Technological Forecasting & Social Change 176 (2022) 121373

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

COVID-19 and automation in a developing economy: Evidence from Chile☆

Pablo Egana-delSol[a,*], Gabriel Cruz[a], Alejandro Micco[b]

[a] Adolfo Ibanez University, UAI School of Business, Santiago and Vina del Mar, Chile
[b] Department of Economics, Faculty of Economics and Business, University of Chile, Santiago, Chile

ARTICLE INFO

JEL:
E24
J01
J64
O33

Keywords:
Automation
Computerization
Covid-19
Labor market
Employment
Technological change

ABSTRACT

This paper analyzes the Covid-19 pandemic impact of the global process of automation on employment in a developing economy. This is particularly interesting because developing economies characteristics, such as having larger informal sectors and weaker social safety nets, shapes the impact of automation on labor markets. We show that occupations with a higher risk of automation exhibit the most significant employment contraction. More specifically, we find that one standard deviation higher in sectoral share of employment in occupations at risk of automation (OaRA) implied around 7% less employment on average between the last quarter of 2019 and the first quarter of 2021. The effect on informal employees is three times more in comparison to formal employees, and the estimation for self-employed workers is not statistically significant. We also find that employees in sector with relatively low compared to high wages, both vis-à-vis the US, exhibit a 20% smaller reaction on employment due to the pandemic restrictions. We do not find robust evidence showing that the employment contraction has been larger among female workers or in jobs with higher at-work physical proximity, but we do find a positive relationship related to the capacity of working remotely.

1. Introduction

Covid-19 had an immediate effect on the labor market worldwide, destroying millions of jobs in 2020 alone due to the restrictions put in place to control the spread of the virus and due to the fall in the aggregate demand (Atkeson 2020; Beland et al., 2020; Dingel and Neiman 2020; Sanchez et al., 2020; Barrero et al., 2020; Coibion et al., 2020; Beirne et al., 2020; Hong and Werner 2020). Chile has not been exempted from the global recession produced by the Covid-19 crisis: two million jobs were destroyed between January 2020 and June 2020, almost one-third of the country's labor force. The collapse in employment in Chile, larger than in the vast majority of other nations, adds weight to the supposition that the impact of Covid-19 may be more significant in developing countries, which generally have larger informal sectors, weaker social safety nets, and shallower financial markets (Meghir et al., 2015; Loayza and Pennings, 2020).

Cognitive computing developments, artificial intelligence, digitalization, and robotics have been transforming labor markets in developed economies.[1] There is empirical evidence indicating that numerous occupations have already become redundant.[2] Automation may increase the demand for some occupations (the complementarity effect or new tasks) and decrease the demand for others (the substitution effect).[3] Jaimovich and Siu (2020) and Micco (2020) show a "cleansing effect"[4] during the Great Recession in the US, during which employment in

☆ We gratefully acknowledge the financial support provided by the Columbia University Global Center in Santiago, Chile, and by COES, CONICYT-ANID Grant FONDAP #15130009.

* Corresponding author.
E-mail address: pablo.egana@uai.cl (P. Egana-delSol).

[1] E.g., Acemoglu and Restrepo (2018), Frey and Osborne (2017), Arntz et al., 2016, Manyika, 2017, Fort (2017), Egana-delSol, 2021), Egana-delSol and Joyce (2020), Gruetzemacher et al. (2020) , among others, argue that due to recent developments a significant proportion of current jobs are susceptible to automation.

[2] For literature reviews on this topic, see Autor et al, 2003; Chuah, Loayza & Schmillen, 2018; Winick, 2018; and Acemoglu and Restrepo, 2018; Egana-delSol, 2021

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

[4] Jobless recoveries or the "cleansing effect" of a crisis (i.e., the destruction of relatively less efficient firms) has been studied regarding previous economic crises, see, for instance, Caballero and Hammour (1994).

https://doi.org/10.1016/j.techfore.2021.121373
Received 2 February 2021; Received in revised form 1 July 2021; Accepted 16 November 2021
Available online 25 November 2021

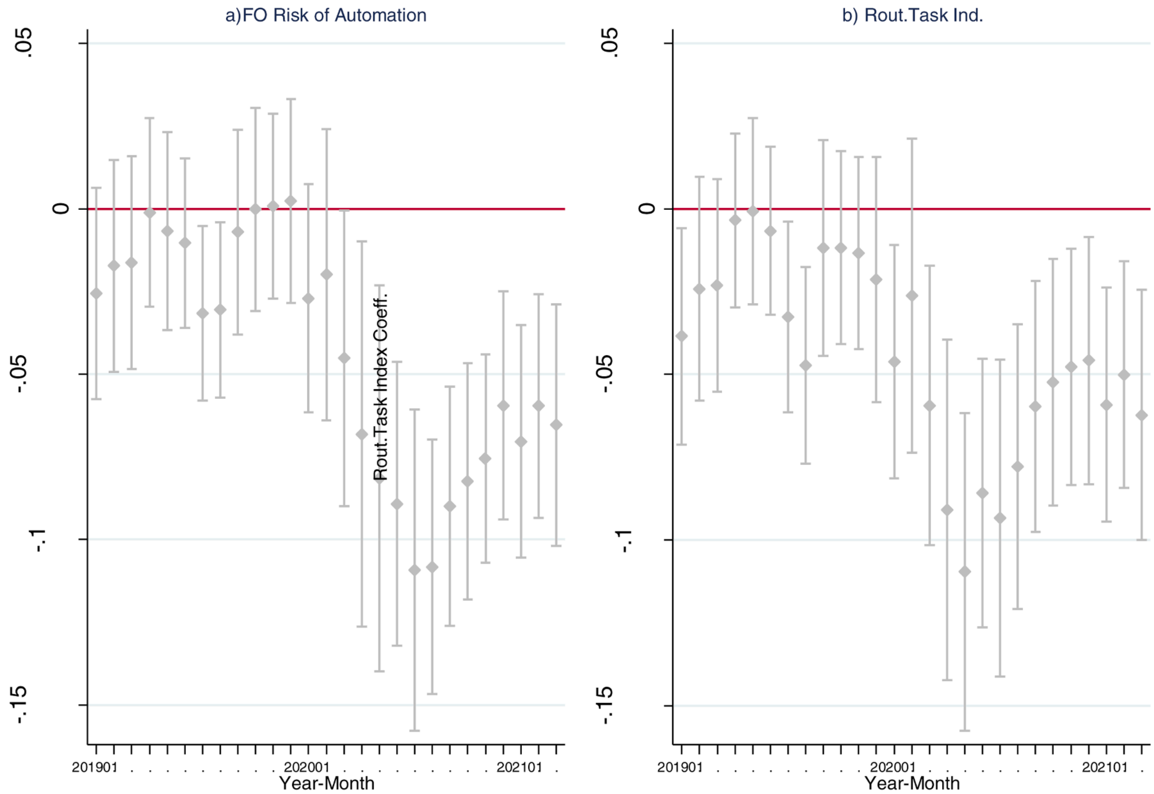

Fig. 1. Employment evolution and OaRA based on Frey and Osborne (2017) and Autor et al. (2003) automation and routine task indices. Note: Risk of Aut. Coeff. are the estimated time dummies times Frey and Osborne (2017) Automation Probability. The regression model controls for the share of women, (ln) sector activity index, and times, occupation-sector and seasonality (month-sector dummies) fixed effects. Rout Task Index Coeff. are the same estimated dummies for Autor et al. (2013) Routine Task Index. Variables are normalized to have a standard deviation of 1. Source: INE employment data, Frey and Osborne (2017) and Autor et al. (2013).

occupations at risk of automation (OaRA) fell significantly more than in other occupations. Since the end of the Great Recession, employment in OaRA never recovered to its previous levels, which help to explain the jobless recovery in the US.[5] Complementarily, a recent paper by Kopytov et al. (2018) provides evidence that crises are catalysts for technological change.

In Chile's case, there is evidence of a jobless recovery. In fact, output levels already recovered to pre-pandemic levels, employment is still 10% below its January 2020 level.

We claim that the Covid-19 pandemic will be shown to have accelerated many technological changes related to automation (such as the use of chatbots, virtual agents, automatic financial reports, and middlemen in the delivery or supply chain, among many others), and will therefore have a permanent effect on the labor market (Autor and Reynolds, 2020). Lee and Trimi (2020) and Bello et al. (2020) discuss how the Covid-19 pandemic induced an overnight digital transformation—that is, the ongoing pandemic has already catalyzed automation processes in numerous firms across sectors and occupations. Firms that have anticipated the evolution of technology capital and prices will use the pandemic recession to adjust their employment composition towards new technologies. Predicting any situation is an incredibly complicated task and foreseeing what the labor market situation will be like when the pandemic fades out is no exception, but in this paper will provide some results to advance the discussion on this topic.

The paper presents evidence consistent with the following hypotheses: Due to the Covid-19 pandemic, industries are accelerating their employment composition adjustment to align with the current or future availability of new technologies at lower prices. Employment in sectors with a large share of occupations with a higher probability of automation will experience a steeper fall in employment. During the pandemic, other industries' characteristics should affect the evolution of sector employment. The initial level of female participation in sectoral employment, the degree of at-work physical proximity with coworkers, the capability to work remotely, the informality of employment, and the weakness of social safety nets are all significant factors to consider in predicting the occupations and sectors that will be most affected by the Covid-19 pandemic. The last two factors, informal employment and weak social safety nets, are more likely to be characteristic of labor markets in developing economies.

