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The Risk of Automation in Argentina

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Abstract

In this paper we characterize workers' vulnerability to automation in the near future in Argentina as a function of the exposure to routinization of the tasks that they perform and the potential automation of their occupation. In order to do that we combine (i) indicators of potential automatability by occupation and (ii) worker's information on occupation and other labor variables. We find that the ongoing process of automation is likely to significantly affect the structure of employment. In particular, unskilled and semi-skilled workers are likely to bear a disproportionate share of the adjustment costs. Automation will probably be a more dangerous threat for equality than for overall employment.

Keywords: jobs, employment, labor markets, income distribution, technology, automation

JEL codes: J21, J23, J24, O33

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1. Introduction

Technological change is one of the main engines of economic growth and social progress. However, technical advances typically alter the production process and hence modify the productivity and ultimately the demand for different factors. Large changes in technology are profoundly disruptive, at least in the short run.

The concerns for the social and labor impacts of the technological changes are not new: the rebellion of the *luddites* against the machines of the Industrial Revolution, and the worries of J.M. Keynes about the technological unemployment are just examples of the fears raised by technical innovations. These fears, however, proved to be largely misplaced: although in the short run machines did displace workers, productivity increased and new jobs were created, so that in the long run economic growth was strongly boosted by new technologies and unemployment did not significantly increase.

A new wave of strong technological advances seems to be under way. Automation and digitization are the new technologies that boost productivity, growth, and wealth, but also disrupt labor market's structure. The major concern is that new technologies may displace a significant share of workers out of the labor market. Will this time be different? Some argue that the nature of the new technological innovations places a much stronger threat on employment than previous "industrial revolutions". But even if overall employment is not significantly affected, it is likely that the new technologies modify the relative demands for different types of workers, affecting the structure of employment and ultimately the income distribution.

The main goal of this paper is to characterize workers' vulnerability to automation in the near future in Argentina as a function of the exposure to routinization of the tasks they perform and the potential robotization of their occupation. In order to do that we combine two different sets of data: (i) indicators of potential automatability by occupation and (ii) worker's information on occupation and other labor variables.

In particular, we rely on two different measures of risk of automation recently developed by Arntz *et al.* (2016, 2020) and Frey and Osborne (2017), along with a measure we construct with microdata of the PIACC survey carried out in Chile. These indicators of risk of automation by occupation are combined with microdata on workers drawn from the main national household survey of Argentina (EPH).

According to our preferred estimates, we find that the ongoing process of automation is not likely to make a large dent on the overall rate of employment in Argentina. Instead, it is more likely for the expected technological changes to significantly affect the *structure* of employment. In particular, unskilled and semi-skilled workers are likely to bear a disproportionate share of the adjustment costs, since the automatability of their occupations is higher compared to skilled workers. Therefore, automation will probably be a more dangerous threat for equality than for overall employment.

The rest of this paper is organized as follows. In section 2 we review the literature on automatability by occupation. In section 3 we provide details on the methodology applied and the data used to estimate the risk of automation in Argentina. The main results are presented in section 4. The paper closes in section 5 with a discussion on the interpretation of the results and some policy implications.

2. Literature review

The early literature on skill-biased technological change dates back to the works of Katz and Murphy (1992), Bound and Johnson (1992) and Card and Lemieux (2001). Following the Tinbergen's idea of the race between technology and education this literature assumes that technology is complementary with skilled labor, therefore positively affecting the relative demand and wage of skilled workers. Technological change is thus associated to an unambiguous unequalizing effect on the income distribution.

More recently, with the proliferation of automation processes in the form of digital technology and robotics, the literature that studies technology and labor markets has shifted to the task-based approach of Autor *et al*. (2003) and Acemoglu and Autor (2011). The task approach argues that the complementarity or substitutability between technology and labor does not occur at the worker category level but rather depending on how susceptible different tasks are for automation. In particular, routine tasks that follow well-defined rules can be more easily automated based on rule-based algorithms, using increasingly powerful computers. As a consequence, labor demand for routine tasks has declined. Since routine tasks are more widespread among middle-skilled, medium-wage workers, automation has led to a polarization of the labor market with declining shares of middle-wage workers. A growing literature for developed countries documents that recent technological change replaces labor routine tasks that are heavily concentrated in the middle of the skills distribution. This hypothesis is known as *job polarization* (Autor and Dorn, 2013; Goos *et al*. 2014).

Whereas the main objective of this line of research is to assess the impact of automation in the past decades, a recent strand takes a more prospective view, motivated by the acceleration in the implementation of new technologies. How many tasks or occupations might be automatable in the near future? What could be the effect on the labor market and on the income distribution? There have been a number of initiatives to estimate the capability of substituting occupations with machines in the near future. Naturally, the exercises are highly conjectural, as they imply predicting the spreading of recent technologies and the implementation of new ones. However, given the relevance of the potential economic and social impact of those changes, a new literature that estimates the risk of automation and the potential threat to jobs has recently emerged. The critical component of this body of research is how to define a job as "automatable".

So far, the most popular approach follows the study of Frey and Osborne (2017) (FO thereafter). Their empirical analysis proceeds in two steps. First, they use the 2010 version of O*NET, a database of information on the task content of 903 occupations in the US, constructed from the assessments of labor market analysts, experts and workers. The O*NET data is matched to the 702 occupations of the Labor Department's Standard Occupational Classification (SOC). Second, they assign to each occupation a probability of automation. In order to do that, they asked machine learning researchers to classify occupations into being either automatable or not, based on the reported task content.[1] In particular, they select 70 occupations whose labelling the experts were highly confident about, and then they impute the automatability to the remaining occupations based on a model of occupation's automatability on some attributes (*e.g.* manual dexterity, originality, social perceptiveness). The model returns an estimate of the automation potential: the likelihood that an occupation is technically automatable or, "strictly speaking, it is an estimate of the probability that the experts would have classified a given occupation as automatable during the workshop" (Arntz *et al*., 2020). For simplicity FO divide occupations into three groups according to the probability of automation: low-risk (less than 30%), medium-risk (30-70%) and high-risk (>70%) occupations. They report that 47% of all jobs in the US are in the high-risk category.[2]

[1] The specific question asked was: "*Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment*?"

