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Automation and the jobs of young workers

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New automation technologies affect workers in a heterogeneous manner according to their demographic characteristics, skills, and the tasks they perform. In this paper we study the effects of automation on labor market outcomes in a developing country, Chile. We focus our analysis on the heterogeneous impacts of automation across cohorts. Does automation affect young workers differently than older workers? Do young workers tend to perform routine tasks? Are young workers in routine occupations more exposed to negative effects of technology?

Our empirical strategy is based on exploiting differences in the routinization of tasks across districts and occupations and a change in the trend of automation technology adoption in Chile. We find that young workers are more easily displaced by automation than older workers of similar characteristics. At the same time, cohorts of young workers are more skilled and more mobile than older workers, which implies that they have good prospects of working in complement with automation technology in the near future. The young and unskilled are the most vulnerable group of workers.

Keywords: technology adoption, automation, labor markets, young workers, age groups, unemployment, wages, occupations, tasks, routinization

JEL classification: O30, J21, J23, J24

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Introduction

Automation and digitalization are technologies that boost productivity and growth, but may also disrupt labor market structures. Some examples include manufacturing robots, self-driving cars, electronic passport gates, automated customer relations, and digital work platforms. There is concern that these new technologies may displace a significant share of workers as tasks previously performed by labor are increasingly met by computers and robots.

The issue of whether new technologies may threaten jobs has been under discussion since the Industrial Revolution. Technological change does affect some jobs, tasks, and employment opportunities. However, the process of structural transformation also involves job creation, and as countries become richer and more productive, demand for goods and services rises.

Various branches of the literature have identified winners and losers from this process. Early works on skill-biased technological change can be found in 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: technology boosts productivity of skilled workers, while it replaces unskilled workers. 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, Levy and Murnane (2003) and Acemoglu and Autor (2011). The task-based approach argues that the complementarity or substitutability between technology and labor does not occur at the worker category level but rather depends on how susceptible different tasks are to automation: it is tasks, not skills, that are more prone to be complementary or substitutable by technology. In particular, routine tasks that follow well-defined rules are susceptible to becoming codifiable and performed by a computer or robot. In contrast, flexible tasks that require a complex decision-making process, intuition, creativity, and communication ability, need a human input and can only be performed by workers with high analytical capacity and adaptability. Other tasks that challenge automation are the ones requiring social interactions, inventiveness and on-site performance (e.g. artisans, chefs, manicures, hairdressers, mechanics, plumbers).

Several authors find that in developed economies the relation between skills, tasks and automation is non-monotonic. Autor et al. (2003), Autor and Dorn (2013), Goos, Manning, and Salomons (2014) conclude that tasks performed by workers in the middle of the skill (and income) distribution are more likely to be substitutable by machines. From the point of view of firms, Bresnahan, Brynjolfsson and Hitt (2002) and Michaels, Natraj and Van Reenen (2014) argue that investment in digital technology requires complementary organizational capacities and human capital, and that differences in these variables explain heterogeneous success of digital technology adoption on productivity.

The general message of these studies is that the effects of technology are heterogeneous and that this heterogeneity relates to skills and tasks. Workers and firms that adapt to new technologies and that can work in complement with them see productivity and compensation rise, whereas demand for other types of jobs, occupations, and tasks may decline.

The literature on employment and automation in Latin America is still incipient, but growing. There are firm level studies regarding adoption of information and communication technology (ICT) for Argentina, Chile and Mexico by Brambilla and Tortarolo (2018), Almeida, Fernandes and Viollaz (2020), and Brambilla, Iacovone and Pereira-Lopez (2019). They find that the adoption of ICT increases firm productivity and output, leading to growing demand for labor. These firm-level studies do not address the impact on total employment or average wages.[1] Related to the task approach, Bustelo et al. (2020) study gender gaps in routinization;

1 See the volume by Dutz, Almeida and Packard (2018) for a summary of findings.

and Almeida, Corseuil and Poole (2017) find that Brazilian municipalities with an industrial composition more exposed to digital technology adoption exhibit a relative decline in employment between 1996 and 2006. Das and Hilgenstock (2018), Maloney and Molina (2016) and Messina, Pica and Oviedo (2016) test the polarization hypothesis in developing countries and do not find strong evidence in favor of it.[2] Their documented changes in the occupational structure are more in line with traditional skill-biased technological change mechanisms.

In this paper we study the effects of new automation technologies on labor market outcomes in a developing country, Chile, which has recently experienced a significant increase in the adoption of automation technologies. We focus the analysis on the heterogeneous impacts of automation across cohorts. Does automation affect young workers in a different manner than older workers? Do young workers tend to perform routine tasks? Are young workers in routine occupations more exposed to negative effects of technology? The effect of automation may be heterogeneous by age, since age is a major individual characteristic that explains differences in wages, employment, and mobility across workers (see for example Topel, 1991, and Topel and Ward, 1992). Young workers have less experience and job tenure, and they are more mobile across jobs since they do not have yet a significant sunk investment in specific skills. They also have a faster changing set of skills than older generations of workers.

In order to explore these issues we combine labor market microdata from the Chilean national household survey (CASEN) with our own indicators of routine task content by occupation constructed from the Programme for the International Assessment of Adult Competencies (PIACC) survey, conducted by the OECD in Chile in 2014. The survey asks individuals about the characteristics of their jobs and what type of tasks they perform. In particular, we are interested in tasks that help define whether an individual or an occupation is at risk of automation. Tasks that require flexibility and creativity are difficult to automatize, whereas tasks that are repetitive and codifiable are more prone to automation. Specifically, we consider four tasks that require flexibility: planning, supervising others, solving problems, and producing written output. These tasks are not codifiable and require human input. We aggregate individual responses related to tasks in order to create an index of routine task content for each occupation.

We follow two approaches to study the effect of automation on labor market outcomes. First, we exploit heterogeneity across local labor markets assuming that geographical mobility is limited in the short run. We build measures of unemployment, average wages and a routine task content index at the district level. Since the occupational structure differs across geographical areas, the routinization index varies across districts as well. The index captures the exposure of workers in a district to the possibility of being replaced by automation technology. We also exploit the fact that there was a change in the time trend of the adoption of automation technology in Chile, as suggested by data from the International Federation of Robotics on the adoption of industrial robots. We use this fact to define changes in labor market outcomes, during periods of low and high exposure to automation. The changing automation trends across time, taken together with the difference in routinization across districts, allow us to identify the impact of automation on unemployment and wages in local labor markets.

Second, we study employment and mobility across occupations. In particular, we exploit differences in routinization indexes across occupations, which are combined with the change in trends in automation technology adoption in order to identify the impact of automation on employment and wages at the occupational level.

We find that automation has a significant impact on unemployment. As the adoption of technology expanded over time, unemployment increased more in districts where the structure of production implied a higher degree of routinization, relative to other districts. The impact is

2 "Job polarization" refers to comprehensive increases in employment in high and low skills occupations relative to middle skill jobs (Acemoglu and Autor, 2011).

not homogeneous: young workers are more easily displaced by automation than older workers with similar characteristics. This result is stronger for the group of early entrants to the labor market: workers in the age group 18-22. Adjustment costs could be playing a role: workers with more experience and years of tenure are more costly to replace, whereas younger workers tend to have informal jobs that are more easily terminated or less job tenure which implies lower severance payments.

At the occupational level, there is an increase in mobility of young workers towards occupations with low exposure to automation. This result is mostly observed for the age group 23-29. In fact, the higher mobility of this group protects them against higher unemployment. The youngest group aged 18-22 is less mobile across occupations due to lower skills and experience, and is thus more exposed to unemployment.

The occupational structure of young workers puts them at a high risk of exposure to technology. This risk, however, is decreasing with age. The difference in risk across age is related to differences in the career path of an individual and also to differences across cohorts. Young workers are more skilled than older workers, and also more mobile. This is good news for young workers as skills correlate with performing flexible tasks and with being able to work in a complementary manner with technology. The probability of performing particular flexible tasks peaks between 30 and 40 years of age, indicating a decrease in routine task content over the course of the career path. We conclude that the most vulnerable workers, in the sense of a higher probability of displacement, are young workers with low skills, a narrow set of alternatives, and low possibilities to perform flexible tasks.

The rest of the paper is organized as follows. Section 2 describes the data and the trends in employment and automation in Chile. Section 3 explains the methodology used to study the impact of automation on labor market outcomes and presents results. Section 4 concludes.

Data and trends in employment and automation

Data sources

We combine two data sources. Our primary source is the Chilean National Household Survey (*Encuesta de Caracterización Socioeconómica Nacional*, CASEN), conducted by Chile's Ministry of Planning (MIDEPLAN) every two or three years. We use the surveys for 1996, 1998, 2000, 2003, 2006, 2009, 2011, 2013 and 2015. The employment module of the survey includes information on age, gender, education, labor income, hours worked, industry affiliation at the ISIC classification Revisions 2 and 3, and occupation at the ISCO 88 classification. The surveys are not a panel and individuals cannot be tracked over time.

Table 1 shows descriptive statistics from the CASEN surveys computed using sampling weights. The total number of observations is between 78,000 and 167,000 per year, for a total of 1,239,000 observations. We work with employed individuals, aged 18 to 65, with a total of 730,000 observations (between 46,000 and 105,000 observations per year). The table splits workers into four age categories: 18-22, 23-29, 30-39 and 40-65. We consider the first two groups to be young workers. The first group corresponds to early entrants into the labor market and represents 15 percent or less of the labor force. The second group is comprised of young workers with some years of experience, or young workers who have entered the labor market at a latter age, for example due to enrollment in tertiary education or college. This group represents less than 20 percent of the labor force. The total participation of young workers in the labor force has decreased from 34 percent in 1996 to 31 percent in 2015, a trend that follows population aging.

Table 1. CASEN survey

	1996	1998	2000	2003	2006	2009	2011	2013	2015
Surveyed individuals									
Number of obs.									
All	78636	110880	149516	153665	163435	152587	125415	137557	167543
Share									
	0.15	0.14	0.14	0.14	0.14	0.15	0.15	0.14	0.13
	0.19	0.19	0.18	0.17	0.17	0.16	0.17	0.17	0.18
	0.27	0.26	0.26	0.24	0.22	0.20	0.19	0.19	0.19
	0.39	0.41	0.42	0.44	0.47	0.49	0.49	0.50	0.50
Employed individuals									
Number of obs.									
All	45699	63743	82274	88180	97211	86397	75850	84826	104966
Share									
	0.09	0.08	0.08	0.08	0.08	0.08	0.08	0.07	0.07
	0.20	0.20	0.19	0.17	0.17	0.17	0.17	0.17	0.18
	0.31	0.30	0.30	0.28	0.25	0.24	0.23	0.24	0.22
	0.40	0.42	0.44	0.46	0.49	0.51	0.52	0.52	0.53

Notes: Data from CASEN. Table is based on individuals between 18 and 65 years old. Statistics are computed using sampling weights.

Our second data source is a survey from the Programme for the International Assessment of Adult Competencies (PIAAC) conducted by the OECD in Chile in 2014. The survey asks individuals about the characteristics of their jobs and what type of tasks they perform. The survey also classifies occupations according to the ISCO 08 classification. We aggregate individual responses related to tasks in order to create an index of routine task content for each occupation. We then match the occupations with those in the CASEN household survey. Table 2 reports basic statistics. The total number of observations is 2,782. The percentages corresponding to each of the four age groups are 6, 16, 24, and 54.