Companies are being forced to rely heavily on technology during the pandemic, and this could become the new normal in several economic sectors. Fig. 1 shows the estimation of a monthly dichotomic variable multiplied by the automation probability index based on Frey and Osborne (2017) and the routine task index from Autor et al. (2003) for occupations undertaken in the Chilean economy during the analyzed period. The monthly data suggests that, during the Covid-19 crisis, the share of occupations at risk of automation has fallen dramatically in the Chilean labor market, and that employment has fallen between 5 percentage points (pp) and 10 pp more in sectors with a larger share of OaRA.

We use different sources of data to test our hypotheses. First, we use the methodologies applied by Autor et al. (2003) and Frey and Osborne (2017) to define and investigate OaRA. Autor et al. (2003) use a task model to identify OaRA. The model suggests that routine tasks, both cognitive and manual, are prone to automation. By contrast, nonroutine

[5] Micco (2020) uses methodologies developed by Autor et al. (2003) and Frey and Osborne (2017) to define and investigate the OaRA. Total employment in OaRA declines at an annual rate of 1.5% in comparison to riskless occupations in the US between 2004 and 2016.

cognitive, analytic, interpersonal, manual and physical, or manual interpersonal tasks are difficult to automate. Frey and Osborne (2017) adjust the approach taken by Autor et al. (2003) and claim that computerization can be extended to any nonroutine task that is not subject to any engineering bottlenecks with respect to computerization. For additional robustness, we also use the index developed by Webb (2019) that capture the capacity of computers, software, and robots to perform tasks within occupations based on patent records.[6]

Using indices based on work by Frey and Osborne (2017) and Autor et al. (2003), we estimate the automation risk of synthetic groups based on already available technology. We incorporate a further index for two features of occupations that are closely related to the employment evolution in the Covid-19 pandemic, the first one is the physical proximity to coworkers in the workplace based on the work of Beland et al. (2020), and the second one is the capability to perform remote work developed by Dingel and Neiman (2020). We also control for occupations in the health services sector and the initial level of female participation in sectoral employment.

More specifically, we construct 188 synthetic groups, defined by an occupation classification crosswalk (ISCO-88 to SOC2010), sector (ISIC Rev.3), and age (classified into three groups). We characterize workers in each group and estimate their automation risk using the 2017 Chilean household survey (CASEN). And we use Chile's National Employment Survey (ENE) to obtain employment data from January 2018 to March 2021 in order to calculate the evolution of employment by synthetic group, characterized by the share of employment in occupations at risk of automation and sectors.

We find evidence that Covid-19 acts as a catalyst for companies to adjust their employment structure towards digital transformation. Employment in a synthetic group with one standard deviation higher risk of automation fell between 5 pp and 7 pp more than employment in other occupations between the last quarter of 2019 and the first quarter of 2021 in Chile.

After controlling for OaRA, employment in the health service, and by sector of economic activity, we do not find evidence that the collapse in employment is larger among female workers. In addition, we do not find evidence that employment is negatively related to the degree of at-work physical proximity, but we do find a positive relationship related to the capacity of working remotely. Beland et al. (2020) using US data found that these two dimensions are important factors explaining the movement in employment during the Covid-19 pandemic. In Chile's case, the high level of employment informality, and the weak social safety net may explain why the degree of at-work physical proximity is not significant because workers tend to continue working regardless of the pandemic-related restrictions.

To study empirically the effects of informality and weak social safety net, we first replicate our estimations with different specifications to analyze the possible effects on informal and formal employee, as well as on self-employed workers as proxies of the former. Second, we study the potential effects of weak social safety net by estimating the effects on workers whose average wage in Chile relative to the US is below or above the median value across all synthetic groups in our sample. In fact, we find that employment informality and the weak social safety net are relevant to the process of automation in Chile, and that informal employee are more affected.

There is no clear evidence in the literature for the effect of employment informality on technology adoption (Perry et al., 2007), which suggests the consequences of informality in employment are more nuanced. Our hypothesis is that informality in the employment sector has two potential effects on technology adoption. On the one hand, greater informality can spur the deployment of technology or use of technology platforms that would be unlawful under stricter regulatory frameworks. On the other hand, in a context of high burden employment protection laws, employment informality reduces labor costs and thus reduces the incentive to adopt new technology. Informality can also reduce firms access to the financial market, and the lack of credit can reduce technology adoption.

Although self-employed workers must contend with the weak social safety net, they are less affected because they continue working however of the pandemic-related restrictions. We also find that the risk coefficient for formal employees is −0.045 and is statistically significant at the standard level (1%), and the same coefficient for informal employees is −0.15, which is an increase in absolute value of 11 pp. In the case of self-employed workers is not significant. Finally, when we study the weak social safety net we find that the coefficient is −0.057 when the relative wage is lower than the relative wage in the US, and the coefficient is −0.069 when the relative wage is higher the US wage. Although, the difference between both coefficients is not significant.

Our argument that the restrictions on movement and the economic crisis generated by the Covid-19 pandemic are serving as a catalyst of technological change in developing economies such as Chile is supported by at least three facts. First, we observe a more severe fall in employment in sectors with occupations with a higher risk of automation. Thus, according to both the Frey and Osborne and the Autor et al. (2003) indices, our results show a jobless recovery that is particularly impacting workers in occupations with a higher risk of automation, which is consistent with Jaimovich and Siu (2020) findings for the US. Second, according to a 2016 World bank report entitled "Digital Divide", Chile is between 10 and 20 years behind the US in terms of technology adoption (World Bank, 2016). Third, the secular downtrend in technology capital prices from 2008 makes this process of technological change even faster(Micco, 2019).

Our paper contributes to the literature in three main ways.

First, we contribute to an ongoing debate on the effects of automation on labor markets. We provide the first validation of the frequently used automation risk indices (i.e., from Frey and Osborne (2017) and Autor et al. (2003)) on developing economies by showing that the employment rate has fallen faster in OaRA during the last year, as would be expected.[7] We also contribute to the literature by incorporating characteristics factors of developing economies into the debate. We consider the effects of large informal sectors and weak social safety nets on the relationship between automation risk and employment.

We add to the literature that aims to predict how many jobs will be created and destroyed as a result of automation (Frey and Osborne, 2017; Arntz et al., 2016; Winick, 2018; Brussevich et al., 2018; Dengler and Britta, 2018; Nedelkoska and Quintini, 2018; Arntz et al., 2016; Egana-delSol, 2021).[8] Thus far, these studies have been focused on developed nations, and mostly on the US and OECD countries, which differ significantly from developing economies, particularly in terms of their labor market characteristics. Previous literature that focus on

[6] Results upon request.

[7] In the appendices we provide more information to support the idea of using automation risk indices originally designed to evaluate developed economies in our context. We correlated the routine task index from Autor et al. index using data from O*NET 2000 and O*NET 2021, with the probabilities of automation index from Frey and Osborne (Table A1). Furthermore, we estimated our model with both index (Table A2 and Table A3).We find high correlations and very similar results in estimations, which suggests that these indices are valid for countries that are potentially 20 years behind developed nations in terms of technology adoption. Using the results from the PIACC, we also compared the Chilean skills indices with the US skills indices by sector, gender, and education. Table A4 shows that there is a high correlation between the skills of both countries. Although there are different levels of development in the US and Chile, the high correlation between adult skills suggests that certain sectors have tasks that require skills and they are the same across countries, including across countries with different levels of development.

[8] There is a larger literature covering the automation effects on polarization (Autor, 2019) and the relationship between automation and perceived job insecurity (Nam, 2019; Brougham and Haar, 2020).

developing countries only estimate automation risks, thus, without considering neither labor market characteristics (informality or social safety net) nor outcomes (Egana-delSol, 2021) .

Second, we contribute to the scant literature about the possible effects of Covid-19 on the labor market in a developing economy. To the best of our knowledge, there is only one contemporaneous study by Hoehn-Velasco et al. (2021) considering the case of Mexico. The literature has been focused mainly on developed countries showing significant levels of heterogeneity. Beland et al. (2020), for example, find that Covid-19 increased the unemployment rate in the US, especially among men, younger workers, Hispanics, and less-educated workers. There is evidence that distancing policies to control the pandemic have affected some sectors more than others (Goolsbee and Syverson, 2021). The closure of public spaces, such as nonessential shops, bars, or restaurants, was enforced in 30 out of 31 EU countries for an average duration of 56 days OECD 2020). Enforcement of Covid-19 policies is weaker in the context of high informality levels and weak social safety net. We provide evidence on differences in the impact of Covid-19 on developing economies, considering the distinctive characteristics such as employment informality and weaker social safety nets.

Third, our study also enlarges the literature documenting the impact of economic crises on the labor market and technology adoption (Kopytov et al., 2018). Regarding technology adoption in emerging economies, data shows that they potentially 20 years behind the developed world (see World Bank, 2016).[9] Our results that show the impact of the employment automation process does not require Chile's current level of technology adoption to be similar to the current level of technology adoption in the US. It only requires that Chilean firms anticipate the need for investment in technology capital that will substitute employment in some occupations. Nonetheless, due to the average lag in technology adoption, we claim that the technology adoption and investment and labor market adjustment observed in developed economies during the Great Recession (Kopytov et al., 2018) could be occurring in developing countries during the Covid-19 pandemic. To the best of our knowledge, thus far the incipient studies on the possible joint effects of Covid-19 and automation on the labor market have been focused, without exception, on developed countries (see Egana-delSol and Micco, 2020).

In short, based on evidence from Chile, we argue that developing economies might experience a jobless recovery in many economic sectors, especially those where automation technologies are available, and the price of technology continues to fall.

The rest of the article is organized as follows. Section II presents the data and methodology. Section III presents the main results. Finally, Section IV offers some conclusions.