[2] These occupations "are potentially automatable over some unspecified number of years, maybe a decade or two" (Frey and Osborne, 2017).

Service, sales and office jobs are over-represented in that category. The risk of automation is higher for low-skilled workers and for low-wage occupations, suggesting that automation could disproportionately affect these groups of workers. Several authors have replicated the FO analysis in other countries, assuming that the automatability by occupation is the same as in the US.[3] Santos *et al*. (2015) apply this approach to ten developing countries and a Chinese province. They include a simple adjustment for the fact that technologies are adopted and diffused with a time lag in the developing world. In World Bank (2016) this methodology is extended to a larger sample of developing countries.

Other authors have followed the FO approach but using different sources to assess the automation probabilities. Vermeulen *et al*. (2018) construct an expert assessment with inputs from roboticists, whereas Manyika et al. (2017) use a machine-learning algorithm to score the more than 2,000 work activities in relation to 18 performance capabilities. Josten and Lordan (2019) introduce an alternative classification of automatable occupations based on patent data from *Google Patents*. They argue that patents activity is a better proxy to identify the jobs that will be automatable in the near future. The authors take the non-automatable jobs defined by Autor and Dorn (2013) and assess the chances of becoming automatable in the near future based on patent activity in the area. Josten and Lordan (2019) find that 47% of all current jobs in the US are automatable over the next decade, an estimate similar to that of FO. The authors stress that the jobs with less risk of automation are those that involve abstract, strategic or creative thinking, with high interactions with people.

The FO approach assumes that occupations are homogeneous in terms of tasks. This is however a strong assumption, since workers of the same occupation usually conduct different tasks, and thus may be differently exposed to automation depending on the tasks performed (Autor and Handel, 2013).[4] In reaction to this concern, Arntz *et al*. (2016, 2017) follow a task-based instead of an occupation-based approach, by focusing on what people actually do in their jobs rather than relying on occupational descriptions of jobs. Information on tasks is obtained from the Programme for the International Assessment of Adult Competencies (PIAAC), a unique dataset which contains micro-level

[3] Lawrence *et al*. (2017) for England, Brzeski and Burk (2015) for Germany, Pajarinen and Rouvinen (2014) for Finland, Bowles (2014) and PWC (2018) for a group of European Countries.

[4] In fact, the evidence suggests that the recent decline in routine tasks was driven by declining shares of routine tasks within occupations instead of declining shares of routine occupations (Spitz-Oener, 2006).

indicators on socio-economic characteristics, skills, job-related information, job-tasks and competencies for a sample of countries.

Based on US observations in the PIAAC, Arntz *et al.* (2017) estimate a model of the automatability indicator of FO on workers' actual tasks, and use the predictions of this model as indicator of true automatability. A worker may have an occupation whose job description led FO to classify it as highly automatable, but if the actual tasks performed by the worker in that occupation (as reported to the PIAAC) imply less routine activities, the predicted automatability from the model will be lower. Following this approach Arntz *et al.* (2016) find that the threat to jobs is much less severe than estimated by other studies. While Frey and Osborne (2017) estimate that 47 percent of all U.S. workers are subject to a high risk of their jobs being automated over the next two decades, Arntz *et al.* (2017) reduce this estimate to 9 percent. The difference stems from the large variation of workers' tasks within occupations. In particular, many seemingly automatable jobs also include tasks for which machines are not well suited, such as problem solving or influencing decision making. Recently, other authors have applied variants of this task-based approach and found results in line to those of Arntz *et al.* (2016).[5]

3. Data and methodology

Our analysis combines workers' characteristics drawn from national household surveys with some of the automatability (or "risk of automation") indicators described above, defined at the occupation level.

Indicators of risk of automation

Our main results are based on the automatability estimations of Arntz *et al.* (2016, 2020).[6] Following the methodology described in the previous section, they compute in 20 OECD countries an automatability occupation index that reflects the share of workers in that occupation with high automation potential (higher than 70%). The information is available at the ISCO08 2-digit level. We take a weighted average of these indexes across countries, using the number of

[5] Nedelkoska and Quintini (2018) use PIAAC and find that 10% of U.S. workers are in the "high-risk" group. Pouliakas (2018) uses the European Skills and Jobs Survey (ESJS), and finds that 14% of workers in the European Union work in automatable jobs.

[6] We are very grateful to the authors for the data provided.

workers in each occupation as weights.[7] The main assumption is that this average is representative of the risk of automation in Argentina. This assumption may not be strong if technologies spread globally (even if they do it with lags) and if the structure of tasks by occupations are similar across countries. A comforting observation is that the characteristics and tasks by occupation reported in the PIAAC survey do not differ much among countries (Arntz, *et al.* 2017), even when including Chile, the only Latin American country in PIAAC, in the comparison.

According to this task-based index there is substantial heterogeneity in the degree of automatability across occupations (Figure 1). Whereas the risk of automation in the near future is negligible for teaching, health, information and communication professionals, the risk is high for clerks, machine operators, sales workers, drivers, construction workers, and food preparation assistants. Around 30% of the jobs in these groups are severely threatened of being replaced by machines.

Our second risk-of-automation index is adapted from Frey and Osborne (2017). We match the 702 occupations of the Labor Department's Standard Occupational Classification (SOC) to the ISCO08 two-digit classification using a crosswalk provided by the Bureau of Labor Statistics. Table 1 shows the risk of automation under this alternative (labeled as #2) in comparison with the previous one (labeled as #1). As discussed above, the risk of automation is higher under this approach. However, the correlation across occupations between the two alternative indices is high: the Pearson correlation is 0.707, and the Spearman rank correlation is 0.796, both highly significant.

It is important to point out that these two automatability indicators refer to what theoretically could be automated in the future, given the projections about the technology. This must not be equated with job-losses. The fact that automation is technically feasible for a task performed by some workers does not necessarily imply that all of these workers will actually be replaced by automated devices. The decision to utilize automation technologies or workers is ultimately based on economic considerations (Bosch *et al.*, 2018).[8]

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[7] The dataset for OECD countries has very few observations for the following occupations: Market-oriented Skilled Forestry; Fishery and Hunting Workers; Subsistence Farmers, Fishers, Hunters and Gatherers; Agricultural, Forestry and Fishery Labourers. We set the index of these sectors similar to the Market-oriented Skilled Agricultural Workers. Also, there were no observations for Street and Related Sales and Services Workers, so we assigned to them the mean index of related occupations: Personal Services Workers, Sales Workers, Food Preparation Assistants, Refuse Workers and Other Elementary Workers.