Table 2. PIAAC survey

	Number of obs.	Share
Surveyed individuals		
All	2782	
Age 18-22	162	0.06
Age 23-29	447	0.16
Age 30-39	660	0.24
Age 40-65	1513	0.54

Notes: Data from PIAAC. Table is based on individuals between 18 and 65 years old.

There are multiple questions in the PIAAC survey related to job tasks. We are interested in tasks that help define whether an individual or an occupation is at risk of automation. Tasks that require flexibility and creativity are difficult to automatize, whereas tasks that are repetitive and codifiable are more prone to automation. In particular, we consider four tasks that require flexibility: planning, supervising others, solving problems, and producing written output. These tasks are not codifiable and require human input. The choice of these four tasks is based on several conditions: tasks that represent flexibility, questions that are unambiguously related to the job performed and not to characteristics of the working environment, and questions with sufficient variation in responses. Workers in the PIAAC survey report whether they perform each of these tasks often or rarely.[3]

We define our main routinization content index at the individual level, $\boldsymbol{INDEX_1}$, as a dummy variable that is equal to one when an individual does not perform any of the previously mentioned flexible tasks often. Individuals with an index of one are at high risk of automation, whereas individuals with an index of zero are at low risk of automation.

As a robustness test we also work with two alternative definitions, similar in spirit to the one above, but that capture the intensity of the risk. The first alternative index, $\boldsymbol{INDEX_2}$, is a number between zero and one that can take the following values: 1, 3/4, 2/4, 1/4, 0, according to whether the worker performs none, one, two, three or the four flexible tasks often. The other alternative index, $\boldsymbol{INDEX_3}$, adds three more tasks to the list of flexible tasks: 1) giving presentations, sales pitches or acting as a consultant; 2) calculating budgets, costs or prices; and 3) making mathematical calculations. It can take the following values: 1, 6/7, 5/7, 4/7, 4/7, 3/7, 2/7, 1/7, 0, according to the (inverse) number of the seven flexible tasks that the worker performs often, in a manner analogous to $\boldsymbol{INDEX_2}$.

Table 3 shows the percentage of individuals that report performing each flexible task often, using data from PIAAC. Regarding the main four tasks, only 14 percent of the surveyed individuals report supervising, whereas 30, 37 and 34 percent report planning, solving problems and producing written output. The first index shows that 38 percent of workers do not perform any flexible tasks. Young workers are less likely to perform flexible tasks than workers age 30 to 39, particularly the first four tasks in which we based $\boldsymbol{INDEX_1}$. They also have higher routine content indexes. This is more marked for the group of youngest workers, age 18 to 22. Routinization decreases with age for the first three age categories and increases in the last category, ages 40 to 65.

Table 3. Flexible tasks and routinization content indexes. Individual level

	All	Age 18-22	Age 23-29	Age 30-39	Age 40-65
Flexible tasks					
Supervising	0.14	0.09	0.14	0.14	0.14
Planning	0.30	0.23	0.28	0.33	0.29
Solving problems	0.37	0.31	0.39	0.42	0.36
Written output	0.34	0.31	0.39	0.40	0.30
Presentations	0.59	0.66	0.63	0.61	0.56
Budgets	0.43	0.46	0.46	0.46	0.40
Math calculations	0.57	0.60	0.60	0.65	0.53
Individual indexes					
Routinization Index 1	0.38	0.40	0.35	0.33	0.40
Routinization Index 2	0.71	0.76	0.70	0.68	0.73
Routinization Index 3	0.61	0.62	0.59	0.57	0.63

Notes: Data from PIAAC. Table is based on individuals between 18 and 65 years old. It shows the percentage of workers that report performing each of seven tasks often, and averages of the routinization indexes across individuals. Index 1 is a dummy variable equal to one when an individual does not perform any of the main four flexible tasks often (supervising, planning, solving problems, written output). Index 2 is a number between zero and one that can take the following values: 1, 3/4, 2/4, 1/4, 0, according to whether the worker performs none, one, two, three or the four flexible tasks often. Index 3 adds three more tasks to the list of flexible tasks included

3 Surveyed individuals reply with a number between 1 and 5 meaning: 1=never; 2=less than once a month; 3= less than once a week; 4=at least once a week; 5=every day. In our main definition we consider replies of 4 and 5 to mean often. Results are very similar when we include option 3 (not shown in the paper).

in Index 2 (giving presentations, calculating budgets, making mathematical calculations) and it can take the values 1, 6/7, 5/7, 4/7, 4/7, 3/7, 2/7, 1/7, 0.

At the occupation level, we define the index of routine task content (***RTC***) as the average across workers in that occupation. Formally,

$$RTC_{1j} = \frac{1}{n_j}\sum_{i \in j} INDEX_{1i} \quad (1)$$

where j denotes occupations, $\boldsymbol{i}$ denotes workers, and $\boldsymbol{n_j}$ is the number of workers in occupation j. We proceed in an analogous manner with definitions of $\boldsymbol{INDEX_2}$ and $\boldsymbol{INDEX_3}$ and compute occupation level indexes $\boldsymbol{RTC_2}$ and $\boldsymbol{RTC_3}$ as the average across individuals. All these indexes are computed using the PIAAC survey.

Notice that the index is an ordering of occupations based on how prone they are to automation according to their task content. It is not directly interpreted as the risk of automation or as the probability of automation. Opportunities for automation depend on prices and availability of technology and other factors that cannot be captured in an index based only on job tasks.

Our approach and definitions of the RTC indexes are similar to those in other studies that use occupation surveys, such as Autor et al. (2003), Autor, Katz and Kearney (2008), Spitz-Oener (2006) and Frey and Osborne (2017). These studies use the DOT or O*NET surveys.[4] Following the task-based approach of Autor et al. (2003), Spitz-Oener (2006) divides tasks into four categories: abstract, routine-cognitive, routine-manual, and non-routine-manual, and constructs an RTC index by weighting the frequency of each type of tasks within occupations. Almeida et al. (2020) and Messina et al. (2016) follow the same approach and data sources for case studies in Latin America. Frey and Osborne (2017) use the O*NET survey on task content of occupations. For each task they define whether they are computer codifiable based on the responses of machine learning researchers and they aggregate information up to the occupation level to compute a risk index.

There are several advantages to using the PIAAC survey from Chile in this paper.[5] First, unlike the PIAAC surveys, the public information available from O*NET is aggregated at the occupation level and therefore does not allow for a direct comparison of surveyed individuals or the construction of individual-level indexes. Moreover, the occupation level statistics reported by O*NET involve the average of ad-hoc numerical values given to categorical variables and therefore do not have a direct quantitative interpretation. Finally, the PIAAC survey was conducted in Chile, among other countries, whereas the DOT and O*NET surveys are based on surveyed individuals in the United States. For completeness, we explore robustness to using the Frey and Osborne (2017) index in all of our specifications.

A list of the 39 matched occupations is in Table A1 in the Appendix.[6] Occupations are sorted according to the $\boldsymbol{RTC_1}$ index, with occupations with higher routinization content at the top. These are occupations at a higher risk of routinization and correspond to cleaners, workers in

4 The Occupational Information Network (O*NET) is the successor of the Dictionary of Occupational Titles (DOT) and it is developed by the U.S. Department of Labor/Employment and Training Administration. Similarly to the PIAAC surveys, the DOT and O*NET surveys record information on task characteristics and activities performed at each occupation.

5 Bustelo et al. (2020) use a combination of PIAAC and STEP surveys to construct routinization indexes for several countries in Latin America. The STEP survey is conducted by the World Bank in several developing countries and is similar in spirit to the PIAAC surveys.

6 Two occupations included in the CASEN household surveys are not present in the PIAAC surveys: (i) subsistence farmers, fishers, hunters, and gatherers (ISCO08 = 63) and (ii) assemblers (ISCO08 = 82). The RCT indexes for these occupations are computed as the weighted average RCT index of occupations in the corresponding 1-digit category: 61 and 62 (for ISCO08 = 63) and 81 and 83 (for ISCO08 = 82). All results remain robust to the exclusion of these two occupations.

the primary sector, workers in occupations that involve processing or assembling. Occupations with the lowest risk of routinization include management, IT technicians, professionals. Figure A1 plots the four indexes of routine task content at the occupation level. The correlation among the four indexes is high. We work with $\boldsymbol{RTC_1}$ as our main index of routinization.

Descriptive statistics and stylized facts

Table 4 shows descriptive statistics of employment by age and skill level using the microdata from CASEN. The employment rate of workers under 30 years of age follows a slightly declining trend from an average of 50 percent between 1996 and 2006, to an average of 48 percent between 2009 and 2015. This decline is explained by the group of early entrants to the labor market, whose employment rate declines from 35 to 32 percent. In contrast, the employment rate of young workers in the age group 23 to 29 increases by one point from 62 to 63 percent. The employment rate of workers above 30 markedly increased over the period under study.

Table 4 also reports the distribution of skills across age groups. We define three skill levels. Low-skilled individuals are those who do not have a high-school degree; medium-skilled are individuals with a high school degree; and highly-skilled are individuals with tertiary education or a college degree. There is a sharp trend in Chile towards an increase in skills. This can be observed across age groups and over time. During the 2009-2015 period, the percentage of individuals with medium or high skills, that is, with at least a high school diploma, was 82 percent for the 23-29 age group, 71 percent for the 30–39 age group, and merely 49 percent for individuals over 40. Individuals in the 18–22 age group may not yet have completed their formal education, and therefore their recorded skill level might not reflect their future level.

Table 4. Employment and skills of workers by age

	All	Age 18-22	Age 23-29	Age 30-39	Age 40-65
1996-2006					
Employment	0.60	0.35	0.62	0.69	0.62
Low skills	0.50	0.43	0.33	0.44	0.62
Medium skills	0.37	0.55	0.52	0.38	0.25
High skills	0.12	0.02	0.14	0.17	0.12
2009-2015					
Employment	0.62	0.32	0.63	0.75	0.66
Low skills	0.38	0.30	0.18	0.28	0.50
Medium skills	0.46	0.68	0.61	0.46	0.33
High skills	0.17	0.02	0.21	0.25	0.16

Notes: Data from CASEN. Table is based on individuals between 18 and 65 years of age. Employment is the employment rate. Low, medium, and high skills refer to the percentage of individuals with that skill level. Low skills=no high school degree; medium skills=high school degree; high skills=tertiary or college degree. Statistics are computed using sampling weights.

Similar differences are observed over time, for all age groups. The percentage of individuals with medium or high skills increased between 1996-2006 and 2009-2015. The increases go from 49 to 63 for all individuals, 57 to 70 percent for individuals in the 18 to 22 age group, 66 to 82 percent for individuals in the 23 to 29 group, 56 to 71 percent for individuals in the 30 to 39 age group, and 37 to 49 percent for individuals in the over 40 group. Differences of a very similar order of magnitude are observed within the group of individuals that report having a job (not in table).

Table 5 looks at labor participation by age group across occupations using data from CASEN. Occupations typically intensive in skilled young workers include professionals related to ICT, business, health and teaching activities. Occupations intensive in semi-skilled young workers are sales and customer services, and occupations intensive in unskilled labor are mining, construction and some general tasks related to manufacturing. Occupations that require experience are least common among young workers, mostly managerial occupations, machine operators, drivers. The participation of young workers is also low in janitorial work.

