employment in the sectors expected to be positively affected by automation and performed a comparison with the overall evolution of jobs in the economy, estimating as a result jobs created that can be attributed to automation. Secondly, we considered the impact of automation on employment creation determined by the WEF (2,021,000 employments created between 2015 and 2020 in 15 countries[13]), and by assuming an equivalent effect for Chile, we extrapolated a figure of jobs created within the country according to its weight in the original WEF's sample. Lastly, we categorized the occupations in the CASEN survey according to their automation risks: low, medium, and high, by using Frey and Osborne (2017) probabilities. Following this, we analyzed the evolution of the low risk jobs from 2013 to 2017. By extracting from that figure those jobs created as a result of the overall economic cycle, we were able to estimate the employment creation associated to automation.

4. Results

According to the CASEN survey, there were 7.8 million workers in Chile in 2017. The largest economic sector in terms of the labor force is retail and wholesale commerce, with over 20% of the whole workforce. After commerce, largest sectors in terms of employment are manufacturing (9.4%), construction (9%) and agricultural activities (8.3%). Unemployment rate has remained stable between 7% and 8% in the time-period covered by the reviewed data (2013–2017). Table 1 summarizes the local employment distribution across the main 17 economic sectors.

In terms of production and exports, the other economic activity that stands is mining (mainly due to the country large copper reserves), although it only occupies 1.8% of the workforce. With this background, we proceed next to present the main results from our empirical analysis.

4.1. Results for the occupational analysis

The occupational analysis provides some interesting results (see Table 2). In the first place, according to data from 2017, 57.81% of jobs are facing a high automation probability within the next two decades (according to the baseline temporal estimate of Frey and Osborne 2017).

This estimation is consistent with other findings, such as ECLAC (2017), that estimated 56% of jobs at risk for Chile in 2015. An interesting finding is that the percentage of jobs at risk due to automation seems to be declining when comparing the data from 2013, 2015, and 2017. This declining trend is statistically significant (at a 5% level for 2013–2015 and at a 1% level for 2015–2017). In addition, when comparing the findings from Chile to the studies carried out in other countries, the results

Table 1. Distribution of the employed population economic activity (2017).

Economic sector	Percentage over total employment
Agriculture, livestock, hunting and forestry	8.27
Fishing	0.94
Mining and quarrying	1.79
Manufacturing industries	9.42
Electricity, gas and water supply	0.74
Construction	8.97
Commerce (wholesale and retail)	20.10
Hotels and restaurants	5.08
Transportation, storage and communications	7.25
Financial intermediation	1.60
Real estate and business activities	7.58
Public administration and defense	5.01
Education	7.64
Social services and health	5.71
Other community service activities	3.81
Private households with domestic service	6.10
Extraterritorial organizations and bodies	0.01

Source: CASEN survey for year 2017.

Table 2. Chile: Percentage of jobs facing high risk of automation.

	2013	2015	2017
Observations (considering expanding factor)	7,237,068	7,504,430	7,830,935
Probability	58.91%	58.53%	57.81%
Standard Deviation	0.285	0.293	0.292
T-statistic for difference in probabilities with respect to previous period		−2.235**	−4.210***

Note: ***p* < 5%; ****p* < 1%. *p*-values calculated by considering a sample of 200.000 observations as those included in the survey. Source: Prepared by the authors.

seem to be consistent with the fact that emerging economies are facing a higher risk of job losses than advanced ones.

4.2. Results for the task analysis

Results for the task analysis indicate an overall automation probability of 51.76% (weighted by the expansion factor), with a standard deviation of 0.204 and minimum (maximum) value of 4.51% (90.12%). Figure 1 reports the corresponding density function.

As the quantification of occupations under risk depends on the reference threshold used for the percentage of automatable tasks, we conducted a sensitivity analysis by varying that threshold, as reported in Table 3.

