Covid-19's Impact on the Labor Market shaped by Automation: Evidence from Chile[1]

Pablo Egaña del Sol
Escuela de Negocios
Universidad Adolfo Ibáñez

Gabriel Cruz
Escuela de Negocios
Universidad Adolfo Ibáñez

July 1st, 2020

[1] We thank the financial support provided by the Columbia University´s Global Center in Santiago, Chile.

I Introduction

In this article, we argue that the ongoing COVID-19 pandemic would serve as a catalyzer for automation processes in several firms across industries and territories. It is a desolate fact that many workers had lost their job in the recent months due the restrictions (quarantine and confinements, curfews, general physical movement restrictions, etc.) put in place to control for the COVID-19 pandemic (Superintendencia de Pensiones, 2020; INE, 2020; Coibion et al., 2020). Many of those workers are expecting to return to their previous occupation when the current situation turns out to be safer and the government lift restrictions. Regardless is a very complicated, rather speculative, task to predict the situation in the labor market when the pandemic fades out, we will expose a couple of stylized fact that are consistent with the following hypothesis: industries are accelerating the digital transformation of their operations and we will experience a jobless recovery in many sectors, especially those were the automation technologies are available, the degree of at-work physical proximity is high, the level of exposure of covid-19 is high, and the capabilities to work remotely are low.[2] In other words, companies are forced to operate relying heavily on technology during the pandemic, and this would become the new normal in several economic sectors. We will provide empirical evidence supporting our hypothesis using data at individual and industry/sector level in Chile.

Recent developments on digitalization, cognitive computing, artificial intelligence, and robotics, which are key parts of the so-called automation in the Industry 4.0 context, have been offering countless benefits through increased productivity and efficiency.[3] Irrespective of these positive effects, automation may have undesirable consequences on the labor market, at least in the medium term. There is empirical evidence indicating that various occupations have become redundant, and in some cases, have become unnecessary (Winick, 2018). Furthermore, Automation may increase demand of some occupations (the complementarity effect or new tasks) and decrease others (the substitution effect).[4] Indeed, Webb (2020) finds that the exposure to robots is associated with a decline in wages of between 8 and 14% and a decline in the employment share of between 9 and 18% in the United States between 1980 and 2010. For example, Arntz et al. (2016) found that the fraction of jobs at

---

[2] This jobless recovery, or "cleansing effect", has been studied regarding previous economic crisis, such as the Great Recession in 2009 (Micco, 2020).

[3] E.g. Acemoglu and Restrepo (2018), Frey and Osborne (2017), Arntz et al. (2017), McKinsey (2017), Fort (2017), Egana-delSol (2019), Egaña-delSol and Joyce (2020), among others, argue that due to recent developments, a significant proportion of current jobs are susceptible to automation.

[4] See Graetz and Michaels (2018), Brynjolfsson and McAfee (2014), and Acemoglu and Restrepo (2018; 2019).

high risk of automation (that is, with a predicted probability greater than 70% at the individual level), among member countries of the Organization for Economic Co-operation and Development (OECD), was 9%, with a range of 6 to 12%, while Egaña-delSol and Joyce (2020) estimate that the percentage of jobs under high risk of automation are in the 11-42% range for developing economies. Bustelo et al. (2020) finds that women have a higher risk of been replaced by automation than their male peers in Latin America. In Chile, there is a recent report showing that the share of workers at high risk of automation is around 17% (Bravo et al., 2019).

On the other hand, COVID-19 has had an immediate effect on the labor market, destroying thousands of jobs (Atkeson, 2020; Beland et al, 2020; Sanchez et al., 2020; Superintendencia de Pensiones, 2020). In particular, Beland et al. (2020) find that COVID-19 increased the unemployment rate especially in men, younger workers, Hispanics, and less-educated workers in the United States. They also built three indexes to identify what type of occupations are (1) more exposed to disease, workers that work with (2) proximity to coworkers, and workers who can easily (3) work remotely. Their data suggest that employees in occupations working in proximity to others are more affected while occupations able to work remotely are less affected.

We claim that the COVID-19 pandemic has been accelerating many of these technological changes, such as the use of chatbots, virtual agents, automatic financial reports, middle-men in the delivery or the supply chain, among many others. Unfortunately, there is no reliable and validated source of information regarding the degree of recent adoption of technology. Therefore, we build our analysis on well-known metrics of the potential of automation of certain occupations (Frey and Osborne, 2017) as well as indices capturing the capacity of computers, software and robots to perform task within occupations, based on recent patent records in the US (Webb, 2020). That is to say, we will estimate the potential of each sector of the Chilean economy to replace workers by machines or computers unrelatedly to the COVID-19 pandemic, but based on the current information that we have of the available technology to perform it.

In short, the current sanitary crisis may result in an acceleration of the effects of automation on the labor market. We will show the heterogenous impacts that COVID-19 fueled by automation may have industries and territories would have in Chile. In this milieu, this article has two objectives: (1) Identify which sectors, territories, and workers would be most affected by automation in Chile; and (2) identify what sectors would be most affected by COVID-19 and shed lights on how this is related with automation in Chile.

In this paper we use CASEN dataset, Frey and Osborne (2017) probabilities of automation at occupation level, and Webb (2020) new index of automation capabilities based on patent records in the US.

We use an expectation-maximization algorithm to predict the index of automation of each occupation in Chile. With this analysis, we identify what productivity sectors and geographical areas are more likely to be automated.