[8] As discussed in Arntz et al. (2020) there are three reasons that may disconnect the risk of automation from actual employment losses. "First, the utilisation of new technologies is a slow process, due to economic, legal

As an additional robustness exercise, we also compute an *ad hoc* index based on the Chilean PIACC. The index is based on the frequency within each occupation of some activities that are assumed to be harder to automatize: supervision, planning, negotiation, problem-solving and written-outputs. In particular, we compute for each worker the proportion of these five tasks that she reports performing in her job. Our measure of risk of automation in a given occupation is defined as 1 minus the mean of that proportion across workers in that occupation. For instance, an occupation where everybody reports performing those five activities difficult to automatize will have a measure of risk of automation equals to zero. In the other extreme, an occupation where nobody performs those activities will be considered fully automatable. Table 2 shows this measure for the occupations included in the Chilean PIAAC. The correlations with the other two alternatives are statistically significant and high: 0.58 with alternative 1 and 0.62 with alternative 2.

National household surveys

Information on workers' characteristics are drawn from the main national household survey in Argentina (Encuesta Permanente de Hogares, EPH). In order to gain power we combine the surveys of 10 quarters and work with a database that covers years 2016 to 2018. This allows us to have information on more than 200,000 workers. Nominal variables are deflated by the national CPI in order to make them comparable, given the high levels of inflation. Argentina uses its own system of occupation codes (The "Clasificador Nacional de Ocupaciones"). We convert these codes to the two-digit ISCO08 classification using an official crosswalk.[9]

4. Results

Given the occupation structure of workers in Argentina, the overall risk of automation for the urban areas in this country is 16% under alternative 1. This value is higher than the OECD mean computed in Arntz *et al.* (2016) (9% of automatable jobs). The value for Argentina is actually a bit higher than the maximum in the OECD countries (12% in Austria). The difference is driven by

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and societal hurdles, so that technological substitution often does not take place as expected. Second, even if new technologies are introduced, workers can adjust to changing technological endowments by switching tasks, thus preventing technological unemployment. Third, technological change also generates additional jobs through demand for new technologies and through higher competitiveness."

[9] Available at https://www.indec.gob.ar/ftp/cuadros/menusuperior/eph/CONVERSION_CNO-01_CIUO-08.xls.

an occupation structure in Argentina biased towards low-skill jobs, associated with a larger threat of automation in the near future.

The overall risk of automation is 58.9% under alternative 2. We already discussed the reasons behind the difference with alternative 1. The value for Argentina is a bit lower than the one computed for this country in World Bank (2016) with a similar methodology, and higher than the index reported for the US by Frey and Osborne (2017) (47%).

As discussed above, these figures are highly speculative. In fact, it is probably more relevant to analyze the structure of the jobs at risk more than the mean probability of automation.

Table 3 shows the proportion of jobs with high risk of automation by sector. The threat of automatability is higher in Commerce, Restaurants and Hotels, Transportation, Communications and Domestic Services, and lower in Teaching, Health and Social Services. However, there is high variability within industries, as production in each sector requires a wide range of occupations.

According to the occupation structure in Argentina, the risk of automation is slightly higher for male (16.8%) than for female (14.9%) workers (Table 4). This gender gap also holds under A2 (60.9% for males and 56.3% for women), and under our measure based on PIAAC (65.0 for men and 60.5 for women). The gender gap is more noticeable for young adults, and shrinks for older workers.

The household survey in Argentina only covers large urban areas, which do not differ much in terms of their economic and employment structures. Consequently, the mean risk of automation is similar across regions (Table 5). This result will probably be different in other more spatially heterogeneous countries, such as many of the Latin American ones.

The age pattern is interesting: the risk of automation is high for young workers and decreases until around the age of 30 when it reaches a plateau (Figure 2). Remarkably, in general this pattern also holds when using A2 and A3 to define automatability.[10] According to these results, the prospect of automation poses a special threat on the jobs of young workers. This fact adds to the concerns on the job perspectives of youngsters, a group with the highest unemployment rates in the region.

Despite the increased perspectives of computerization in some high-skill occupations, the risk of automation remains higher in low and medium-skilled jobs that involve routine-intense tasks. Figure 3 shows the results for

[10] Under A2 the risk of automation falls after age 68.

Argentina: the proportion of jobs with high risk of automation is high and almost constant for those with less than secondary education (less than 11 years of education). Around a third of workers in Argentina are in this low-skill group, for which the risk of automation is around 20%. From that point on automatability falls with years of education, almost linearly. For those in the high-skill group, with 17 or more years of formal education, the risk of automation is lower than 5%. The patterns are similar when using alternatives A2 and A3, and also consistent with those found elsewhere (Arntz *et al*. 2016).

The decreasing pattern of risk of automation by labor income is not surprising given the results by skills (Figure 4). When using A1, the threat is higher and rather constant in the first three deciles of the earnings distribution; then falls almost linearly with the income percentiles, and accelerates its fall from percentile 90 on.[11] Instead, under A2 the pattern is more stable until percentile 70, then falls slowly until percentile 90 and more strongly thereafter. When applying A3 the fall occurs more smoothly along the earnings distribution. The results are similar when using the hourly wage rather than the earnings distribution. Also, the pattern of automatability is decreasing in a measure of household rather than worker income (Figure 6). While the risk of automation is around 21% in the bottom deciles of the household income distribution, it falls to 9% in the top decile. In sum, although specific results vary across the alternative methodologies and income distributions, the main pattern remains: the risk of automation is higher for low-skill, low-earnings, poor workers.

Impact on income inequality

Assessing the impact of the risks of automation on the income distribution is a highly speculative endeavor. Even if we could estimate which workers are more likely to be directly affected by automation, it is almost impossible to estimate the general-equilibrium effects of such a major shock on the economy. Workers replaced by machines could become unemployed, or find a job in the same firm by performing a different task, or end up employed in other sector of the economy. And of course the implications could extend beyond workers initially reached by the introduction of robots and computers: the whole labor market will be affected in ways that are difficult to predict.