Results reported in Table 3 are close to the findings of Nedeloska and Quintini (2018). In the case of Chile, our results indicate that when considering the 50% threshold of tasks yielding a high automation likelihood, the percentage of occupations at risk is 55.94%, while if we consider the 70% reference, the percentage is reduced to 22.51%. Based on these results, we believe that jobs facing probabilities above 50% will be somehow affected by automation, and among those, we can distinguish between two levels of labor disruption. The 70% threshold can be interpreted as the reference for high automation probability, from which we can infer that those jobs will be lost (22.51% of jobs). In contrast, for jobs with probabilities ranging from 50%-70%, we can

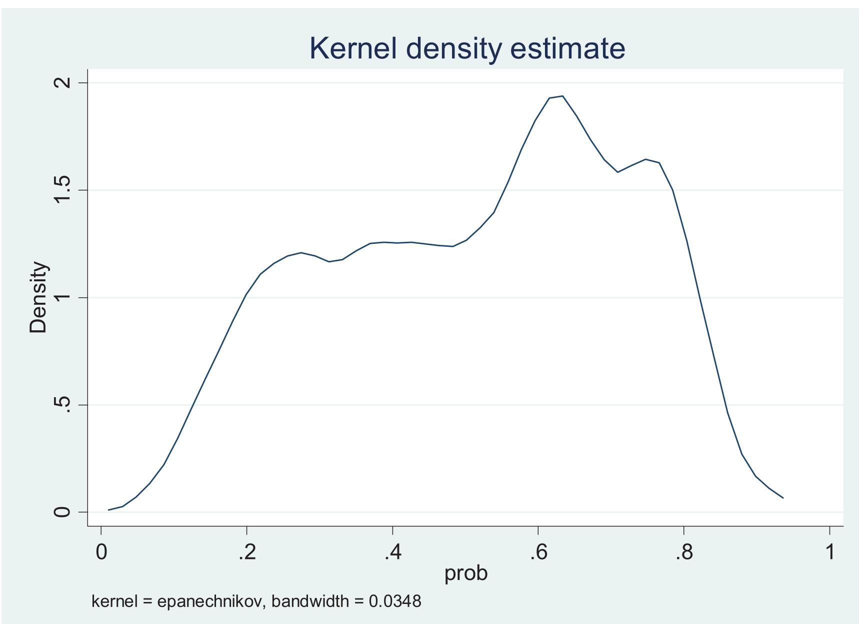

Figure 1. Automation probability in Chile (2015) – density function. Source: Prepared by the authors.

Table 3. Percentage of automatable occupations in Chile (2015).

	Percentage of occupations
50	55.94
55	49.54
60	41.95
65	30.45
70	22.51
75	14.98
80	5.22
Mean	51.75

expect a restructuring process due to automation (33.43% of occupations). The percentage of affected jobs in accordance to the task analysis seems to be consistent with that of the occupational analysis, expected to consider not only disappearing jobs, but also potential job restructuring as a result of digitization (see comparison in Figure 2).

When comparing our results for Chile with the estimates calculated by Nedeloska and Quintini (2018) for other OECD countries for 2012, they seem to be consistent with our hypotheses that the automation impact on employment should be larger in emerging economies (Figure 3). According to the referred authors, the variance by country is related to sectoral composition (30%) and by the task distribution within each economic sector (70%). In addition, as pointed out by Arntz, Gregory, and Zierahn (2016), task organization within each occupation may vary considerably across countries.

The estimation of disappearing annual jobs considers that the effect of automation will grow over time driven partly by the commercial availability of technology, the rate of innovation in production, and the economics of capital-labor substitution. Therefore, the initial impact in 2018 has not affected more than 1% of the workforce, but it will reach 10.58% by 2030. Considering the 2018 workforce level of 8,747,109, we estimate that 35,199 jobs (0.40%) have already disappeared as a result of automation, while 52,273 (0.60%) have been significantly restructured. However, by 2030, we forecast 426,000 jobs to have disappeared while 633,000 will be significantly restructured.

4.3. Social implications derived from the occupational and task analysis

In order to further the analysis regarding the jobs facing the risk of automation, we computed the probabilities of the occupational analysis by allowing heterogeneities from population groups. The results reported in Table 4 provide relevant insights to characterize those social groups facing larger risk and the potential implications.

First, as expected, automation probability seems to decrease the higher the educational level required for the job. Conversely, those jobs being carried out by workers without any basic education level are the most vulnerable (72.48%), whereas, on the other hand, only 38.22% of jobs performed by highly educated professionals are considered at risk.