Table 5. Age intensity of employment by occupation. Year 2015

ISCO 08	Occupation	RTC_1	Age intensity by occupation			
			18-22	23-29	30-39	40-65
91	Cleaners and Helpers	0.72	2.9	6.9	15.7	74.5
61	Skilled Agr. Workers	0.68	5.2	9.8	16.0	69.0
63	Subsistence Farm./Fish.	0.67	3.6	6.9	11.2	78.3
92	Agricultural Labourers	0.67	8.9	13.2	19.7	58.2
62	Forestry/Fish. Workers	0.67	6.9	13.0	18.2	61.8
73	Handicraft Workers	0.62	4.3	13.8	15.6	66.4
96	Elementary Workers	0.61	7.8	16.5	17.9	57.7
75	Food Processing Workers	0.55	5.2	11.7	20.9	62.3
93	Labourers	0.54	17.3	22.5	18.2	42.0
83	Drivers/Mobile Operators	0.54	2.4	12.1	20.1	65.4
82	Assemblers	0.49	7.4	26.5	16.5	49.5
53	Personal Care Workers	0.46	7.8	14.3	19.0	58.9
52	Sales Workers	0.46	13.1	19.8	22.0	45.1
51	Personal Serv. Workers	0.45	10.5	21.2	20.4	47.9
71	Building Workers	0.40	7.2	13.7	19.7	59.5
81	Plant/Mach. Operators	0.37	7.0	16.1	23.2	53.8
34	Legal Assoc. Prof.	0.36	8.6	29.1	30.0	32.3
95	Street Sales Workers	0.30	5.4	14.0	20.2	60.5
14	Retail Managers	0.29	1.5	8.6	18.2	71.7
44	Clerical Workers	0.28	4.8	18.1	22.9	54.3
42	Customer Serv. Clerks	0.28	11.8	28.7	23.3	36.2
32	Health Assoc. Prof.	0.27	4.6	32.5	23.8	39.1
41	General Clerks	0.26	18.3	34.7	26.2	20.9
72	Metal/Machinery Workers	0.25	9.1	18.4	22.5	50.0
43	Recording Clerks	0.21	9.7	19.8	25.0	45.4

Table 5 (continued).Age intensity of employment by occupation. Year 2015

ISCO 08	Occupation	RTC_1	Age intensity by occupation			
			18-22	23-29	30-39	40-65
22	Health Professionals	0.21	1.0	33.3	28.6	37.1
54	Protect. Serv. Workers	0.19	5.7	26.3	23.8	44.2
33	Business Professionals	0.19	3.8	18.2	23.9	54.2
23	Teaching Professionals	0.18	2.3	24.3	27.8	45.6
26	Legal/Social Prof.	0.18	3.0	28.7	36.5	31.8
74	Electrical Workers	0.18	9.5	19.9	28.5	42.2
25	ICT Professionals	0.15	1.1	38.3	35.2	25.4
31	Sc./Engin. Assoc. Prof.	0.13	5.3	21.5	28.8	44.5
24	Business Prof.	0.12	1.4	23.1	29.3	46.2
21	Sc./Engin. Prof.	0.09	0.7	22.6	36.9	39.8
35	ICT Technicians	0.07	6.6	25.1	38.7	29.6
13	Production Managers	0.03	0.3	8.8	24.2	66.7
12	Administrative Managers	0.00	0.8	4.3	29.6	65.3
11	Chief Executives	0.00	0.0	36.5	9.6	54.0

Notes: own calculations from CASEN survey. Occupations are sorted by the RTC index (in column RTC_1). A higher index represents a higher content of routinization of the occupation. Each line shows the participation of each age group in total occupation employment. Lines add up to 100. Statistics are computed using sampling weights.

To sum up, in the last decade there has been a decline in the participation of young workers in the labor force, and important changes in their distribution of skills. The distribution of workers across occupations depends on age as well. In what follows we study whether the changing set of skills and tasks that young workers perform are more prone to routinization and therefore potentially substitutable by automation in production, or whether, by contrast, young workers are more likely to work in complement with new technologies.

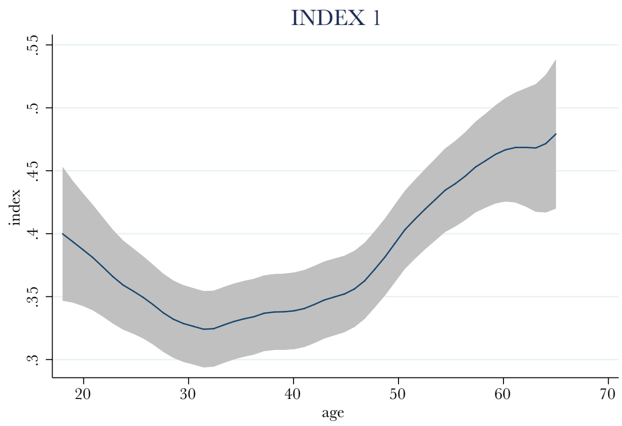
The risk of automation

We have shown that young workers are less likely to perform flexible tasks (Table 3). Here we look at this fact in greater detail. Figure 1, top panel, shows the expectation of the individual-level routine task content $INDEX_1$ conditional on age. Results are smoothed with a local polynomial regression. The figure has an asymmetric U-shape. The risk of automation markedly decreases for young workers. While it is high for early entrants, it is lowest for workers that are close to 30 years old (it bottoms at 32). Thus, very young workers are at a higher risk of automation, and that risk decreases until age 32. This result correlates with the fact that younger workers tend to be employed in repetitive unskilled occupations. The opposite happens for older workers, the risk of automation increases by age from year 32 onwards. Figure A2 in the Appendix shows that similar U-shaped results are obtained when we look at the alternative definitions $INDEX_2$ and $INDEX_3$.

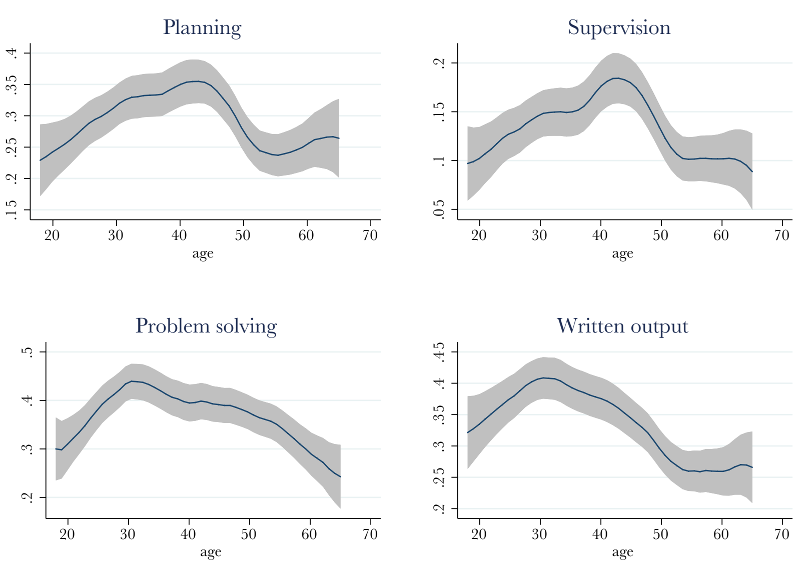
Figure 1 may reflect differences in the flexibility of the career-paths of individuals as well as compositional changes across cohorts. To gain more insight into the drivers of routinization and flexibility, we look at the four flexible tasks: supervising, planning, solving problems, and producing written output. The probability of performing these tasks often, conditional on age, are depicted in the bottom panel. The figures have an inverted U-shape (as expected since task flexibility is the opposite of the routinization index). The probability of performing planning and supervising increases initially and peaks between ages 40 and 45. These are activities that reflect changes in the career paths of individuals, as planning and supervising correlate with experience and job tenure, and they work in the direction of increasing job flexibility over time for a given individual.

Figure 1. The risk of automation. Individual data from PIAAC survey

(a) Routinization content index



(b) Flexible tasks



Notes: Own calculations from PIAAC survey. Local polynomial regressions. Dependent variable (top panel): individual level index of tasks that are at risk of automation. The index is constructed based on individual responses to performing the following flexible and non-routine tasks: planning, supervising others, solving problems or producing written output. The dependent variable is equal to zero for individuals who do not perform any of the four tasks. Dependent variable (bottom panel): probability of executing tasks that require planning, supervising others, solving problems and producing written output.

The probability of solving problems and producing written output peaks at about age 30. These activities relate to individual skills and human capital and undergo little change along the career path; as a result, they peak earlier than planning and supervising. The peak at age 30 reflects a compositional change in the set of skills across cohorts creating a U-shaped curve in the top panel.

There are two simultaneous phenomenon that explain the U-shape. One is that as we move along the horizontal axes, from the group of workers ages 18–22 to those ages 23–29, individuals who have finished higher education (tertiary or college) join the labor market. A large fraction of these individuals are employed as technicians and professionals and perform tasks that are at a lower risk of automation. This does not imply that a given individual's risk is lower in their early years in the labor market. The second phenomenon is the increase in skills over time. The participation of medium-skilled and high-skilled workers has been increasing over the last two decades. The cohort of older workers is less skilled than the cohort of younger and middle-aged workers and thus more prone to be employed in occupations with high routine task content. As before, this does not imply that a particular individual's risk is higher in the second half of his career.

We now look at differences across skill levels. The PIAAC survey has a relatively small sample size that does not allow us to look at additional worker characteristics. In Figure 2, top panel, we start by plotting the risk of automation based on computations from the CASEN survey. We first compute the occupation level index $\boldsymbol{RTC_1}$. We then assign a value of the RTC index to each individual in the CASEN survey based on their reported occupation. Finally, we average the RTC index of individuals of the same age (and smooth it with a local polynomial). Results show a similarly U-shaped curve with a minimum risk at about 30 years of age. This is reassuring since our regression analysis in the next sections is based on the CASEN survey. Figure A3 in the Appendix shows that results are very similar as well when we consider the alternative definitions of the RTC indexes.

The second panel of Figure 2 plots the risk of automation for two different skill groups: unskilled workers (no high school degree), and skilled workers (high school degree or more). The figure shows that indeed the risk of automation is markedly higher for unskilled workers, and that, thus, skills correlate with flexibility. The difference across skill groups explains two facts: (i) that the RTC index is higher for workers age 18–22 than for workers 23–29, because more workers in the 23–29 group have tertiary or college degrees; and (ii) that the RTC index is higher for older workers, as skill composition has been changing across cohorts and workers in the older group are on average less skilled (Table 4).

Automation trends in Chile

The indexes on the risk of automation do not necessarily represent a probability. They are to be interpreted as a sorting of individuals and occupations based on the routinization of their reported tasks. Whether those tasks are in fact automatized with workers replaced by machines depends on several factors: price of technology, availability, complementarity of human capital, government policy, credit constraints, and labor market regulations. These are factors that change over time. The last decade has seen a huge increase in the adoption of automation technology such as digitalization and robotization.

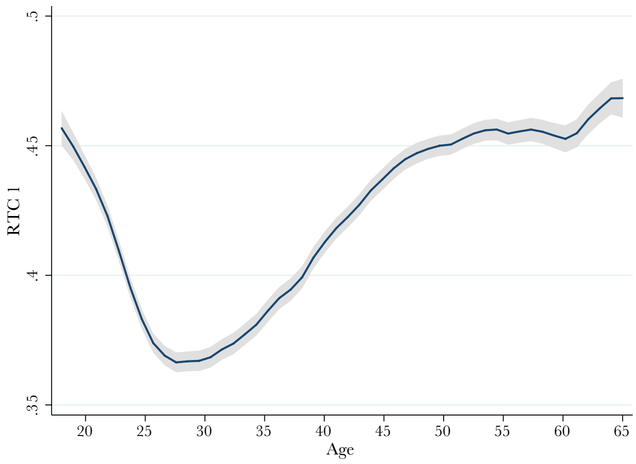
Figure 3 shows the evolution of the adoption of industrial robots in Chile across time. These data come from the International Federation of Robotics.[7] Chile is in a very early stage of robotization. Interestingly, the stock of robots was zero between 1995 and 2004, and it markedly increased yearly since 2005, representing an important change in trend.