We find evidence that COVID-19 might act as catalyzer on the digital transformation of firms in Chile. In particular, we find that the automation risks have a significant geographical heterogeneity, even within subnational areas. This heterogeneity is partly determined by their economic activities ---e.g. agriculture, mining, and services--- as well as demographic characteristics (i.e. worker's average age, income, and gender). In addition, we argue that Chile might experience a jobless recovery in many economic sectors, especially in those were the automation technologies are available, the degree of both at-work physical proximity and the level of exposure to COVID-19 are high, and the capabilities to work remotely are low.
The rest of the article is organized as follows. Section II presents the data and methodology. Section III presents the main results. Then, section IV offers some conclusions.

II Data and Methodology

We use three sources to measure the automation prediction in Chile. First, Encuesta de Caracterización Socioeconómica Nacional (CASEN) provides information about workers' occupations, age, gender, region, and other relevant characteristics that help to answer our first objective. Particularly, each person that works is associated to some International Standard Classification of Occupations (ISCO) occupation code.

Then, we use Webb (2020) to predict the automation score by occupations controlled by workers' characteristics. Moreover, we also estimated the same predictions using Frey and Osborne (2017) as a robustness check of our results.

Webb (2020) uses patent data to show what occupations are most exposed to robotics and new technologies such as software and artificial intelligence. In particular, he quantifies the overlap between the text of patents and the text of job description using the Google Patents Public Data, and the O*Net database of occupations and tasks[5]. Then, he uses the text of patents to identify what the technology can do. [6]

[5] Table A1 shows an example.
[6] Figure A1 illustrates the method how Webb (2020) builds technology exposure measures.

Frey and Osborne (2017) use machine learning experts that manually analyzed 70 occupations and labelled them as either automatable or not. Then, they label the remaining 632 occupation contained on the O*Net data base using an algorithm. They find that 47% of total US employment is highly susceptible to automation, this means that 47% of occupations have a probability to be automated higher to 70%. Webb (2020) does not choose a threshold to classify occupations in high risk, but we classify occupations in high risk when their result is higher than the mean plus one standard deviation.[7]

Table 1: Example Crosswalk ISCO to SOC code

ISCO 4-Digit	ISCO-08 Title	2010 SOC Code	2010 SOC Title	Frey & Osborne (2017) Index	Webb (2020) Index
2341	Primary school teachers	25-2021	Elementary School Teachers, Except Special Education	0.0044	0.2182
2341	Primary school teachers	25-2022	Middle School Teachers, Except Special and Career/Technical Education	0.17	0.1937
2342	Early childhood educators	25-2011	Preschool Teachers, Except Special Education	0.0074	0.3141
2342	Early childhood educators	25-2012	Kindergarten Teachers, Except Special Education	0.15	0.2867

On the other hand, Beland et al. (2020) provide information about three indexes that allow estimating the impact of COVID-19 on occupations. They use ACS (American Community Survey) and O*NET data to classify occupations in three: exposure to disease, physical proximity to other people and how easily occupations can work from home. Specifically, the exposure to disease index is built using a survey question asking: "How often does this job exposure to disease/infection?."[8] The remote work index is taken from a question that asks about method of transportation to work where an option is "I work at home". Then, they divide the share of workers by the median occupation's share of home workers.

Both Webb (2020) and Frey & Osborne (2017) indexes are associated to SOC[9] Codes. Since SOC code is associated with one or more ISCO codes, we use a crosswalk to

[7] Mean Webb Index is 0.384 and one standard deviation is 0.184. Then, an occupation with an index higher than 0.568 is classified like high risk of automation.

[8] Beland et al. (2020) find that acute care nurses, dental hygienists, family and general practitioners, and internists are the occupations with the highest exposure disease index.

[9] Standard Occupational Classification System.

match them (Table 1). Following Egaña-delSol and Joyce (2020), whenever there are multiple jobs, we create a weight, calculated as the inverse number of duplicates matches.

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

In this sense, we implement an expectation-maximization (EM) algorithm following Ibrahim (1990) to identify of occupations which are more automatable. We regress the Frey & Osborne (2017) index and Webb (2020) separately, onto N occupations of each duplicated job for every individual controlling by demographic characteristics.

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

y = F&O Automation
i = Participant
j = Duplicates
X = Occupation and demographic characteristics

Then, we recalculate the weights for each occupation duplication. This is calculated by taking the regression equation automation output and subtracting the training input and then dividing it by the summation of all the duplicate automation value differences. This entire process is repeated until the weights converge.[10]

III Results

With these empirical models, we analyze trends among occupations and demographic characteristics. First, Table 3 shows that the predicted automation monotonically increases when workers become older than 24 years old. On the other hand, Table 4 indicates that male workers are more likely to be affected by new technologies than women. This may be because of women work relatively more in sectors with less probability of automation such as education and social services (Bustelo et al., 2020). Precisely, 13% of female workers, compared to a 21% of their male colleagues, are under high risk of automation. Furthermore, Table 5 shows that the lowest income quintiles have higher risk of automation. This result is disturbing due to the current

[10] More details in Egaña-del Sol and Joyce (2020)

high levels of inequality in Chile (CASEN, 2017). The adoption of automation technologies would exacerbate this problem.