More surprising is the result that while overall automation risk seems to be decreasing from 58.91% in 2013 to 57.81% in 2017 (as reported in Table 2), the percentage of workers facing the

Occupational Analysis

2013	58.91%
2015	58.53%
2017	57.81%

Task Analysis

Restructured jobs	Eliminated jobs
33.43%	22.51%

Figure 2. Comparison of results from task and occupational analysis. Source: Prepared by the authors.

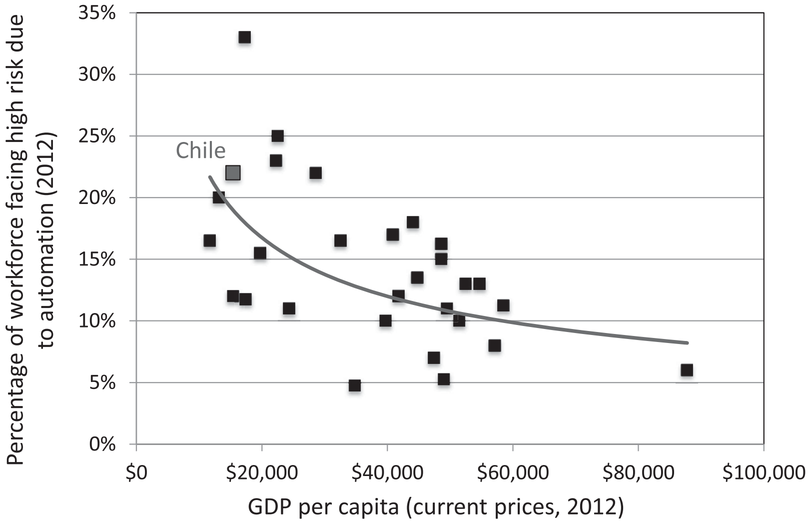

Figure 3. GDP per capita and percentage of jobs facing high risk in OECD countries. Source: IMF, Nedeloska and Quintini (2018), authors analysis.

risk for different educational levels remains fairly stable. However, the percentage increases for the more educated group. A deeper analysis of the workforce distribution across the different educational levels provides an explanation for this surprising result. The percentage of workers with higher education in the labor force increased during the period considered (from 28.4% in 2013 to 32.9% in 2017). As a result, the increase of highly educated workers surpassed the rise in automation risk for those occupations. Despite this result, this evidence points to a key policy recommendation: to reduce job vulnerability, it seems to be essential to emphasize skills development of the labor force.

The analysis of affected workers by national origin points out a directional change taking place in recent years. In 2013, Chilean nationals were on average more affected than foreign workers; however, in the following years that pattern was inverted. In 2017 among the 468,000 foreign workers, 60.23% were facing high risks due to automation. According to data from the Immigration Department, 23.8% of foreign workers in Chile are of Peruvian origin, 13% Colombian, and 11% Bolivian.

Table 4. Percentage of jobs facing high risk of automation in Chile – heterogeneities by groups.

Group	Characteristic	2013	2015	2017
By education level	Without basic education	72.37	70.83	72.48
	Basic education	68.81	68.24	68.87
	Medium education	65.94	66.03	65.38
	High education	36.34	38.01	38.22
By nationality	Chilean	58.95	58.49	57.65
	Foreign	57.01	59.69	60.23
By gender	Male	60.26	60.01	59.51
	Female	57.04	56.58	55.60
By origin	Native		62.70	61.27
	No native		58.16	57.48
By income level	1st quintile		69.09	69.81
	2nd quintile		66.72	67.39
	3rd quintile		63.99	63.59
	4th quintile		59.06	58.29
	5th quintile		40.69	38.42

Source: Prepared by the authors.

In addition, the analysis by origin points out that workers from indigenous population are facing higher risk of job automation than the rest of Chileans. Particularly, while the figures of Chileans belonging to groups that have immigrated from other geographies are close to that of the national average, the risk for indigenous workers scales up to 61.27% (2017). This figure points to the potential social exclusion effect of automation for this population segment, aggravated by the fact that already 23.4% of indigenous workers are under poverty, and the unemployment for this group is 2–3% higher than for the rest of workers, as well as the illiterate population (5% in contrast to 3.6% for non-native).