2. Data and methodology

We use different sources to predict automation in Chile. First, the Chilean household survey (known by its Spanish acronym, CASEN) provides information about the occupation, age, gender, and the region of workers, as well as other relevant characteristics. Specifically, each person in Chile who works is associated with an International Standard Classification of Occupations (ISCO-88) occupation code. Then, we use Autor et al. (2003) and Frey and Osborne (2017) to predict the automation score of an occupation. Moreover, for robustness, we use recently developed index by Webb (2019). Additionally, we use Chile's National Employment Survey (known by its Spanish acronym, ENE), which provides employment information at an individual level for the period between January 2018 and March 2021, observing the sector, occupation, and age of workers in a representative sample of the Chilean labor market on a monthly basis. Finally, we use the Monthly Economic Activity Index (IMACEC) generated by the Central Bank of Chile to control for sector economic activity.[10]

We use a set of proxies to calculate the occupation risk of automation, borrowing the method used by Autor et al. (2003) to classify 795 occupations according to the number of routine and nonroutine tasks performed in 2010. The model developed by Autor et al. (2003) suggests that routine tasks, both cognitive and manual, are prone to automation. By contrast, nonroutine cognitive, analytic, interpersonal, manual and physical, or manual interpersonal tasks are more challenging to automate. For instance, a machine operator is an occupation with a high risk of automation, while the positions of director or manager are occupations with a low risk of automation. We constructed an automation risk measure as follows:

$$PROB_o^{Autor} = \sum_{\tau \in routine} T_\tau^o - \sum_{\tau \in Nonroutine} T_\tau^o$$

where T_τ^o denotes the index for task τ in occupation o. Each task is normalized to have mean 0 and standard deviation 1. Tasks are defined as routine cognitive, routine manual, nonroutine cognitive analytic, nonroutine interpersonal, nonroutine manual physical, and nonroutine manual interpersonal.

Frey and Osborne (2017) extend the task model proposed by Autor et al. (2003) to identify OaRA, and claim that computerization can be extended to any nonroutine task that is not subject to any engineering bottlenecks with respect to computerization. They sort the main bottlenecks for automation into three task categories: perception and manipulation tasks, creative intelligence tasks, and social intelligence tasks, using Bureau of Labor Statistics (BLS) data as well as expert opinion from machine learning (ML) researchers to develop a methodology to estimate the probability of computerization. Using an econometric method, they assign the risk of automation (FO PROB) and a risk index equal to 1 when FO PROB is equal to or higher than 0.7 to 702 occupations. We use an extended version of this index, which covers 795 occupations.[11]

For robustness, we use the index recently developed by Webb (2019), who uses patent data to show which occupations are more exposed to robotics and new technologies, such as software and artificial intelligence, and the text of patents to identify what the technology can do. Webb (2019) does not choose a threshold to classify occupations as high risk. Nevertheless, we decided to classify occupations as high risk when the result for a particular occupation is higher than the mean plus one standard deviation.[12]

We use an index developed by Beland et al. (2020) that provide information about the possible direct impacts of Covid-19 on occupations. Beland et al. (2020) use the American Community Survey (ACS) and O*NET data to classify occupations into physical proximity to other people. We also use an index developed by Dingel and Neiman (2020) that classify the feasibility of working at home for all occupations using O*NET data.

We merge the Frey and Osborne (2017); Autor et al. (2003); Webb (2019) and Beland et al. (2020) indices with the 2017 Chilean household survey using an occupation classification crosswalk between SOC2010 and 4-digit ISCO-88 occupations.[13] We compute the weighted average of these indices for each of the 188 synthetic groups defined by the one-digit ISCO-88 occupation classification and one-digit ISIC Rev.3 sector classification.

Finally, we merge 188 weighted indices by sector and occupation into Chile's National Employment Survey. We end up with a monthly

[9] Given the fact that developing economies lag in the adoption of new technologies, the cleansing process observed in developed economies in 2008 could be occurring now in developing economies.

[10] Data available at https://www.bcentral.cl/en/area/statistics/imacec.

[11] The index was extended by Micco (2020).

[12] The mean for the Webb Index is 0.384 and one standard deviation is 0.184. Thus, an occupation with an index higher than 0.568 is classified as having a high risk of automation.

[13] Following Egana-delSol (2021), whenever there are multiple occupations we create a weight, which is calculated as the inverse number of duplicate matches.

Table 1
Summary statistics.

Variable	Obs.	Mean	Std. dev	Min	Max
FO RISK	2348	0.53	0.33	0.00	1.00
FO Probability	2348	0.63	0.27	0.04	0.94
Rout.Task.Index 2021	2340	0.13	2.48	−5.84	3.81
Rout.Task.Index 2000	2348	0.08	2.44	−5.95	4.59
Co-worker proximity	2340	−0.22	0.58	−1.58	1.66
Posibility Rem Work	2340	−0.12	0.72	−0.83	1.20
Sex Household Survey (Man=1)	2401	1.34	0.26	1.00	2.00
Total Emp.	2401	26,378	50,659	20	482,693
Women	2401	9732	25,021	0	291,215
Men	2401	16,646	32,044	0	241,963
Survey Obs.	2401	115	244	1	2449

Note: Estimation calculated using Autor et al. (2003), Frey & Osborne (2017), Webb (2019), and Beland et al. (2020). Gender and Employment from Chile's monthly employment survey (ENE). The variable "Surveys Obs." shows the number of observations used to calculate the information per group.

Table 2
Automation indices by economic activity.

	Autor et al.		Frey and Osborne		Webb	
	Index	Share high risk	Index	Share high risk	Index	Share high risk
Agriculture and Fishing	0,78	0,68	0,85	0,83	0,73	0,72
Mining	0,38	0,31	0,55	0,33	0,27	0,33
Manufacture	0,62	0,60	0,69	0,62	0,23	0,03
Water/Electricity	0,43	0,33	0,56	0,43	0,21	0,03
Construction	0,64	0,66	0,67	0,66	0,26	0,09
Commerce	0,61	0,57	0,70	0,64	0,18	0,02
Transport	0,24	0,19	0,55	0,27	0,26	0,14
Hotel/Restaurant	0,41	0,34	0,68	0,39	0,18	0,01
Finance	0,49	0,36	0,51	0,22	0,11	0,01
Real Estate	0,43	0,25	0,55	0,30	0,21	0,05
Public Administration	0,33	0,20	0,46	0,27	0,15	0,01
Education	0,16	0,05	0,25	0,08	0,14	0,01
Social Services	0,30	0,14	0,38	0,20	0,14	0,01
Other Services	0,49	0,42	0,52	0,26	0,19	0,02
Domestic Services	0,75	0,79	0,70	0,81	0,69	0,68

Note: Estimation calculated using Autor et al. (2003), Frey & Osborne (2017) and Webb (2019) with CASEN (2017). Productive Sectors classified by CASEN (2017) based on isco-88.

dataset for 188 synthetic groups. Table 1 presents the summary statistics of these variables.

Table 2 shows the predicted automation by economic activity. The economic activities that have a relatively lower risk of automation are teaching, social and health services, hotels, restaurants, public services, and the retail sector. These are all sectors that share the characteristic of needing a physical presence in the delivery of the services, and the necessity to perform tasks or have skills that are hard to automate, also known as "automation bottlenecks," such as perception and manipulation, persuasion, and empathy (Frey and Osborne, 2017). The construction, mining, domestic service (i.e., cleaning and cooking in private homes), agriculture, farming, and silviculture sectors have a high likelihood of automation. Some of these activities have been greatly affected by the pandemic (e.g., construction, domestic service, and, most recently, mining). And these are the type of sectors for which we may expect a significant acceleration in new technology adoption. Nonetheless, please note that these results are irrespective of the Covid-19 pandemic.[14]

Fig. 2 presents the situation when considering the economic sector as a unit of interest. Considering both the automation risk and the remote work index, we observe that manufacturing, construction, hotel and restaurant, and fishing are located in the lower right side of the graph, which indicates high automation risk and low remote work capability. In addition, we can consider the index of proximity to Covid-19 of each sector: construction is in the 4th quartile (i.e., the highest exposure), domestic services in the 3rd quartile, and manufacture, and transport are located in the 2nd quartile, indicating that if the pandemic takes longer than expected to wane these sectors will face greater impediment and complexity to return to "normal." This may generate an extra level of pressure to intensify the use of labor-saving technologies in the short term. On the other hand, finance, education, and public administration have a low risk of automation and a high possibility of remote work. These results are consistent overall with recent evidence from the US (Papanikolaou and Schmidt, 2020).

3. Results

In this section, we report our main results. We first present regressions in employment level and then in growth rate.

3.1. Results in employment levels

In our first set of results, we regress the level of employment on the automation index interacted by time dummies (year-quarter). We run a panel data fixed-effect model where the panel variable is the group "i" defined by sector, age, and occupation defined as a two-digit ISOC-88 occupation classification. We also include time dummies. We estimate weighted least square regression. We use as weight the number of observations used to calculate the group automation risk index in the CASEN 2017 dataset.

$$\ln Emp_{it} = \alpha_i + \alpha_t + \sum_t \beta_t^R\ D_t\ x\ RISK_i + \beta^C\ D_{Cov}\ x\ \mathrm{CovIndex}_i^C\ + \gamma Z_{it} + \epsilon_{it} \tag{1}$$

where $lnEmp_{it}$ is the level of employment of the group "i" in year-month "t". α_i and α_t are group and time fixed effects. $RISKj$ and $CovIndex_i^c$ are proxies for the risk of automation indices and Covid-19 indices. D_{Cov} is a dummy variable equal to 1 for the 2nd and 3rd quarter of 2020. β_t^R captures the evolution of employment as a function of the share of jobs in the group at risk of automation in 2017. Z_{it} is a control for sector (ln) activity. Finally, ϵ_{it} is an error term. We also control for sector (ln) activity

Table 3 shows coefficients for model specified in Eq. (1) imposing only two periods: the pre-Covid-19 period and the Covid-19 period. All regressions use Frey and Osborne's risk index of automation (FO RISK Index) to compute the OaRA of the groups, but Column (6) uses the routine task index from Autor et al. (2003)

Column (1) shows that a group with one standard deviation higher FO RISK Index presents a 6% greater fall in employment during the Covid-19 period. The employment fall in groups with a higher share of women is also greater, although this difference is not statistically significant at standard levels.