In this section we carry out two very simple, yet illustrative exercises. First, we compute changes in the labor income distribution assuming a

[11] Figure 5 shows automatability as a function of earnings (not earnings percentiles). The risk of automation strongly falls in the upper-tail of the earnings distribution.

proportional fall in earnings only for those workers initially affected by automation. Second, we estimate changes in the household per capita income distribution arising from the combined effect of two sources: (i) change in earnings according to the previous exercise and (ii) change in capital income after the replacement of workers by machines.

The first exercise is extremely simple. We focus on the initial partial-equilibrium effect of the technological change and assume that only earnings of workers directly affected by automation are modified. In addition, for simplicity we assume that the earnings fall is similar (in proportional terms) for all affected workers. Therefore, the wage after automation is equal to a factor β of the wage before automation. What would be the increase in earnings inequality in that simple scenario? Table 6 shows the Gini coefficient for alternative values of β.[12] The original Gini (β=1) for the period 2016-2018 in Argentina is 41.1. A reduction of 25% in wages of workers affected directly by automation (β=0.75) would increase the Gini coefficient only slightly to 41.9 (a 2% increase in inequality). Instead, if the fall is 50%, the Gini would rise to 43.6 (a 6% increase in inequality), whereas if automation drives workers to permanent unemployment (i.e. setting β=0), the Gini would dramatically increase to 50.5 (a 23% increase).

The second exercise adds the likely increase in capital income due to automation. We assume that the introduction of robots implies an increase in capital income by the amount of the wages of the displaced workers. We also consider an alternative where the increase in capital income is just 50% of the saved wages.[13] We consider three alternatives in order to assign those rents: (i) to the top percentile of the household per capita income distribution (as Koru (2019) suggests), (ii) proportional to capital income, and (iii) proportional to household per capita income. Table 7 and Figure 7 show the results. The original Gini coefficient for the household per capita income distribution is 41.3. If for instance automation reduces earnings of affected workers by 25% while the capital incomes from automation go to the top percentile, then the Gini coefficient will increase to 52.3: a dramatic jump in inequality of 26.7%. The increase is even larger if rents are distributed as the current distribution

[12] To compute the results of the table we proceed as follows. Suppose the probability of automation of a given job j is p_j and that a given person i working in that job has a sample weight in the survey of m_i. Then, we assume that $p_j.m_i$ workers similar to i are fully affected by automation while $(1-p_j).m_i$ workers similar to i are not affected at all.

[13] Notice that the amount of these rents may be independent of the reduction in earnings for the displaced workers. For instance, capitalists could obtain rents by the same amount of the replaced wages, and at the same time the displaced workers could find other jobs and ultimately may not suffer any wage loss. This is possible because automation implies an increase in overall productivity and income.

of capital income: the Gini will rise to 59.0. The increase is smaller, although still economically very substantial, if rents are just 50% of the replaced wages, or if rents are distributed as the current total income distribution (only to the skilled population or to everybody). The general conclusion from the results in Table 7 is that at least the direct partial-equilibrium effect of automation on inequality could be very sizeable, especially without some mechanism that allows distributing the proceeds of the technological advances to all the population.

5. Discussion

According to our preferred estimates, the ongoing process of automation is not likely to make a very large dent on the rate of employment in Argentina. Instead, it is more likely for the expected technological changes to significantly affect the *structure* of employment. In particular, unskilled and semi-skilled workers are likely to bear a disproportionate share of the adjustment costs, since the automatability of their occupations is higher compared to skilled workers. Therefore, automation will probably be a more serious threat for income equality than for overall employment.

The results resemble the story of skill-biased technological change (Katz and Murphy, 1992), invoked as one driving factor behind the increase in inequality in Latin American in the 1990s, rather than the more recent polarization story of technological changes biased against middle-skilled workers who perform routine-intensive tasks.

The results entail a general policy implication. In the short and medium term, dislocation can be severe for certain types of work, and inequality may rise. This likely outcome will call for policies to smooth the adjustments caused by shifts in demand against low and medium paid jobs, especially for those groups of workers who could be most affected (the less educated and the youngsters). In the transition period, policies will be needed to facilitate labor market flexibility and mobility, introduce and strengthen safety nets and social protection, and improve education and training.

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Table 1: Proportion of jobs with high risk of automation, by occupation
Alternatives 1 and 2

Occupation	ISCO	High risk of automation A1	High risk of automation A2
Chief Executives, Senior Officials and Legislators	11	0.4%	8.8%
Production and Specialized Services Managers	13	0.6%	10.4%
Hospitality, Retail and Other Services Managers	14	3.5%	14.8%
Science and Engineering Professionals	21	0.5%	11.1%
Health Professionals	22	0.4%	3.6%
Teaching Professionals	23	0.2%	7.1%
Business and Administration Professionals	24	0.9%	33.6%
Information and Communications Technology Professionals	25	0.3%	11.8%
Legal, Social and Cultural Professionals	26	0.5%	16.8%
Science and Engineering Associate Professionals	31	3.3%	49.0%
Health Associate Professionals	32	4.3%	37.0%
Business and Administration Associate Professionals	33	4.9%	52.7%
Legal, Social, Cultural and Related Associate Professionals	34	1.3%	37.1%
Information and Communications Technicians	35	2.0%	55.2%
General and Keyboard Clerks	41	12.0%	94.0%
Customer Services Clerks	42	22.2%	71.6%
Numerical and Material Recording Clerks	43	13.0%	93.5%
Other Clerical Support Workers	44	11.6%	83.5%
Personal Services Workers	51	19.1%	48.2%
Sales Workers	52	32.4%	78.5%
Personal Care Workers	53	5.9%	42.3%
Protective Services Workers	54	7.7%	40.3%
Market-oriented Skilled Agricultural Workers	61	8.3%	71.0%
Market-oriented Skilled Forestry, Fishery and Hunting Workers	62	8.3%	74.0%
Building and Related Trades Workers (excluding Electricians)	71	12.2%	70.0%
Metal, Machinery and Related Trades Workers	72	15.2%	72.9%
Handicraft and Printing Workers	73	13.0%	61.6%
Electrical and Electronic Trades Workers	74	10.0%	54.9%
Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers	75	18.5%	71.3%
Stationary Plant and Machine Operators	81	27.7%	84.4%
Drivers and Mobile Plant Operators	83	31.1%	64.2%
Cleaners and Helpers	91	20.8%	63.5%
Agricultural, Forestry and Fishery Labourers	92	8.3%	88.0%
Labourers in Mining, Construction, Manufacturing and Transport	93	34.4%	70.9%
Food Preparation Assistants	94	34.6%	86.0%
Street and Related Sales and Services Workers	95	29.9%	94.0%
Refuse Workers and Other Elementary Workers	96	33.6%	77.9%

Source: own calculations based on EPH-INDEC (years 2016-2018), Arntz *et al.* (2016, 2020) (A1) and Frey and Osborne (2017) (A2).