In turn, the analysis performed by income level indicates that workers with the lower incomes are those facing the bigger risks. For the first quintile segment, nearly 70% of workers seem to be facing high risks of losing their job due to automation. This will contribute to increase unemployment and poverty for those groups at the low end of the income distribution and accelerate the polarization of the socioeconomic structure.

The data provided in Table 4 indicates that male workers are facing larger risks of job automation than females. This is consistent with some studies conducted in other Latin American countries such as Argentina and Uruguay (Aboal and Zunino 2017), as well as the findings from PwC (2018). However, it is worth pointing out that other research studies estimate the risks to be higher for females, due to the different tasks carried out by this gender (Brussevich et al. 2018). A possible explanation for the case of Chile may be related to the fact that female workers have on average higher educational level than their male counterparts.

The analysis by gender group was also performed following the task analysis. Figure 4 reports the corresponding density function by a sample of male and female workers.

The sensitivity analysis of the percentage of occupations under risk by gender suggest that male workers present a more uniform distribution than females. Even if the mean seems to be slightly larger for the case of females (52.32% in contrast to 51.29% of males), this difference does not seem to be statistically significant. In addition, when considering thresholds over 60% in terms of probabilities of automatable tasks, male workers seem to be more affected than female workers. In contrast, if we consider lower thresholds (under 60%), female workers seem to be facing the larger risks. All in all, results from the task analysis are inconclusive in terms of which gender is more affected.

4.4. Estimate results for the job creation analysis

To estimate employment creation associated to automation, we started by considering the research conducted by the WEF (2016) that estimates that 2,021,000 jobs would be created for the period

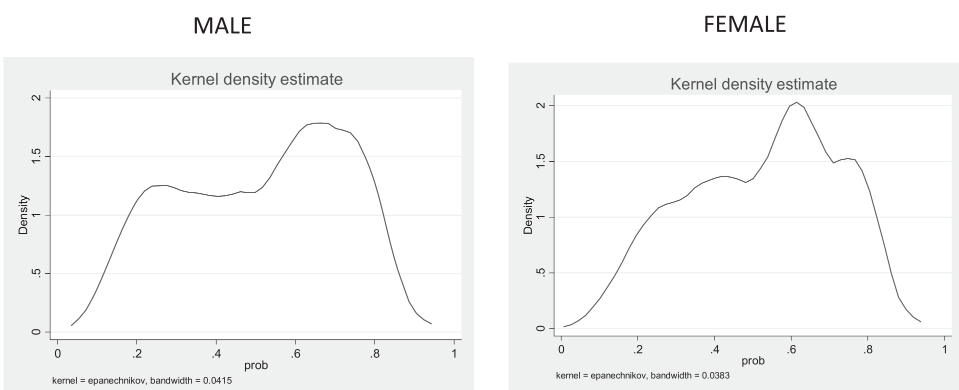

Figure 4. Automation probability in Chile by gender (2015) – density function. Source: Prepared by the authors.

2015–2020 due to automation in big enterprises from Australia, China, India, Japan, France, Germany, Italy, Turkey, United Kingdom, South Africa, Brazil, Mexico, United States, and the Gulf countries. According to this study, job creation is expected to occur primarily in the following occupations: (1) Financial Business and Operations, (2) Business Administration and Management, (3) Computing and Mathematics, (4) Architecture and Engineering, (5) Commerce, and (6) Education. The evolution of the jobs in these occupations was analyzed for the 2013–2017 period in Chile relying on the CASEN survey: they yielded an increase of 187,898 jobs during that period.[14] However, not all of these jobs can be attributed to automation, since the overall employment in the economy has grown as well. Therefore, considering that overall employment grew during that period at a compound annual growth rate of 1.57%, we can estimate that among the jobs created in the sectors positively affected by automation, 60,070 may have increased as a result of the overall growth of the economy. In order to estimate job creation associated to automation, we should discount those jobs created as a result of the positive economic cycle. The results reported in Table 5 suggest that 31,957 annual jobs were created due to automation.