Covid-19 hits the sectors of economic activity in different ways. Column (2) controls for (ln) sector activity and the health sector in the economy. Even though the aggregate activity falls, Covid-19 implies a large demand for health services. The sector output coefficient (0.61) has the expected positive sign and is highly significant, and it means a labor-output elasticity of 0.6. Employment in the health sector increases during the Covid-19 period by 10% in comparison to the other economic sectors. Our coefficient of interest, the FO RISK index during the Covid-19 period, does not vary significantly. To control Covid-19, Chile has imposed social distancing. This measure should mainly affect the hotel and restaurant sector. In fact, Column (3) does not include the hotel and

[14] To compute averages we use employment data from the 2017 Chilean household survey.

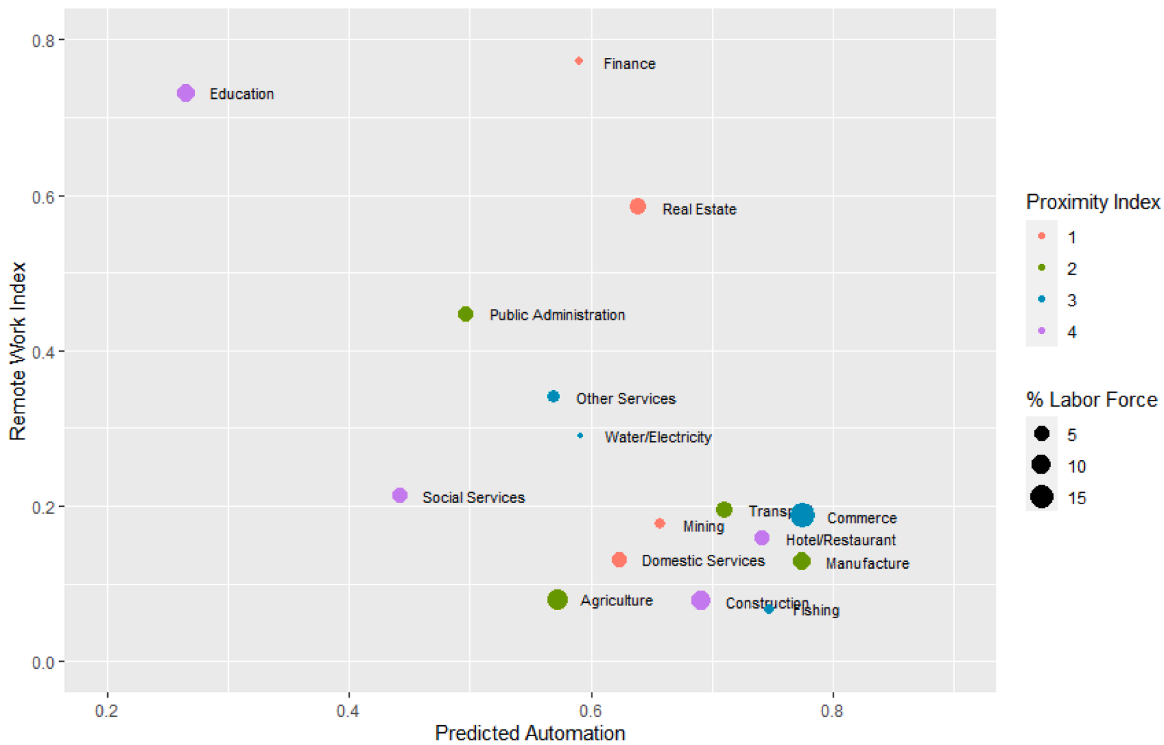

Fig. 2. Predicted Automation, Remote Work, and Proximity by Economic Sector. Note: Each circle represents a sector. The size of each circle represents the Labor Force calculated with CASEN (2017). The x-axis plots the predicted automation of each sector estimated using Autor et al. (2003). The farther to the right, the more probability to be automated. The y-axis plots the remote work index built by Dingel and Neiman (2020). Farther 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. Results are similar if we use either Frey and Osborne (2017).

Table 3
(ln) Total employment and risk of automation.

Prxy Aut.Risk	(ln) Total Emp. (1) FO RISK	(2) FO RISK	(3) FO RISK	(4) FO RISK^{+}	(5) FO RISK	(6) Rout.Task.Ind.	(7) FO RISK	(8) FO RISK
Aut.Risk x D.COVID19	−0.053	−0.057	−0.051	−0.057	−0.024	−0.046	−0.057	−0.043
	(0.013)***	(0.013)***	(0.013)***	(0.012)***	(0.021)	(0.012)***	(0.012)***	(0.012)***
Women (=2) x D.COVID19	−0.033	−0.022	0.007	−0.023	0.109	−0.027	−0.028	−0.055
	(0.039)	(0.037)	(0.036)	(0.035)	(0.080)	(0.038)	(0.043)	(0.042)
(ln) Sector Act.		0.610	0.447	0.570	0.715	0.590	0.612	0.600
		(0.077)***	(0.082)***	(0.105)***	(0.138)***	(0.080)***	(0.077)***	(0.076)***
Health Sector x D.COVID19		0.099	0.075	0.098	0.053	0.134	0.096	0.122
		(0.048)**	(0.046)	(0.049)**	(0.083)	(0.048)***	(0.048)**	(0.050)**
D.COVID19	−0.040	−0.020	−0.060		−0.200	−0.021	−0.008	0.031
	(0.056)	(0.052)	(0.050)		(0.114)*	(0.052)	(0.061)	(0.059)
Coworker Prox. x D.COVID19							−0.009	
							(0.023)	
Remote Work x D.COVID19								0.0034
								(0.016)**
Fixed Effect	Group	Group	Group	Group & time	Group	Group	Group	Group
Sectors	All	All	w/o Hotel &Rest.	All	All	All	All	All
N	2347	2297	2181	2297	2297	2289	2289	2289

Note: All regressions include group (188 synthetic groups defined by sector -one digit ISIC rev3- and occupation -ISCO88-) fixed effect, (ln) Sector Monthly Economic Activity Index (IMACEC), and the interaction of the Health Service Sector and the Covid-19 Dummy.

restaurant sector. The coefficient for (ln) economic activity falls by 27%, but it remains significant at standard levels. The point estimate for OaRA falls by 10% but the difference is not statistically significant.

Column (4) redoes Column (2) using time dummies instead of the Covid-19 period dummy. Results do not change. Column (5) redoes Column (2) using unweighted ordinary least squares (OLS). Unsurprisingly, the risk coefficient is estimated with a lower precision, although its level is in the same range. In an unreported model, we estimate Column (4) using quantile regression: here the risk coefficient is 0.54 and it is statistically significant at the standard level (1%). These results

Table 4
(ln) Total, relative wages, formal, and informal employment, risk of automation.

Prxy Aut.Risk	(ln) Total Emp. (1) FO RISK	(2) FO RISK	(3) FO RISK	(4) FO RISK	(5) FO RISK	(6) FO RISK
Aut.Risk x D.COVID19	−0.057	−0.069	−0.060	−0.045	−0.150	0.051
	(0.023)**	(0.014)***	(0.030)**	(0.012)***	(0.032)***	(0.036)
Health Sector x D.COVID19	0.051	−0.102	−0.023	−0.014	−0.113	0.070
	(0.055)	(0.047)**	(0.039)	(0.039)	(0.113)	(0.182)
(ln) Sector Act.	0.686	0.492	0.612	0.516	0.997	0.611
	(0.111)***	(0.101)***	(0.079)***	(0.075)***	(0.200)***	(0.215)***
D.COVID19	0.070	0.140	0.096	0.125	−0.120	−0.027
	(0.062)	(0.061)**	(0.059)	(0.045)***	(0.134)	(0.163)
Model	OLS	OLS	IV	OLS	OLS	OLS
Fixed Effect	Group	Grioup	Group	Group	Group	Group
Sample	Low Wage	High Wage	All	Formal	Informal	All
	Dependant	Dependant	Dependant	Dependant	Dependant	Self. Emp
Emp. 2020M12	2690,285	2026,869	4717,155	4025,935	691,220	1471,003
Obs.	1131	1158	2289	2266	1851	1499

Notes: Column (1) use only groups in which the average Chile's wage relative to the USA is below the median value across all groups. Column (2) use only groups in which the average Chile's wage relative to the USA is above the median value across all groups.

Table 5
(ln) Female and male employment and risk of automation.