Table 3. Predicted Automation by Age

	Frey & Osborne		Webb	
Age Range	Index	High Risk	Index	High Risk
18 to 24 years	0,52	0,17	0,37	0,12
25 to 34 years	0,49	0,15	0,33	0,09
35 to 44 years	0,53	0,22	0,36	0,14
45 to 59 years	0,60	0,33	0,42	0,23
60 years or more	0,65	0,43	0,47	0,31

Note: Estimation calculated using Frey & Osborne (2020) and Webb (2020) with CASEN (2017).

Table 4. Predicted Automation by Gender

	Frey & Osborne		Webb	
Gender	Index	High Risk	Index	High Risk
Male	0,63	0,33	0,43	0,21
Female	0,47	0,16	0,33	0,13

Note: Estimation calculated using Frey & Osborne (2020) and Webb (2020) with CASEN (2017).

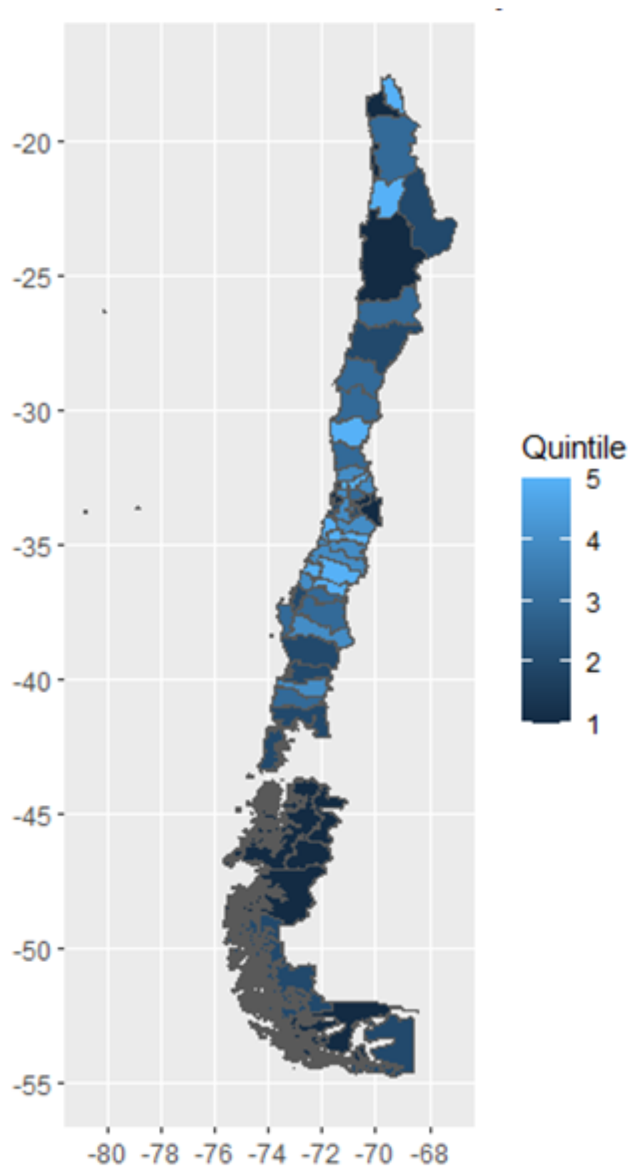
Table 5. Predicted Automation by Quintile Income

	Frey & Osborne		Webb	
Quintile	Index	High Risk	Index	High Risk
I	0,67	0,44	0,50	0,35
II	0,61	0,33	0,45	0,24
III	0,57	0,26	0,41	0,18
IV	0,53	0,21	0,37	0,14
V	0,42	0,08	0,24	0,04

Note: Estimation calculated using Frey & Osborne (2020) and Webb (2020) with CASEN (2017).

These results are consistent with previous evidence for Chile documented by Bravo et al. (2019). The authors use CASEN data and Frey & Osborne (2017)'s indices to predict the automation risk in the Chilean context. Some results are slightly different, most likely due the fact that they use Frey and Osborne (2017) following a binary classification, while we use the continuous automation likelihood at occupational level.

Figure 1: Predicted Automation Quantile Index at Sub-national Level (Province)



Note: Estimation calculated using Webb (2020) with CASEN (2017). Darker colors represent a lower quantile (i.e. lower value).

Figure 1 shows that there is an interesting heterogeneity at regional level. There is also at a sub-regional level, the province level, a significant heterogeneity in terms of expected impact of automation on average but also regarding the fraction of the current labor market under high risk. For example, in Antofagasta region, the

Antofagasta province has a 0.06 fraction of its workers under high risk of automation, while the Tocopilla province it´s around 0.35, both according the Webb´s index of automation exposure. Antofagasta is a service-oriented city for the whole North macrozone, while Tocopilla has an economy based on mining, energy and fishing (and particular, fishmeal production), which, as we will review in the next table, has a larger probability to be affected by different sort of automation technologies. The case of the Metropolitan Region, we have, on one side, Santiago province, with the highest concentration of services in the country (financial, teaching, health, legal, etc., and Talagante, a province with an old tradition in agriculture since the colonial era: Santiago has a predicted share of workers under high risk of 0.05, while Talagante represent 0.27.