The change in the trend of robotization represents a change in market conditions as well as an increase in the risks posed by automation. We exploit this change in automation trends in our empirical strategy. The risk of automation is higher for the period 2005–2015 than for 1995–2005.

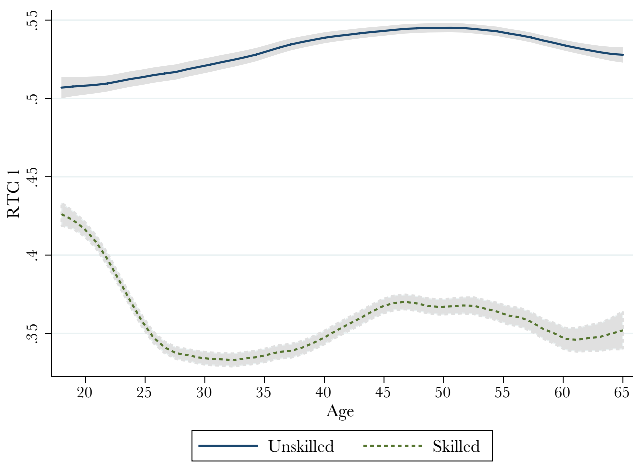
7 The IFR reports yearly data on the number of robots for close to one hundred countries from 1993 to date. These data have been used by recent papers for the United States (Acemoglu and Restrepo, 2020), Mexico (Faber, 2020), and a sample of 17 countries (Graetz and Michaels, 2018).

Figure 2. The risk of automation. Occupational data from CASEN

(a) All workers

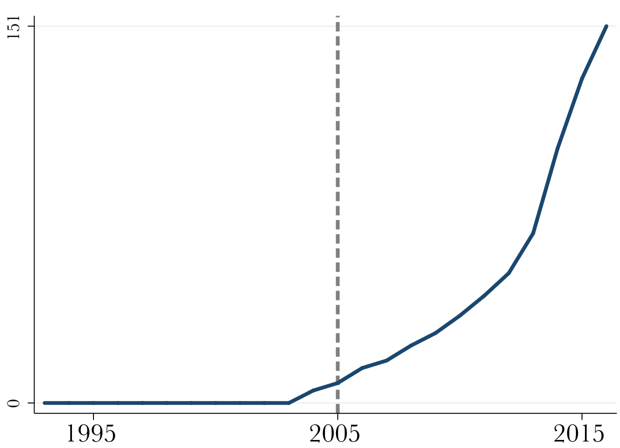


(b) By skill level



Notes: Own calculations from CASEN survey. Local polynomial regressions. Dependent variable: routinization task index of occupation $\boldsymbol{RTC}_1$. In the bottom panel separate regressions are run from two skill groups. Unskilled workers: no high school degree. Skilled workers: high school degree or more.

Figure 3. Robotization



Notes: Own calculations from International Federation of Robotics. Total number of robots in Chile per year.

Routinization and labor market outcomes

In this section we test the idea that automation affects job market outcomes, with a particular focus on young workers. We are interested in three outcomes: employment, possibilities of substitution across occupations, and wages. We also test the idea that some workers are more prone to being replaced by technology and that the possibility of replacement is related to the routine task content of each occupation. An occupation that demands non-routine tasks such as creative thinking and problem solving is difficult to automatize, whereas machines are more likely to replace workers in occupations that involve routine tasks that are susceptible to being codified. Notice that routine tasks may be manual, in which case they may be carried out by production machinery such as robots, or cognitive, and may be carried out with digital technology.

The effects of automation on employment are theoretically ambiguous. While technology may displace some workers, it also allows for a reduction in costs at the firm level, firm growth, and output growth. As technology becomes cheaper, firms may expand and become more technology intensive at the expense of the worker/capital ratio, but not necessarily at the expense of total employment (Brambilla, 2018). Technology also creates new job opportunities for workers that are complementary with technology, such as IT technicians, and more generally workers who utilize machines and computers as a working tool. Total employment may also be affected by a reshuffling of workers across occupations. Technology may displace workers from codifiable occupations towards occupations that involve more flexible tasks.

The effect of automation on wages is ambiguous as well. Workers that find themselves in lower demand due to the competition exerted by technology may find their wages reduced. At the same time, as firms flourish they may be able to afford higher wages (through non-competitive profit sharing mechanisms such as efficiency wages), see Brambilla (2018), Brambilla and Tortarolo (2018), Brambilla et. al. (2019). Workers that complement technology may also see increases in wages as they become more productive.

In the subsections that follow we study labor markets at the district level and at the occupation level. At the district level we test for the impact of technology on unemployment and on average wages. At the occupation level we test for mobility and changes in wages across jobs.

Employment and wages in local labor markets

The CASEN survey has information on the district in which each surveyed individual is located. There are a total of 59 districts.[8] Districts vary in terms of economic conditions, geography, size, and production. Notably, they also vary in their occupational structure. In some districts, workers concentrate in occupations with a high routine task content, whereas in other districts workers shift towards more flexible occupations. We define a district level RTC index as a weighted average of the occupation level index as follows:

$$RTC_r = \sum_j \theta_{jr} RTC_j \qquad (2)$$

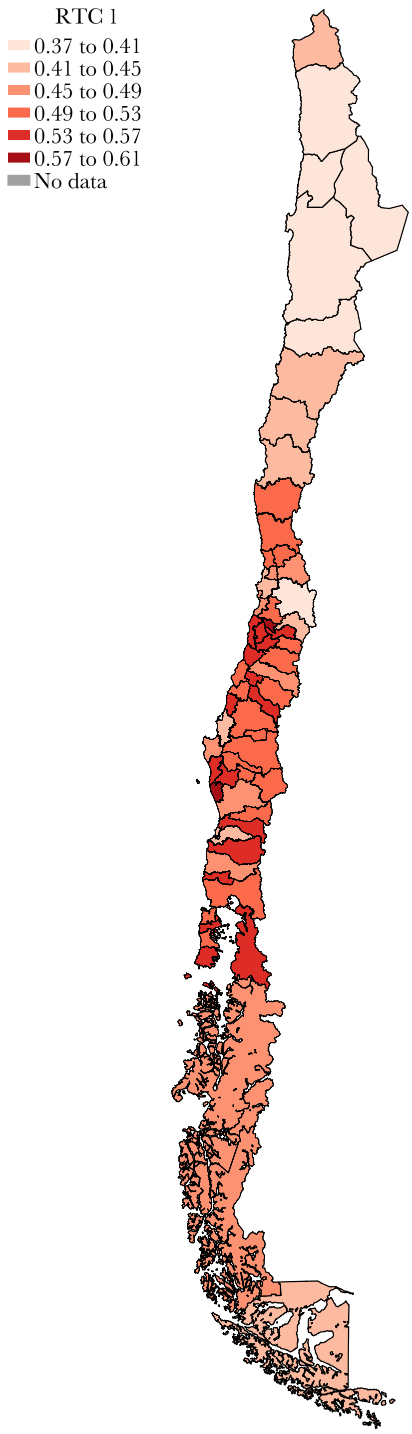
where r and j denote districts and occupations, $\boldsymbol{RTC_j}$ is the RTC index defined at the occupation level, and θ_{jr} is the participation of occupation j in total employment in district r. We define four RTC indexes at the district level based on our four indexes at the occupation level, $\boldsymbol{RTC_1}$, $\boldsymbol{RTC_2}$, $\boldsymbol{RTC_3}$, and Frey and Osborne.

The index varies across districts. Figure 4 displays its geographical variability. Districts in the center of the country tend to concentrate production in activities that demand more flexible tasks than districts in the North and the South of the country.

8 We use the definition of functional labor market areas from Casado-Díaz, Rowe, and Martínez-Bernabéu (2017) who classify municipalities into labor markets using commuting data from the Chilean Internal Migration Database (CHIM) and Chilean Census data for 1982, 1992 and 2002.

Our empirical strategy is as follows. First, we exploit the structural change in the trend of automation in Chile that took place around 2005. In 2005, the adoption of robotization began to accelerate and rapidly increased (Figure 3). We thus split the data into two time periods using the following cutoff years: $t_0 = 1995$, $t_1 = 2005$, and $t_2 = 2015$. We expect the bulk of the effects of automation to occur between 2005 and 2015. Second, we exploit the variance in the $\boldsymbol{RTC}$ indexes across districts. We expect the impact of automation on employment to be larger in districts with a higher $\boldsymbol{RTC}$ index as they are more exposed to the risk of technology. In this strategy, we do not rely on a direct measure of automation technology but instead we use a district-level measure of routinization (the RTC index) as a proxy for the risk of automation.

Figure 4. Variability of RTC index across districts



Notes: Figure plots district-level $\boldsymbol{RTC}_1$ index.

Unemployment

We start by studying the average effect of automation on unemployment. We run the following baseline regression specification in first differences:

$$\Delta U_{rt} = \alpha_0 + \alpha_1 RTC_r \times D_{1t} + \alpha_2 RTC_r \times D_{2t} \quad (3)$$

$$+x_{r0}{}'\alpha_3 \times D_{1t} + x_{r0}{}'\alpha_4 \times D_{2t} + \Delta x_{rt1}{}'\alpha_5 + \Delta\epsilon_{rt}$$

where r denotes districts and ΔU_{rt} is the change in the unemployment rate. The variable $\boldsymbol{RTC_r}$ is the (time-invariant) routine task content index of district r. In the regression it is interacted with two dummy variables; the first one (D_{1t}) is equal to one for changes between t_0 and t_1, whereas the second one (D_{2t}) is equal to one for changes between t_1 and t_2. The coefficients of interest are α_1 and α_2, which capture the impact of technology adoption on unemployment. The term $\Delta\epsilon$ is a random error term.

The regression is in first differences and therefore implicitly includes district fixed effects. To minimize endogeneity concerns, we construct the index $\boldsymbol{RTC_j}$ with weights from the initial year t_0 and we argue that the initial level at t_0 does not correlate with the change in random shocks $\Delta\epsilon$.

The initial variability of the routinization index RTC across districts may correlate with district level unobserved characteristics related to the level of development. To proxy for unobserved factors we include district-level characteristics both in first differences (Δx) as well as their initial level (x_0) interacted with the time dummies D_1 and D_2. These variables capture differential trends across time according to observed initial characteristics. Variables included in x are: percentage of male workers in the labor force, percentage of individuals below 30 years of age in the labor force, share of workers without a high school degree, employment rate, share of workers in manufacturing, and share of workers in services.

Table 6 shows results using the four different definitions of the RTC index ($\boldsymbol{RTC_1}$, $\boldsymbol{RTC_2}$, and $\boldsymbol{RTC_3}$, all computed from the PIAAC survey, and the Frey and Osborne index). Column (1) shows that the estimate of α_2 is positive, whereas the estimate of α_1 is statistically indistinguishable from zero, and the difference between α_1 and α_2 is statistically significant at the 10% level, meaning that as adoption of technology progressed from t_1 to t_2, unemployment increased in districts where the structure of production implies higher routinization relative to other districts. In the first panel, for $\boldsymbol{RTC_1}$, a 10 percentage point difference in the RTC index across two districts implies a differential increase in the unemployment rate of 0.8 percentage points. The average unemployment rate across all ages is 7.3 percent. This is evidence of workers being substituted by technology.