Table 2: Ad-hoc measure of automatability based on PIAAC Chile

Occupation	ISCO	index based on PIACC
Chief Executives, Senior Officials and Legislators	11	23.3%
Production and Specialized Services Managers	13	56.4%
Science and Engineering Professionals	21	51.3%
Health Professionals	22	59.7%
Teaching Professionals	23	51.8%
Legal, Social and Cultural Professionals	26	43.7%
Science and Engineering Associate Professionals	31	47.2%
Health Associate Professionals	32	67.9%
Business and Administration Associate Professionals	33	53.2%
Legal, Social, Cultural and Related Associate Professionals	34	57.1%
General and Keyboard Clerks	41	53.2%
Customer Services Clerks	42	62.5%
Personal Services Workers	51	68.7%
Sales Workers	52	67.7%
Market-oriented Skilled Agricultural Workers	61	84.3%
Building and Related Trades Workers (excluding Electricians)	71	64.4%
Metal, Machinery and Related Trades Workers	72	58.9%
Handicraft and Printing Workers	73	80.0%
Food Processing, Woodworking, Garment and Other Craft and Related	75	76.4%
Stationary Plant and Machine Operators	81	62.9%
Drivers and Mobile Plant Operators	83	78.2%
Agricultural, Forestry and Fishery Labourers	92	88.1%
Labourers in Mining, Construction, Manufacturing and Transport	93	77.9%
Refuse Workers and Other Elementary Workers	96	84.8%

Source: own calculations based on EPH-INDEC (years 2016-2018) and PIACC.

Table 3: Proportion of jobs with high risk of automation, by sector

	High risk of automation		
Occupation	A1	A2	Observations
Agriculture & forestry	10.7%	73.4%	3,181
Fishing	14.1%	70.0%	224
Mining & quarrying	12.6%	58.6%	1,338
Manufacturing	16.5%	61.1%	11,629
Utilities	10.9%	63.2%	1,496
Construction	16.1%	66.1%	24,169
Commerce	25.2%	71.9%	43,414
Restaurants & hotels	23.9%	65.1%	8,468
Transportation & communications	23.5%	65.9%	12,766
Finance	11.0%	67.0%	3,554
Business services	10.4%	53.8%	13,002
Public administration	10.3%	64.2%	25,088
Teaching	4.2%	23.2%	20,410
Haealth & social services	6.4%	38.5%	13,754
Other services	13.5%	53.3%	11,336
Domestic servants	17.3%	58.9%	17,980
Extra-territorial organizations	11.6%	84.3%	14
Total	16.0%	58.8%	211,823

Source: own calculations based on EPH-INDEC (years 2016-2018), Arntz *et al.* (2016, 2020) (A1) and Frey and Osborne (2017) (A2).

Table 4: Proportion of jobs with high risk of automation, by gender

	High risk of automation		
	A1	A2	Observations
Females	14.9%	56.3%	93,911
Males	16.8%	60.9%	119,915
Total	16.0%	58.9%	213,826

Source: own calculations based on EPH-INDEC, (years 2016-2018), Arntz *et al.* (2016, 2020) (A1) and Frey and Osborne (2017) (A2).

Table 5: Proportion of jobs with high risk of automation, by region

	High risk of automation		
	A1	A2	Observations
GBA	16.0%	58.7%	40,264
Pampeana	15.8%	58.8%	62,028
Cuyo	16.3%	59.1%	19,823
NOA	16.6%	59.7%	45,556
Patagonia	14.7%	59.2%	25,862
NEA	15.8%	60.3%	20,293
Total	16.0%	58.9%	213,826

Source: own calculations based on EPH-INDEC, (years 2016-2018), Arntz *et al.* (2016, 2020) (A1) and Frey and Osborne (2017) (A2).

Table 6: Gini coefficient of labor income
Alternative impact of automation on labor incomes of affected workers

Beta	Gini
1	41.1
0.75	41.9
0.5	43.6
0.25	46.4
0	50.5

Source: own calculations based on EPH-INDEC (years 2016-2018) and Arntz *et al.* (2016, 2020).

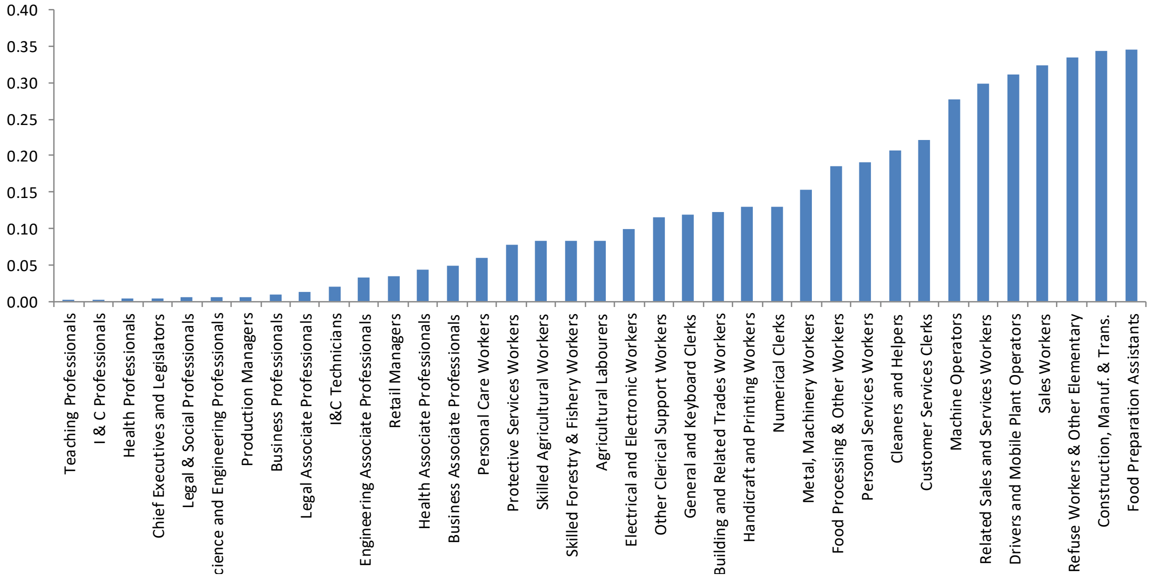
Table 7: Gini coefficient of household per capita income
Alternative impact of automation