Table 6. Predicted Automation by Sector

	Frey & Osborne		Webb	
Sector	Index	High Risk	Index	High Risk
Finance	0,35	0,00	0,18	0,00
Education	0,35	0,00	0,22	0,00
Social Services	0,38	0,00	0,24	0,00
Hotel and Restaurants	0,42	0,00	0,30	0,00
Commerce	0,42	0,01	0,29	0,00
Public Administration	0,42	0,01	0,26	0,00
Other Services	0,47	0,02	0,32	0,01
Real Estate	0,54	0,08	0,37	0,05
Manufacture	0,58	0,10	0,40	0,01
Water and Electricity	0,59	0,17	0,38	0,02
Transport	0,65	0,38	0,47	0,16
Fishing	0,65	0,34	0,46	0,15
Consturction	0,67	0,42	0,47	0,09
Mining	0,71	0,57	0,49	0,37
Domestic Services	0,84	0,97	0,69	0,93
Agriculture	0,94	0,99	0,67	0,89

Note: Estimation calculated using Frey & Osborne (2020) and Webb (2020) with CASEN (2017). Productive Sectors classified by CASEN (2017) based on isco-88.

Finally, this geographical heterogeneity is partly determined by the main economic activities ---e.g. agriculture, mining, and services--- as well as demographic characteristics of these geographic areas.

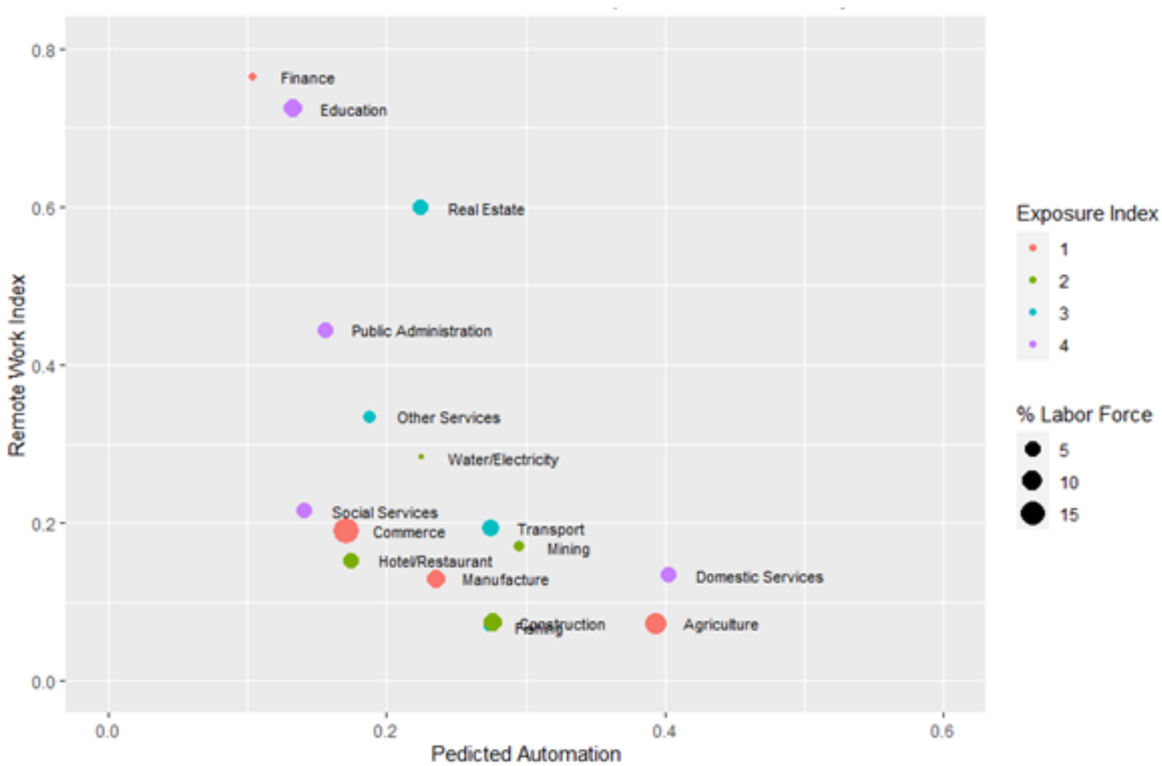
In general, the results using Frey and Osborne and Webb's Robots+Software indices are consistent across economic activity. It is important to note that FO measures are a forecast based on experts' assessment of the probability of certain occupations to be fully automatable, while Webb's exposure index is a weighted average of likelihoods at tasks level based on patent records pairs of nouns/verbs in their description. Thus, we expect that the Webb's index will be lower than the FO given that the construction is based on past information on current abilities of robots and software to perform certain tasks, and not a hypothetical and prospective exercise that can be affected by several biases.

Teaching, social and health services, hotel and restaurant, public service and defense, retail, are among the economic activities that experience a relatively lower risk of automation. These sectors have in common the need of physical presence in the delivery of the services and the necessity to perform task or have skills that are hard to automate, also known as "automation bottlenecks", such as perception and manipulation, persuasion, empathy, and the like (Frey and Osborne, 2017).

On the other side, we have construction, mining, domestic service (i.e. house cleaning and cooking), agriculture, farming and silviculture with a high predicted likelihood of automation. Some of these activities have been heavily affected by the pandemic, e.g. construction, domestic service, and most recently, mining. These are the type of sectors that we may expect a greater acceleration on the new technology adoption.

Nonetheless, please note that these results are irrespective of the COVID-19 pandemic. In the following we will extrapolate our results with characteristic associated to COVID-19 effects on different economic activities in order to have a more reliable analysis of potential affected areas.