Columns (2) to (5) report results from regressions run separately for the four age groups. The effects concentrate on young workers, both for the 18–22 and 23–29 age groups, for all four definitions of RTC indexes.[9] In the first panel ($\boldsymbol{RTC_1}$), the differential increases in unemployment across the two first differences ($\alpha_2 - \alpha_1$) are of 2.27 percentage points (18-22 age group) and 1.77 percentage points (23-30 age group) for a 10 percentage point difference in the RTC index across districts. The average unemployment rates are 17.8 and 10.5 percent. This shows that young workers are more vulnerable to being replaced by technology.

It is important to interpret regression results correctly. Workers of different ages perform different tasks and have different average RTC indexes. This is not, however, what is being tested here. We test the impact of the RTC index on unemployment, controlling for skills and gender in the vector x. This impact is shown to be different across age groups, for a same RTC index, other things equal. Young workers are more prone to suffering unemployment due to

9 The only exception are the estimated coefficients using the Frey and Osborne index, which are positive but not statistically significant. However, the difference between α_1 and α_2 is statistically significant at the 1% level for workers aged 18–22.

technology because of being young. One possible explanation for this result is adjustment costs. Replacing workers has a cost of adjustment, both monetary, given settlement costs, and in terms of workplace morale. Workers with more experience and years of tenure are more costly to replace, whereas younger workers tend to have informal jobs that are more easily terminated, or less job tenure which implies lower severance payments. Unemployment also need not involve losing a job; instead, it can be due to not finding job opportunities. As employers adopt technology they might keep older workers that are costly to replace and not create new opportunities for younger workers.

Table 6. Unemployment rate in local labor markets

	(1)	(2)	(3)	(4)	(5)
	All	18-22	23-29	30-39	40-65
RTC 1					
RTC x D1 (α_1)	0.004	0.271	0.009	-0.064	0.027
	(0.051)	(0.171)	(0.148)	(0.062)	(0.066)
RTC x D1 (α_2)	0.081^*	0.498***	0.186***	-0.003	0.025
	(0.046)	(0.169)	(0.066)	(0.091)	(0.035)
p-value: (α_1 = α_2)	0.093	0.001	0.280	0.380	0.971
RTC 2					
RTC x D1 (α_1)	0.033	0.546*	0.140	-0.091	0.021
	(0.082)	(0.315)	(0.177)	(0.112)	(0.099)
RTC x D1 (α_2)	0.095	0.730**	0.240**	-0.042	0.040
	(0.080)	(0.313)	(0.114)	(0.139)	(0.085)
p-value: (α_1 = α_2)	0.082	0.000	0.308	0.320	0.388
RTC 3					
RTC x D1 (α_1)	0.041	0.464	0.129	-0.066	0.037
	(0.070)	(0.292)	(0.179)	(0.100)	(0.092)
RTC x D1 (α_2)	0.11	0.675**	0.245**	-0.012	0.055
	(0.072)	(0.295)	(0.108)	(0.135)	(0.079)
p-value: (α_1 = α_2)	0.088	0.000	0.324	0.367	0.453
Frey and Osborne					
RTC x D1 (α_1)	0.001	0.033	0.153	-0.156*	0.071
	(0.073)	(0.459)	(0.246)	(0.092)	(0.100)
RTC x D1 (α_2)	0.079	0.309	0.249	-0.107	0.105
	(0.072)	(0.406)	(0.205)	(0.118)	(0.098)
p-value: (α_1 = α_2)	0.078	0.010	0.327	0.394	0.251
N	118	118	118	118	118
Average unemployment rate	0.073	0.178	0.105	0.061	0.045

Notes: Coefficients α_1 and α_2 from regression equation (3). Dependent variable: unemployment rate. Explanatory variable: routine task content index of district $\boldsymbol{RTC}$ interacted with time dummies D_1 and D_2. We work with four definitions of RTC indexes: $\boldsymbol{RTC}_1$, $\boldsymbol{RTC}_2$, $\boldsymbol{RTC}_3$ and Frey and Osborne. Regressions run at the district level and weighted by the fraction of working age population in each district in 1996. Significance at the 10, 5, and 1 percent level indicated with *, ** and ***.

Wages

To explore the effect on wages we adopt the same empirical specification as in regression (3), with the log average district wage on the left-hand side. Results are in Table 7. Most coefficients in the table are positive, albeit not statistically significant.[10] Yet what matters is the difference between α_2 and α_1, which is positive for most specifications and age groups, it is statistically significant for young workers in the 18–22 age group, and is in line with the idea that young workers who remained employed may have seen their productivity enhanced as working in complement with new automation technologies. Due to the large confidence intervals we interpret these results with caution as mild evidence that wages do not fall due to technology adoption.

In summary the increase in the unemployment rate shows that some workers do not find job opportunities, or that they are displaced by technology. This effect is highest for young workers. Workeres that remain employed on average do not suffer a decrease in wages. There are several reasons that explain why wages do not fall, while there is an increase in unemployment. One reason are nominal rigidities. Wages may tend not to fall and adjustment may occur through quantities (unemployment).[11] A second reason are compositional and non-competitive forces that operate in the direction of increasing wages. With technology adoption there are compositional changes in employment. Workers that are not displaced are those that can work in complement with technology and whose productivity and wages are increased. At the same time, technology adoption increases firm profits through reductions in variable costs. In non-competitive settings workers that remain employed may participate in firm profits from technology adoption through bargaining or effort exertion (efficiency wages schemes).

Table 7. Wage in local labor markets

	(1)	(2)	(3)	(4)	(5)
	All	18-22	23-29	30-39	40-65
RTC 1					
RTC x D1 (α_1)	0.365	-0.268	0.062	0.550	0.083
	(0.539)	(0.450)	(0.813)	(0.588)	(0.548)
RTC x D1 (α_2)	0.470	0.411	0.035	0.779**	0.109
	(0.419)	(0.434)	(0.516)	(0.385)	(0.602)
p-value: ($\alpha_1 = \alpha_2$)	0.755	0.054	0.953	0.637	0.932
RTC 2					
RTC x D1 (α_1)	0.653	-0.020	0.118	1.049	0.081
	(0.850)	(0.761)	(1.154)	(0.843)	(1.010)
RTC x D1 (α_2)	0.794	0.403	0.140	1.323*	0.148
	(0.796)	(0.771)	(1.057)	(0.745)	(1.040)
p-value: ($\alpha_1 = \alpha_2$)	0.364	0.034	0.882	0.211	0.693
RTC 3					
RTC x D1 (α_1)	0.232	-0.440	-0.271	0.731	-0.341
	(0.656)	(0.547)	(0.978)	(0.636)	(0.830)
RTC x D1 (α_2)	0.391	0.041	-0.202	1.015*	-0.268

10 By contrast, most coefficients are negative when using the Frey and Osborne index.

11 In particular, wage losses due to automation are expected to be concentrated among unskilled workers with earnings around the minimum salary, which can impose an important nominal rigidity in the adjustment process of the labor market.

Table 7 (continued). Wage in local labor markets

	(1)	(2)	(3)	(4)	(5)
	All	18-22	23-29	30-39	40-65
	(0.627)	(0.561)	(0.898)	(0.613)	(0.905)
p-value: ($\alpha_1 = \alpha_2$)	0.382	0.029	0.675	0.279	0.729
Frey and Osborne					
RTC x D1 (α_1)	-0.924	-1.009	-0.215	-0.362	-1.536
	(0.666)	(0.929)	(1.002)	(0.885)	(0.936)
RTC x D1 (α_2)	-0.614	-0.507	-0.065	0.263	-1.412
	(0.658)	(0.947)	(0.993)	(0.956)	(0.994)
p-value: ($\alpha_1 = \alpha_2$)	0.088	0.034	0.235	0.017	0.601
N	118	118	118	118	118
Average unemployment rate	7.016	6.593	6.868	7.038	7.091

Notes: Coefficients α_1 and α_2 from regression equation (3). Dependent variable: log hourly wage in the district. Explanatory variable: routine task content index of district RTC interacted with time dummies D_1 and D_2. We work with four definitions of RTC indexes: $\boldsymbol{RTC_1}$, $\boldsymbol{RTC_2}$, $\boldsymbol{RTC_3}$ and Frey and Osborne. Regressions run at the district level and weighted by the fraction of working age population in each district in 1996. Significance at the 10, 5, and 1 percent level indicated with *, ** and ***.

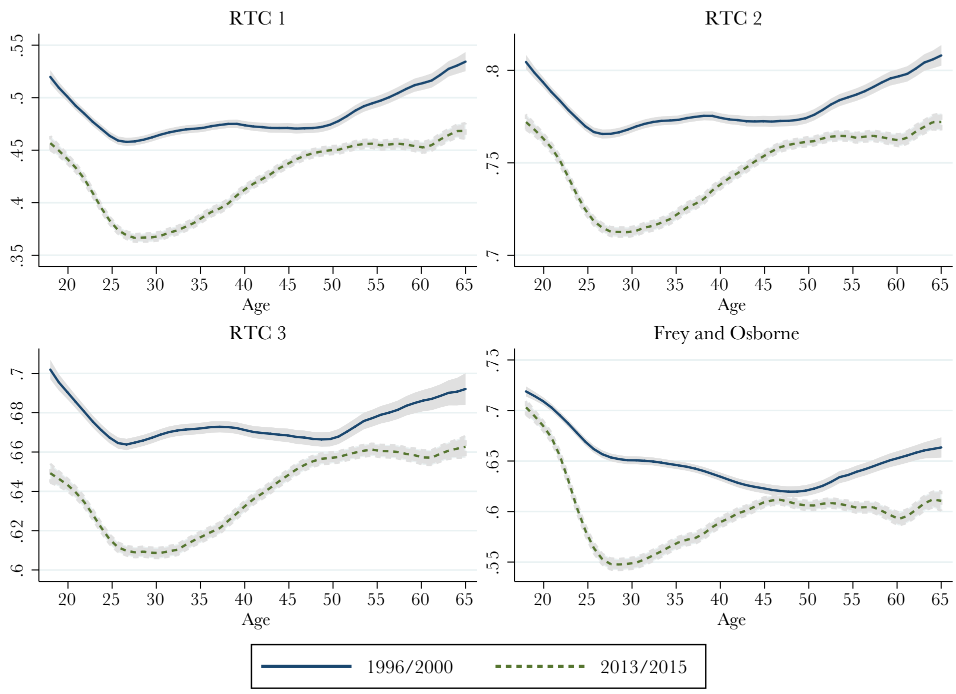
Mobility across occupations

The previous section looks at unemployment and wages at the district level. These are average (relative) effects across districts. At the same time, there is turnover and job creation across occupations. While some jobs are replaced by technology, new opportunities to work in complement with technology are also created. In this section we look at job reshuffling. In particular, we test whether occupations that are more intensive in routine tasks lose participation relative to occupations that involve flexibility.

Figure 5 shows different trends in the risk of automation. We plot local polynomial regressions of the expectation of the occupation level RTC indexes conditional on age for two different time periods, 1996-2000 and 2013-2015. This is a compositional change. The RTC indexes are based on characteristics of occupations and are fixed over time. The changes in the graphs across time periods reflect movements of individuals across occupations.

The figure shows that across all ages, and for the four RTC indexes, there is a shift towards lower-risk of automation, more flexible occupations. As expected, the highest shift occurs in the 23–29 age group. This is a group of workers with high skills, and at the same time a low sunk investment in terms of experience and tenure. It is a group with high mobility. The youngest workers are less skilled and experienced and the range of occupations that they can perform is more limited. Older workers have invested in human capital at specific occupations and switching occupations may be more limited as well.