Prxy Aut.Risk	(ln) Women (1) FO RISK	(ln) Men (2) FO RISK	(ln) Women (3a) FO RISK	(ln) Men (3b) FO RISK	(ln) Women (4a) FO RISK	(ln) Men (4b) FO RISK	(ln) Women (5) Rout.Task.Ind.	(ln) Men (6) Rout.Task.Ind.
Aut.Risk x D.COVID19	−0.080	−0.063	−0.068	−0.068	−0.066	−0.077	−0.057	−0.043
	(0.024)***	(0.013)***	(0.010)***	(0.010)***	(0.021)***	(0.018)***	(0.020)***	(0.013)***
Health Sector x D.COVID19	0.796	0.474	0.544	0.544	0.544	0.544	0.763	0.449
	(0.195)***	(0.097)***	(0 0.068)***	(0 0.068)***	(0.068)***	(0.068)***	(0.193)***	(0.103)***
(ln) Sector Act.	0.033	0.214	0.218	0.031	0.222	0.016	0.085	0.257
	(0.056)	(0.099)**	(0.054)***	(0.093)	(0.054)***	(0.093)	(0.052)*	(0.099)***
D.COVID19	−0.020	−0.038	−0.032	−0.039	−0.034	−0.034	−0.035	−0.050
	(0.033)	(0.013)***	(0.012)***	(0.019)**	(0.011)***	(0.011)***	(0.033)	(0.014)***
Model	OLS	OLS	Zellner's SUR		Zellner's SUR		OLS	OLS
Fixed Effect	Group	Group	Group		Group		Group	Group
Obs.	1986	2255	1951		1951		1986	2247

Note: All regressions include group (188 synthetic groups defined by sector -one digit ISIC rev3- and occupation -ISCO88-) fixed effect. Column (3a) and (3b) are estimated using seemingly unrelated regression equations.

reinforce the importance of controlling for precision when we compute our automation risk index. Column (6) uses the routine task index from Autor et al. (2003) to proxy for automation risk. Results are similar to the ones in Column (2).

The last two columns in Table 3 control for coworker proximity from Beland et al. (2020) and the possibility of doing remote work proxies from Dingel and Neiman (2020). Coworker proximity implies a higher level of Covid-19 contagion. Therefore, there is a higher probability that the worker does not attend work because of fear of contagion. The coefficient is negative, as expected, but not statistically significant. For the possibility of doing remote work the estimated coefficient is 0.03.

Table A5 reports results for Table 3 using the routine task index from Autor et al. (2003) instead of the FO RISK index. Results hold. The appendix also presents some results using the Webb (2019) index (Table A6).

Table 4 replicates the estimations on Table 3 with different worker groups to analyze different hypotheses. First, column (4) shows that the risk coefficient for formal employees is −0.045 and is statistically significant at the standard level (1%). The effect increases 200% in the case of informal workers. Column (5) considers only self-employed workers; the coefficient is positive but is not significant. Furthermore, columns (1) and (2) separate groups in which the average wage in Chile relative to the US is below or above the median value across all groups. These estimations show that employment fall in OaRA is lower in cases where the relative wage in Chile is lower than the relative wage in the US. This could mean that the incentive to adopt new technology is lower because labor is relatively cheaper, which is consistent with the economic intuition posited in referee's question. However, the difference between both coefficients is not statistically significant at standard levels (Columns 1 and 2).

Finally, Table A7 adds the proximity index to these specifications finding that for lower-income workers the degree of at-work physical proximity is less relevant than for higher-income workers. This suggests that lower-income workers had to go out to work more compared to higher-income workers during the Covid-19 period.

This could mean that the incentive to adopt new technology is lower because labor is relatively cheaper, which is consistent with the economic intuition posited in referee's question. However, the difference between both coefficients is not statistically significant at standard levels.

Previous studies have claimed that women should be more affected because childcare supply falls drastically during a pandemic (Alon et al., 2020; del Boca et al., 2020). In Table 5, we split female and male employment. Columns (1) and (2) present the estimated coefficients for female and male workers. The estimated coefficients for OaRA and (ln) sector activity suggest that the pandemic affects similarly women and men. Columns (3) and (4) redo the previous two models imposing that

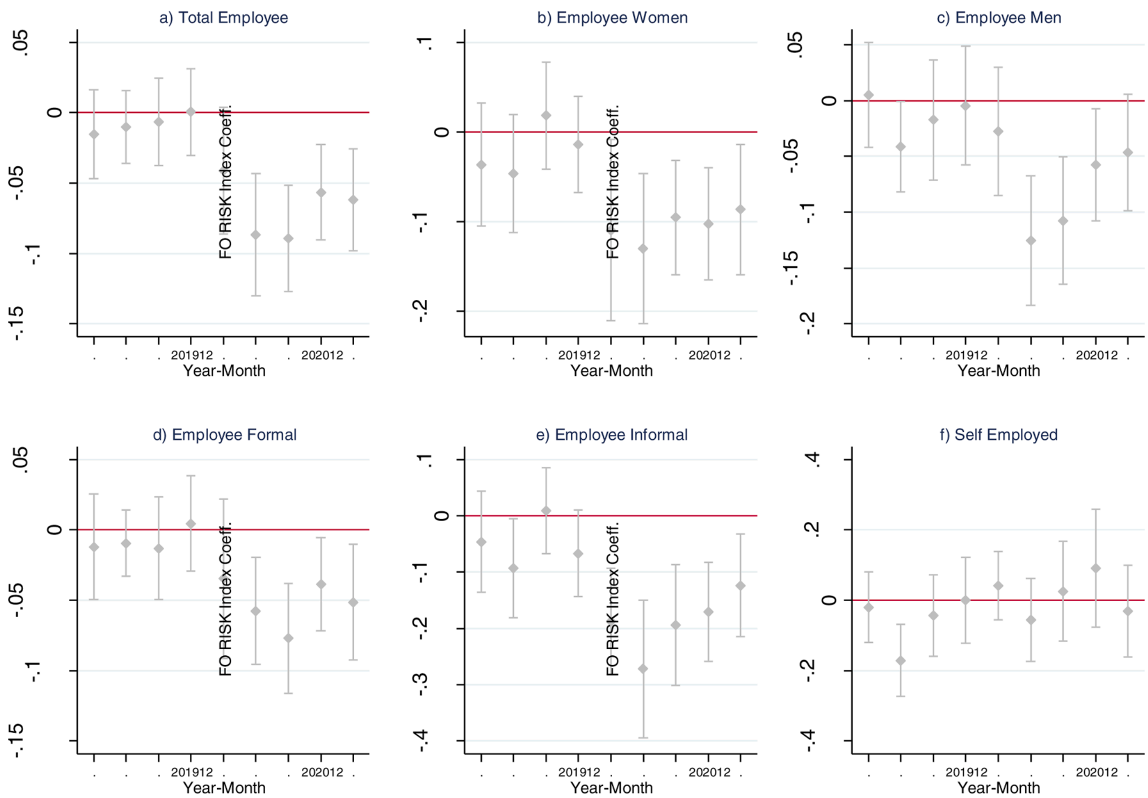

Fig. 3. Employment, Covid-19, and Risk of Automation. Note: Estimated year OaRA index coefficients from Table 3. All regressions include group, time and Quarter-Risk dummy (this set of 4 dummies controls for specific seasonality of sector with different share of occupation with risk of automation. Groups are defined by sectors at 1 digit SITC and 1 digit ISCO88.

Table 6
(Ln) Total employment and automation risk by year-quarter.

Prxy Aut.Risk	(ln) Emp. (1) FO RISK	(ln) Women (2) FO RISK	(ln) Men (3) FO RISK	(ln) Emp. (4) FO RISK	(ln) Emp. (5) FO RISK	(ln) Emp. (6) FO RISK
Women (=2)	−0.014					
	(0.034)					
Health Sector x D.COVID19	0.117	0.071	0.239	0.135	−0.075	−0.065
	(0.044)***	(0.104)	(0.056)***	(0.047)***	(0.134)	(0.176)
(ln) Sector Act.	0.671	1.075	0.491	0.558	0.988	0.616
	(0.074)***	(0.179)***	(0.097)***	(0.079)***	(0.226)***	(0.293)**
Aut.Risk 2019Qrt1	−0.016	−0.036	0.005	−0.012	−0.046	−0.020
	(0.017)	(0.042)	(0.023)	(0.019)	(0.053)	(0.068)
Aut.Risk 2019Qrt2	−0.010	−0.046	−0.042	−0.009	−0.093	−0.172
	(0.017)	(0.042)	(0.023)*	(0.019)	(0.054)*	(0.069)**
Aut.Risk 2019Qrt3	−0.007	0.018	−0.017	−0.013	0.009	−0.043
	(0.018)	(0.043)	(0.023)	(0.019)	(0.055)	(0.070)
Aut.Risk 2019Qrt4	0.001	−0.014	−0.005	0.005	−0.067	−0.000
	(0.018)	(0.043)	(0.023)	(0.019)	(0.054)	(0.070)
Aut.Risk 2020Qrt1	−0.041	−0.109	−0.028	−0.035	−0.187	0.042
	(0.019)**	(0.047)**	(0.025)	(0.021)*	(0.059)***	(0.078)
Aut.Risk 2020Qrt2	−0.087	−0.130	−0.126	−0.058	−0.272	−0.056
	(0.021)***	(0.051)**	(0.028)***	(0.023)**	(0.065)***	(0.085)
Aut.Risk 2020Qrt3	−0.089	−0.095	−0.108	−0.077	−0.194	0.025
	(0.021)***	(0.050)*	(0.027)***	(0.022)***	(0.064)***	(0.083)
Aut.Risk 2020Qrt4	−0.057	−0.103	−0.058	−0.039	−0.170	0.091
	(0.020)***	(0.048)**	(0.026)**	(0.021)*	(0.060)***	(0.079)
Aut.Risk 2021Qrt1	−0.062	−0.086	−0.046	−0.051	−0.124	−0.032
	(0.019)***	(0.046)*	(0.025)*	(0.020)**	(0.058)**	(0.074)
Fixed Effect	Group & Time	Group & Time	Group & Time	Group & Time	Group & Time	Group & Time
	Quarter-RISK	Quarter-RISK	Quarter-RISK	Quarter-RISK	Quarter-RISK	Quarter-RISK
Sample	All	Women	Women	Formal	Informal	All
	Employee	Employee	Employee	Employee	Employee	Self-Emp.
Obs.	2283	1927	2242	2250	1781	1412

Note: All regressions include time, group (Sector 1 digit and ISCO88) fixed effect, (ln) Monthly Economic Activity Index (IMACEC), and dummies with the interaction of "physical proximity to coworkers" and Covid-19 months. The results, using the metric of Webb (2019) working paper, are similar and are available upon request.