Figure 2: Predictive Automation, Remote Work and Exposure to Disease by Economic Sector



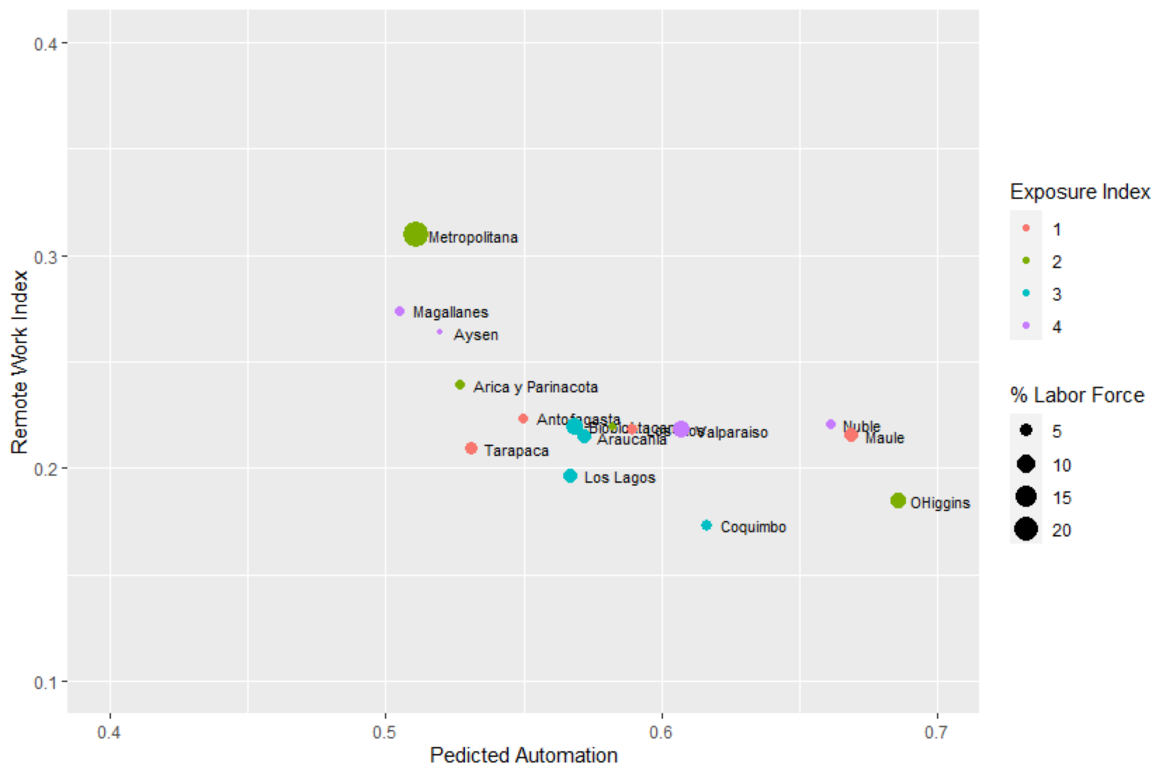
Note: Each circle represents a sector. The size of each circle represents the Labor Force calculated with CASEN (2017). The x-axis plots the predicted automation of each sector estimated using Webb (2020). The further to the right, the more probability to be automated. The y-axis plots the remote work index built by Beland et al. (2020). Further up, employees work from home more commonly. Finally, the color of the circle corresponds to the quartile of each sector in the exposure index created by Beland et al. (2020). Sectors in the 4th quartile have workers that have higher exposure to COVID-19 at the workplace.

Figure 2 presents the situation when considering the economic sector as unit of interest. Taking together the automation risk and the remote work index, we observe that agriculture, domestic services, construction, mining, transport, and fishing are in the lower right side of the graph, which indicates a delicate situation for the labor market in these sectors: high automation risk and low remote work capability.

In addition, we can consider the level of exposure to COVID-19 of these sectors, having domestic service in the 4^{th} quartile (i.e. highest exposure), transport in the 3^{rd} quartile, and construction, mining and fishing in the second quartile, indicating that if the pandemic takes longer than expected to be surpass, these sectors will face a greater impediment and complexity to return to the "new normal". This may generate an extra level of pressure to intensify labor-saving technologies in the short term. On the other hand, Finance, Education, Real Estate, and Public Administration have low risk of automation, high possibility of remote work. All but Education have a low exposure to COVID-19 as well. The results are analogous if we consider proximity to coworkers at workplace instead of exposure to COVID-19 (See Figure A2 in the Appendix). These results are overall consistent with recent evidence for the US (Papanikolaou and Schmidt, 2020).

Figure 3 suggest that geographic areas with low capabilities of remote work and high predicted automation risk are in a delicate situation. We can visibly identify the O'Higgins, Maule, Ñuble and Coquimbo geographic areas (regions). In addition, if we complement this analysis with the measure of how exposed these areas are to COVID-19 and the size of the workforce, the outlook is even more dramatic. Conversely, regions such as the metropolitan area, with a low probability of automation due to their focus on low-risk activities, and the feasibility of implementing remote work, are more protected from these risks.

Figure 3: Predictive Automation, Remote Work and Exposure to Disease by Geographic area



Note: Each circle represents a sector. The size of each circle represents the Labor Force calculated with CASEN (2017). The x-axis plots the predicted automation of each sector estimated using Webb (2020). The further to the right, the more probability to be automated. The y-axis plots the remote work index built by Beland et al. (2020). Further up, employees work from home more commonly. Finally, the color of the circle corresponds to the quartile of each sector in the exposure index created by Beland et al. (2020). Sectors in the 4th quartile have workers that have higher exposure to COVID-19 at the workplace.