A second approach to estimate job creation consists in extrapolating the WEF (2016) estimates to Chile. Table 6 summarizes the extrapolation carried out for the case of Chile.

As Chile represents 0.48% of the GDP of the countries analyzed by the WEF (2016), by considering an equivalent impact 9616 jobs should have been created in Chile over that 5-year period due to automation (1923 annual jobs). However, the WEF study only considered big enterprises. Therefore, by assuming a homogeneous impact regardless of company size, plus the fact that only 23.5% of Chilean workers are employed by big enterprises (with more than 250 employees), and that the companies considered in the original study only match with 25% of the Chilean big enterprises, we estimated the annual positive result on job creation to be 32,734.

Finally, and following the criteria previously defined by Frey and Osborne (2017), Chilean jobs were classified into four groups according to the risk they face of being automated (Table 7).

Table 5. Employment evolution 2013–2017 in Chile – recent trends in specific occupations.

Employments	Increase 2013–2017
Employments in sectors positively affected by automation	187,898
Employments in sectors positively affected by automation (estimate based on the overall increase rate of the rest of the economy)	60,070
Employment creation attributable to automation	127,828
Annual impact attributable to automation	31,957
Annual job creation (in percentage of 2017 total workforce)	0.41%

Source: Prepared by the authors.

Table 6. Employment evolution 2013–2017 in Chile – extrapolation of WEF estimates.

Item	Concept	Value	Source
A	GDP of countries considered in the WEF sample (2016)	58,235,520 $ million	World Bank
B	GDP of Chile	277,076 $ million	World Bank
C	GDP of Chile (percentage of WEF's sample)	0.48%	(Item B)/(Item C)
D	Positive employment impact in countries considered by the WEF	2,021,000	WEF (2016)
E	Impact on job creations in Chile (according to the weight of Chilean GDP in WEF's sample)	9616	(Item C)*(Item D)
F	Annual impact on job creations in Chile in big enterprises	1923	(Item E)/5 years
G	Employees in big enterprises in Chile	23.50%	CASEN
H	Big enterprises included in the analysis	25.00%	Estimate
Annual impact on job creation in Chile		32,734	(Item F)/(Item G)/(Item H)
Annual job creation (in percentage of 2017 total workforce)		0.42%	

Note: Job creation estimated for Chile in Item F can only be attributed to a specific sample of big enterprises. To have an appropriate estimate for the country, the value reported in Item H extrapolates Item F to the overall economy.
Source: Prepared by the authors.

The low risk group is composed by those jobs with a 33.33% or lower probability of becoming automated. Those low risk jobs have grown at a compound annual growth rate of 3.85% over the 2013–2017 period, a much larger figure than the country average. Thus, the employment growth in this group can be in part attributable to the overall employment growth of the economy (1.99%, yearly), while the remaining increases can be interpreted as the direct positive effect of automation (1.86%, per annum). Therefore, a 48.27% of the employments created in low risk occupations during 2013–2017 can be attributed to automation (128,419 jobs). This figure equals to a positive direct effect of 32,205 annual jobs.

In sum, the estimates of job creation due to automation provide consistent results following the three different methodologies carried out, all indicating that the digital revolution will create approximately 32,000 jobs per year in Chile. However, and despite the consistent results from the three approaches followed, we understand that these results should be taken with caution in terms of causal links and further research may be necessary in order to confirm the nature of this effects.

4. Conclusions and policy recommendations

As the analysis concludes that approximately 35,000 jobs were lost in Chile in 2018, and that 32,000 created jobs can be associated with automation, the net effect between job creation and destruction was likely to be negligible under the current circumstances. However, the fact that the overall effect seems to be negligible now does not mean that jobs are not being restructured. As indicated in the task analysis we must consider that 52,000 jobs have been restructured as a result of the digital revolution. On the other hand, jobs created demand accelerated higher education while jobs lost are primarily in the lower income groups. This situation is likely to result in employment polarization and social exclusion, as jobs lost are those linked to the most vulnerable social groups, such as the indigenous population, foreign workers, and low-income segments.