Table 7
Quarterly growth (IV model).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	(Δln) Total Emp.		(Δln) Total Emp.		(Δln) Women	(Δln) Men	(Δln) Total Emp.	(Δln) Women	(Δln) Men
Prox.Aut.Risk	FO RISK	FO RISK	FO RISK	FO RISK	FO RISK	FO RISK	Rout.Task.Ind.	Rout.Task.Ind.	Rout.Task.Ind.
Aut. Risk x D. COVID19	−0.042	−0.039	−0.042	−0.027	−0.053	−0.042	−0.032	−0.128	0.040
	(0.014)***	(0.014)**	(0.014)***	(0.015)*	(0.026)**	(0.015)***	(0.012)***	(0.034)***	(0.214)
Women (=2) x D. COVID19	−0.042	0.005	−0.044	−0.076			0.00		
	(0.038)	(0.036)	(0.045)	(0.043)*			(0.00)		
Health Sector x D. COVID19	0.034	0.017	0.033	0.059	−0.001	0.069	0.052	−0.289	−0.044
	(0.042)	(0.042)	(0.042)	(0.045)	(0.051)	(0.091)	(0.041)	(0.129)**	(0.172)
(ln) Sector Act.	0.221	0.166	0.221	0.218	0.151	0.183	0.159	0.464	0.592
	(0.108)**	(0.106)	(0.108)**	(0.107)**	(0.230)	(0.115)	(0.093)*	(0.215)**	(1.472)
Co-worker Prox. x D. COVID19			0.003						
			(0.025)						
Remote Work x D. COVID19				0.036					
				(0.017)**					
D.COVID19	−0.019	−0.077	−0.014	0.035	−0.072	−0.052	−0.059	−0.116	−0.152
	(0.052)	(0.052)	(0.063)	(0.060)	(0.036)**	(0.015)***	(0.012)***	(0.032)***	(0.586)
Lag (ln) Emp.	−0.760	−0.846	−0.761	−0.766	−0.637	−0.678	−0.711	−1.012	−0.386
	(0.125)***	(0.141)***	(0.127)***	(0.126)***	(0.250)**	(0.137)***	(0.099)***	(0.061)***	(2.337)
Fixed Effect	Group	Group	Group	Group	Group	Group	Group	Group	Group
Sectors	All Employee	w/o Hotel &Rest.	All Employee	All Employee	All Employee	All Employee	Formal Employee	Informal Employee	All Self-Employment
N	1880	1784	1878	1878	1535	1846	1845	1276	1047

Note: All regressions include group fixed effect. Women (Men=1 & Women=2). We instrument Lag (ln) Emp. with employment from the previous quarter. Cowoker Prox is Beland (2020) index and Remote Work is Dingel and Neiman (2020). D.COVID19 is a dummy equals to 1 in March, June and September 2020.

the coefficients for OaRA and (ln) sector activity are the same for men and women. We compute this econometric model using a seemingly unrelated regression developed by Zellner (1962). The estimated coefficient for the Covid-19 dummy is smaller for men than it is for women, although the difference is not statistically significant at the standard levels. Columns (5) and (6) impose the same coefficients for (ln) sector activity and the Covid-19 dummy and are the same for men and women. The estimated coefficients for OaRA show that the pandemic affects more women in OaRA than men in OaRA. Although the difference is not statistically significant, when we control for the (ln) sector activity and the health service sector, results do not show that the pandemic has more of an affect on women than it does on men.

Fig. 3 shows each quarterly beta-risk coefficient calculated using routine task index from Autor et al. (2003) and the FO RISK Index of automation during the period between January 2018 and March 2021 based on model describe in Eq. (1). The panels in Fig. 3 should the coefficients presented in Table 6. We control for (ln) sector activity and the health service sector. Estimated coefficients show that before the Covid-19 pandemic, employment in a group with a large share of OaRA shows no clear trend. But in March 2020, employment in these groups started to fall. Using the routine task index from Autor et al. (2003), the results show a group with one standard deviation above the mean would experience a 9 pp fall in their employment in the 2nd quarter of 2020, and 7 pp in the 3rd quarter of 2020. This difference is statistically significant at the 1% level. We find a similar result using FO RISK index instead of the routine task index.

Fig. 3 also shows that estimated coefficients for men are more stable than they are for women. For women, risk coefficients oscillate between 0 and −0.2. When we compare panels (c) and (e), and (d) and (f), we can observe that employment levels for both women and men have been similarly affected by Covid-19. Female employment in groups with more jobs in OaRA decreased between 5 pp and 10 pp between September 2019 and March 2021. Male employment also fell 10 pp during the same period.

3.2. Results in employment in differences

For robustness, we report the second set of results using a growth model. We regress the quarterly employment rate of growth on the automation index before and during the pandemic period (the year 2020).

$$\Delta \ln Emp_{it} = \mathrm{B}^{Cov\,x\,R} D^{Cov} x RISK_i + \sum_{C} \beta^{Cov\,x\,C} D^{Cov} x \mathrm{CovIndex}_i^C + \gamma Z_{it} + \gamma \ln Emp_{it-1} + D^{Cov} + D^i + \in_{it} \tag{3}$$

$\Delta \ln Emp_{it}$ is the quarter (ln) change in employment in the group "i". D^{Cov} is a dummy variable equal to one for 2020. D^i is the dummy variable for each group. $\ln Emp_{it-1}$ is the lag (ln) employment level in "t-1″ instrumented by the (ln) employment in "t-2″. $\mathrm{CovIndex}_i^C$ control for the health service sector, coworker proximity, and the possibility of doing remote work during the pandemic period (Beland et al., 2020). Z_{it} accounts for (ln) sector activity. Finally, $\mathrm{B}^{Cov\,x\,R}$ are our coefficients of interest that account for the risk of automation, and $\beta^{Cov\,x\,C}$ health sector Beland indices during the Covid-19 period.

Table 7 reports the results in differences for the period from the 1st quarter of 2018 to the first quarter of 2021. Columns (1) to (6) use FO RISK Index to proxy for OaRA, and the rest use the routine task index from Autor et al. (2013). Column (1) shows that employment in a group with one standard deviation more OaRA jobs decreased their employment quarterly growth rate by 4.2 pp during the Covid-19 period, and the result is significant at the 1% level. Column (2) excludes the hotel and restaurant sector and shows that this fall is not driven by employment in this particular sector. The pandemic affects employment more in groups with a higher share of women and higher share of health sector workers, although this difference is not significant. The results are similar with or without controlling for Beland indices related to coworker proximity and the possibility of doing remote work. Both coefficients have the expected sign, although they are not significant at the standard levels.

Columns (5) and (6) redo the econometric exercise in Column (1) for female and male employees. As in our results in the model in levels, estimated coefficients suggest that women lost more jobs in OaRA than men, although the difference is not significant. The last three columns redo Column (1) for total employment for male and female workers using the routine task index from Autor et al. (2003) instead of FO RISK Index. We obtain very similar results.

4. Conclusion

We chose Chile and the Covid-19 pandemic shock to analyze the impact of the global process of automation on employment in a developing economy. This is particularly interesting because developing economies characteristics, such as having larger informal sectors and weaker social safety nets, shapes the impact of automation on labor markets.

We find that employment in a synthetic group with one standard deviation higher share of employment in OaRA than average fell around 7 pp more during the first semester of 2021 (i.e., during the pandemic). This is the first empirical validation of the frequently used automation risk indices (i.e., from Frey and Osborne (2017) and Autor et al. (2003)) on developing economies because we show that the employment rate has fallen faster in OaRA during the pandemic, as would be expected.

Our results show that the effect on informal employees is three times larger in comparison with formal employees. For informal employees we can expect that the effects will be larger because the termination costs for these workers are lower (severance payments, which can be up to one-year salary, are not applicable for workers without contacts, for example). Replacing workers that do not have contracts with technology is therefore cheaper.

Our results for self-employed workers is not statistically significant. One explanation for the self-employed worker result could be that automation and Covid-19 as accelerators of technological transformation has no effect on their employment circumstances because they are likely to be undertaking activities that are harder to automate and their activities do not involve tasks that fall within a particular production process, such as delivery or low-skilled services. Furthermore, self-employed workers are only likely to invest in technologies that are complementary to the specific task they undertake

Our null results for self-employed workers is also consistent with the facts of having relatively lower wages and weak social safety net in developing economies. Self-employed workers must continue working however of the pandemic-related restrictions. We reassure the impact of weak social safety net in our context by estimating the effects on workers whose average wage in Chile relative to the US is below or above the median value across all synthetic groups in our sample.

Consistent with our results for self-employed workers, we find that employees in sector with relatively low compared to high wages, both vis-à-vis the US, exhibit a 20% smaller reaction on employment due to the pandemic restrictions, although this estimated difference is noisy.

Furthermore, our results on relative wages of Chile compared to the US is coherent with the idea that firms have more incentive to adopt automation technologies in sectors in which labor is relatively more expensive in Chile relative to the US.

After controlling for OaRA, employment in the health service, and by sector of economic activity, there is no significant difference in the impact on employment between male and female workers.

In addition, we do not find evidence that employment is negatively related to the degree of at-work physical proximity, but we do find a positive relationship related to the capacity of working remotely.