Figure 5. The risk of automation. Trends



Notes: Analogous to Figure 2. Local polynomial regressions. Dependent variable: routinization task index of occupation $\boldsymbol{RTC_1}$, $\boldsymbol{RTC_2}$, $\boldsymbol{RTC_3}$ and index of Frey and Osborne. Regressions run separately for two time periods.

The quantitative interpretation is straightforward for $\boldsymbol{RTC_1}$ as it represents the percentage of at-risk individuals. For 18 year-olds, the percentage decreases from 52 to 46 percent. For 30 year-olds, the decrease is highest, from 46 to 37 percent. While for 65 year-olds the decrease is from 53 to 47 percent. Similar patterns are observed for the other indexes.

Participation of occupation in total employment

We now look at the participation of each occupation in total employment. The empirical strategy is similar to the local labor market approach of the previous section, with the difference that we now work at the occupational level instead of at the district level. The baseline regression is:

$$\Delta N_{jt} = \gamma_0 + \gamma_1 RTC_j \times D_{1t} + \gamma_2 RTC_j \times D_{2t} \quad (4)$$

$$+x_{j0}{}'\gamma_3 \times D_{1t} + x_{j0}{}'\gamma_4 \times D_{2t} + \Delta x_{jt}{}'\gamma_5 + \Delta\epsilon_{jt}$$

where j denotes occupations and ΔN_{jt} is the change in the participation of occupation j in total employment. The variable $\boldsymbol{RTC_j}$ is the (time-invariant) routine task content index of occupation j. The dummy variables are defined as before, and ϵ is a random error term. Because the regressions are in first differences, time-invariant occupation characteristics (fixed effects) are differenced out. Variables included in the control vector x, both in first differences and the initial value interacted with the two time dummies, are: percentage of male workers in the occupation, percentage of individuals below 30 years of age in the occupation, and share of workers without a high school degree in the occupation.

Results are reported in Table 8. Column (1) shows results for workers of all ages. The coefficient γ_2 is negative, while γ_1 is nearly zero, meaning that in the second first-difference, as the adoption of technology progresses, there is a decline in the share of routine occupations in total employment. The counterpart is an increase in the share of flexible occupations. The difference between γ_1 and γ_2 is statistically significant, a result that holds for the four RTC indexes. For

RTC$_1$, a 10 percentage points difference in the index across occupations results in a (differential) decrease in the occupation share of 0.18 percentage points. The average occupation share is 2.6 percent.

In columns (2) to (5) we split results by age group, by running four separate regressions. As advanced in Figure 5, workers in the age groups 18 to 22 and 40 to 65 are the less mobile across occupations. The coefficients γ_2 and γ_1 are not statistically significant. In contrast, workers in the age groups 23-29 and 30-39 are highly mobile across occupations. Moreover, this mobility is due to automation, as only γ_2 is statistically significant, meaning that the switch across occupations occurred between t_1 and t_2 simultaneously with automation technology adoption. The (differential) impact of a 10 percentage points difference in ***RTC***$_1$ across occupations is a decrease in the occupation share of 0.18 and 0.45 percentage points for the 23–29 and 30–39 age groups. These are the groups with highest skills and more flexibility to switch occupations.

To better understand the time patterns of mobility across occupations, we introduce a semi-parametric specification given by:

$$\Delta N_{jt} = \delta_0 + RTC_j \delta_1{}'(\tau_t) + x_{j0}{}'\{\delta_{2t} \times D_t\} + \Delta x_{jt}{}'\delta_3 + \Delta v_{jt} \quad (5)$$

This specification captures the time-varying nature of technology adoption. In the previous specification we had two first-differences, $t_1 - t_0$ and $t_2 - t_1$. In this second specification we work with annual data from 1995 to 2015. The changes are defined as $t - t_0$, where $t_0 = 1995$ is the first year of data, as in Author, Katz and Kearney (2008). We define the variable $\tau = t - t_0$ as the years elapsed since the initial year of data. In this regression the effect of RTC on job market outcomes is non-parametric on time. We approximate this non-parametric function with a fourth-order polynomial in τ. We therefore estimate a flexible time-variant effect of the RTC index on occupational employment.

Table 8. Occupation share

	(1) All	(2) 18-22	(3) 23-29	(4) 30-39	(5) 40-65
RTC 1					
RTC x D1 (α_1)	0.002	-0.019	-0.010	-0.000	0.009
	(0.004)	(0.014)	(0.006)	(0.004)	(0.006)
RTC x D1 (α_2)	-0.020**	-0.008	-0.028***	-0.045***	-0.015
	(0.008)	(0.018)	(0.010)	(0.012)	(0.009)
p-value: ($\alpha_1 = \alpha_2$)	0.007	0.502	0.039	0.002	0.009
RTC 2					
RTC x D1 (α_1)	0.004	-0.011	-0.008	0.002	0.012
	(0.006)	(0.017)	(0.009)	(0.007)	(0.008)
RTC x D1 (α_2)	-0.024**	0.000	-0.035***	-0.060***	-0.017
	(0.011)	(0.023)	(0.013)	(0.019)	(0.011)
p-value: ($\alpha_1 = \alpha_2$)	0.017	0.593	0.050	0.003	0.013
RTC 3					
RTC x D1 (α_1)	0.004	-0.035*	-0.016*	0.002	0.017*
	(0.008)	(0.020)	(0.009)	(0.006)	(0.010)
RTC x D1 (α_2)	-0.025*	-0.035	-0.034**	-0.061***	-0.022
	(0.014)	(0.030)	(0.015)	(0.018)	(0.017)
p-value: ($\alpha_1 = \alpha_2$)	0.026	0.992	0.159	0.003	0.012

Table 8 (continued). Occupation share

	(1) All	(2) 18-22	(3) 23-29	(4) 30-39	(5) 40-65
Frey and Osborne					
RTC x D1 (α_1)	-0.003	-0.003	-0.010**	-0.002	0.005
	(0.004)	(0.006)	(0.005)	(0.004)	(0.004)
RTC x D1 (α_2)	-0.020***	0.001	-0.022**	-0.026***	-0.012*
	(0.008)	(0.010)	(0.009)	(0.010)	(0.007)
p-value: (α_1 = α_2)	0.016	0.640	0.176	0.009	0.041
N	78	74	78	78	78
Average unemployment rate	0.026	0.027	0.026	0.026	0.026

Notes: Coefficients γ_1 and γ_2 from regression equation (4). Dependent variable: share of occupation in total exployment. Computed using population weights. Explanatory variable: routinization task index of occupation $\boldsymbol{RTC}$ interacted with time dummies D_1 and D_2. We work with four definitions of RTC indexes: $\boldsymbol{RTC}_1$, $\boldsymbol{RTC}_2$, $\boldsymbol{RTC}_3$ and Frey and Osborne. Regressions run at the occupation level. Significance at the 10, 5, and 1 percent level indicated with *, ** and ***.

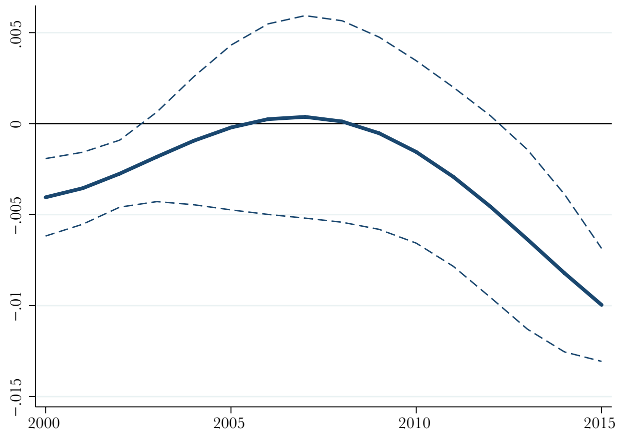
Figure 6 plots the coefficient $\delta_1(\tau_t)$. It shows the change in the share of occupations in total employment as a function of the RTC index. We show results for the index $\boldsymbol{RTC}_1$. Results for $\boldsymbol{RTC}_2$, $\boldsymbol{RTC}_3$ and Frey and Osborne are qualitatively similar. The first panel shows the change in occupations for workers of all ages. Starting in the year 2008, the RTC index has a negative impact on the occupation share. This is consistent with the hypothesis that as technology adoption accelerates workers switch to more flexible occupations. The confidence intervals are large, however, and the effect is statistically significant starting in 2012.

The second panel splits regressions by age group. As expected from the previous parametric results, the more mobile age group are workers aged 23-29. They switch towards more flexible occupations during the 2000-2015 period. This effect accelerates over time, in a manner consistent with technology adoption. Workers in the 18–22 and 30–39 age groups start to switch towards flexible occupations in 2007, as automation accelerates. Finally, workers above 40 are also mobile but their time pattern is less consistent and they switch towards more flexible occupations in the final years of data, starting in 2012.

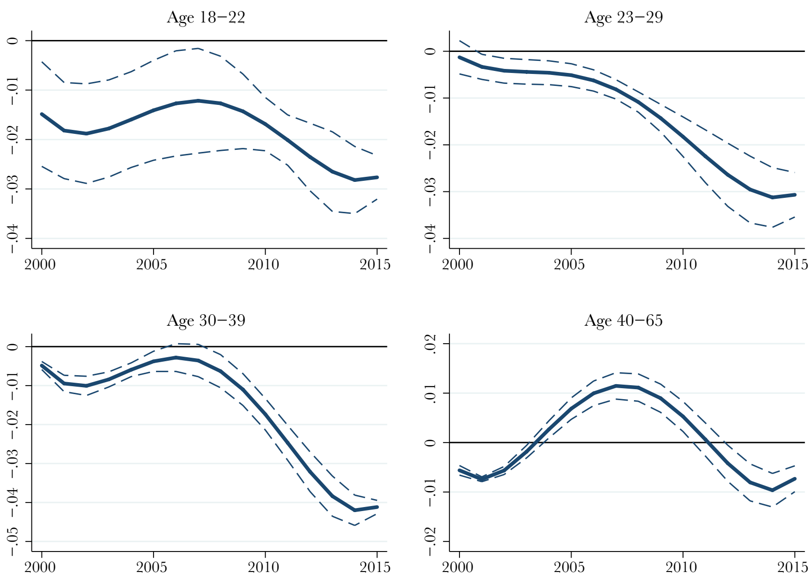
What are the occupations that have ejected and that have attracted young workers? Table 9 lists the occupations sorted from less to more flexible and their change in share in total employment. Noticeably, young workers have left the less flexible occupations: cleaners and helpers, agriculture, fishing, handicraft, food processing, general laborers. They have been attracted to somewhat flexible occupations such as personal services, customer service, and to the most flexible occupations such as health professionals, legal professionals, teaching, ICT, and science and engineering. Similar patterns are observed for all ages, but are more marked for workers in the 23–29 group.

Figure 6. Share of occupation in total employment

(a) All workers



(b) By age group



Notes: Figure plots coefficients $\delta_1(\tau_t)$ from equation regression (5) and **95%** confidence intervals. It estimates the changing effect of the RTC index on the share of occupation in total employment over time. Dependent variable: share of occupation in total employment. Explanatory variable: routinization task index of occupation $\boldsymbol{RTC_1}$. Regressions run at the occupation level.