Going forward, job automation losses are expected to exceed the amount of employment created by the digital revolution. Under this situation, in addition to job polarization a future scenario would indicate growing unemployment to be added to the ongoing social disruption.[15]

The results of the study indicate the urgent imperative to improve education and training among the Chilean workforce. From a public policy perspective, this suggests the need to assess the potential impact of automation and estimate the nature of future jobs required. In light of the evidence, training and educational programs need to be developed in advance to prepare the country workforce for future labor needs.

To estimate the nature of the jobs to be demanded in the future, there are some methodological tools that can be carried out, such as forecasts based on quantitative models, surveys implemented among employers to understand future demand, development of sectoral observatories, plus the performance of Delphi exercises and focus groups. This kind of activities should be specifically focused on the training, skills and educational programs that are expected to be demanded. International best practices should be considered, such as the activities conducted by the Office of Literacy and Essential Skills from the Canadian Government, the Labor Market Monitor from Germany, and France's Industry of the Future.

Table 7. Evolution of Chilean employment under the basis of the automation risk determined by Frey and Osborne (2017).

Indicator	Low risk	Medium risk	High risk	Non determined	Total
Employment 2013	1,630,669	1,848,841	3,757,558	42,054	7,279,122
Employment 2017	1,896,712	2,104,052	3,830,194	45,694	7,876,652
Variation 2013–2017	266,043	255,211	72,636	3640	597,530
CAGR	3.85%	3.29%	0.48%	2.10%	1.99%

Source: Prepared by the authors with data provided by the CASEN surveys of 2013 and 2017.

Once the profile of future workers to be demanded is estimated, public policies need to be put in place to promote the development of programs aiming for worker retraining, while encouraging on-the-job training activities. Also, it will be essential to revise the suitability of current formal educational programs and implement the corresponding changes. The implementation of the concept of continuous education is key in that respect.

Other relevant public policies may include the introduction of subsidies for labor transition process, formalization of informal jobs, as well as the implementation of specific initiatives to mitigate potential social disruption effects (such as unemployment insurance, relocation services, and personal counseling services). Economic incentives to promote continuous learning by private enterprises are also desirable, particularly in the case of Small and Medium Enterprises. The public sector has a key role to play by coordinating these kinds of activities with the private sector and social organizations.

From an institutional perspective, the coordination among different public agencies and ministerial offices involved is critical. Barriers affecting institutional coordination among ministries of education, labor, and social development need to be removed or mitigated, and current responsibilities may need to be expanded or redesigned in order to formulate employment services and formation systems that contribute to the success of the public programs. These recommendations, while illustrated in the case study of the Chilean economy, are applicable to other emerging countries.

Notes

1. See Katz and Callorda (2018).
2. The choice of Chile for the case study is also justified that, as a member of the OECD, the country disposes of an extensive database of labor statistics, including the much-needed Survey for the Program for the International Assessment of Adult Competencies (PIAAC).
3. They refer to the prohibition imposed by Queen Elizabeth I to spread the mechanical loom created by William Lee in 1589, given the concern on potential unemployment.
4. She describes the reaction of the Paris's guild of copyists when Faust arrives to the city offering bibles printed with Gutemberg's technology.
5. It is worth to state that distinguishing between these two approaches can be debatable, since occupational impacts are usually constructed as aggregate measures based on the impact of automation technologies on tasks, of which occupations are composed. We thank an anonymous referee for raising up this point.
6. The authors define 'automatable occupations' as those that can be replaced by technologies that combine Machine Learning and robotic mobile systems. However, there is not a consensus on the definition and scope of this concept across the literature of occupational impact analysis.
7. https://itif.org/publications/2017/08/07/unfortunately-technology-will-not-eliminate-many-jobs.
8. The question defined by Delphi is: 'Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state-of-the-art computer-controlled equipment?'
9. Acronym for *Encuesta de Caracterización Socioeconómica Nacional*
10. In a first step, the taxonomy ISCO-88 was converted into ISCO-08 according to the criteria defined by the International Labor Organization. Secondly, we allocated each ISCO-08 occupation to into a SOC category, by relying on the conversion table provided by the U.S. Bureau of Labor Statistics (complete details on the procedure are included in Appendix A.1).
11. The database considers the 4-digit ISCO-88 classification, which can be considered an acceptable disaggregation level for the purpose of this study.
12. The desirable procedure would have been to run a logistic regression with Chilean data. However, we decided against doing so, given that PIAAC data from Chile does not include many records of occupations.
13. Sample composed by Australia, China, India, Japan, France, Germany, Italy, Turkey, United Kingdom, South Africa, Brazil, Mexico, United States, and the Gulf nations.
14. The complete detail of employment evolution across all the occupations positively affected by automation is available upon request.
15. We intend to address this issue in a forthcoming research.
16. http://www.ilo.org/public/spanish/bureau/stat/isco/index.htm.
17. http://www.bls.gov/soc/ISCO_SOC_Crosswalk.xls.