IV Conclusion

In this article we argue that the ongoing COVID-19 pandemic would serve as a catalyzer for automation processes in several firms across industries. We consider Chile, a small open developing economy, as a case study. Nonetheless is a very complicated, rather speculative, task to predict the situation on the labor market after the COVID-19 pandemic, we expose a couple of stylized facts that are consistent with the following hypothesis: industries are accelerating the digital transformation of their operations and we might experience a jobless recovery in many sectors, especially those where the automation technologies are available, the degree of at-work physical proximity is high, the level of exposure of covid-19 is high, and the capabilities to work remotely are low.

In this context, we Identify which industries, territories and economic activities will be most affected by automation given the COVID-19. We provide empirical evidence supporting our hypothesis using data at individual and industry/sector level in Chile. Using a comprehensive and novel dataset, we are able to predict the degree of automation risk by worker's demographics, occupations, industries, territories and economic activities in Chile.

We find evidence that COVID-19 might act as catalyzer on the digital transformation of firms in Chile. We estimate that the automation risks have a significant geographical heterogeneity, even within subnational areas. This heterogeneity is partly determined by their economic activities ---e.g. agriculture, mining, and services--- as well as demographic characteristics (i.e. worker's average age, income, and gender). In addition, we argue that Chile might experience a jobless recovery in many economic sectors, especially in those were the automation technologies are available, the degree of both at-work physical proximity and the level of exposure to COVID-19 are high, and the capabilities to work remotely are low.

REFERENCES

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, *108(6),* 1488-1542.

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: how technology displaces and reinstates labor. *Journal of Economic Perspectives, 33(2),* 3-30.

Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries. *Future Skills Centre*

Atkeson, A. (2020). How deadly is covid-19? understanding the difficulties with estimation of its fatality rate (No. w26965). *National Bureau of Economic Research.*

Barrero, J. M., Bloom, N., & Davis, S. J. (2020). Covid-19 is also a reallocation shock (No. w27137). National Bureau of Economic Research.

Beland, L. P., Brodeur, A., & Wright, T. (2020). The short-term economic consequences of Covid-19: exposure to disease, remote work and government response. *IZA Discussion Papers, No. 13159*

Bravo, J., García A., & Schlechter H. (2019). Mercado Laboral Chileno para la Cuarta Revolución Industrial. *Documento de Trabajo N°59. CLAPES UC*

Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. *WW Norton & Company.*

Bustelo, M., Egana-delSol P., Ripani L., y Soler N. (2020), "Automation and Gender in Latin America." *IDB Working Paper Series.*

Coibion, O., Gorodnichenko, Y., & Weber, M. (2020). Labor markets during the covid-19 crisis: A preliminary view (No. w27017). National Bureau of Economic Research.

Egana-delSol, Pablo & Connor Joyce (2020), "The Future of Work in Developing Economies." *Sloan Management Review. Vol. 3, January.*

Egana-delSol, Pablo, The Future of Work in Developing Economies: What can We Learn from the South? (December 3, 2019). *Available at*

SSRN: https://ssrn.com/abstract=3497197 or http://dx.doi.org/10.2139/ssrn.3497197

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation?. *Technological forecasting and social change, 114*, 254-280.

Fort, Teresa C. 2017. "Technology and production fragmentation: Domestic versus foreign sourcing." *The Review of Economic Studies 84(2):* 650–687.

Graetz, G., & Michaels, G. (2018). Robots at work. *Review of Economics and Statistics, 100(5),* 753-768.

Instituto Nacional de Estadísticas, INE (2020). Encuesta Nacional de Empleo: contingencia COVID-19. Nota Técnica N° 4.

McKinsey & Company, & Manyika, J. (2017). Technology, jobs, and the future of work. *McKinsey Insights.*

Micco, A. (2019). Automation, Labor Markets, and Trade. Departmen of Economic Working Papers Series, University of Chile.

Papanikolaou, D., & Schmidt, L. D. (2020). Working Remotely and the Supply-side Impact of Covid-19 (No. w27330). National Bureau of Economic Research.

Sanchez, D. G., Parra, N. G., Ozden, C., & Rijkers, B. (2020). Which Jobs Are Most Vulnerable to COVID-19? What an Analysis of the European Union Reveals. *Research & Policy Brief,* (34).

Superintendencia de Pensione (2020). Ficha estadística semanal Ley de Protección al Empleo y Ley del Seguro de Cesantía. 22 de Junio de 2020.

Webb, M. (2019). The Impact of Artificial Intelligence on the Labor Market. Available at SSRN 3482150.