Table 9. Share of occupations in total employment. Year 2006 vs. 2015

ISCO 08	Occupation	$\boldsymbol{RTC_1}$	Occupation share	Change in occ. Share by age 18-22	23-29	30-39	40-65
91	Cleaners and Helpers	0.72	7.85	-4.1	-3.0	-1.9	2.9
61	Skilled Agr. Workers	0.68	3.41	-0.3	-1.3	-1.1	-1.1
63	Subsistence Farm./Fish.	0.67	0.31	-0.9	-0.9	-0.9	-1.6
92	Agricultural Labourers	0.67	3.82	-5.9	-5.0	-3.4	-1.8
62	Forestry/Fish. Workers	0.67	0.69	-0.2	-0.4	-0.5	-0.2
73	Handicraft Workers	0.62	0.63	-0.9	-0.7	-1.0	-0.5
96	Elementary Workers	0.61	3.09	-0.8	-0.3	-0.1	0.7
75	Food Processing Workers	0.55	2.88	-1.3	-1.0	-1.1	-0.9
93	Labourers	0.54	3.07	0.2	-1.6	-1.7	-0.2
83	Drivers/Mobile Operators	0.54	6.52	-1.4	-0.5	-0.8	0.4

Table 9 (continued). Share of occupations in total employment. Year 2006 vs. 2015

ISCO 08	Occupation	***RTC***$_1$	Occupation share	Change in occ. Share by age			
				18-22	23-29	30-39	40-65
82	Assemblers	0.49	0.07	0.1	0.0	-0.1	0.0
53	Personal Care Workers	0.46	2.18	1.7	0.6	0.3	0.7
52	Sales Workers	0.46	9.54	5.8	0.8	0.4	-1.0
51	Personal Serv. Workers	0.45	5.12	3.7	2.8	1.3	1.0
71	Building Workers	0.40	5.40	1.5	-1.0	-0.9	0.3
81	Plant/Mach. Operators	0.37	2.12	-1.3	-1.3	-1.5	-0.7
34	Legal Assoc. Prof.	0.36	0.95	0.4	0.6	0.9	0.1
95	Street Sales Workers	0.30	1.02	0.3	0.4	0.2	0.3
14	Retail Managers	0.29	3.00	0.4	0.4	0.5	-0.2
44	Clerical Workers	0.28	1.27	0.3	0.3	0.1	0.2
42	Customer Serv. Clerks	0.28	3.25	3.1	2.6	1.6	1.3
32	Health Assoc. Prof.	0.27	1.40	0.7	1.5	0.9	0.3
41	General Clerks	0.26	0.17	-0.8	-0.7	-0.6	-0.3
72	Metal/Machinery Workers	0.25	3.58	0.7	-0.9	-0.1	-0.2
43	Recording Clerks	0.21	2.66	1.1	0.1	0.4	0.5
22	Health Professionals	0.21	1.55	0.1	1.9	0.3	0.0
54	Protect. Serv. Workers	0.19	0.85	0.1	-0.1	-0.3	-0.2
33	Business Professionals	0.19	5.81	-2.5	-0.7	0.1	1.1
23	Teaching Professionals	0.18	4.81	0.9	2.8	1.9	-1.0
26	Legal/Social Prof.	0.18	2.06	-0.1	2.0	2.5	0.3
74	Electrical Workers	0.18	1.48	0.4	0.0	0.5	0.1
25	ICT Professionals	0.15	0.57	0.1	1.1	0.8	0.2
31	Sc./Engin. Assoc. Prof.	0.13	1.56	-0.6	0.0	0.6	0.3
24	Business Prof.	0.12	2.01	-0.7	-0.1	0.0	0.1
21	Sc./Engin. Prof.	0.09	3.07	0.3	1.6	2.5	0.7
35	ICT Technicians	0.07	0.55	0.0	-0.4	0.5	-0.1
13	Production Managers	0.03	0.99	-0.1	0.1	0.0	-1.2
12	Administrative Managers	0.00	0.51	0.1	0.0	0.3	0.2
11	Chief Executives	0.00	0.16	0.0	0.1	-0.7	-0.7

Notes: own calculations from CASEN survey. Columns show: the ***RTC***$_1$ index, the share of each occupation in total employment in 2015 (column adds up to 100), changes in occupation share from 2006 to 2015 by age group. Statistics computed using population weights are representative at the national level.

Occupation wages

We use the same empirical strategy of regression (4) to study the change in occupation wages. We run regressions with the average occupation wage on the left-hand side. Results are in Table 10. Column (1) shows results for workers of all ages. The coefficient γ_1 is positive, indicating that between t_1 and t_0 wages are on average higher in occupations with a high RTC index. The coefficient γ_2, however, is smaller than γ_1, indicating that the differential impact of technology $\gamma_2 - \gamma_1$ is negatively associated with routinization. The impact of automation on wages is negatively related to routinization of the occupation. This holds for the four definitions of the RTC index.

A similar pattern holds for workers in the 23–29 age group, that is, the more mobile group. The impact of automation on wages is negatively related to the routinization of the occupation. For a 10 percentage point increase in ***RTC***$_1$, the differential decrease in wages is 4.8 percent. These impacts are statistically significant for all specifications of the RTC index. For the other age groups results are mixed, implying that results for all workers (column 1) are mostly driven by the 23–29 age group.

The decrease in wages is indicative of a decrease in demand. We conclude that the mobility of workers in the 23–29 group towards lower RTC occupations is due to a decrease in demand for those tasks. These results control for skills and gender, and are compatible with the increase in unemployment of young workers and with the explanation that adjustment costs are higher for older workers.

Table 10. Occupation wage

	(1)	(2)	(3)	(4)	(5)
	All	18-22	23-29	30-39	40-65
RTC 1					
RTC x D1 (α_1)	0.412***	0.558	0.600***	0.297	0.283*
	(0.112)	(0.628)	(0.161)	(0.247)	(0.157)
RTC x D1 (α_2)	0.198	0.746*	0.126	0.212	0.132
	(0.145)	(0.436)	(0.175)	(0.220)	(0.194)
p-value: ($\alpha_1 = \alpha_2$)	0.026	0.831	0.052	0.776	0.512
RTC 2					
RTC x D1 (α_1)	0.562***	1.264	0.766***	0.415	0.428*
	(0.187)	(0.850)	(0.254)	(0.408)	(0.233)
RTC x D1 (α_2)	0.255	0.748	0.057	0.317	0.142
	(0.203)	(0.703)	(0.295)	(0.333)	(0.302)
p-value: ($\alpha_1 = \alpha_2$)	0.018	0.707	0.084	0.831	0.413
RTC 3					
RTC x D1 (α_1)	0.529***	0.446	0.698***	0.991***	0.439*
	(0.168)	(0.971)	(0.186)	(0.305)	(0.229)
RTC x D1 (α_2)	0.210	1.223**	0.283	0.546**	0.253
	(0.137)	(0.566)	(0.201)	(0.255)	(0.197)
p-value: ($\alpha_1 = \alpha_2$)	0.043	0.591	0.143	0.269	0.580
Frey and Osborne					
RTC x D1 (α_1)	0.249**	0.770**	0.310**	0.128	0.200*
	(0.119)	(0.375)	(0.146)	(0.183)	(0.106)
RTC x D1 (α_2)	0.193	0.256	-0.019	0.034	0.176
	(0.127)	(0.281)	(0.140)	(0.150)	(0.117)
p-value: ($\alpha_1 = \alpha_2$)	0.596	0.387	0.102	0.652	0.872
N	78	73	78	78	78
Average unemployment rate	6.978	6.557	6.833	7.028	7.072

Notes: Coefficients γ_1 and γ_2 from regression equation (3). Dependent variable: log occupation hourly wage. Computed using population weights. Explanatory variable: routinization task index of occupation $\boldsymbol{RTC}$ interacted with time dummies D_1 and D_2. We work with four definitions of RTC indexes: $\boldsymbol{RTC}_1$, $\boldsymbol{RTC}_2$, $\boldsymbol{RTC}_3$ and Frey and Osborne. Regressions run at the occupation level. Significance at the 10, 5, and 1 percent level indicated with *, ** and ***.

Discussion

We uncover several facts regarding the impact of automation on young workers and the tasks they perform. Some refer to the possibility of being replaced by technology and others refer to trends across cohorts and the career paths of individuals.

First, we find that young workers are displaced by automation. At the district level we observe an increase in unemployment among young workers in districts with high exposure to automation, measured by differences in the RTC index and by differences in automation technology adoption over time. We compare young and older workers of similar characteristics and conclude that, other things equal, young workers are more easily substitutable by technology. Labor adjustment costs may explain why older workers are less prone to being displaced. This result is mostly observed for the group of early entrants to the labor market, that is, workers in the 18–22 age group.

At the occupation level, there is an increase in mobility among young workers towards occupations with low exposure to automation (low RTC index). This result is mostly observed for the 23–29 age group. The increased mobility of this group protects them against unemployment. The youngest group, ages 18–22, is less mobile across occupations due to lower skills and experience and because they perform a more narrow set of tasks, being thus more exposed to unemployment.

Equilibrium wages and employment are a result of supply and demand. The fall in the participation of routine occupations in total employment is consistent with a reduction in the (relative) supply and (relative) demand of workers that perform routine tasks. The reduction in relative supply occurs due to the increase in skills across cohorts. The reduction in demand occurs because of automation and worker substitution. These are forces that work in the same direction regarding employment but in opposite directions regarding wages. The decrease in wages among young workers in routine occupations validates the channel of the reduction in demand for routine jobs as a prevalent force and represents empirical evidence of automation replacing workers. At the same time, district level estimates show that average district wages do not fall, highlighting that there is mobility and reshuffling across occupations and that on average, workers that remain employed do not lose income to technology adoption. Our findings also show that the main margin of local labor market adjustment are quantities (employment) rather than prices (wages).

Second, worker characteristics are not static across cohorts. The cohort of young workers is on average more skilled than the cohort of older workers. This is good news for young workers as skills correlate with performing flexible tasks and with being able to work in a complementary manner with technology.

Along their career-path, the probability of young workers performing flexible tasks such as creative thinking and solving problems is increasing in age cohort; and it peaks around age 30 due to the cohort's increase in skills. The probability of performing flexible tasks of supervising and planning peaks around age 40, with career-path experience and tenure.

Young workers are easier to displace than older workers, other things equal, but as a cohort they are stronger in terms of skills and mobility. They have been switching proportionally more than older workers to jobs that involve flexible tasks. The most vulnerable workers, in the sense of having a higher probability of displacement, are young workers with low skills, a narrower set of alternatives, and low possibilities to perform flexible tasks.

Conclusion

We assess the impact of automation on labor market outcomes of young workers and examine whether the channel works through the routine task content of occupations, with routine occupations being more prone to automation. We find that young workers are more easily displaced than older workers with similar characteristics. Young workers in the age group 18-22 are more likely to be unemployed due to automation than other age groups, while young workers in the 23-29 age group are able to ameliorate the potential increase in unemployment by switching occupations. At the same time, cohorts of young workers are more skilled and more mobile than older workers, which implies that they have better prospects of working in complement with automation technology in the near future. The most vulnerable group of workers are young unskilled individuals.