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Appendix 1. Methodology to convert Frey and Osborne (2017) probabilities to the data available in the CASEN survey.

Frey and Osborne (2017) probabilities are defined for each of the 702 occupations defined in the *Standard Occupation Classification* (SOC) of the US census bureau. As the CASEN survey is based under the ISCO-88 classification, a conversion was needed for each case in order to be able to use the referred probabilities.

Firstly, for each occupation defined in the ISCO-88 classification we proceeded to convert them to ISCO-08 according to the criteria defined by the International Labor Organization.[16] There may be a situation in which a single occupation under ISCO-88 can be assigned to two or more categories under the ISCO-08. Alternatively, different ISCO-88 codes may converge in a single ISCO-08 classification.

Afterwards, each occupation classified under ISCO-08 definitions must be converted into a SOC category. For that purpose, we relied on the conversion table provided by the *U.S. Bureau of Labor Statistics*.[17] The procedure consists in assigning to each SOC classification one (or more) corresponding category under ISCO-08. In some cases, different SOC codes ended up under the same ISCO-08 classification.

In the cases that for some ISCO-08 occupations there is not an exact match under the SOC classification, we relied on the probabilities provided by other activities considered as similar or close to the first one. When a single ISCO activity is associated to more than one SOC codes, the average probabilities of the SOC related groups are used. Similarly, in the case that a single ISCO-88 code is related to more than one ISCO-08 categories, average probabilities are calculated.

Finally, for each CASEN observation the corresponding probability under the ISCO-88 classification is assigned. The only category not considered is that of military occupation, as there is no automation possibility there. With that information, a weighted average is calculated considering the expansion factor for years 2013, 2015 and 2017.

The complete list of probabilities for each ISCO-88 occupation is not shown here in order to save space but remains available from the authors upon request.

Table A1. PIAAC: main components of the questionnaire.

Pillars	Components
Direct evaluation	• Literacy • Quantitative analysis • Reading comprehension • Resolution of simple and complex technical problems
Skills use	• Use of cognitive skills – lecture, writing, ICT use • Social and personal interaction – cooperation, training, planning, communication, negotiation, contact with clients • Physical aptitudes – motor skills • Learning capabilities – formal and informal learning
Baseline questionnaire	• Demographic characteristics • Education and training • Social and linguistic origin • Employment and income • ICT use

Source: PIAAC.

Table A2 . PIAAC questions considered to identify bottlenecks.

Bottleneck	PIAAC variable	Code	Description
Perception and manipulation	Physical aptitudes – motor skills	F_Q06C	How often do you use hand and finger manipulation competences and skill?
Creative intelligence	Resolution of simple technical problems	F_Q05A	How often do you solve simple problems that do not require more than 5 min to find a good solution?
	Resolution of complex technical problems	F_Q05B	How often do you solve complex problems requiring at least 30 min to find a good solution?
Social intelligence	Employee training	F_Q02B	How often do you train individuals or groups?
	Recommendation	F_Q02B	How often do you advise or provide recommendations to individuals?
	Planning	F_Q03B	How often do you plan work for others?
	Communication	F_Q02A	How often do you share information with other workers?
	Negotiation	F_Q04B	How often do you negotiate with individuals inside and outside your organization?
	Advice	F_Q04A	How often do you advise or influence individuals?
	Sell	F_Q02D	How often do you sell a product or service?

Source: PIAAC.