Winick, E. (2018). Every study we could find on what automation will do to jobs, in one chart. *MIT Technology Review.*

APPENDIX

Table A1. Tasks and exposures scores for precision agriculture technicians (Webb, 2020)

Task	Weight in occupation	Extracted pairs	AI exposure score x100
Use geospatial technology to develop soil sampling grids or identify sampling sites for testing characteristics such as nitrogen, phosphorus, or potassium content, ph, or micronutrients.	0.050	(develop, grid)	0.050
		(identify, site)	0.234
		(test, characteristic)	0.084
Document and maintain records of precision agriculture information.	0.049	(maintain, record)	0.000
Analyze geospatial data to determine agricultural implications of factors such as soil quality, terrain, field productivity, fertilizers, or weather conditions.	0.048	(analyze, datum)	0.469
		(determine, implication)	0.837
Apply precision agriculture information to specifically reduce the negative environmental impacts of farming practices.	0.048	(apply, information)	0.000
		(reduce, impact)	0.151
Install, calibrate, or maintain sensors, mechanical controls, GPS-based vehicle guidance systems, or computer settings.	0.045	(maintain, sensor)	0.000
Identify areas in need of pesticide treatment by analyzing geospatial data to determine insect movement and damage patterns.	0.038	(identify, area)	0.234
		(analyze, datum)	0.469
		(determine, movement)	0.502

Notes: Table displays six of the twenty-two tasks recorded for precision agriculture technicians in the O*NET database. For each task, the weight is an average of the frequency, importance, and relevance of that task to the occupation, as specified in O*NET, with weights scaled to sum to one. The capability pairs in the third column are extracted from the task text by a dependency parsing algorithm. The AI exposure score for an extracted pair is equal to the relative frequency of similar pairs in the titles of AI patents. The score multiplied by 100 is thus a percentage; for example, pairs similar to "determine implications" represent 0.84% of pairs extracted from AI patents.

Figure A1. Illustration of process for constructing technology exposure measures (Webb, 2020)

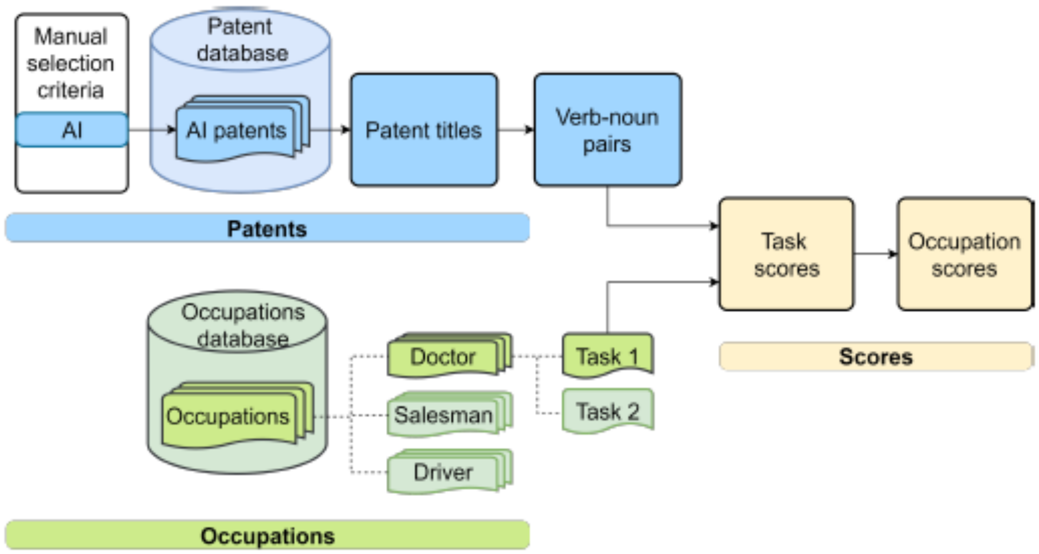
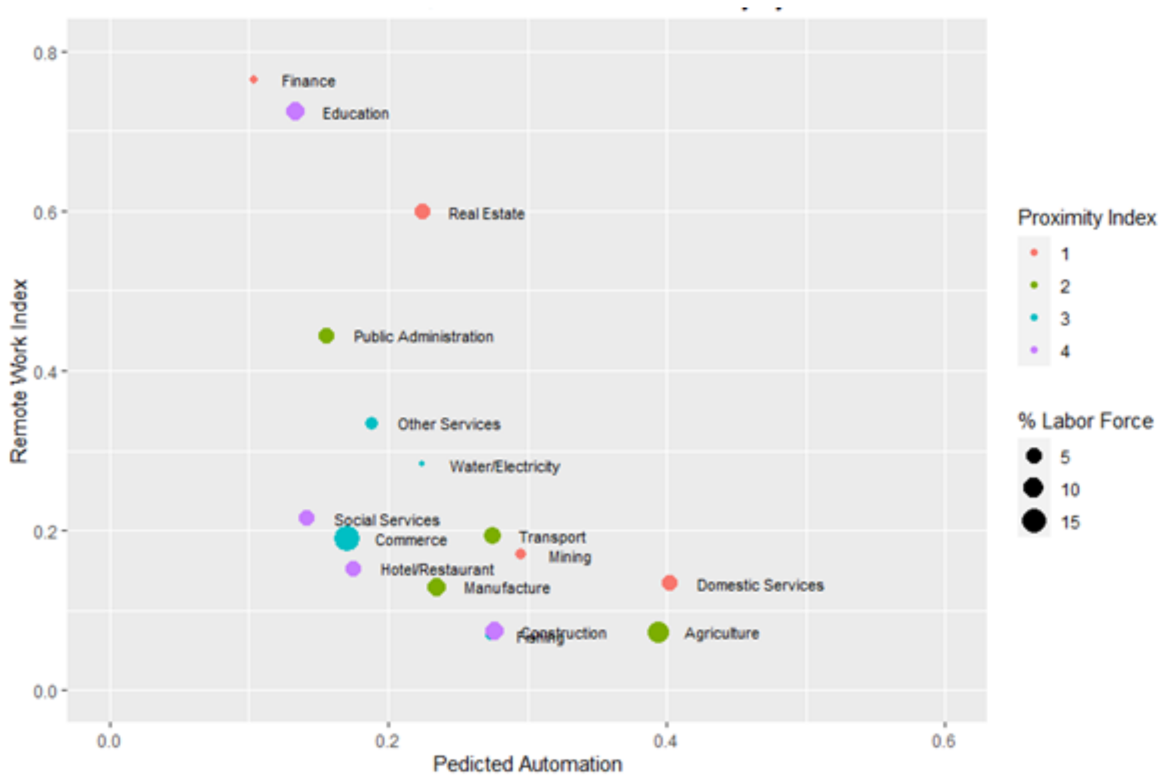