Our results contribute to an understanding of why some sectors and occupations are more affected than others by the Covid-19 pandemic and, therefore, to the design of sound economic policies to deal with both the short-term and medium-term impacts of the Covid-19 pandemic in emerging markets.

Finally, in terms of fruitful areas for further research, a study of the role of financial markets in the process of technology adoption and its impact on labor markets would certainly be useful to advance the literature.

CRediT authorship contribution statement

Pablo Egana-delSol: Conceptualization, Funding Acquisition, Writing original draft; **Gabriel Cruz:** Investigation, Empirical work; **Alejandro Micco:** Conceptualization, Methodology.

Appendix

Fig. A1
Table A1, A2, A3, A4, A5, A6 and A7

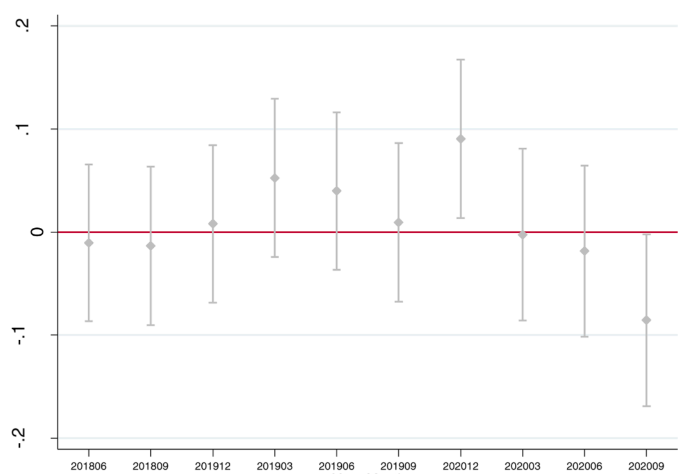

Fig. A1. Employment and Pct. Robots and Software (Webb 2019). Note: Estimated coefficients for Column (1) in Table (5) using Webb (2019) exposures to robot and software indices instead of FO RISK index.

Table A1
Correlation between ONET indices (2000 and 2020) and Frey and Osborne (2017) indices.

	ONET 2000	ONET 2020	FO Prob
ONET 2000	1		
ONET 2020	0.8881*	1	
FO Prob.	0.6990*	0.7261*	1

Note: * $p < 0.05$.

Table A2
Total, formal and informal (ln) employment and routine task index using 2021 index.

Proxy Aut.Risk	(ln) Emp. (1) Rout.Task	(2) Rout.Task	(3) Rout.Task	(4) Rout.Task	(5) Rout.Task	(6) Rout.Task	(7) Rout.Task
Aut.Risk x D.COVID19	−0.046	−0.036	−0.047	−0.023	−0.036	−0.120	0.014
	(0.012)***	(0.012)***	(0.011)***	(0.013)*	(0.011)***	(0.033)***	(0.046)
Women (=2) x D.COVID19	−0.027	0.006	−0.023	−0.073	−0.018	−0.126	0.053
	(0.038)	(0.037)	(0.041)	(0.043)*	(0.041)	(0.115)	(0.200)
(ln) Sector Act.	0.590	0.430	0.588	0.581	0.500	0.942	0.640
	(0.080)***	(0.086)***	(0.079)***	(0.077)***	(0.077)***	(0.203)***	(0.212)***
Health Sector x D.COVID19	0.134	0.110	0.135	0.159	0.152	−0.027	−0.080
	(0.048)***	(0.046)**	(0.048)***	(0.051)***	(0.045)***	(0.134)	(0.153)
D.COVID19	−0.021	−0.068	−0.028	0.052	−0.020	0.104	−0.285
	(0.052)	(0.051)	(0.057)	(0.059)	(0.056)	(0.165)	(0.265)
Coworker Prox. x D.COVID19		−0.007					
		(0.023)					
Remote Work x D.COVID19			0.053				
			(0.018)***				
Fixed Effect	Group	Group	Group	Group & time	Group	Group	Group
Sample	All	w/o Hotel &Rest.	All	All	Formal	Informal	All
	Employee	Employee	Employee	Employee	Employee	Employee	Self.Emp.
N	2289	2173	2289	2289	2258	1851	1499

Table A3
Total, formal and informal (ln) employment and routine task index using 2000 index.

Proxy Aut.Risk	(ln) Emp. (1) R.Task 2000	(2) R.Task 2000	(3) R.Task 2000	(4) R.Task 2000	(5) R.Task 2000	(6) R.Task 2000	(7) R.Task 2000
Aut.Risk x D.COVID19	−0.040	−0.032	−0.043	−0.019	−0.034	−0.105	0.011
	(0.012)***	(0.012)***	(0.011)***	(0.013)*	(0.011)***	(0.033)***	(0.051)
Women (=2) x D.COVID19	−0.041	−0.005	−0.036	−0.085	−0.032	−0.159	0.056
	(0.040)	(0.040)	(0.042)	(0.043)**	(0.043)	(0.120)	(0.217)
(ln) Sector Act.	0.587	0.424	0.585	0.579	0.498	0.934	0.641
	(0.082)***	(0.087)***	(0.080)***	(0.077)***	(0.078)***	(0.208)***	(0.213)***
Health Sector x D.COVID19	0.147	0.119	0.149	0.167	0.162	0.007	−0.084
	(0.049)***	(0.047)**	(0.049)***	(0.052)***	(0.045)***	(0.134)	(0.153)
D.COVID19	−0.005	−0.056	−0.013	0.069	−0.004	0.142	−0.288
	(0.054)	(0.054)	(0.059)	(0.060)	(0.058)	(0.171)	(0.289)
Coworker Prox. x D.COVID19		−0.010					
		(0.024)					
Remote Work x D.COVID19			0.059				
			(0.017)***				
Fixed Effect	Group	Group	Group	Group & time	Group	Group	Group
Sample	All	w/o Hotel &Rest.	All	All	Formal	Informal	All
	Employee	Employee	Employee	Employee	Employee	Employee	Self.Emp.
N	2297	2181	2289	2289	2266	1851	1499

Table A4
Correlations between PIACC Chile and PIACC US.

		Chile Numeracy	Literacy	Technology	Organization	Learning	Physical
USA	Numeracy	**0.5792***	0.128	0.5782*	0.4850*	0.4721*	−0.2851*
	Literacy	0.5022*	**0.2471***	0.4454*	0.4409*	0.2960*	−0.2583*
	Technology	0.6093*	0.1661*	**0.7757***	0.5228*	0.5484*	−0.4014*
	Organization	0.4752*	0.0855	0.3270*	**0.3040***	0.4505*	−0.0650
	Learning	0.4777*	0.0987	0.4322*	0.3946*	**0.5236***	−0.2822*
	Physical	−0.2335*	−0.1977*	−0.5692*	−0.2992*	−0.3464*	**0.4175***

Note: * $p < 0.05$.

Table A5
Robustness results using Autor et al. (2003) Routine task index.

Prxy Aut.Risk	(ln) Total Emp. (1) Rout.Task.Ind.	(2) Rout.Task.Ind.	(3) Rout.Task.Ind.	(4) Rout.Task.Ind.	(5) Rout.Task.Ind.	(6) FO RISK	(7) Rout.Task.Ind.	(8) Rout.Task.Ind.
Aut.Risk x D.COVID19	−0.042	−0.044	−0.036	−0.045	−0.046	−0.058	−0.037	−0.033
	(0.015)***	(0.015)***	(0.016)**	(0.015)***	(0.024)*	(0.018)***	(0.014)***	(0.020)*
Women (=2) x D.COVID19	−0.022	−0.001	0.018	−0.009	0.076	−0.009	0.028	−0.018
	(0.055)	(0.050)	(0.050)	(0.046)	(0.099)	(0.051)	(0.050)	(0.057)
(ln) Sector Act.		0.580	0.419	0.474	0.713	0.584	0.557	0.570
		(0.100)***	(0.104)***	(0.119)***	(0.153)***	(0.095)***	(0.099)***	(0.100)***
Health Sector x D.COVID19		0.169	0.147	0.166	0.081	0.131	0.189	0.187
		(0.066)***	(0.064)**	(0.068)**	(0.106)	(0.064)**	(0.071)***	(0.071)***
D.COVID19	−0.077	−0.049	−0.086		−0.143	−0.027	−0.086	−0.025
	(0.076)	(0.067)	(0.065)		(0.143)	(0.069)	(0.068)	(0.075)
Coworker Prox. x D.COVID19							−0.044	
							(0.029)	
Remote Work x D.COVID19								0.022
								(0.025)
Fixed Effect	Group	Group	Group	Group & time	Group	Group	Group	Group
Sectors	All	All	w/o Hotel &Rest.	All	All	All	All	All
N	1983	1950	1852	1950	1950	1950	1950	1950

Note: All regressions include group (188 synthetic groups defined by sector -one digit ISIC rev3- and occupation -ISCO88-) fixed effect, (ln) Sector Monthly Economic Activity Index (IMACEC), and the interaction of the Health Service Sector and the Covid-19 Dummy.

Table A6
Robustness results using Webb (2019) indices.