	Beta				
	1	0.75	0.5	0.25	0
Top percentile - 100%	48.9	52.3	59.8	69.8	82.3
Top percentile - 50%	45.1	47.6	54.2	63.1	76.5
Capital income - 100%	52.9	59.0	66.2	74.7	87.3
Capital income - 50%	47.5	52.5	58.6	66.2	81.6
Income (only skilled)-100%	43.1	47.0	51.5	64.4	68.4
Income (only skilled)-50%	42.2	45.9	49.9	62.9	66.2
Income - 100%	41.3	44.7	47.9	51.3	67.3
Income - 50%	41.3	44.7	47.9	51.3	67.3

Source: own calculations based on EPH-INDEC (years 2016-2018) and Arntz *et al.* (2016, 2020). Note: In the *top percentile* alternative rents are distributed evenly to the top percentile of the household income distribution. In the *capital income* alternative rents are distributed as the current distribution of capital incomes. In the *income* alternative rents are distributed similar to the distribution of household per capita income. The *income (only skilled)* alternative is similar to the previous one but rents go only to households with skilled workers (more than 12 years of education).

Figure 1: Proportion of jobs with high risk of automation, by occupation

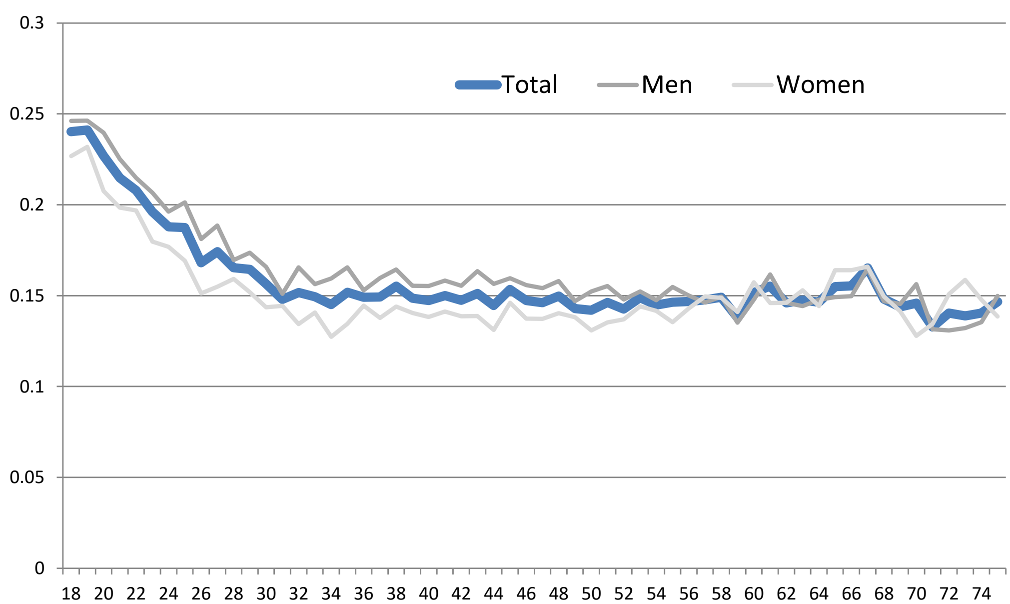
Alternative 1



Source: own calculations based on EPH-INDEC (years 2016-2018) and Arntz *et al.* (2016, 2020).

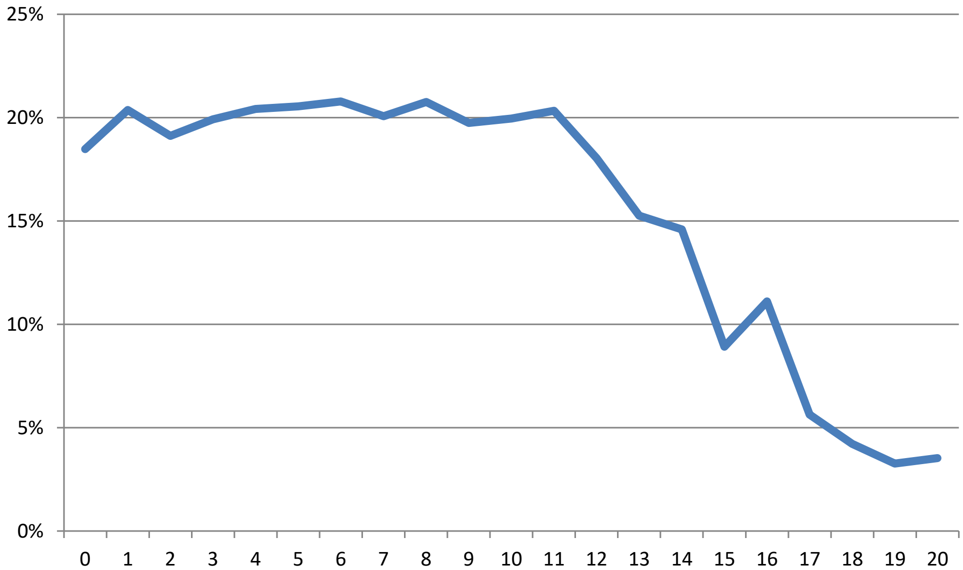
Figure 2: Proportion of jobs with high risk of automation, by gender and age