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Appendix

Figure A1. Correlation of RTC indexes

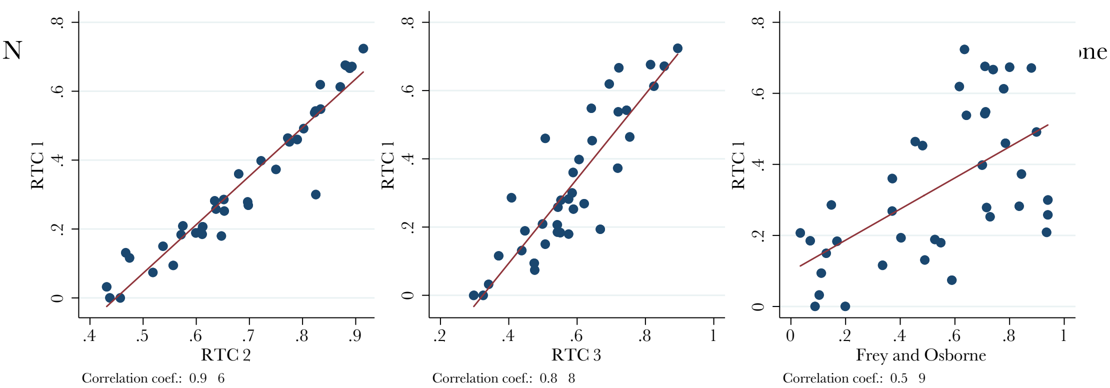


Figure A1 (continued). Correlation of RTC indexes

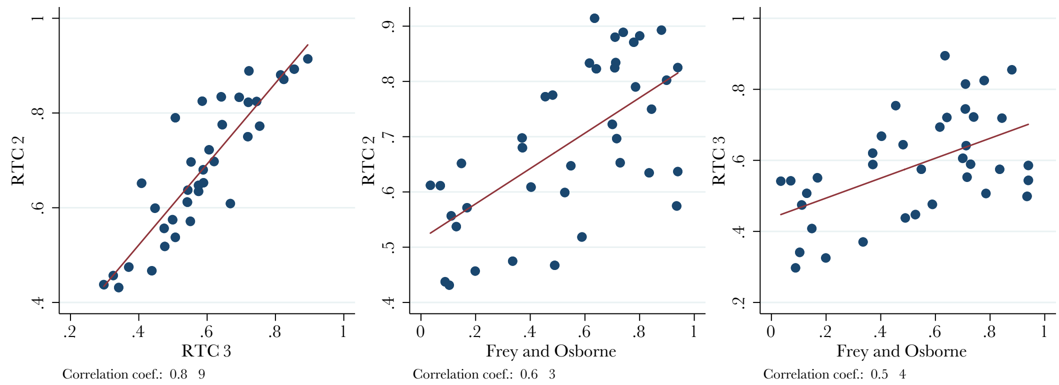
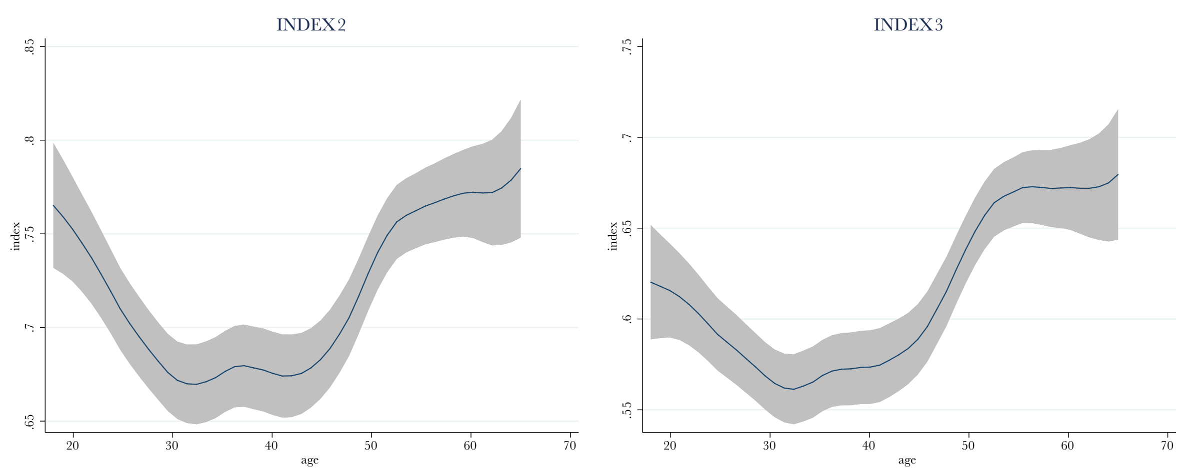


Figure A2. The risk of automation. Robustness from PIAAC



Notes: Own calculations from PIAAC survey. Local polynomial regressions. Dependent variable: individual-level index of content of tasks that are at risk of automation (Index2 and Index3). The dependent variable is defined as between 0 and 1 according to the number of non-routing tasks that individuals perform. In the left figure the non-routine tasks are planning, supervising others, solving problems, and producing written output. In the right panel, three more tasks are added: participating in sales, presentations or consulting, calculating prices, costs or budgets, and making math calculations.

Figure A3. The risk of automation. Robustness from CASEN

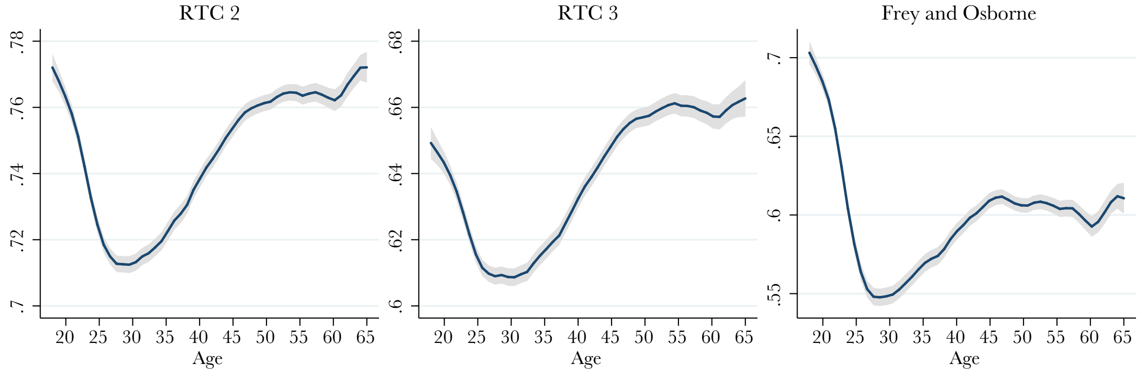
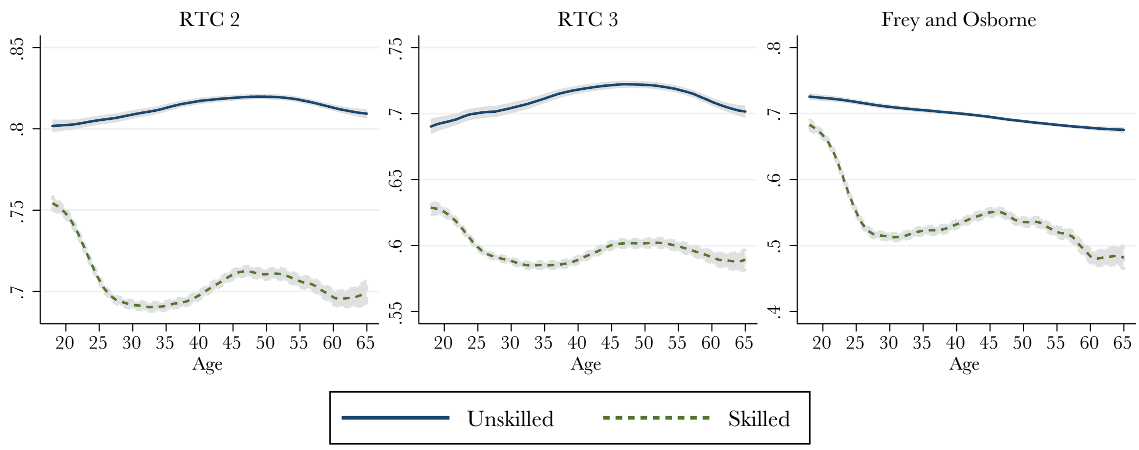


Figure A3 (continued). The risk of automation. Robustness from CASEN



Notes: Own calculations from CASEN survey and Frey and Osborne (2017). Local polynomial regressions. Dependent variable: routinization task index of occupation; definitions:$\boldsymbol{RTC_2}$, $\boldsymbol{RTC_3}$ and RTC of Frey and Osborne (2017).

Table A1. Classification of occupations ISCO 08 and RTC indexes

ISCO 08	Occupation	N	$\boldsymbol{RTC_1}$	$\boldsymbol{RTC_2}$	$\boldsymbol{RTC_3}$	Frey and Osborne
91	Cleaners and Helpers	210	0.72	0.91	0.89	0.63
61	Skilled Agr. Workers	71	0.68	0.88	0.81	0.71
63	Subsistence Farm./Fish.		0.67	0.88	0.79	0.80
92	Agricultural Labourers	70	0.67	0.89	0.86	0.88
62	Forestry/Fish. Workers	18	0.67	0.89	0.72	0.74
73	Handicraft Workers	21	0.62	0.83	0.69	0.62
96	Elementary Workers	31	0.61	0.87	0.82	0.78
75	Food Processing Workers	104	0.55	0.83	0.64	0.71
93	Labourers	94	0.54	0.82	0.74	0.71
83	Drivers/Mobile Operators	158	0.54	0.82	0.72	0.64
82	Assemblers		0.49	0.80	0.72	0.90
53	Personal Care Workers	112	0.46	0.77	0.75	0.46
52	Sales Workers	287	0.46	0.79	0.51	0.79
51	Personal Serv. Workers	128	0.45	0.78	0.64	0.48
71	Building Workers	108	0.40	0.72	0.61	0.70
81	Plant/Mach. Operators	59	0.37	0.75	0.72	0.84
34	Legal Assoc. Prof.	25	0.36	0.68	0.59	0.37
95	Street Sales Workers	10	0.30	0.82	0.59	0.94
14	Retail Managers	28	0.29	0.65	0.41	0.15
44	Clerical Workers	39	0.28	0.63	0.58	0.84
42	Customer Serv. Clerks	61	0.28	0.70	0.55	0.72
32	Health Assoc. Prof.	67	0.27	0.70	0.62	0.37

Table A1 (continued). Classification of occupations ISCO 08 and RTC indexes

ISCO 08	Occupation	N	RTC_1	RTC_2	RTC_3	Frey and Osborne
41	General Clerks	31	0.26	0.64	0.54	0.94
72	Metal/Machinery Workers	103	0.25	0.65	0.59	0.73
43	Recording Clerks	134	0.21	0.57	0.50	0.94
22	Health Professionals	29	0.21	0.61	0.54	0.03
54	Protect. Serv. Workers	62	0.19	0.61	0.67	0.40
33	Business Professionals	159	0.19	0.60	0.45	0.53
23	Teaching Professionals	119	0.18	0.61	0.54	0.07
26	Legal/Social Prof.	49	0.18	0.57	0.55	0.17
74	Electrical Workers	39	0.18	0.65	0.58	0.55
25	ICT Professionals	20	0.15	0.54	0.51	0.13
31	Sc./Engin. Assoc. Prof.	61	0.13	0.47	0.44	0.49
24	Business Prof.	69	0.12	0.47	0.37	0.34
21	Sc./Engin. Prof.	53	0.09	0.56	0.47	0.11
35	ICT Technicians	27	0.07	0.52	0.48	0.59
13	Production Managers	62	0.03	0.43	0.34	0.10
12	Administrative Managers	12	0.00	0.44	0.30	0.09
11	Chief Executives	29	0.00	0.46	0.33	0.20

Notes: Own calculations from PIAAC survey. Classification at 2 digits of disaggregation. Columns show the number of observations in the PIAAC survey and the four routine task content indexes. Indexes RTC1 to RTC3 are constructed from the PIAAC survey. The last column shows the index of Frey and Osborne. A higher index represents a higher content of routinization of the occupation. The indexes for occupations 63 and 92, which are missing in the PIAAC survey, were constructed as the weighted average of the indexes of occupations in the same first digit level of aggregation.