Table A2. Predicted Automation by Geographic Areas

	Frey and Osborne		Webb			Frey and Osborne		Webb	
Region	Index	High Risk	Index	High Risk	Provincia	Index	High Risk	Index	High Risk
Tarapaca	0.51	0.18	0.35	0.07	Iquique	0.50	0.17	0.35	0.06
					Tamarugal	0.61	0.36	0.42	0.24
Antofagasta	0.53	0.16	0.36	0.08	Antofagasta	0.52	0.15	0.35	0.06
					El Loa	0.54	0.14	0.36	0.05
					Tocopilla	0.66	0.47	0.46	0.36
Atacama	0.56	0.28	0.39	0.20	Copiapó	0.55	0.27	0.38	0.18
					Chañaral	0.60	0.31	0.42	0.27
					Huasco	0.59	0.32	0.42	0.23
Coquimbo	0.59	0.34	0.43	0.24	Elqui	0.57	0.29	0.41	0.20
					Choapa	0.58	0.33	0.42	0.24
					Limarí	0.67	0.47	0.48	0.36
Valparaíso	0.58	0.29	0.42	0.21	Valparaíso	0.49	0.13	0.34	0.09
					Los Andes	0.62	0.36	0.46	0.26
					Petorca	0.62	0.39	0.45	0.31
					Quillota	0.67	0.42	0.48	0.34
					San Antonio	0.54	0.21	0.38	0.12
					San Felipe	0.69	0.46	0.51	0.38
					Marga Marga	0.62	0.35	0.45	0.24
O'Higgins	0.65	0.44	0.46	0.35	Cachapoal	0.64	0.41	0.45	0.33
					Cardenal Caro	0.68	0.49	0.47	0.35
					Colchagua	0.68	0.48	0.49	0.40
Maule	0.64	0.43	0.46	0.36	Talca	0.63	0.40	0.45	0.31
					Cauquenes	0.67	0.49	0.49	0.42
					Curicó	0.63	0.41	0.45	0.35
					Linares	0.67	0.49	0.49	0.42
Biobío	0.55	0.25	0.39	0.15	Concepción	0.52	0.19	0.36	0.10
					Arauco	0.60	0.33	0.43	0.22
					Biobío	0.60	0.36	0.43	0.25
La Araucanía	0.55	0.26	0.39	0.19	Cautín	0.53	0.22	0.37	0.15
					Malleco	0.61	0.36	0.44	0.30
Los Lagos	0.56	0.25	0.39	0.16	Llanquihue	0.56	0.25	0.39	0.16
					Chiloé	0.52	0.16	0.36	0.10
					Osorno	0.59	0.30	0.41	0.20
Aysén	0.50	0.16	0.34	0.11	Coyhaique	0.50	0.17	0.33	0.12
					Aysén	0.52	0.14	0.35	0.08
					Capitán Prat	0.46	0.14	0.29	0.04
					General Carrera	0.52	0.17	0.36	0.17
Magallanes	0.48	0.11	0.32	0.05	Magallanes	0.47	0.09	0.31	0.04
					Tierra del Fuego	0.59	0.33	0.40	0.20
					Última Esperanza	0.52	0.14	0.37	0.09
Metropolitana	0.48	0.12	0.32	0.09	Santiago	0.46	0.08	0.29	0.06
					Cordillera	0.50	0.12	0.35	0.10
					Chacabuco	0.60	0.27	0.42	0.17
					Maipo	0.57	0.20	0.40	0.13
					Melipilla	0.66	0.44	0.46	0.33
					Talagante	0.63	0.33	0.45	0.26
Los Ríos	0.57	0.30	0.39	0.21	Valdivia	0.54	0.25	0.37	0.17
					Ranco	0.66	0.49	0.46	0.38
Arica y Parinacota	0.51	0.21	0.35	0.14	Arica	0.51	0.21	0.35	0.13
					Parinacota	0.65	0.38	0.46	0.34
Ñuble	0.62	0.36	0.44	0.28	Diguillin	0.59	0.29	0.42	0.22
					Itata	0.64	0.40	0.44	0.32
					Punilla	0.67	0.47	0.48	0.37

Note: Estimation calculated using Frey & Osborne (2020) and Webb (2020) with CASEN (2017).

Figure A2: Predicted Automation, Remote Work and Proximity by Economic Sector



Note: Each circle represents a sector. The size of each circle represents the Labor Force calculated with CASEN (2017). The x-axis plots the predicted automation of each sector estimated using Webb (2020). The further to the right, the more probability to be automated. The y-axis plots the remote work index built by Beland et al. (2020). Further up, employees work from home more commonly. Finally, the color of the circle corresponds to the quartile of each sector in the proximity index created by Beland et al. (2020). Sectors in the 4th quartile have workers that have higher proximity with their coworkers.