Alternative 1



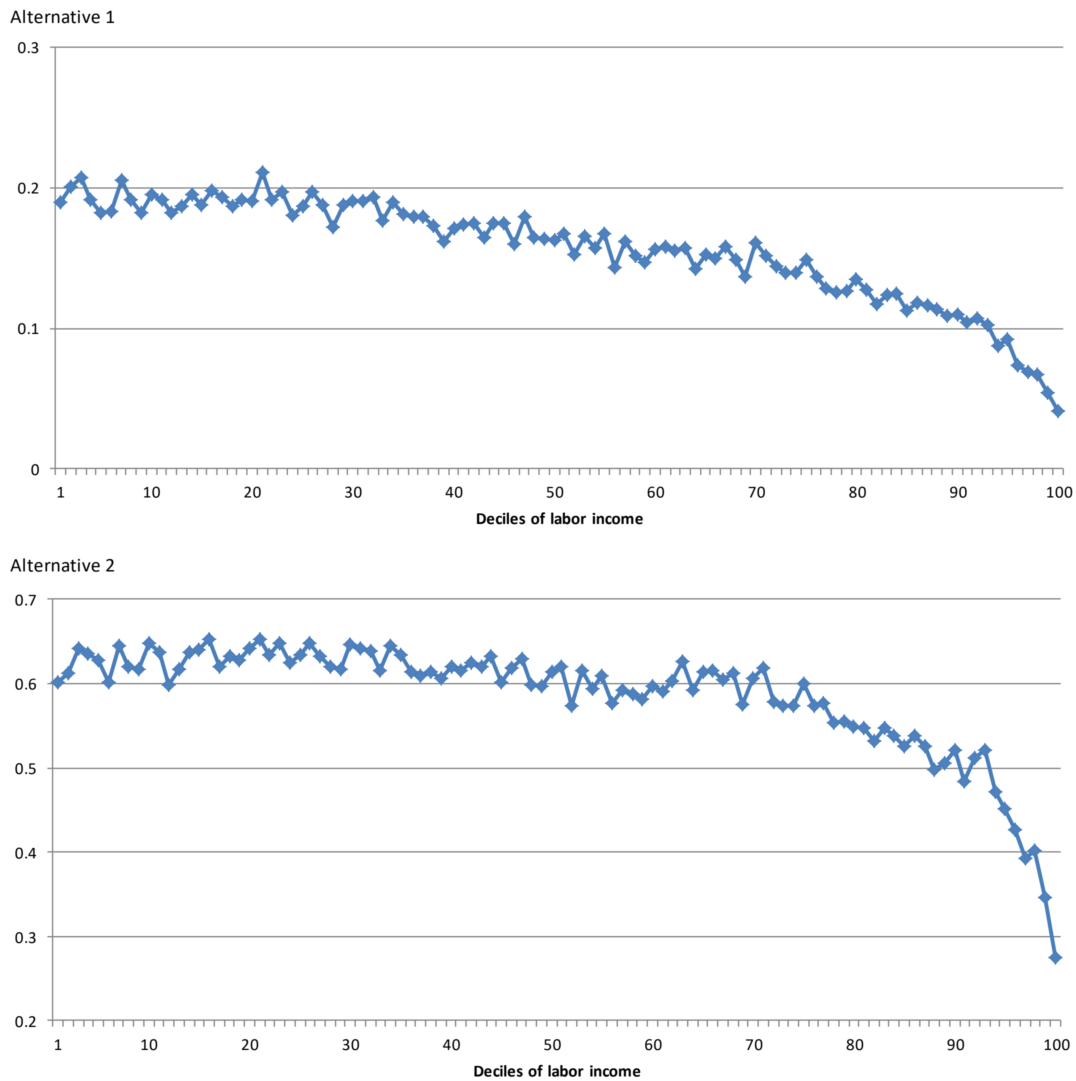
Source: own calculations based on EPH-INDEC (years 2016-2018) and Arntz *et al.* (2016, 2020).

Figure 3: Proportion of jobs with high risk of automation, by years of education
Alternative 1



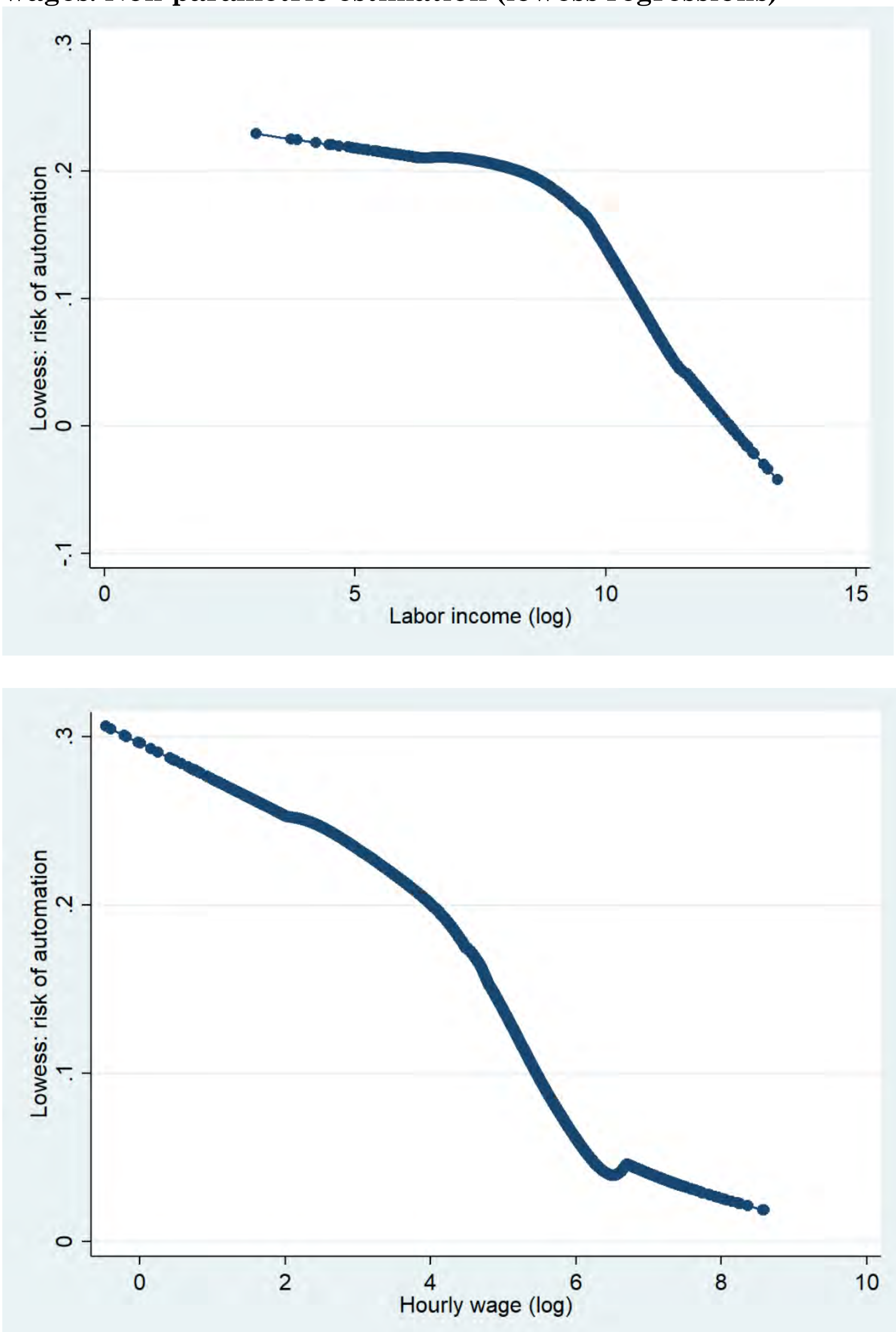
Source: own calculations based on EPH-INDEC (years 2016-2018) and Arntz *et al.* (2016, 2020).