Prox.Aut.Risk	(Δln) Total Emp. Exposure Robot	(Δln) Total Emp. & Softwage	(Δln) Total Emp. Exposure to Robot Webb (2019)	(Δln) Men
Aut. Risk x D. COVID19	−0.041	−0.066	−0.044	−0.062
	(0.025)*	(0.028)**	(0.019)**	(0.024)***
Women (=2) x D. COVID19	−0.133	−0.041	−0.097	0.006
	(0.091)	(0.120)	(0.064)	(0.117)
Health Sector x D. COVID19	0.156	−0.030	0.144	−0.036
	(0.072)**	(0.111)	(0.069)**	(0.110)
(ln) Sector Act.	0.218	0.376	0.219	0.373
	(0.116)*	(0.159)**	(0.112)*	(0.159)**
D.COVID19	0.071	−0.025	0.029	−0.089
	(0.117)	(0.155)	(0.083)	(0.149)
Lag (ln) Emp.	−0.853	−0.583	−0.854	−0.584
	(0.177)***	(0.430)	(0.178)***	(0.429)
Fixed Effect	Group	Group	Group	Group
Weighted	Yes	No	Yes	No
Obs.	1547	1547	1547	1547

Note: All regressions include synthetic group (defined by sector and occupation) fixed effect. We instrument Lag (ln) Emp. with employment from the previous quarter. D.COVID19 is a dummy equal to 1 in March, June, and September 2020. Weighted least squares use the number of observations in each group in the household survey as weight.

Table A7
Relative wages and proximity index.

Prxy Aut.Risk	(ln) Total Emp. (1) FO RISK	(2) FO RISK
Aut. Risk x D.COVID19	−0.049	−0.064
	(0.015)***	(0.012)***
Coworker Prox. x D.COVID19	0.039	−0.067
	(0.015)***	(0.024)***
Women (=2) x D.COVID19	0.042	−0.006
	(0.049)	(0.057)
(ln) Sector Act.	0.676	0.459
	(0.085)***	(0.081)***
Health Sector x D.COVID19	0.059	0.121
	(0.055)	(0.099)
D.COVID19	0.059	0.121
	(0.055)	(0.099)
Model	OLS	OLS
Fixed Effect	Groups	Groups
Sample	Low Wage Employee	High Wage Employee
Emp. 2020M12	2690,285	2026,869
Obs.	1131	1158

Notes: Column (1) use only groups in which the average Chile's wage relative to the USA is below the median value across all groups. Column (2) use only groups in which the average Chile's wage relative to the USA is above the median value across all groups.

References

Acemoglu, D., Restrepo, P., 2018. The race between man and machine: implications of technology for growth, factor shares, and employment. Am. Econ. Rev. 108 (6), 1488–1542.

Acemoglu, D., Restrepo, P., 2019. Automation and new tasks: how technology displaces and reinstates labor. J. Econ. Perspect. 33 (2), 3–30.

Alon, T.M., Doepke, M., Olmstead-Rumsey, J., Tertilt, M., 2020. The Impact of COVID-19 On Gender Equality (No. w26947). National Bureau of economic research.

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 an Estimation of Its Fatality Rate (No. w26965). National Bureau of Economic Research.

Autor, D.H., Handel, M.J., 2013. Putting tasks to the test: Human capital, job tasks, and wages. Journal of labor Economics 31 (S1), S59–S96.

Autor, D.H., Levy, F., Murnane, R.J., 2003. The skill content of recent technological change: an empirical exploration. Q. J. Econ. 118 (4), 1279–1333.

Autor, D., Reynolds, E., 2020. The Nature of Work After the COVID crisis: Too few Low-Wage Jobs. The Hamilton Project, Brookings.

Barrero, J.M., Bloom, N., Davis, S.J., 2020a. Covid-19 is Also a Reallocation Shock (No. w27137). National Bureau of Economic Research.

Beirne, K., Doorley, K., Regan, M., Roantree, B., & Tuda, D. (2020). The potential costs and distributional effect of Covid-19 related unemployment in Ireland. Budget Perspectives, 2021.
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.
Bello, J., Collins, S., Dreischmeier, R., Libarikian, A., 2020. Innovating From Necessity: The Business –Building Imperative in The Current Crisis. McKinsey Digital. April 16.
Brussevich, M., Dabla-Norris, M.E., Kamunge, C., Karnane, P., Khalid, S., Kochhar, M.K., 2018. *Gender, technology, and the future of work*. International Monetary Fund, Washington, DC.
Brynjolfsson, E., McAfee, A., 2014. The Second Machine age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. WW Norton & Company.
Egana-delSol, Pablo, Monserrat Bustelo, Laura Ripani, Nicolas Soler, Mariana Viollaz, Automation in Latin America: Are Women at Higher Risk of Losing Their Jobs?, Technological Forecasting and Social Change, 2021, 121333, ISSN 0040-1625.
Brougham, D., Haar, J., 2020. Technological disruption and employment: the influence on job insecurity and turnover intention: a multi-country study. Technol. Forecast. Soc. Change 161.
Caballero, R.J., Hammour, M.L., 1994. On the Time and Efficiency of Creative Destruction. National Bureau of Economic Research.
Chuah, L.L., Loayza, N., Schmillen, A., 2018. The future of work: race with—not against—the machine. Research and Policy Briefs 129680. The World Bank.
Coibion, O., Gorodnichenko, Y., Weber, M., 2020. Labor Markets During the Covid-19 crisis: A Preliminary View (No. w27017). National Bureau of Economic Research.
Del Boca, D., Oggero, N., Profeta, P., Rossi, M., 2020. Women's and 'men's work, housework and childcare, before and during COVID-19. Rev. Econ. Househ. 18 (4), 1001–1017.
Dengler, K., Britta, M, 2018. The impact of digital transformation on labour market: substitution potential of occupations in Germany. Technol. Forecast. Soc. Change 137, 304–316.
Dingel, J.I., Neiman, B., 2020. How many jobs can be done at home? J. Public Econ. 189.
Egana-delSol, Pablo, Joyce, Connor, 2020. The future of work in developing economies. Sloan Manag. Rev 3. January.
Egana-delSol, Pablo, The Future of Work in Developing economies: what can we learn from the South? (May 4, 2021). Available at SSRN: https://ssrn.com/abstract=3497197 or 10.2139/ssrn.3497197.
Egana-delSol, Pablo and Micco, Alejandro, Can COVID-19 accelerate technological transformations? (September 8, 2020). Available at SSRN: https://ssrn.com/abstract=3688690 or 10.2139/ssrn.3688690.
Frey, C.B., Osborne, M.A., 2017. The future of employment: how susceptible are jobs to computerization? Technol. Forecast. Soc. Change 114, 254–280.
Fort, Teresa C., 2017. Technology and production fragmentation: domestic versus foreign sourcing. Rev Econ Stud 84 (2), 650–687.
Goolsbee, A., Syverson, C., 2021. Fear, lockdown, and diversion: comparing drivers of pandemic economic decline 2020. J. Public Econ. 193, 104311.
Graetz, G., Michaels, G., 2018. Robots at work. Rev. Econ. Stat. 100 (5), 753–768.
Gruetzemacher, R., Paradice, D., Lee, K.B., 2020. Forecasting extreme labor displacement: a survey of AI practitioners. Technol. Forecast. Soc. Change 161, 120323.
Hoehn-Velasco, L., Silverio-Murillo, A., de la Miyar, J.R.B., 2021. The long downturn: the impact of the great lockdown on formal employment. J. Econ. Bus. 115, 105983.
Hong, S., Werner, D., 2020. US States hit the hardest by covid-19 have lower unemployment risks. Econ. Synopses (12).
Kopytov, A., Roussanov, N., Taschereau-Dumouchel, M., 2018. Short-run pain, long-run gain? Recessions and technological transformation. J. Monet. Econ. 97, 29–44.
Jaimovich, N., Siu, H., 2020. Job polarization and jobless recoveries. Rev. Econ. Stat 102 (1).
Lee, S., & Trimi, S. (2020). Convergence innovation in the digital age and in the COVID-19 pandemic crisis, J. Bus. Res., forthcoming.
Loayza, N.V., Pennings, S., 2020. Macroeconomic policy in the time of COVID-19: a primer for developing countries. Res. Policy Briefs (28). World Bank.
Meghir, C., Narita, R., Robin, J.M., 2015. Wages and informality in developing countries. Am. Econ. Rev. 105 (4), 1509–1546.
McKinsey & Company, Manyika, J, 2017. Technology, Jobs, and the Future of Work. McKinsey Insights.
Micco, A., 2020. Automation, Labor Markets, and Trade. Department of Economics Working Papers Series. University of Chile.
Micco, A., 2019. Automation in Developed Countries and Their Impact On LAC. Department of Economics Working Papers Series. University of Chile.
Nam, T., 2019. Technology usage, expected job sustainability, and perceived job insecurity. Technol. Forecast. Soc. Change 138, 155–165.
Nedelkoska, L., Quintini, G., 2018. Automation, skills use and training. OECD Social, Employment and Migration Working Paper 202.
OECD, 2020. Health At a Glance: Europe. OECD/European Union. https://doi.org/10.1787/23056088.
Papanikolaou, D., Schmidt, L.D., 2020. Working Remotely and the Supply-side Impact of Covid-19 (No. w27330). National Bureau of Economic Research.
Perry, G. (Ed.), 2007. Informality: Exit and Exclusion. World Bank Publications.
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. Res. Policy Brief (34).
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.
WorldBank, 2016. Digital Dividends. World Bank, Washington, DC. https://doi.org/10.1596/978-1-4648-0671-1. License: Creative Commons Attribution CC BY 3.0 IGO.
Zellner, A., 1962. An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. J. Am. Stat. Assoc. 57 (298), 348–368.

Pablo Egana-delSol PhD Columbia University, Professor, UAI Business School, Adolfo Ibanez University, Santiago, Chile, and Asia School of Business, Kuala Lumpur, Malasia, e International Faculty Fellow del Massachusetts Institute of Technology (MIT) Sloan School of Management, Cambridge, USA.

Gabriel Cruz MSc in Economics from the Pontificia Universidad Católica de Chile, Research Associate en Abdul Latif Jameel Poverty Action Lab (J-PAL), Santiago Chile.

Alejandro Micco, PhD Harvard University, Professor, Department of Economics, University of Chile, Santiago, Chile