Figure 4: Proportion of jobs with high risk of automation, by earnings percentiles



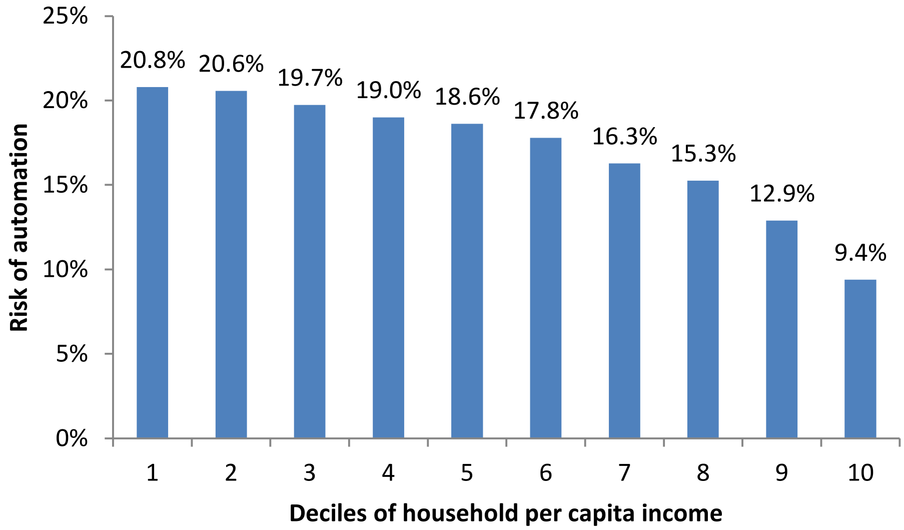
Source: own calculations based on EPH-INDEC (years 2016-2018), Arntz *et al.* (2016, 2020) (Alternative 1) and Frey and Osborne (2017) (Alternative 2).

Figure 5: Proportion of jobs with high risk of automation, by earnings and wages. Non-parametric estimation (lowess regressions)



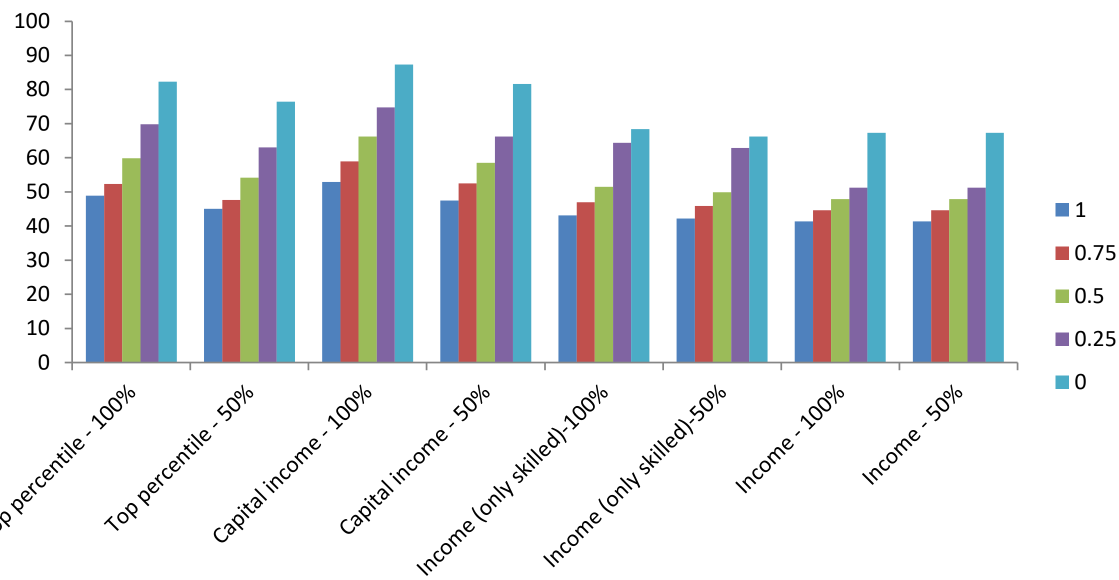
Source: own calculations based on EPH-INDEC (years 2016-2018) and Arntz *et al.* (2016, 2020).

Figure 6: Proportion of jobs with high risk of automation, by household per capita income deciles



Source: own calculations based on EPH-INDEC (years 2016-2018) and Arntz *et al.* (2016, 2020).

Figure 7: Gini coefficient of household per capita income
Alternative impact of automation



Source: own calculations based on EPH-INDEC (years 2016-2018) and Arntz *et al.* (2016, 2020).